Estimating Output Gaps in Open Economies

presented by

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Originality Statement

This is to certify that the content of this thesis is my own work. This thesis has not been submitted for any other degree or purpose.

I certify that the intellectual content of this thesis is the product of my own work, and that all assistance received in preparing this thesis and all sources have been acknowledged.

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I designed the study, analyzed the data, and wrote the drafts of the Manuscript.

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As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

James Morley
March 2026

Generative AI

During the preparation of the thesis the author used Grammarly for the purposes of text enhancement. The use of this generative AI tool includes paraphrasing, sentence structure, spelling, etc. The author confirms that where text was modified by generative AI, the content was reviewed for possible errors, inaccuracies, and bias. The author takes full responsibility for the submitted thesis and ensures the work is their own and has used generative AI within the parameters of use.

Abstract

Estimating the output gap remains one of the most significant challenges for macroeconomic policy, particularly in environments characterized by limited data, reporting lags, and exposure to global shocks. This dissertation applies and extends the Beveridge-Nelson (BN) decomposition framework across three chapters to provide more reliable, informative, and timely indicators of economic slack for emerging Asian economies and Australia. Broadly, these chapters demonstrate that traditional filters and slack measures are often inadequate in these contexts, whereas multivariate and mixed-frequency BN frameworks offer improvements for real-time policy decision-making.

In the first chapter, I show that the BN filter provides more reliable and informative estimates for emerging Asian economies than commonly used filters such as the Hodrick-Prescott, Christiano-Fitzgerald, and Hamilton methods. I document that cyclical consumption is more volatile than the output gap and that less than one-third of GDP growth fluctuations are driven by trend growth shocks, contrasting with the view that the "cycle is the trend." Crucially, BN estimates are subject to smaller and less frequent revisions during large changes in economic conditions.

The second chapter reveals that while traditional slack measures are largely uninformative for Southeast Asian economies due to structural issues and informal employment, financial and external variables are highly relevant. Financial factors were particularly dominant during the Asian and Global Financial Crises, with external variables often explaining a larger share of cyclical fluctuations than domestic output.

The third chapter applies a mixed-frequency framework to the Australian economy and finds that the intensive margin of the labor market, aggregate hours worked, provides a more significant informational contribution than the headline unemployment rate. Furthermore, the Trade Weighted Index (TWI) provides informational value nearly equivalent to the entire financial or macroeconomic sectors combined. While domestic shocks drive most Australian fluctuations, the Global Financial Crisis was largely attributable to foreign shocks. Finally, while a weekly TWI indicator allows for more timely updates, it does not lead to an improvement in the accuracy of nowcasts compared to a monthly frequency.

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In some ways, this section of my thesis is the hardest to write, and also the most important. This is because the work within these pages was only made possible through the collective support and encouragement of many people

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Finally, to our little boy, Ariel, whose not-so-gentle kicks have reminded me I haven't been alone in the final months of this thesis. I hope that I have made you proud.

For Alexei and Ariel

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Introductory Chapter

This dissertation investigates the measurement and drivers of economic slack in small open economies. Estimating the output gap—the deviation of actual output from its potential level—remains one of the most significant challenges for macroeconomic policy, particularly in environments characterized by limited data, structural shifts, and exposure to global shocks. Across these three chapters, the research applies and extends the Beveridge-Nelson (BN) decomposition framework to develop more reliable and informative, real-time indicators of the business cycle that can better inform central bank policy.

In Chapter 1, I discuss how estimating output gaps is challenging for emerging Asian economies due to limited data availability and the potential effects of outliers. I then apply the Beveridge-Nelson (BN) filter, comparing it with commonly used filters—Hodrick-Prescott (HP), Christiano-Fitzgerald (CF), and Hamilton—across four small open Asian economies of Indonesia, Malaysia, Thailand, and the Philippines. The methodology involves benchmarking BN filter output gap estimates against narrower indicators of slack, such as capacity utilization and unemployment, while giving consideration to longer data coverage and controlling for long-run structural changes. Furthermore, I document two systematic results for these economies regarding the volatility of cyclical consumption and the decomposition of GDP growth volatility to determine the extent to which growth fluctuations are accounted for by movements in trend growth versus the cyclical component. I find that cyclical consumption is more volatile than the output gap and that less than one-third of GDP growth fluctuations are driven by trend growth shocks, contrasting with the view in Aguiar and Gopinath (2007) that the "cycle is the trend." Finally, I find that BN estimates are subject to smaller and less frequent revisions during large changes in economic conditions.

In Chapter 2, I talk about how despite the importance of the output gap for guiding macroeconomic policy, little is known about how financial and global factors influence output gap dynamics in small open Asian economies. To address this, I estimate output gaps for the Southeast Asian emerging economies of Indonesia, Malaysia, Thailand, and the Philippines using a multivariate BN decomposition within a Bayesian vector autoregression framework. The model incorporates a range of macroeconomic indicators using an open-economy assumption by including block-exogenous foreign sector variables, imposes an alternative Minnesota prior to avoid an "upward bias" in the signal-to-noise ratio, and accounts for outlier observations that affect emerging economies, including during the pandemic. Through this framework, I investigate the informativeness of traditional slack measures, the role of financial variables during the Asian and Global Financial Crisis, and the extent to which external variables explain cyclical fluctuations relative to domestic output.

In Chapter 3, I address how economic indicators inform the assessment of economic slack for central banks, even as traditional output gap estimates are often limited by the substantial reporting lags of quarterly GDP. To overcome these limitations, this chapter extends a mixed-frequency Bayesian vector autoregressive (MF-BVAR) framework to a small open economy setting appropriate for Australia when applying a multivariate BN decomposition. Compared to existing applications to the US economy, the modeling setup introduces three distinct contributions: the incorporation of a block-exogenous foreign sector, explicit accounting for COVID-19 outliers, and the integration of a weekly indicator. I utilize informational decomposition results to analyze the contribution of every variable in the model, specifically comparing the Trade Weighted Index (TWI) and foreign variables against domestic indicators. I also examine the informational contribution of the intensive margin of the Australian labour market, such as aggregate hours worked, versus the extensive margin, such as the headline unemployment rate. Through sectoral aggregation and shock decompositions, I evaluate the primary sources of information for the output gap and the drivers of cyclical fluctuations, while testing whether the integration of a weekly TWI indicator allows for more timely and improved estimates. The results indicate that foreign variables and the TWI provide important information for the output gap estimate, with aggregate hours worked proving more informative than the headline unemployment rate. While domestic shocks drive most fluctuations, foreign shocks were the primary driver during the Global Financial Crisis. Finally, the inclusion of a weekly TWI indicator allows for more timely updates but does not improve estimate accuracy of the nowcast compared to a monthly frequency.

Chapter 1

Reliable Output Gap Estimates for Emerging Asian Economies[1]

1.1 Introduction

Trend-cycle decomposition of real GDP is important for policymaking, as it provides insights into the economic slack, or the "output gap," relative to the economy's potential. However, the output gap is unobserved and must be estimated, which poses challenges for emerging market economies (EMEs) due to shorter data availability and the potential impact of outliers (Perron and Wada, 2009). Accurate output gap estimates are essential for informing monetary and fiscal policy, especially for determining the appropriate policy stance. Unlike advanced economies, which have standardized output gap estimates provided by institutions such as the Congressional Budget Office (CBO) or the Centre for Economic Policy Research (CEPR), EMEs in Southeast Asia lack such official benchmarks, making it particularly challenging for policymakers to accurately assess economic conditions and respond effectively. As a result, despite various criticisms (Harvey and Jaeger, 1993; Cogley and Nason, 1995; Hamilton, 2018) against the Hodrick and Prescott (1997) (HP) filter, it remains extensively employed in macroeconomic analysis, notably in estimating output gaps and analyzing business cycles in emerging Asian economies (Gerlach and Yiu, 2004; Peng et al., 2006; Li and Kwok, 2009; Malik et al., 2023).

In this chapter, I apply the Beveridge-Nelson (BN) filter (Kamber, Morley, et al., 2018) to four emerging Asian economies — Indonesia, Malaysia, Thailand, and the Philippines — to evaluate whether it provides more reliable and informative output gap estimates in a real-time setting compared to those derived from the HP filter and some other popular methods of trend-cycle decomposition. The BN filter is attractive because it allows for a stochastic trend in real GDP and is well-suited for structural breaks in the long-run growth rate, which are common in EMEs. This approach aims to address some of the known deficiencies of other methods, including the risk of spurious cycles and the difficulty of handling large economic shocks. In

[1]This chapter is an extended version of the published article: De Gorostiza-Roudnitski, G. Reliable Output Gap Estimates for Emerging Asian Economies. *J Bus Cycle Res* (2026). https://doi.org/10.1007/s41549-026-00122-9

addition, I employ the modifications proposed by Kamber, Morley, et al. (2025) to account for distortions from large shocks, such as the pandemic, including by using a trend-smoothness loss function to determine the signal-to-noise ratio when detrending.

By applying the BN filter to quarterly log real GDP for emerging Asian economies, I find that the BN filter effectively captures changes in trends and cycles around crisis periods. The modified HP filter recommended by Phillips and Shi (2021), in contrast, appears to over-smooth the trend growth ex-post and frequently suggests large positive output gaps before crises. I also consider the Christiano and Fitzgerald (2003) (CF) bandpass filter and the modified Hamilton filter due to Quast and Wolters (2022) to provide a broader comparison. The CF filter exhibits lower amplitude in estimated cycles, which may understate the magnitude of business cycle fluctuations. Meanwhile, the Hamilton filter captures trend growth movements with a substantial delay, often implying strong trend growth for several quarters post-crisis, possibly overstating the magnitude of output gaps after economic contractions. More broadly, my results reinforce a traditional view that, while structural changes characterize trend growth in these economies, transitory shocks, rather than permanent shifts in trend growth, are the dominant drivers of economic fluctuations, challenging the "cycle is the trend" notion from Aguiar and Gopinath (2007) that trend shocks primarily govern growth dynamics in emerging markets.

Economic slack implies that an economy can grow rapidly without necessarily experiencing slower subsequent growth. Consequently, evaluating output gap estimates as indicators of slack is essential, particularly in emerging Asian economies. Comparisons with narrower measures of slack—specifically, capacity utilization and unemployment—reveal strong positive correlations for capacity utilization and, with the notable exception of Indonesia, significant negative correlations for unemployment. Data limitations for Indonesia mean unemployment likely captures structural rather than cyclical elements, raising concerns about using unemployment-based measures in such contexts. While prior work by Barbarino et al. (2024) and others finds that incorporating unemployment data enhances real-time trend growth estimation in the United States, my findings suggest that shorter sample spans, the prevalence of the informal employment, and labor market shifts diminish the cyclical informativeness of unemployment measures in emerging Asian economies. Although potentially useful, capacity utilization is also affected by similar limitations. Moreover, survey-based information is often unavailable for sufficiently long time horizons for these economies, limiting its applicability. Thus, the BN filter output gaps emerge as a more informative business cycle indicator in this setting, given their longer data coverage and emphasis on controlling for long-run structural changes.

My estimates also reveal stronger correlations between the cyclical components of output and consumption within emerging Asian economies compared to the United States, consistent with the presence of more significant credit or liquidity constraints rather than behaving like the permanent income hypothesis (Hall, 1978). A key finding is that cyclical consumption for these economies are more volatile in comparison to the estimated output gap, providing a new interpretation for what has been found for growth rates by Aguiar and Gopinath (2007) than the notion that the "cycle is the trend".

To evaluate how well different filters adjust for structural breaks and outliers in emerging economies, I use a case study for Indonesia by extending its GDP series with forecasted data through 2055, introducing a simulated Asian Financial Crisis (AFC) like shock in 2038Q3. The shock combines a permanent downward shift in trend output and a large temporary decline in the output gap. Comparing the BN, HP, CF, and Hamilton filters shows that the BN filter accurately captures both the permanent and transitory components of the shock. It closely follows the true trend before and after the event. In contrast, the HP filter smooths excessively in the lead-up to the shock, generates spurious positive output gaps, and imposes a gradual rather than abrupt trend adjustment. The CF filter produces volatile trend estimates, which reduces the estimated amplitude of business cycle fluctuations and leads to an underestimation of simulated shock magnitudes. The Hamilton filter exhibits persistence in its trend estimates, reacting with a lag, amplifying the initial shock, and adjusting its trend only well after the event. This can overstate output gaps following economic contractions, making it less suitable for real-time business cycle monitoring and policy formulation, particularly in emerging economies.

Lastly, to address the critique by Orphanides and van Norden (2002) regarding the unreliability of many output gap estimates, I assess the BN filter's revision properties specifically in the context of emerging economies. Compared to the HP filter, the BN filter has smaller and less frequent revisions. This reliability is further demonstrated in pseudo-real-time conditions, where the BN filter accurately predicts the sign of the output gap more than 90% of the time. This is because the BN filter works alongside parsimonious AR models, making it much more reliable than other detrending methods.

The rest of this chapter is structured as follows: Section 1.2 describes the data used, the BN decomposition and the BN filter. Section 1.3 presents the decomposition results for each emerging Asian economy, comparing the BN filter estimates to other popular methods of trend-cycle decompostion, followed by a comparison of output gap estimates with narrower indicators in Section 1.4. Section 1.5 examines cyclical movements and international linkages. Sections 1.6 and 1.7 assess the response to shocks and the stability of output gap estimates, respectively, and finally, Section 1.8 concludes.

1.2 Data and Methods

1.2.1 Data

Real GDP is used to capture macroeconomic patterns in an economy. The dataset includes quarterly data on output and consumption for Indonesia, Malaysia, the Philippines, and Thailand from 1993:Q1 to 2022:Q4, totaling 116 observations. To avoid the impact of COVID-19 outliers, the main analysis focuses on data up to 2019:Q4, with robustness checks including data up to 2022:Q4. A comparative analysis with similar data for the United States is also provided. Prior to detrending, series with multiple base years are spliced using the latest base year for the level, and seasonal adjustments are applied where necessary. The X-13-Arima-SEATS methodology is used for seasonal adjustment in Indonesia and Malaysia, while official

Table 1.1: Real Gross Domestic Product and Consumption

Country	Base Year (period)	Source
Indonesia	1993 (Q1 1993–Q4 2003)	Statistics Indonesia (BPS)
	2000 (Q1 2000–Q4 2014)	
	2010 (Q1 2010–Q4 2022)	
Malaysia	1987 (Q1 1991–Q4 2006)	Department of Statistics Malaysia (DOSM)
	2000 (Q1 2000–Q4 2011)	
	2005 (Q1 2005–Q4 2014)	
	2010 (Q1 2010–Q4 2022)	
Philippines	1985 (Q3 1989–Q4 2010)	Philippine Statistics Authority (PSA)
	2000 (Q1 1998–Q4 2022)	
Thailand	2002 (Q1 1993–Q4 2022)	National Economic and Social Development Council
USA	2012 (Q1 1993–Q4 2022)	Federal Reserve Bank of St. Louis (FRED)

seasonally adjusted data are used for the Philippines, Thailand, and the United States. For Malaysia, seasonally adjusted data are available only from Q1 2005, so the unadjusted series from Q1 1993 is seasonally adjusted using the X-13 filter. Table 1.1 shows the availability of data for GDP and Private Consumption.

1.2.2 Methods

A widely held belief among economists is that transitory movements in the log of real GDP should exhibit large amplitude and persistent behavior, increasing during expansions and decreasing during recessions. In this context, a detrending method yielding small and noisy cycles is considered counterintuitive (Kamber, Morley, et al., 2018). When analyzing GDP growth, standard ARMA model selection typically retains low-order AR variants with positive serial correlation, resulting in high signal-to-noise ratios. By contrast, detrending filters that impose low signal-to-noise ratios, such as deterministic quadratic detrending, the HP filter, and band-pass filters, do produce intuitive estimates but frequently undergo substantial estimation revisions as new data becomes available, and they are often less reliable for out-of-sample forecasts (Orphanides and van Norden, 2002).

Beveridge-Nelson (BN) filter

Following Beveridge and Nelson (1981), any nonstationary $I(1)$ time series Y_t can be decomposed into two components such that:

$$y_t = \tau_t + c_t \tag{1.1}$$

τ_t is the trend component or the long-horizon conditional forecast minus any deterministic drift of a time series, which is given by:

$$\tau_t = \lim_{h\to\infty} \mathbb{E}_t(y_{t+h} - h\mu) \quad \text{where} \quad \mu = \mathbb{E}_t(\Delta y_t) \tag{1.2}$$

Since y_t is an $I(1)$ process, the first difference of the series is stationary. The cyclical component c_t is the deviation of the underlying process from its long-horizon forecast. At the same time, the deviation from the unconditional mean is defined as

$\Delta\tilde{y}_t \equiv (\Delta y_t - \mu)$. The BN decomposition is equivalent to the filtered estimate using the Kalman filter for an equivalent forecasting model, meaning that the estimate is optimal in a minimum mean squared error sense given information up to time t (Morley, Nelson, et al., 2003). By this premise, the BN decomposition should provide intuitive output gap estimates.

While the BN decomposition avoids spurious cycles given unbiased forecasts and is not subject to significant revisions being a one-sided filter, it often produces a counterintuitive output gap that lacks persistence and amplitude. Kamber, Morley, et al. (2018) apply a restricted BN decomposition (henceforth the BN filter) that imposes a low signal-to-noise ratio to reconcile these differences. The signal-to-noise ratio is given by

$$\delta = \frac{1}{(1-\rho(1))^2} \quad \text{where} \quad \rho(1) = \rho_1 + \ldots + \rho_p \tag{1.3}$$

In the case of an AR(p) model of output growth, $\rho(1) < 1$, which implies $\delta > 1$. Thus, the trend will be more volatile than the cycle, which is inconsistent if one expects cyclical shocks explain most of the systematic forecast variance. The signal-to-noise ratio δ can be restricted by first determining restricted estimates of the AR coefficients by inverting the Dickey-Fuller transformation, and then calculating the BN cycle based on these estimates following (Kamber, Morley, et al., 2025). The underlying idea is that the BN filter fixes a low value to the signal-to-noise ratio (i.e., $\delta = \bar{\delta}$), while the autoregressive coefficients for the transformed version of the AR model are fitted by utilizing a "Minnesota" type shrinkage prior.

In light of significant macroeconomic disruptions, such as those experienced during the AFC or the COVID-19 pandemic, I follow the refinements to the BN filter proposed by Kamber, Morley, et al. (2025) to address potential distortions from large shock using a trend-smoothness loss function to determine the optimal signal-to-noise ratio when detrending. Building on the approach of Kamber, Morley, et al. (2025), I select the δ to minimize the volatility of shocks to the stochastic trend rather than maximizing the amplitude-to-noise ratio. This selection process is guided by the loss function that minimizes the variance of the change in trend given by:

$$\min_{\delta \in \mathbb{R}^+} \sigma^2_{\Delta\tau}(\delta) \tag{1.4}$$

where the δ is strictly positive given a finite-order AR model (Kamber, Morley, et al., 2025). This approach allows for the model to capture larger economic cycles that policy makers often expect to see, despite potentially reducing the exact fit of the model to the data (Kamber, Morley, et al., 2025). Following this, the BN decomposition is derived from an AR model, wherein the AR coefficients are constrained to sum to:

$$\bar{\rho}(1) = 1 - \frac{1}{\sqrt{\bar{\delta}}} \tag{1.5}$$

The BN filter is potentially a suitable approach for estimating the output gap, especially in Emerging Asian economies where the estimation is not always straightforward. This method is not only easy to implement but also more efficient than relying on observable multivariate data or MA terms. Moreover, it provides a straightforward procedure for constructing time-varying uncertainty bands around the estimated cycle, allowing the degree of estimation uncertainty to adjust over time as conditional volatility changes (Kamber, Morley, et al., 2025). Furthermore, subsequent studies by Barbarino et al. (2024), Jönsson (2024), and Kuang et al. (2024) find that the BN filter is less subject to revisions and provides reliable real-time estimates than other methods.

Alternative filters for comparison

To benchmark the performance of the BN filter, I employ three alternative detrending methods: the boosted Hodrick–Prescott (HP) filter of Phillips and Shi (2021), the refined Hamilton filter of Quast and Wolters (2022), and the Christiano–Fitzgerald (CF) filter of Christiano and Fitzgerald (2003).[2] Each of these methods represents an improved or modified version of standard approaches, chosen to address known weaknesses such as excessive smoothing, endpoint bias, and spurious high-frequency fluctuations. These refinements ensure that comparisons with the BN-based estimates reflect differences in methodology rather than suboptimal parameterization. [3]

The **boosted HP filter (HP)** improves upon the standard HP filter by recursively applying the filter to the residuals obtained from previous iterations, progressively refining the extracted trend. The number of iterations m acts as a tuning parameter that controls the intensity of the updating and is selected by minimizing the information criterion proposed by the authors. I set the smoothing parameter to the conventional quarterly value $\lambda = 1600$, following standard practice for output gap estimation.

The **Hamilton filter**, originally proposed by Hamilton (2018), estimates the trend as an h-step-ahead forecast of GDP obtained by regressing GDP at $t + h$ on its p lagged values, with the residual representing the cyclical component. I adopt the refinement of Quast and Wolters (2022), which modifies the regression structure and employs rolling estimation windows to reduce spurious cycles and improve real-time performance. Consistent with their recommendations for quarterly macroeconomic data, I set $h = 8$ and $p = 4$.

The **Christiano–Fitzgerald (CF) filter** is a band-pass filter that isolates fluctuations corresponding to typical business-cycle frequencies.[4] It is the most similar

[2] While a number of other methods have also been advanced, including the Butterworth filter as suggested by Canova (2025), who shows that standard statistical filters, such as the HP and Hamilton filters, often distort the theoretical frequency properties of the output gap, whereas polynomial and Butterworth filters can more closely replicate model-consistent cyclical dynamics, consideration of such a broad range of filters is beyond the scope of this chapter. Thus, I only focus on the widely used methods in practice.

[3] The boosted HP and refined Hamilton filters are implemented using the replication codes provided by Phillips and Shi (2021) and Quast and Wolters (2022), respectively.

[4] The CF filter is applied using the `cffilter` function in MATLAB, with settings corresponding to the symmetric band-pass specification described in Christiano and Fitzgerald (2003). One reason the CF filter's trend component appears more volatile than those obtained from other filters is that

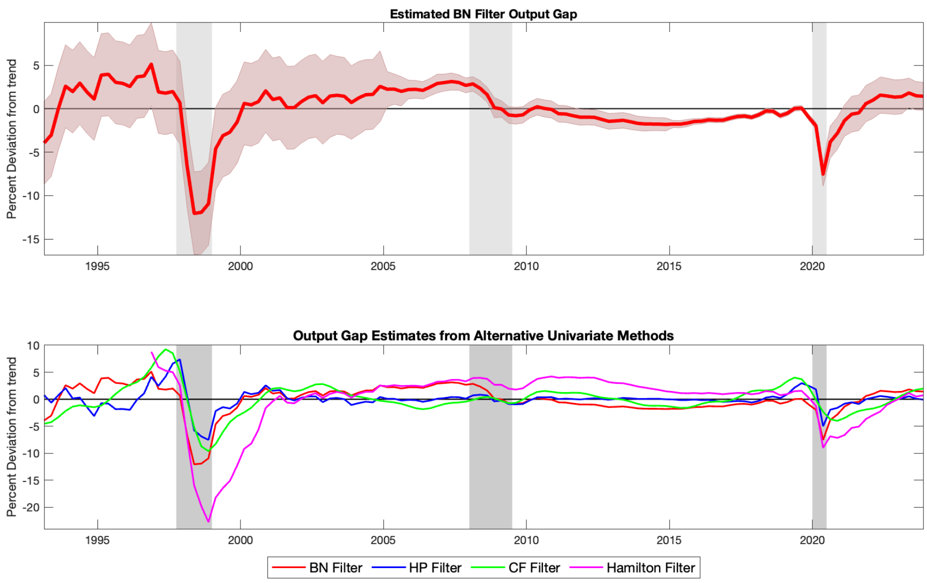
to the Butterworth filter and sometimes outperforms it in the simulated DSGE environment in Canova (2025), specifically in terms of RMSE at low frequencies. I apply the symmetric version of the CF filter with periodicities between 6 and 32 quarters, a standard choice that captures medium-term cyclical movements while minimizing phase distortion.

Overall, these refined filters are implemented with reasonable and replicable parameterizations designed to extract business fluctuations.

1.3 Decomposition Results

1.3.1 Indonesia

Figure 1.1: Estimated Output Gaps for Indonesia.

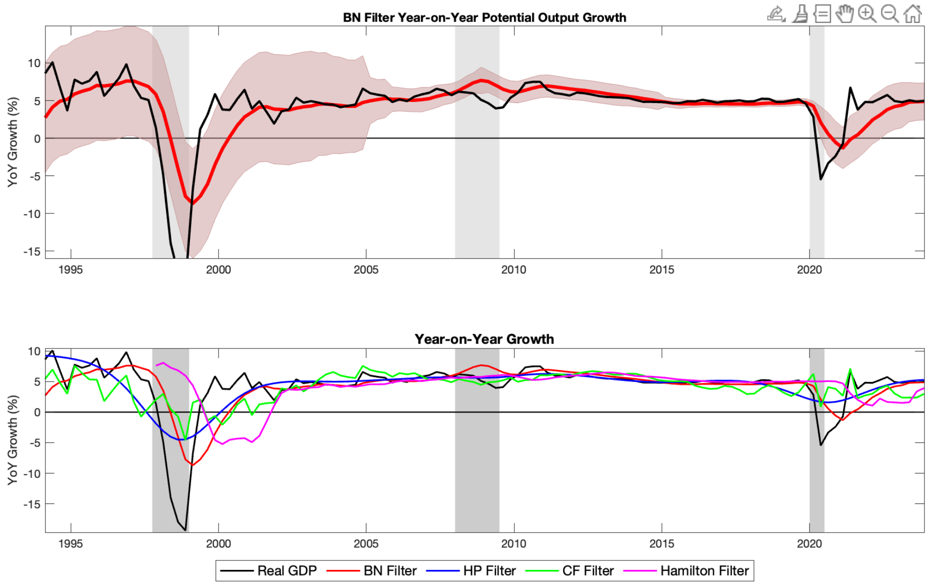


Note: Units are 100 times natural log deviation from trend. Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates.

As seen in Figures 1.1 and 1.2, the BN filter output gap and trend growth (year-on-year growth rate) for Indonesia highlight sharp downturns during the AFC. The early 1990s show a positive output gap at around 5%, indicating strong economic activity. From 1997–1998, trend growth declines sharply. It took a couple of years post AFC, for trend growth to recover. In contrast, the HP filter produces a smoother estimate of trend growth with a more moderate decline during the AFC. The CF filter exhibits more volatile trend growth, particularly in pre-crisis estimates. While it captures the AFC-related contraction, it implies early fluctuations, showing a small decline before the crisis and a faster recovery afterward. The Hamilton filter adjusts more slowly as the estimated trend growth stays elevated into the crisis

it isolates only the medium-frequency components associated with the business cycle, effectively grouping low- and high-frequency movements together in the cyclical component.

Figure 1.2: Estimated Year-on-Year Growth of Trend Output for Indonesia.



Note: Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates

and only drops with a delay. The CF-based output gap remains relatively muted, with smaller amplitude deviations than other filters. This aligns with previous findings that the CF filter tends to smooth cyclical fluctuations (Christiano and Fitzgerald, 2003). The Hamilton filter, in contrast, reacts more gradually to the AFC shock. This delay results in a longer period of positive output gap estimates after the crisis. Post-crisis, the Hamilton filter continues to indicate a large positive output gap, consistent with the delayed correction pattern noted by Kamber, Morley, et al. (2025), with the approach producing sharp reversals following major shocks.

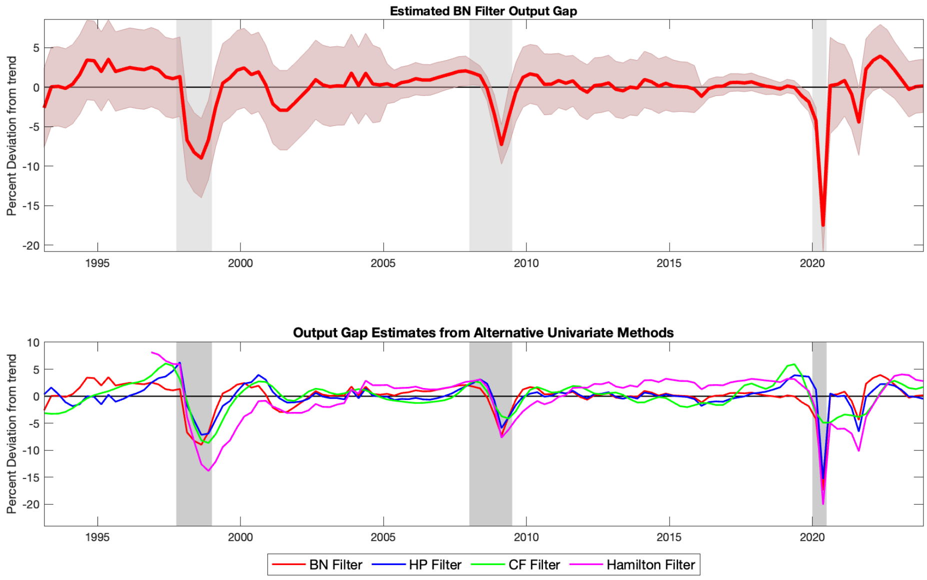
During the Global Financial Crisis (GFC), all filters show only a mild and temporary decline in trend growth. The BN trend growth rate remains positive, dipping only slightly, and then stabilizing. The HP, CF, and Hamilton filters behave similarly. There is no sharp fall in estimated trend growth as in the AFC This is consistent with the view that Indonesia's financial sector was less exposed to toxic assets, and accords with Frankel and Saravelos (2012), who find that emerging markets, including Indonesia, were less affected by the GFC than advanced economies. Output gap estimates for all filters remain positive, with HP and CF output gap estimates close to zero.

During the COVID-19 pandemic, all filters indicate a drop in trend growth, though with differing magnitudes. The BN filter captures a sharp decline in trend growth, while the HP filter shows a smoother decline even prior to the pandemic. The CF filters also implies a decline in trend growth, but the estimated contraction is smaller in magnitude and reverses faster. The Hamilton filter trend growth remained positive during the pandemic and only decelerated after 2 years. All filters suggest a large negative output gap, though the Hamilton filter implies that recovery was slower for

Indonesia.

1.3.2 Malaysia

Figure 1.3: Estimated Output Gaps for Malaysia.

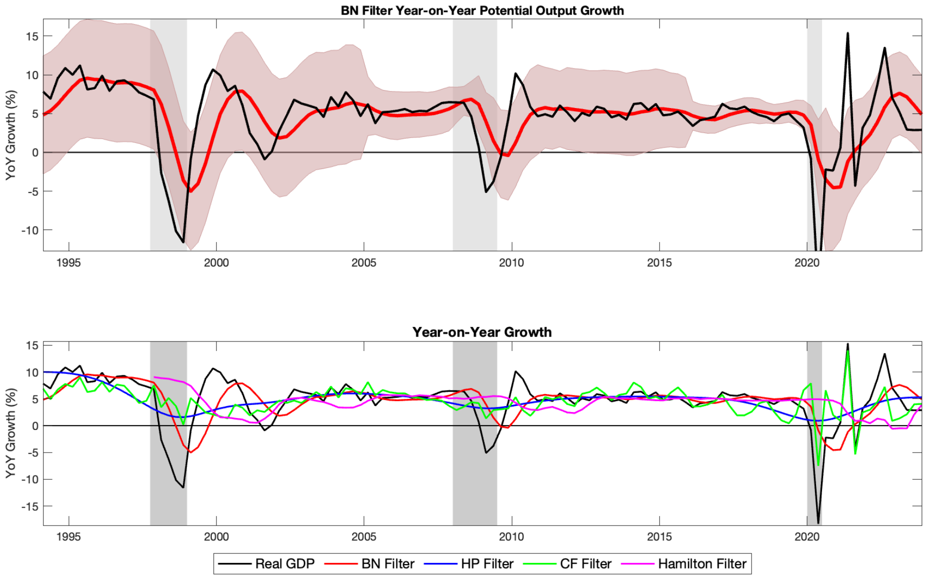


Note: Units are 100 times natural log deviation from trend. Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates.

For Malaysia during the AFC, Figure 1.3 shows that all filters imply a significant and persistent negative output gap, with the Hamilton filter implying a more negative output gap and that recovery after the AFC is slower as its estimate remains negative until 2004. Figure 1.4 shows that all filter estimates display a reduction in Malaysia's trend growth. The BN filter indicates a steep drop in potential output growth, moving from high positive rates before the crisis to -5% at the trough. The confidence band around the BN estimate also widens substantially in this period, indicating elevated uncertainty around potential growth. This suggests long-term structural damage, consistent with studies highlighting the impact of financial contagion on capital flows and investment, ultimately affecting productivity and growth (Kim and Roubini, 2000). The HP and CF filters also register a fall in trend growth during the AFC, but they remain less extreme: they decline more gradually and either stay closer to zero or recover earlier. The Hamilton filter maintains elevated trend growth for several quarters, including positive trend growth even as actual output declines.

During the GFC, all filters identify a negative output gap, but unlike what was observed for the AFC, there is a quicker post-crisis rebound with smaller amplitude fluctuations. The fall in trend growth is more muted during the GFC. The BN filter again shows a decline in potential output growth close to zero, but the drop is not as deep as during the AFC. The HP, CF, and Hamilton filters also show a slowdown in trend growth at this time, but the adjustment is modest and largely remains more positive compared to BN filter estimates. Taken together, the estimates suggest

Figure 1.4: Estimated Year-on-Year Growth of Trend Output for Malaysia.



Note: Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates

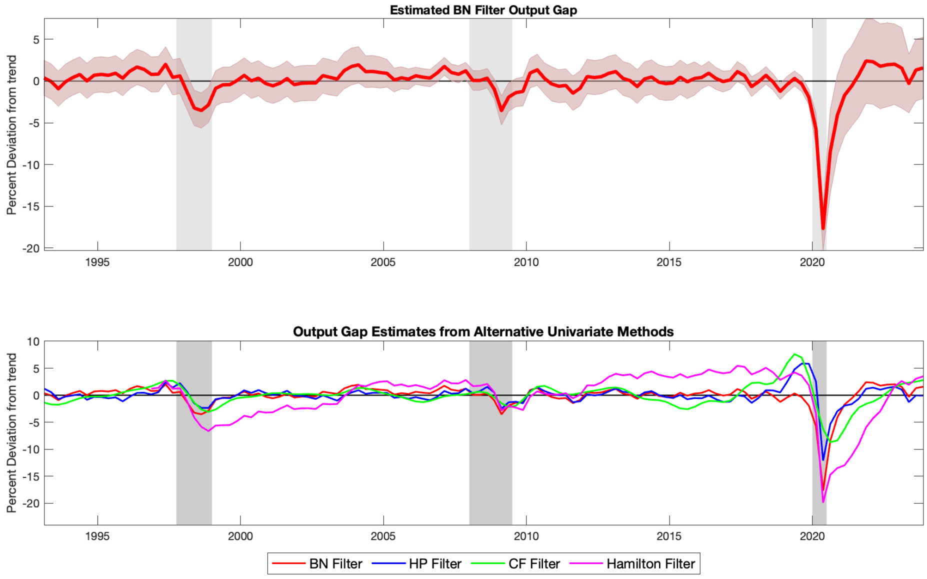
that the GFC is associated with a temporary slowdown in Malaysia rather than a persistent contraction in underlying growth.

The COVID-19 crisis resulted in another negative output gap, with the BN and HP filters suggesting a 17% deviation from trend output. The CF filter follows the overall contraction pattern but shows a smaller amplitude, indicating a milder estimated contraction relative to the BN and HP filters. As seen in previous crises, the Hamilton filter implies a more negative output gap and slower post-pandemic recovery. All filters show a sharp deterioration in trend growth. The BN filter estimates a sudden drop, comparable in size to the AFC. The bands widen significantly, reflecting high uncertainty. The CF filter shows an abrupt decrease in trend growth into negative territory, followed by a strong rebound. The HP filter likewise implies a deceleration in trend growth again although it adjusts more slowly. The Hamilton filter implies that trend growth in Malaysia during the COVID-19 period only fell after approximately 8 quarters after 2020.

1.3.3 Philippines

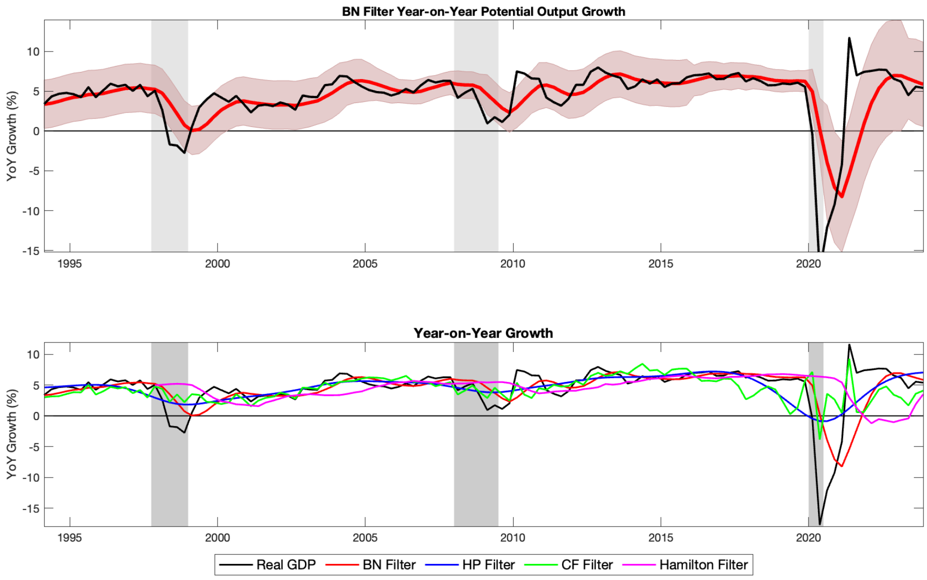
Figures 1.5 and 1.6 show that the BN filter estimates suggest that the Philippine economy was operating near potential before the AFC, with no major signs of overheating. However, in 1998, the filter captures a negative output gap of 0.4%, reflecting a brief but sharp contraction, although not as severe for what was observed for Indonesia and Malaysia above. The HP and CF filter each register a slowdown in growth during this period but generally stay positive or hover near zero rather than turning strongly negative. In contrast, Hamilton filter estimate of trend growth remains positive during the AFC. All other filters show the Philippine economy

Figure 1.5: Estimated Output Gaps for Philippines.



Note: Units are 100 times natural log deviation from trend. Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates.

Figure 1.6: Estimated Year-on-Year Growth of Trend Output for Philippines.



Note: Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates.

experienced a negative output gap during the AFC albeit with a quicker recovery. The Hamilton filter presents a different trajectory, as it implies a persistently negative output gap from 1998 until 2005, suggesting that the Philippine economy operated below potential for an extended period following the AFC.

During the GFC, the BN filter identifies a small negative output gap, indicating that the downturn was transitory with minimal impact on long-term trend growth. The resilience of the Philippine economy during this period is attributed to strong remittance inflows and conservative banking policies, which helped cushion external shocks (Yang and Choi, 2007). The HP and CF filter output gap estimates follows a similar path and showing only a modest decline in trend growth, remaining positive during the crisis. The Hamilton filter again shows a delayed recognition of the slowdown, initially maintaining a positive trend growth before adjusting a few quarters later.

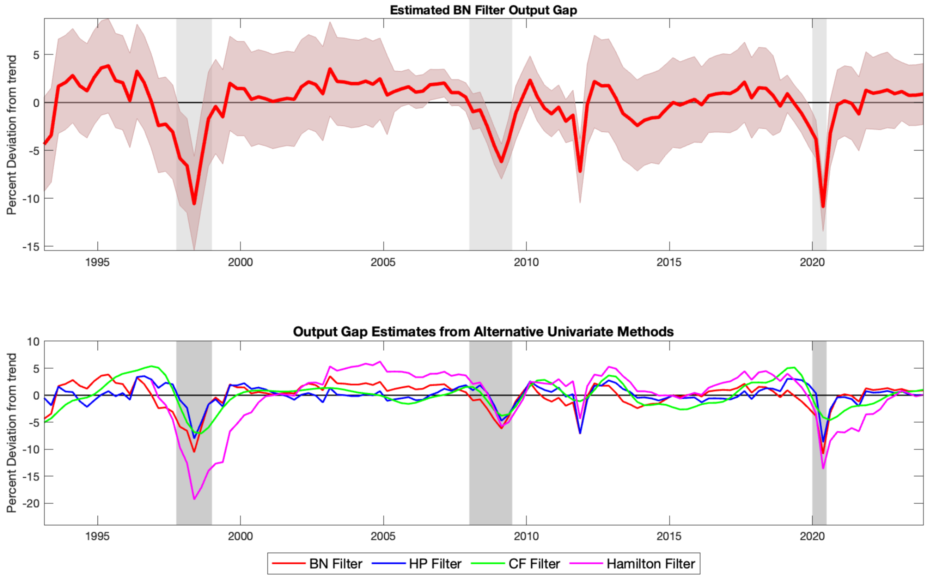
The COVID-19 crisis caused the most severe economic disruption in the observed period for the Philippines, leading to sharp declines in actual and trend output growth. The BN filter captures a negative output gap of 19%, reflecting significant and lasting effects on productive capacity. The HP filter also shows a large negative output gap but with a more moderate deceleration in trend growth. Prior to the pandemic, the HP filter produces a positive output gap of around 5%, indicating stronger activity before the downturn. The CF filter captures the abrupt decline in trend output but with a smaller negative output gap than the other filters, suggesting a milder estimated contraction. Finally, the Hamilton filter estimates again responds with a lag, initially implying higher trend growth and a positive output gap just before the pandemic.

1.3.4 Thailand

In the early 1990s, Thailand's economy steadily grew. As noted by Gerlach and Yiu (2004), many Southeast Asian economies appeared to experienced a cyclical boom before the AFC. However, during the AFC, Thailand faced a significant contraction following speculative attacks on the baht, which led to a liquidity crisis. Figure 1.7 shows the BN filter a negative output gap reaching -12% and captures this downturn with a marked decline in trend growth as seen in Figure 1.8. The HP filter also reflects a negative gap, although slightly less negative than BN filter estimates. The BN filter estimates indicate that the AFC was followed by a decline in Thailand's trend growth. Like the HP filter, the CF filter suggests that the AFC coincided with a gradual, and much less negative drop in trend growth compared to the BN filter estimates. However, unlike the BN filter, the CF filter produces a more variable trend, particularly around the AFC period. The output gap estimated by the CF filter shows a positive gap before the AFC, followed by a downturn. The amplitude of this decline is relatively small and smoother compared to what the other filters imply. Meanwhile, the Hamilton filter captures the crisis with a lag of several quarters. The output gap from the Hamilton filter during the AFC is large at -19.6%, followed by a recovery late in 2001, after which it remains positive until the GFC.

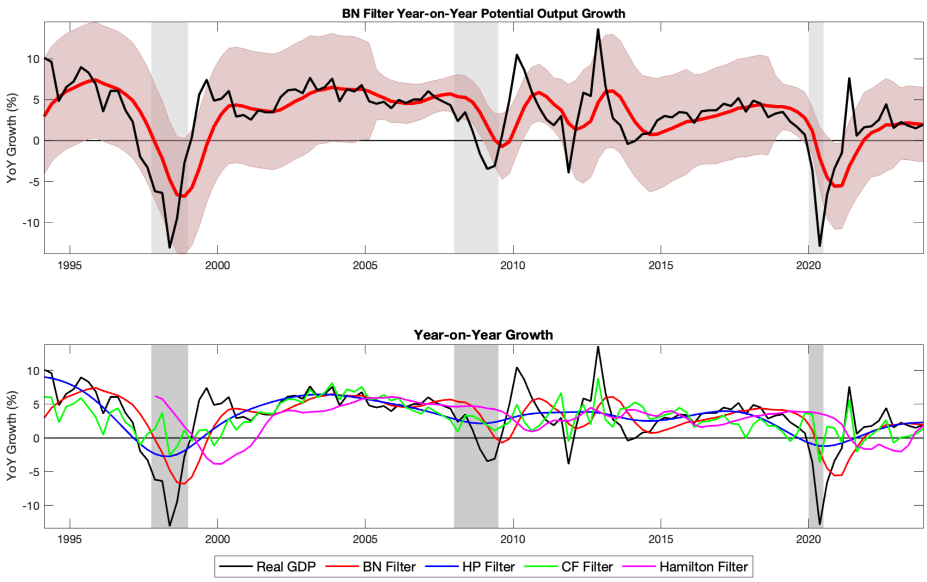
The GFC had a more temporary effect on Thailand's trend growth. The BN

Figure 1.7: Estimated Output Gaps for Thailand.



Note: Units are 100 times natural log deviation from trend. Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates.

Figure 1.8: Estimated Year-on-Year Growth of Trend Output for Thailand.



Note: Shaded bands around the estimate correspond to 95% confidence intervals. The shaded bars correspond to recession dates filter shows a modest dip in trend output growth, with the output gap falling to -5%, a smaller deviation than during the AFC. The recovery occurs relatively quickly, supported by post-AFC reforms and remittance inflows. Similarly, the HP, CF and Hamilton filter estimates of the output gap is negative during the GFC but less pronounced than during the AFC and rebounds promptly. The HP and CF filter also depicts the GFC as a transitory decline in trend growth. The Hamilton filter, in contrast, reflects the drop in trend growth with a delay, only showing the downturn by 2012.

Thailand's economy also experienced disruptions from the 2011 floods and political instability between 2010 and 2014. The economic damage was considerable, costing an estimated $46.5 billion (World Bank, 2011). Political instability during this period further slowed growth. The BN filter captures these events with a temporary dip in the trend growth and a widening output gap of nearly -5%. The HP filter follows a similar pattern: a temporary decline in trend output growth and a quick return to previous levels. The output gap estimates from the Hamilton filter indicate only a mild impact. The CF filter also identifies a transitory drop in trend output growth, followed by a quick recovery. The output gap estimated by the CF filter shows only a slight decline.

During the COVID-19 pandemic, the BN filter captures a decline in trend growth, with the estimated output gap reaching -10%, comparable in magnitude to the AFC's effect. The HP filter, as before, shows a sharp decline in the output gap but produces a smoother trend adjustment. The CF filter, in contrast, suggests that the deviation from trend was abrupt but much less severe. The CF filter estimated output gap magnitude is smaller than that of the BN and Hamilton filters. The Hamilton filter, meanwhile, displays a delayed response to the pandemic shock. The decline in trend output growth occurs later and proceeds more gradually. The Hamilton filter's output gap estimates indicate a steep decline, followed by a slower recovery.

1.3.5 Summary of Decomposition Results

Overall, I find that, in these Asian economies, trend growth is not always smooth, with apparent structural changes in both the slope and level of the long-run growth rate, particularly during major financial episodes such as the AFC and GFC. The BN filter estimates tend to capture large and persistent output gaps, and the trend growth sometimes follows the actual series. The HP filter provides a smoother characterization of the trend and cycle components, showing less sensitivity to sudden changes in slope or level, consistent with Perron and Wada (2016) and Perron and Wada (2009). It also often yields relatively large positive output gaps prior to crises. The CF filter closely tracks actual output movements but tends to generate smaller and noisier amplitude cycles, especially during downturns. The Hamilton filter, while consistently identifying the drop in output gap estimates across recession, its trend growth estimates respond with a lag of several quarters. More importantly, contrary to Aguiar and Gopinath (2007), transitory shocks appear to be the primary source of economic fluctuations rather than shocks to the trend, which challenges the prevailing view that trend shocks drive growth dynamics in emerging markets. Table 1.2 reports on average, less than one-third of GDP growth variance is explained by changes in potential output across methods, suggesting that most fluctuations stem from the cyclical component. This finding holds not only for the BN filter estimates but is consistent across all methods except for the CF filter, which attributes a higher share of variance to trend growth. While this pattern may partly reflect the smooth-trend assumption embedded in univariate filters such as BN, HP, CF, and Hamilton, the results consistently point to the dominance of business cycle rather than trend shocks.

Crucially, this pattern is not completely a mechanical consequence of the filters: these univariate procedures regularize the trend to be smooth, but they do not fix the trend–cycle variance split ex-ante in a sense that the reported shares are determined by the data conditional on each decomposition. The difference observed for the CF filter illustrates this point, as its design allows for higher-frequency movements to enter the trend component. Likewise, any comparison between output and consumption gaps, such as considered below, is not restricted by the methods themselves; the relative volatility between the two series reflects the data rather than the filtering approach. Taken together, the results reported above indicate that short-term fluctuations dominate, suggesting that policy should focus on stabilising cyclical volatility rather than assuming they are the consequence of structural breaks in economic fundamentals.

To assess the statistical properties of the estimated trend growth, I examine the autocorrelation function for year-on-year trend growth. In models of advanced economies, potential output is often modeled as a random walk (e.g., Del Negro et al., 2007; Hasenzagl et al., 2022), which implies that the year-on-year trend growth should be an MA(3) process. For the emerging Asian economies in this study, the autocorrelation functions (ACFs) for year-on-year trend growth show that the series often follow a more persistent process, which implies deviations from a random walk trend.[5] However, BN filter estimates come closest to the random walk assumption among the methods considered.

Table 1.2: Variance Share of GDP Growth Explained by Trend Growth

	BN Filter	**HP Filter**	**CF Filter**	**Hamilton Filter**
Indonesia	0.24	0.18	0.56	0.22
Malaysia	0.10	0.04	0.79	0.05
Philippines	0.15	0.07	0.70	0.08
Thailand	0.16	0.10	0.74	0.11
Average	0.16	0.10	0.70	0.12

Note: The table reports the share of real GDP growth variance explained by the trend component under different univariate methods.

1.4 Comparison to other measures of economic slack

Economic slack implies that an economy can grow quickly without any necessary offsetting slow growth in the future (Morley, 2014). Thus, assessing the plausibility

[5]ACFs reported in the Appendix. See Figures A.1, A.2, A.3, and A.4

of output gap estimates as a measure of economic slack is important. Accordingly, I compare output gap estimates using the BN filter to other, narrower measures of slack when available for emerging Asian economies. To provide a benchmark, I also consider the correlations for the United States.

Similar to the findings in Morley and Piger (2012) and Morley (2014), there is a clear relationship between output gaps and other narrow measures of slack. Figure 1.9 shows that output gap estimates are positively and significantly correlated with capacity utilization, with Malaysia having the strongest correlation—surpassing even that of the United States.[6] Figure 1.10 displays that all economies in the sample, except Indonesia, exhibit a significant and negative correlation with unemployment. For Indonesia, in particular, its unemployment data are only available biannually and span a shorter period, possibly capturing more structural rather than cyclical movements. This observation raises concerns about the reliability of the unemployment rate in such instances, especially since, for all other economies in our sample, the output gap estimates are in line with the expected negative correlations with unemployment.

Barbarino et al. (2024) show that including unemployment data can enhance real-time estimates of trend growth in the United States. However, the evidence presented here suggests that relative to the U.S., unemployment-based measures in emerging Asian economies are generally less informative about business cycles. This discrepancy likely stems from shorter sample spans, more structural change in unemployment, and weak correlations with output growth or detrended output, which limit the viability of multivariate approaches reliant on unemployment data in emerging Asian economies. Although capacity utilization provides an alternative measure of slack, it can also exhibit possible noisy signals, especially with shorter samples.[7] (See the appendix for the full set of correlation tables.)

A further factor contributing to the weak performance of these indicators is the prevalence of informal employment in these economies. Where informal activity is widespread, labor market adjustment to demand shocks often occurs through shifts between formal jobs, informal self-employment, and own-account work rather than through measured unemployment. As a result, official unemployment rates provide a poor signal of cyclical slack. Empirical evidence shows that unemployment-output correlations fall with informality (Horvath and Yang, 2022; Coşkun, 2022), while structural models confirm that unemployment volatility is dampened as informality rises (Lambert et al., 2020). Capacity-utilization indicators face related limitations, since they rely on narrow manufacturing surveys and can be influenced by supply-side disturbances such as inventory cycles or export bottlenecks. Measuring informality directly remains difficult, as survey-based measures often suffer from reporting and coverage gaps, while model-based estimates depend on strong assumptions (Ohnsorge and Yu, 2022). Similar limitations also affect the broader use of survey-based expectations and forecasts in trend-cycle estimation, which recent work by Lee and Mahony (2024) shows can be valuable but remain constrained in their applicability for these

[6] See Table A.1 in the Appendix for the correlation statistics.

[7] Capacity utilization in these countries is typically derived from manufacturing or business tendency surveys, such as Bank Indonesia's Business Survey or Malaysia's industrial performance surveys. Thailand and the Philippines likewise rely on manufacturing-sector surveys.

Figure 1.9: The estimated output gap using the BN filter for 1993:1 – 2022:4 and the capacity utilization rate

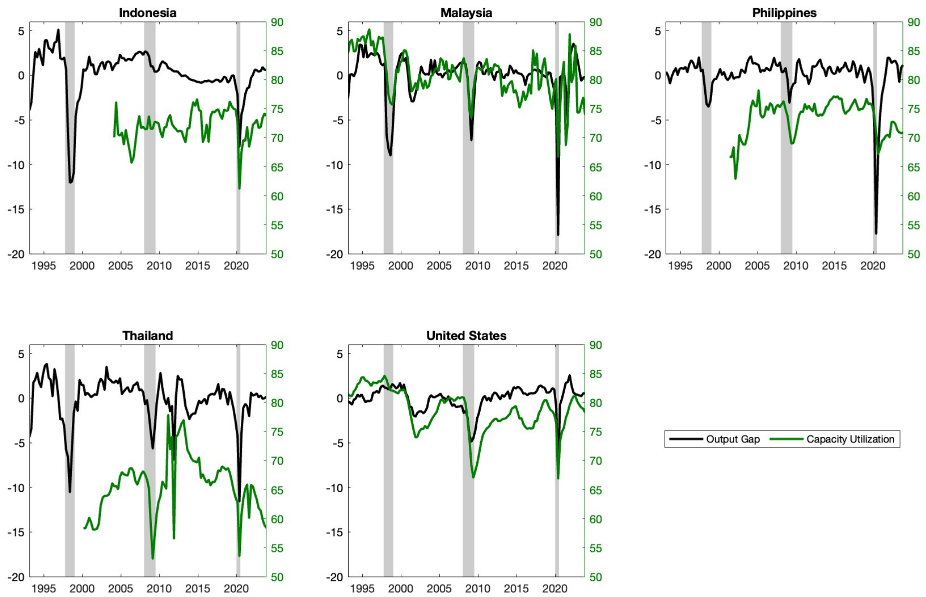
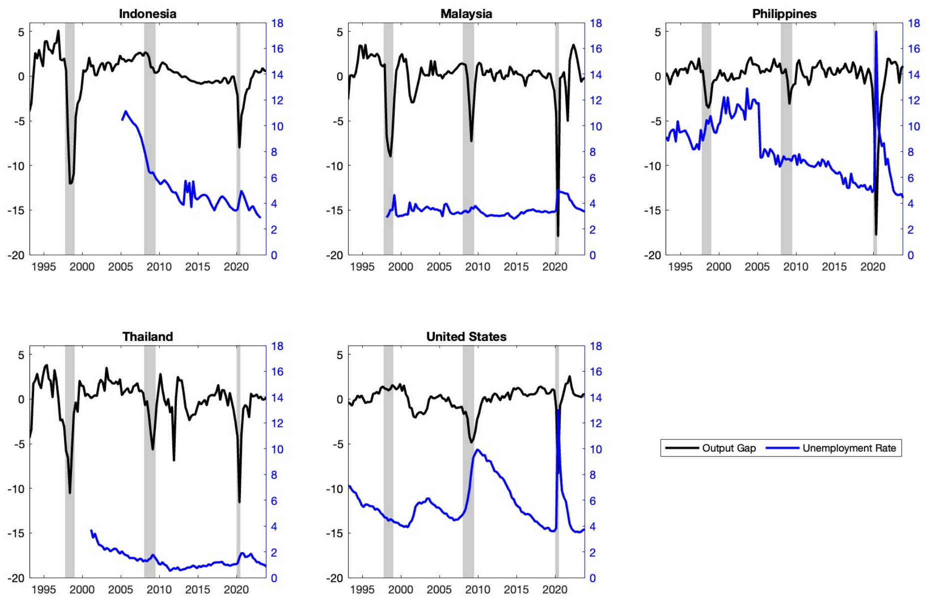


Figure 1.10: The estimated output gap using the BN filter for 1993:1 – 2022:4 and the unemployment rate



emerging economies. Consequently, I have also compared capacity utilization and unemployment gaps to the BN filter output gaps as a robustness check.[8] Although these narrower slack measures display some correlation with the BN filter output gap, many of them exhibit reduced amplitude or appear dominated by secular trends, making them less reliable as cyclical indicators.

Finally, these issues with narrower slack measures contrast with the stronger relationships observed in the United States, where unemployment is often used in multivariate trend-cycle decompositions (e.g., Morley and Wong, 2020; Barbarino et al., 2024; Barigozzi and Luciani, 2023). In many emerging Asian economies, however, such approaches are hindered by the short availability of data, weak cyclical correlations, and the distorting role of informality. Overall, output gap estimates emerge as a reasonable alternative: they are available over longer periods and, by construction, are meant to abstract from long-run structural factors. I leave for future research a more comprehensive multivariate analysis that further investigates the potential value of integrating narrower slack measures and survey-based data in improving output gap reliability for emerging market economies.

1.5 Key Cyclical Movements in Output and Consumption

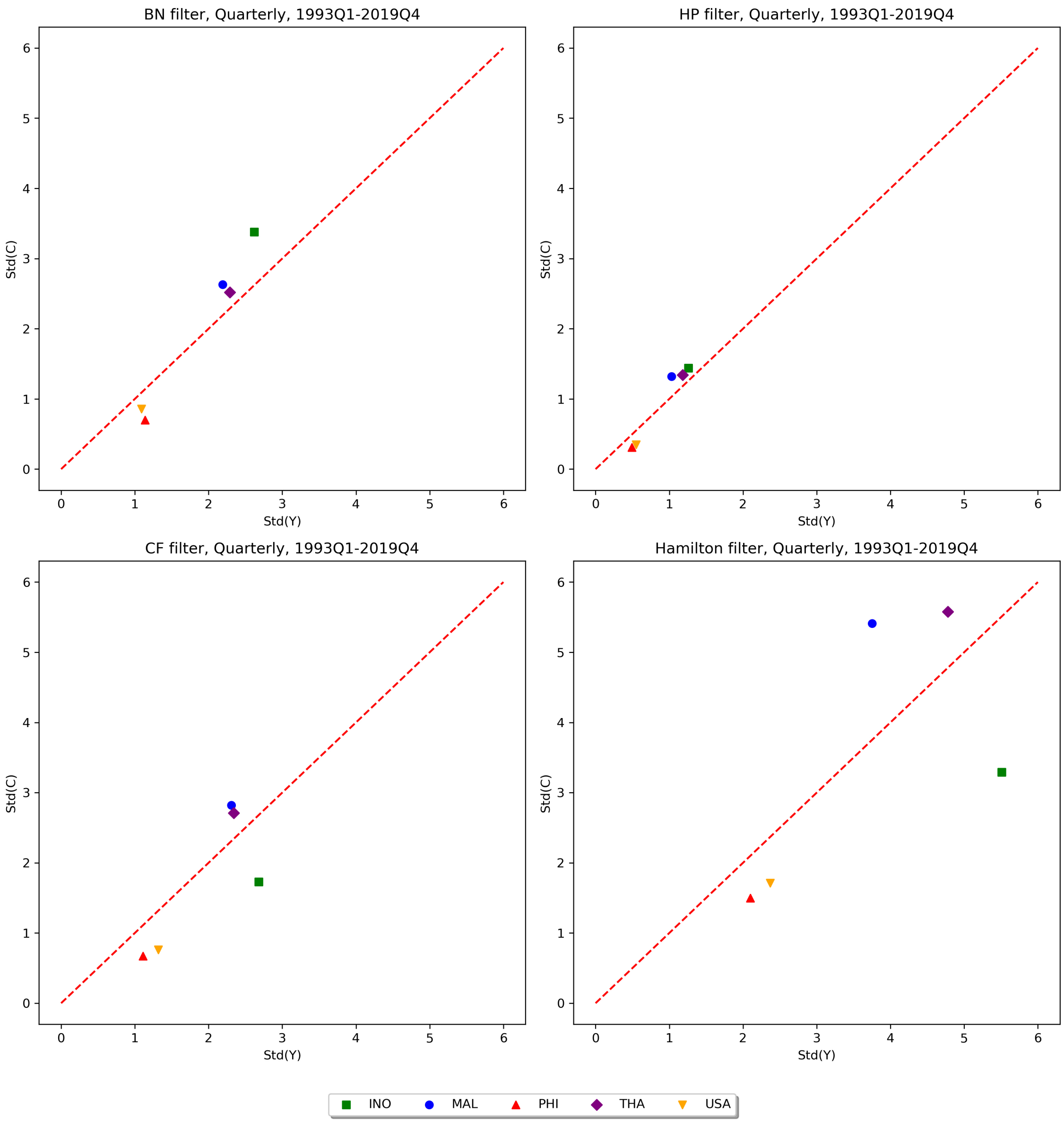
Understanding the cyclical behavior of output and consumption provides important insight into the nature of shocks that drive fluctuations in emerging Asian economies. A well-established feature of these economies is their openness and heightened exposure to external and financial shocks, which often generate more persistent effects than in advanced economies. Such shocks, especially those transmitted through international financial channels, are frequently associated with permanent or highly persistent impacts on output levels rather than purely transitory cyclical deviations (Cerra and Saxena, 2008; Cerra and Saxena, 2017). This stands in contrast to developed economies, where downturns are typically followed by symmetric recoveries. This characterization complements the view of Aguiar and Gopinath (2007), who argue that in emerging market economies, trend shocks dominate cyclical dynamics. Examining the cyclical components of output and consumption therefore provides a useful perspective for assessing how short-run fluctuations relate to these more persistent structural shocks.

1.5.1 Relative volatilities and correlations

I now examine two distinct sets of stylized facts: one from the data sample period leading up to 2019:4 and the other extending to 2022:4, capturing the post-pandemic period. My motivation for considering both sample periods is twofold. First, given that the pandemic acts as a global outlier, it is important to document the salient features of these economies by analyzing output and consumption gaps prior to the pandemic. Second, this approach enables a clear comparison, allowing us to discern how these stylized facts have evolved in the aftermath of the pandemic.

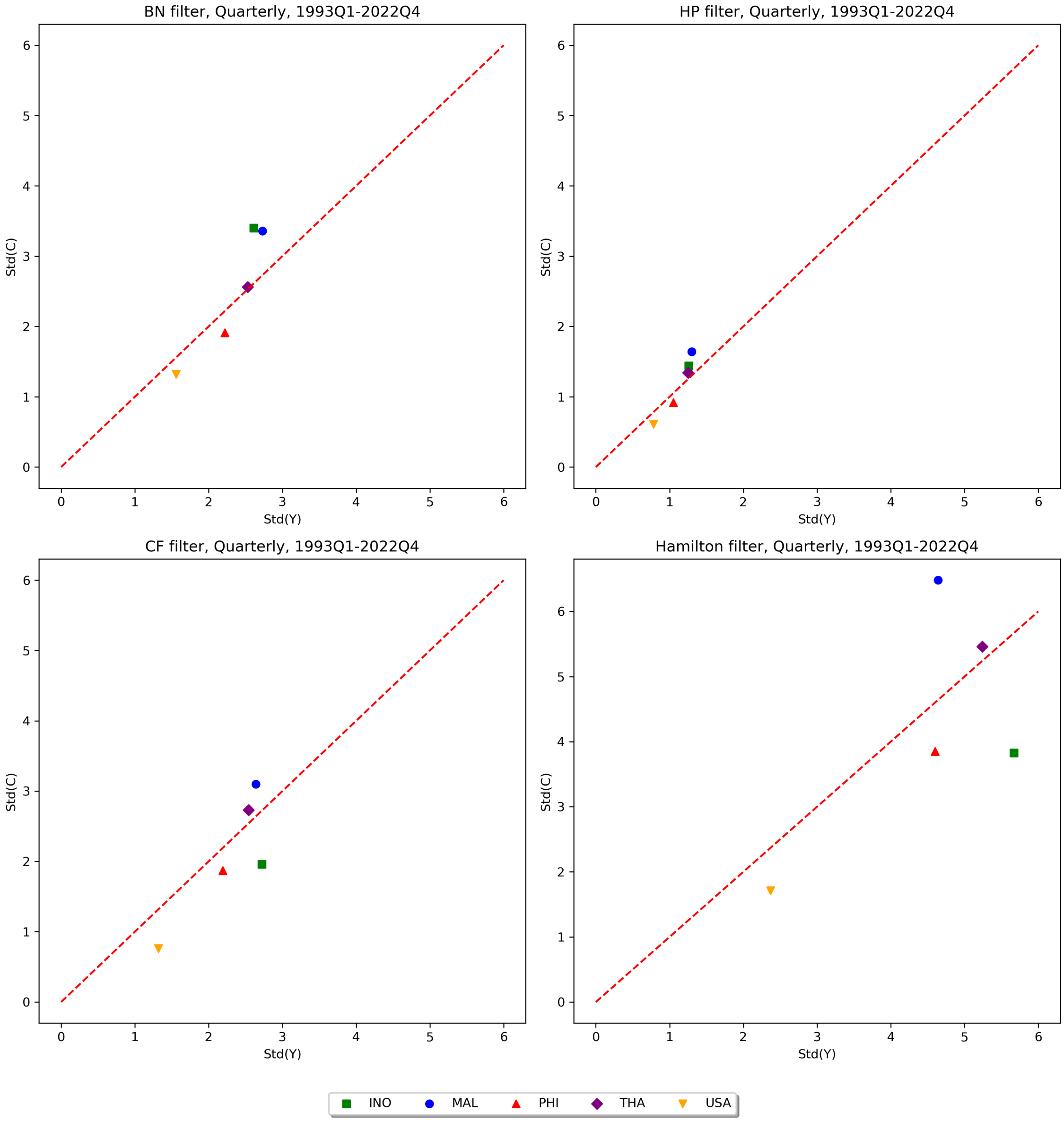
[8] See Figures A.5 and A.6 in the Appendix for the capacity utilization and unemployment gap estimates.

Figure 1.11: Volatilities in the Cyclical Component of Real GDP and Consumption from 1993Q1 - 2019Q4.



Note: The Figure above plots the standard deviations of output and consumption gaps on the horizontal and vertical axes, respectively. The area below the 45° line corresponds to cases for which consumption gap is less volatile than the output gap.

Figure 1.12: Volatilities in the Cyclical Component of Real GDP and Consumption from 1993Q1 - 2022Q4.



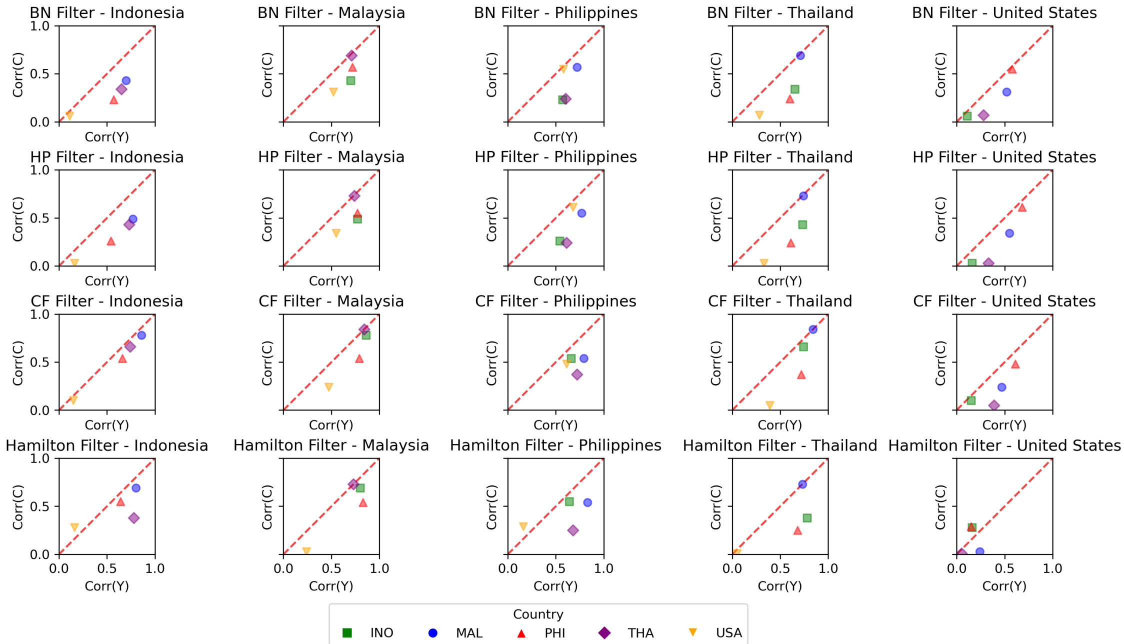
Note: The Figure above plots the standard deviations of output and consumption gaps on the horizontal and vertical axes, respectively. The area below the 45° line corresponds to cases for which consumption gap is less volatile than the output gap.

By their nature, emerging markets often display higher volatility in output and consumption compared to developed countries (Aguiar and Gopinath, 2007) in the context of growth rates, with trend movements possibly dominating cyclical movements. It should be noted however, that my analysis focuses on output and consumption gaps, representing deviations from the trend, rather than overall growth rates. Figure 1.11 displays the standard deviations of output and consumption gaps on the horizontal and vertical axes, respectively, with the area beneath the 45-degree line indicating cases where consumption gap volatility is lower than that of the output gap. With the exception of the Philippines and of Indonesia when estimated using the CF and Hamilton filters, the consumption gap in emerging Asian economies is generally more volatile than the output gap. Aguiar and Gopinath (2007) attribute higher consumption volatility in emerging markets to the dominance of trend shocks in growth rates, a phenomenon they label as "the cycle is the trend". My findings suggest that even after removing the trend component, consumption still remains more volatile than output. This implies that factors beyond permanent productivity shocks contribute to the high consumption volatility in these economies.

The observed volatility patterns in Asian economies, where consumption tends to be more volatile relative to output, can be attributed to several factors. One explanation is consumption smoothing theory, which suggests that consumers aim for stable consumption amidst temporary economic shocks (Hall, 1978), may be hindered by constraints like limited credit access or underdeveloped financial sectors in emerging markets. The Philippines exhibits the lowest consumption-to-output gap volatility ratio, indicating a stable consumption gap relative to its output gap. This stability can be attributed to substantial remittances from abroad and a service-oriented economy. Remittances provide a steady income flow that insulates households from domestic shocks, while the dominance of the service sector leads to more stable employment (Yang and Choi, 2007). This deviation from patterns observed in other emerging markets suggests that external income sources and economic structure significantly affect consumption volatility. In comparison, an advanced economy like the United States displays the least volatility in both output and consumption gaps. This aligns with Aguiar and Gopinath (2007) findings that developed economies experience less volatile business cycles driven by transitory shocks. This stability can be attributed to factors such as better access to credit and savings, allowing consumers to maintain their consumption levels even amidst output fluctuations.

Post-pandemic data as seen in Figure 1.12 reveals significant changes in economic dynamics for these economies. Malaysia exhibits the highest output gap volatility among emerging Asian countries post-pandemic, while the Philippines shows an increased consumption gap volatility. Changes in the correlation between consumption and output gaps, especially in the Philippines, indicate that the pandemic has disrupted traditional economic relationships. Although there are some differences depending on the sample period, the main finding regarding the relative volatilities of consumption and output gaps remains robust, even in the post-pandemic period.

Figure 1.13: Cross-country Correlation of the cyclical component of Real GDP and Consumption.



Note: The Figure above plots cross-country correlations for output and consumption gaps, where the horizontal axis and vertical axis measures the cross-country output and consumption gap correlations respectively. The area above the 45° line indicates that the consumption gap correlation is higher than the output gap correlation.

1.5.2 Linkages Between Countries

Following Backus et al. (1992), it is widely recognized in the study of international business cycles that cross-country correlation between consumption is typically lower than cross-country output correlations. On the other hand, theoretical models that assume agents are risk-averse suggest that consumption correlations should be higher than output because agents tend to smooth out their consumption over time (Baxter, 1995; Backus et al., 1993).

Two approaches have been employed to address these differences in consumption and output correlations. The first involves incorporating market frictions into the basic economic model, which suggests that consumption correlation would be lower than in a complete market scenario. The second approach inspects these "stylized facts" through alternative econometric methodologies. Ambler et al. (2004) tested the robustness of these findings by employing different subsets of countries and utilizing the standard HP filter to deduce the cyclical components. Ambler et al. (2004) shows that the consumption-output gap correlation puzzle is more noticeable than previously reported, with cross-country consumption gap correlations significantly lower than those of the output gap. Pakko (2004) found that a smaller consumption gap correlation is not constant when different frequency bands are used to extract the cyclical component via a band pass filter. However, it is typically smaller within the frequency bands associated with the business cycle. My analysis aims to explore whether a different detrending method can lead to a different outcome or further support these "stylized facts."

When examining cross-country correlations, the link between output and consumption gaps is stronger than the correlation with consumption gaps alone (see Figure 1.13). Within Asian economies, this cross-country correlation with consumption gaps is more distinct than with the United States, except in some cases for the Philippines, where the consumption gap correlation with the United States surpasses that of most other Asian economies. Despite these variations, the trends are consistent across different filters, with correlation coefficients remaining similar.

Geographically close economies tend to have more integrated trade, finance, and investment relationships, leading to more synchronized economic cycles. The AFC in the late 1990s, which started in Thailand and spread to other Southeast Asian countries, exemplifies how interconnected financial systems can synchronize economic downturns. The observed output gap correlations among the emerging Asian economies also reflect their similar economic structures, causing them to react similarly to global economic trends or external shocks.

The output correlations of Asian economies with the United States are generally lower than their intra-Asian correlations, suggesting that the output fluctuations or growth patterns in emerging Asian economies do not always move in tandem with those of the United States. While there is interaction due to trade and finance, the fundamental drivers of consumption and output can differ (Obstfeld and Rogoff, 1996). Moreover, the varying correlations of Asian economies with the United States, especially in consumption, might indicate the depth of financial ties (Corsetti et al., 1999). While there is some correlation between consumption and output patterns in the United States, it is clear that these emerging Asian economies have distinct factors affecting their economic behavior. The variations in correlations might also reflect how each country responds to global economic trends. For instance, a global recession might affect tourism-heavy countries like Thailand differently than manufacturing-heavy countries like Malaysia.

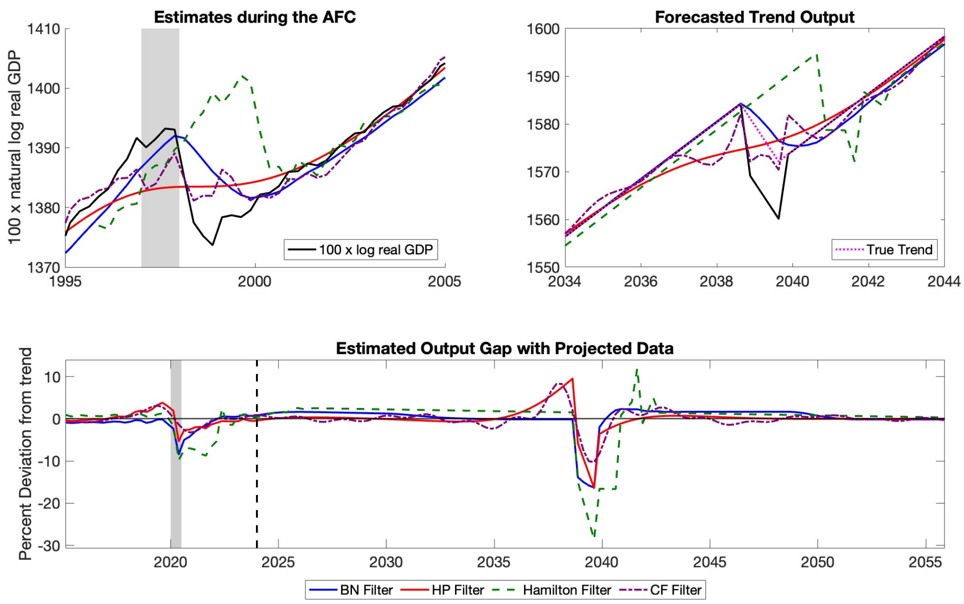
1.6 Trend-cycle decomposition with an AFC-like shock

How well does the BN filter distinguish between permanent and transitory components during large, sudden economic downturns for these emerging economies? To address this, I use Indonesia as a case study. Specifically, I augment Indonesia's real GDP data from 1993Q1 to 2023Q3 with projections of future growth through to 2055Q4, incorporating a simulated shock akin to the AFC, set to occur in 2038Q3 to assess how the filter responds to outlier shocks and forecasts the output gap, where the true impact on the trend level and cycle is known by assumption. The choice to simulate an AFC-like shock reflects the fact that, for these economies, shocks from the AFC were typically larger than those from the COVID-19 pandemic. Moreover, there remains uncertainty about whether the shock from the pandemic represents a permanent shift in the level or merely a transitory change.

Real GDP is projected to grow at a steady rate of 1.5% per quarter, consistent with historical trend. In 2038Q3, two shocks are introduced: (i) a permanent 12%

reduction in the level of real GDP, representing a permanent downward shift in the trend level, and (ii) a transitory 3% reduction per quarter over four quarters, totaling a 12% temporary decline in the output gap. These shocks result in a total 12% drop in real GDP in 2038Q3, followed by partial recovery in the subsequent quarters. Half of the cumulative shock permanently lowers the trend level, while the other half impacts the cyclical component. I then apply the BN, HP, CF, and Hamilton filters to the extended dataset to evaluate how each method captures the trend output and output gap under this scenario.

Figure 1.14: Estimates with projected data with Asian Financial Crisis-like shock for Indonesia.



Note: The Figure presents estimates of log deviations from trend (100 times natural log) for the first two panels and 100 times natural logs for the third panel. The estimates are based on data from 1993Q1 to 2023Q2, augmented with projections from 2023Q3 to 2055Q4. The top-left panel shows actual estimates during the AFC, with the shaded bar indicating recession dates. The top-right panel reports forecasted trend output from 2034Q1 to 2044Q4, capturing the projected impact of an AFC-like shock. The bottom panel displays the estimated output gap over the period 2018Q1 to 2055Q4, with the vertical dashed black line denoting the start of the forecast period (2023Q3)

Looking at Figure 1.14, the forecasted output gaps suggest that the COVID-19 downturn was largely temporary, aligning with the broader economic narrative that activity economies rebounded significantly in 2020Q3 after pandemic restrictions were lifted. However, post-pandemic estimates from the Hamilton filter suggest a longer recovery as seen from the persistently more negative output gap estimates compared to the other filters. Given that the output gap estimates are close to zero by the end of the 2024, with output growth returning to trend before the AFC-like shock in 2038Q3, it is reasonable to anticipate that the forecasted output gaps converge to zero as earlier shocks fade and trend growth stabilizes leading up to the simulated shock.

At the time of the simulated AFC-like shock in 2038, BN filter show a sharp decline in the output gap of -15%, similar to the simulated AFC-like shock of 12%. The BN filter better captures both the permanent and transitory components of the shock, closely following the true trend before and after the event. In contrast, the HP filter displays a spurious positive output gap leading into the shock, resulting in an initial drop of 8% before fully dropping to -15%. Moreover, the HP filter implies a lower pre-shock trend level compared to the true trend and characterizes the trend adjustment as a smooth transition rather than a abrupt structural break. This observation is consistent with what I observe for the HP filter during other crisis periods such as the pandemic and the GFC for the emerging economies in this study, and mirrors the findings by Kamber, Morley, et al. (2025) for the United States. Meanwhile, the CF filter produces a highly volatile trend. Prior to the simulated shock, the estimated CF trend shows a slight premature drop from the true trend. While the CF filter does capture the abrupt drop in 2038Q3, it fails to capture the full amplitude of the structural break in the trend. This is followed by another small drop in trend, then an overshoot in the recovery before eventually converging back to trend. Similarly to the HP filter, the CF filter captures a spurious positive output gap before the simulated shock. Among all the filters, the CF filter produces the smallest amplitude, consistent with what was observed for the historical decomposition results. This suggests that the CF filter tends to underestimate the amplitude of structural breaks. The Hamilton filter, while stable, captures the simulated shock with a lag as the forecasted trend remains well above the true trend for several quarters, despite the drop in the true trend. The Hamilton filter only captures the drop in trend approximately eight quarters after the initial shock. Consistent with the findings of Kamber, Morley, et al. (2025), the Hamilton filter implies a significant mechanical spike exactly two years after the shock. It also implies a persistently large positive output gap for several years before eventually returning to its prior trajectory once the effects of the shock have dissipated. Additionally, the Hamilton filter overstates the decline in the output gap in 2038Q3, falling by approximately 27.3%, whereas the actual transitory decrease in output was 12% in the simulation.

Given the susceptibility of emerging economies to external shocks, the BN filter is better suited for understanding the full impact of such shocks, as it captures both transitory and permanent level changes closer to the true trend more effectively than alternative filters. The HP filter tends to smooth excessively before shocks and overcorrect afterward, while the CF filter introduces excessive volatility, and fails to fully capture structural breaks by producing relatively small output gap amplitude. The Hamilton filter reacts with a lag that overstates the initial shock and maintains a trend estimate above the true level for several quarters before adjusting.

1.7 Stability of Pseudo-Real-time Output Gap Estimates

Orphanides and van Norden (2002) have highlighted that real-time output gap estimates are often revised significantly ex-post, raising concerns about their usefulness in policymaking. This critique points out that most real-time revisions in output gap estimates are attributed more to the filtering method than to the data revisions of Real GDP (Orphanides and van Norden, 2002). To assess the revision

Figure 1.15: Time-series differences between pseudo-real-time and revised output gap estimates obtained from alternative detrending methods.

Note: Values are expressed as 100 times the deviation of log output from trend.

properties of the estimated output gaps in emerging Asian economies, I consider a pseudo-real-time analysis using the quarterly data for output from the sample period 1993:1 to 2005:4, with subsequent additions of one observation at a time until the end of the sample. The evaluation sample is from 2006:1 - 2019:4. The pseudo-real-time analysis emulates the real-time environment by duplicating the delays in data publication according to a stylized, realistic schedule and by employing recursive estimation of the model (Bańbura et al., 2013). However, due to the challenges in obtaining real-time data vintages for these emerging Asian economies, this analysis utilizes final vintage data. Consequently, the impacts of data revisions, which can be substantial, are not taken into account. As highlighted by Croushore and Stark (2001) and Bańbura et al. (2013), this could influence the outcomes of the evaluation and comparison.

Following Orphanides and van Norden (2002), I apply a detrending technique to each available output series to generate a collection of output gap series. This detrending is conducted quarterly, using data available during each respective quarter. Subsequently, these various data estimation sample are used to create a new series called "pseudo-real-time estimate", incorporating the most recent output gap estimate for each time point. To create the "revised estimate" of the output gap, I detrend the full sample period. The output gap revision for a specific quarter, t, is defined as the difference between the revised output gap estimate made during quarter t and the pseudo-real-time estimate. To assess the BN filter's efficacy further, I compare it with the output gap estimates using alternative filters.

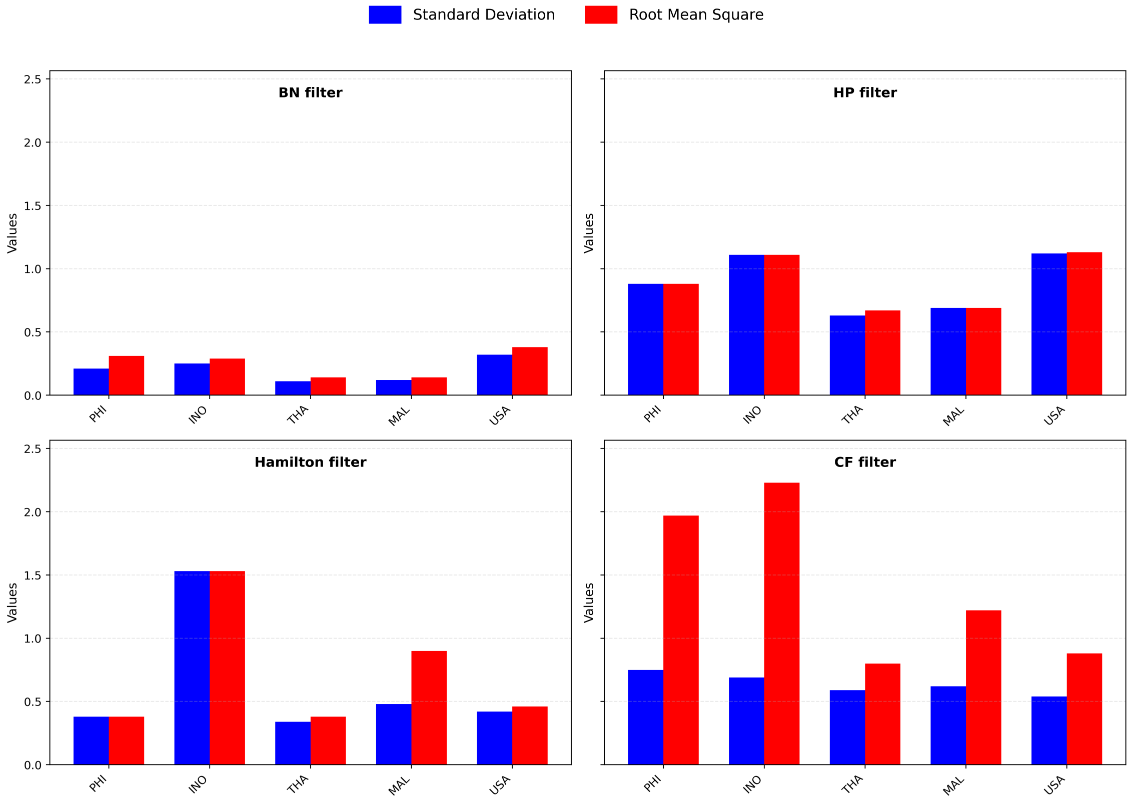
Figure 1.15 reports the time-series differences between pseudo-real-time and subsequently revised output gap estimates obtained from alternative detrending methods. Values close to zero indicate smaller revisions between pseudo-real-time and revised output gap estimates.[9] Figure 1.15 visually shows that the BN filter-based output gap estimates are relatively stable and subject to few revisions as additional information becomes available. Even with the inclusion of post-2020 data, the BN filter continues to exhibit strong revision properties consistent with the findings of Barbarino et al. (2024), Kamber, Morley, et al. (2025), and Barigozzi and Luciani (2023). In contrast, the one-sided HP filter-based output gap estimates undergo heavy revisions with the two-sided version and display high sensitivity towards the endpoint, with pre-pandemic estimates for 2018–2019 later revised substantially upward. CF filter estimates of the output gap are generally less reliable than those produced by the HP filter. In pseudo–real-time settings, the CF filter tends to generate excessively smooth estimates that imply a more positive output gap relative to the corresponding ex-post revisions. In comparison, the Hamilton filter demonstrates relatively stable revisions for the United States, in line with results reported by Quast and Wolters (2022). Yet, for emerging economies, its performance diverges, often producing mechanically large spikes in the estimated output gap following recessions, this pattern could be largely attributed to predictable base effects from the 8-quarter-ahead forecast of log real GDP prior to downturns, as also observed by Kamber, Morley, et al. (2025) for the United States, but it can also be influenced by the shorter sample periods available for these economies, exacerbated by the first eight quarters are dropped when applying the Hamilton filter as proposed by Quast and Wolters (2022). For the emerging Asian economies, the difference between the pseudo-real-time and the revised output gap estimates is noticeable towards the end of the evaluation sample. The US data also shows revisions, but the divergence between the pseudo-real-time and the revised output gap estimates appears less severe than in the emerging Asian economies. This suggests that endpoint sensitivity is more evident in emerging Asian economies compared to the United States. The less volatile revision pattern for the United States also suggests a relatively more stable estimate that could be due to its advanced economy with less volatile data.

I proceed to further evaluate these revision characteristics by following a method similar to that used by Kamber, Morley, et al. (2018), and Kamber, Morley, et al. (2025). Two metrics are used to gauge the magnitude of the revisions: the standard deviation and the root mean square error (RMSE), with the latter specifically structured to impose a greater penalty on any biases in the revisions compared to the standard deviation (Kamber, Morley, et al., 2018). The standard deviation and RMSE are normalized using each method's standard deviation of the revised output gap estimate. This ensures a fair comparison across various methods that may yield estimates of differing magnitudes (Orphanides and van Norden, 2002). I then compute the correlation between the pseudo-real-time and the revised estimate of the output gap. Finally, I evaluate the consistency of pseudo-real-time and revised estimates by measuring the fraction of observations where both estimates indicate the same sign. Figure 1.16 illustrates the magnitude of the revisions while figure 1.17 reports the correlation and frequency of same-sign revisions in the estimates using different filters.

As seen in Figure 1.16 the BN filter performs well in terms of revision size, with the

[9] The pseudo-real-time and revised output gap estimates are presented in Figure A.7 in the Appendix.

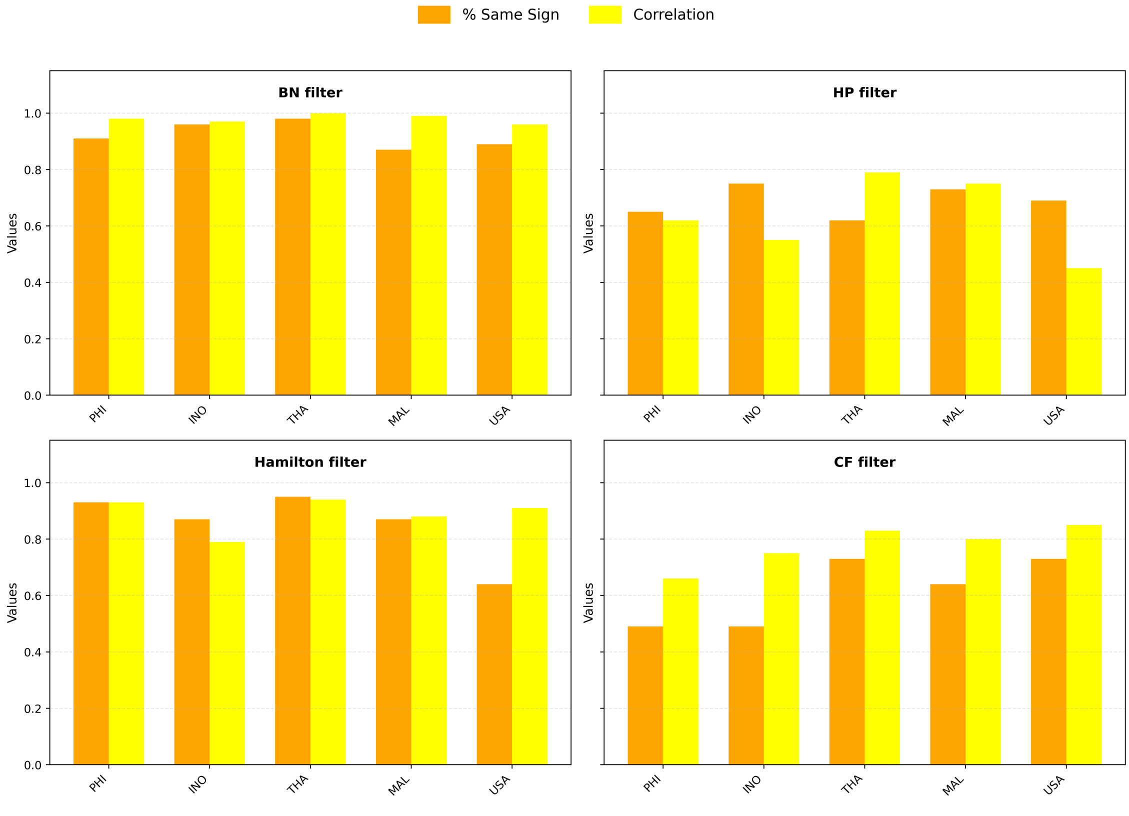
Figure 1.16: Revision statistics of output gap estimates.



Note: Revisions to the pseudo-real-time output gap estimates are expressed in terms of their standard deviation and root mean square error, each standardized by the standard deviation of the output gap's ex post or final estimate.The evaluation sample is from 2006:1 - 2019:4

standard deviation and RMSE statistics amounting to less than 40% of the standard deviation of the revised output gap estimates. The normalized standard deviations and RMSEs across all countries are relatively low, with the United States showing the highest values. The close values between SD and RMSE suggest that there are not many large outliers in the revisions. In contrast, the standard deviation and RMSE of output gap estimates using the HP filter are relatively high compared to the BN filter results, surpassing 80% of the standard deviation of the revised estimates on average. This indicates substantial revisions, considering the relatively large amplitude of the output gap estimates (Kamber, Morley, et al., 2018). The similarity between SDs and RMSEs across countries suggests a lack of large outliers in revisions, but the values are higher, indicating larger revisions overall. The BN filter's revision performance largely reflects its one-sided nature, which avoids the endpoint bias inherent in two-sided filters such as the HP filter. The Hamilton filter also shares this one-sided property and performs well but only when its regression parameters remain stable as new data are added. Turning to the Hamilton filter, the results vary across countries. For the United States, the revision statistics are moderate, reflecting relatively stable estimates. However, the standard deviation and RMSE are higher for emerging Asian economies, particularly Indonesia and Malaysia, which indicates greater sensitivity to sample length and cyclical volatility. This partly arises because the Hamilton filter omits the first eight quarters of data, which reduces the effective sample size for economies with shorter time series. By

Figure 1.17: Correlation, and sign of output gap estimates.



Note: Correlation is used to describe the statistical relationship between the pseudo-real-time and ex post estimates of the output gap. "Same Sign" quantifies the share of pseudo-real-time estimates that match the sign of the final output gap estimate. The evaluation sample is from 2006:1 - 2019:4

contrast, the CF filter displays the least reliable revision performance among all filters. Both the standard deviation and RMSE measures are substantially higher, especially for the Philippines and Indonesia, exceeding the amplitude of the revised output gap itself in some cases.

In terms of correlation between pseudo–real-time and revised estimates seen in Figure 1.17, the BN filter performs best with a near perfect correlation for all countries, with values close to or above 0.9. By contrast, correlations are lower for the HP filter, especially for the Philippines and Indonesia, confirming its poor real-time reliability. The Hamilton filter performs moderately well, with correlations around 0.8–0.9 for most emerging economies and slightly lower for the United States. The CF filter produces the weakest correlations overall, falling below 0.7 for several countries. Regarding the percentage of same-sign observations, whether the pseudo-real-time estimate points to the same sign as the final estimate, the BN filter again performs best, correctly matching the sign around 90% of the time across countries. The Hamilton filter is likewise also reliable, though slightly below the BN filter. In contrast, the HP and CF filters display much weaker results, with same-sign rates often near or below 70 percent, suggesting that real-time estimates frequently misidentify the direction of the output gap once revised.

1.8 Conclusion

In conclusion, the BN filter offers clear advantages over other filters in estimating output gaps in emerging Asian economies. It is particularly effective at distinguishing between permanent and transitory components during periods of extreme economic volatility, such as the AFC. This allows for a more accurate and responsive assessment of economic slack, as confirmed by strong positive correlations between output gap estimates and capacity utilization and negative correlations with unemployment. Moreover, BN filter output gap estimates provide a more informative alternative to capacity utilization and unemployment in this setting, given their longer data coverage and ability to abstract from long-run structural changes. Additionally, survey-based measures, while useful, are often available only for limited time periods, are not reported at higher frequencies, and frequently contain missing observations. I plan in future research to examine what information is potentially relevant for estimating multivariate output gaps in emerging market economies.

In contrast, the HP filter tends to smooth out trend growth and often fails to adjust to structural breaks and large outlier shocks. The CF filter tend to smooth out the cycle amplitudes, leading to a muted representation of business cycle fluctuations. Meanwhile, the Hamilton filter reacts with a delay, often implying a positive trend growth during recession periods. My results show that the BN filter yields smaller and less frequent revisions in output gap estimates, addressing concerns about the reliability of real-time economic assessments.

Applying the filter in a simulated crisis setting for Indonesia demonstrates its robustness in capturing both immediate and longer-term economic impacts. This robustness stems from the BN filter's ability to separate permanent and transitory components by allowing for a stochastic trend, which ensures that structural breaks and large economic shocks are appropriately incorporated into output gap estimates. As a result, it accurately follows the true trend before and after the shock.

Decomposing growth variance shows that most fluctuations are driven by the cyclical component rather than changes in trend. On average, less than one-third of GDP growth variance is attributed to movements in trend growth across methods. This pattern holds for BN, HP, and Hamilton. The CF filter is the main exception, assigning a larger share of variance to the trend. These results indicate that transitory shocks dominate and that shocks to trend growth play a smaller role than suggested by Aguiar and Gopinath (2007). Importantly, this is not purely mechanical: while these univariate filters regularize the trend, they do not impose a fixed trend–cycle split ex-ante. The differences across filters, especially in the CF case, confirm that the data, not the filtering approach alone, helps drives these conclusions.

An interesting extension would be to see how different measures of output gap perform in forecasting inflation. However, for emerging markets the role of domestic output gaps is generally seen to be less important in Phillips curve relationships given a bigger role of energy prices and foreign drivers (e.g., Kamber, Mohanty, et al., 2020). Thus, a full analysis of forecasting inflation for these emerging markets is left to future research that considers a wider range of variables in addition to domestic output gaps.

A Appendix to Chapter 1

Table A.1: Contemporaneous Correlation with Narrower Measures of Slack on Output Gap using the BN filter

	INO	MAL	PHI	THA	USA
Unemployment	0.24*	-0.32*	-0.38*	-0.10*	-0.55*
Capacity Utilization	0.43*	0.64*	0.37*	0.43*	0.55*

Figure A.1: ACF of the Year-on-Year growth rates of potential output for Indonesia using different filters

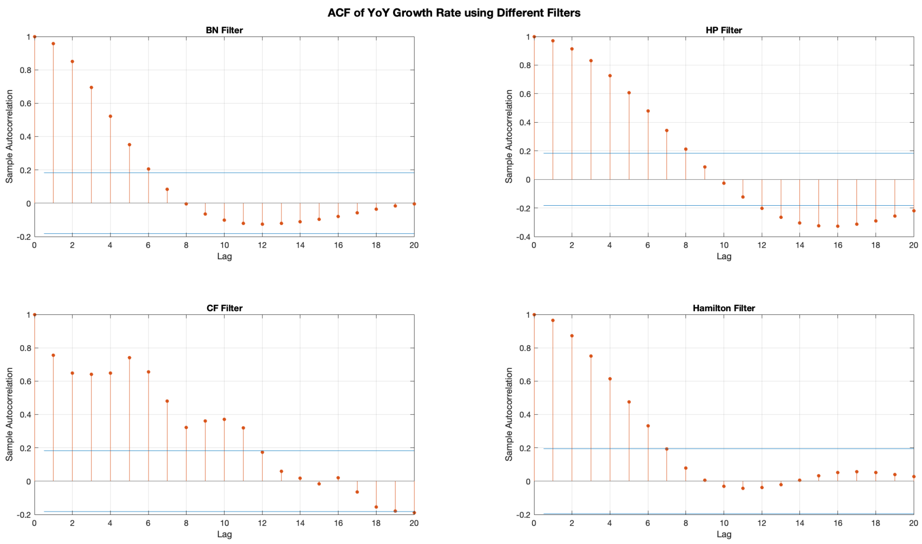


Figure A.2: ACF of the Year-on-Year growth rates of potential output for Malaysia using different filters

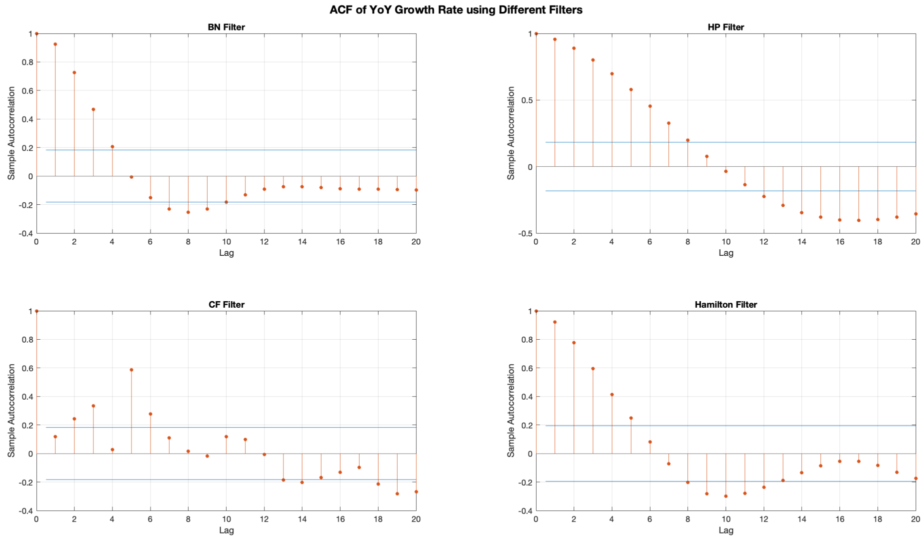


Figure A.3: ACF of the Year-on-Year growth rates of potential output for the Philippines using different filters

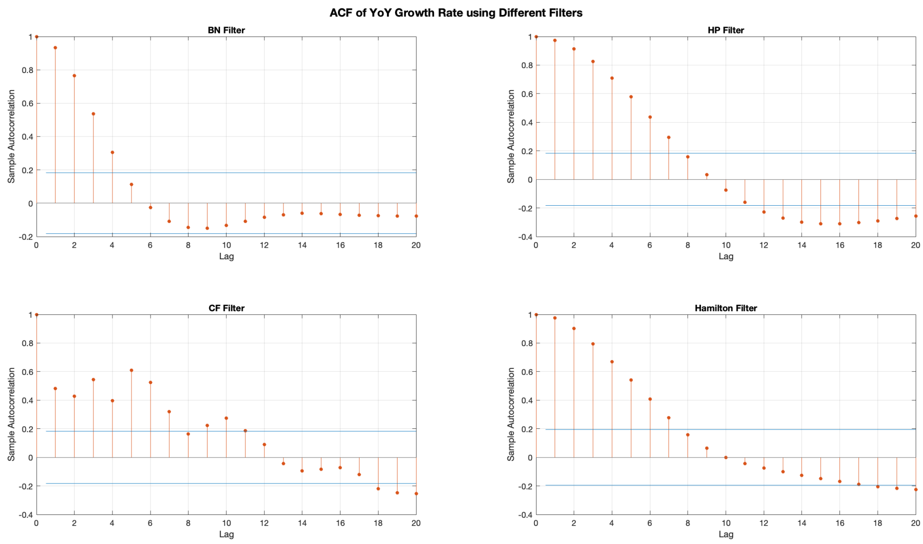


Figure A.4: ACF of the Year-on-Year growth rates of potential output for Thailand using different filters

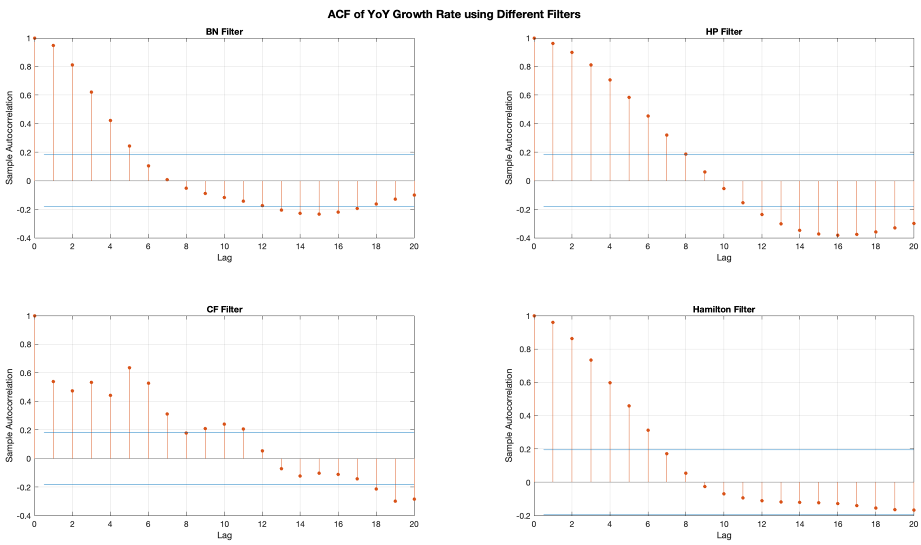


Figure A.5: The estimated output gap and the capacity utilization gap using the BN filter for 1993:1 – 2022:4

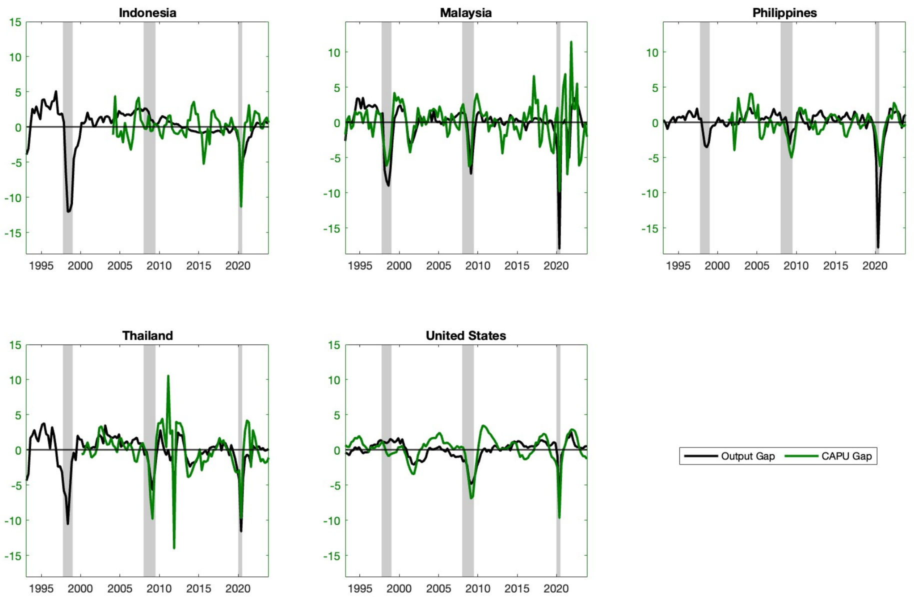


Figure A.6: The estimated output gap and the unemployment gap using the BN filter for 1993:1 – 2022:4

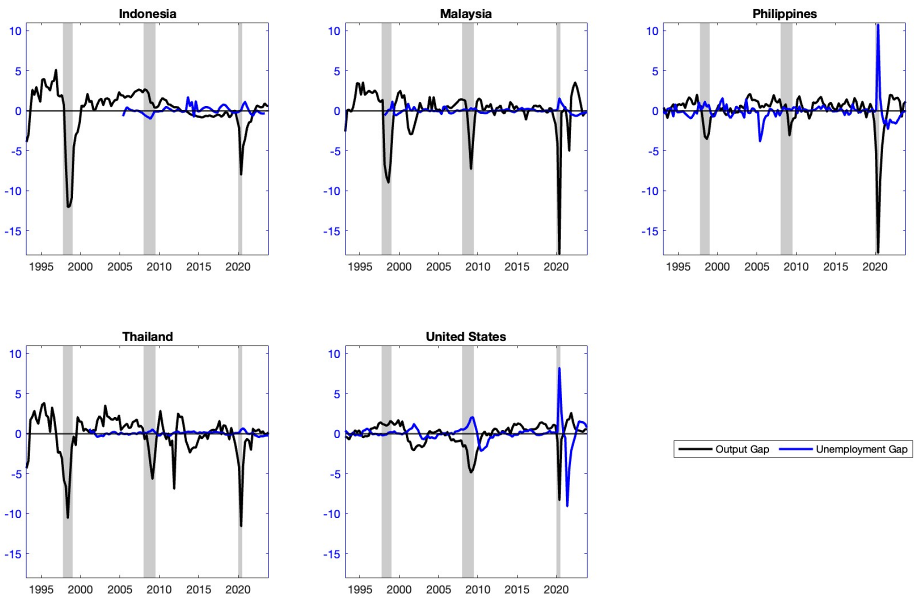
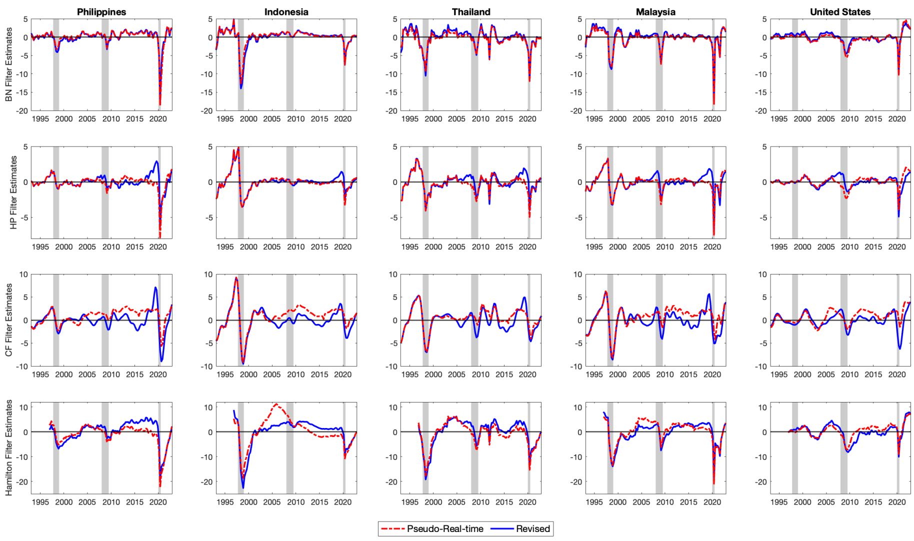


Figure A.7: Pseudo-Real-time vs Revised Output Gap Estimates obtained from alternative detrending methods.



Note: Units are 100 times natural log deviation from trend. The pseudo-real-time estimated output gap is in red and the revised output gap estimated is in blue

Chapter 2

What Information is Most Relevant for Estimating Output Gaps in Emerging Economies?

2.1 Introduction

Estimating the output gap, which is defined as the cyclical deviation of actual output from its potential, has been extensively studied, with numerous methodologies proposed in the existing literature (e.g., Hodrick and Prescott, 1997; Christiano and Fitzgerald, 2003; Hamilton, 2018; Kamber, Morley, et al., 2018). Common approaches, such as univariate unobserved components models, Hodrick-Prescott (HP) or Bandpass filters, derive estimates solely from real GDP data and therefore do not incorporate multivariate information, such as from unemployment rates or other macroeconomic indicators. A limitation of these univariate models is that the estimates they produce generally must be validated against information external to the model. Several recent studies have demonstrated the feasibility and advantage of explicitly incorporating multivariate information into trend-cycle decompositions (Garratt, Robertson, et al., 2006; Sinclair, 2009; Fleischman and Roberts, 2011; Garratt, Lee, et al., 2016; Chan and Grant, 2017; Barbarino et al., 2024; Morley and Wong, 2020). Unlike univariate models, multivariate estimation inherently allows for incorporating a broader range of indicators that capture influences from other sources of fluctuations than real GDP. Despite this, multivariate output gap estimation for emerging economies has remained largely unexplored. Several factors complicate the application of standard multivariate trend-cycle decomposition methods to emerging economies, including shorter data availability, higher economic volatility, outlier events including but extending beyond the COVID-19 pandemic, and distinct economic dynamics compared to developed countries. Furthermore, the lack of established institutional benchmarks for the output gap in these economies means researchers have fewer reference points to validate estimates.

To address these challenges, this chapter investigates which sources of information are most important for accurately estimating output gaps in the Southeast Asian emerging economies of Indonesia, Malaysia, Thailand, and the Philippines. These four economies are selected as a representative group of emerging Southeast Asian economies that share high levels of trade and financial openness in the region and have comparable economic structures.[1] Over the past three decades, these countries have frequently experienced synchronized macroeconomic fluctuations driven by external shocks, most notably during the Asian Financial Crisis (AFC) in the late 1990s. This shared regional experience suggests that financial and global indicators carry significant informational weight, something that univariate models inherently miss. However, this specific regional context also presents a limitation to the broader generalizability of the findings. Because all four economies were central to the AFC, the results likely reflect a heightened informational importance of financial variables unique to this historical experience. Consequently, while the framework is applicable to other open emerging markets, the relative weight of these indicators may differ in other regions, such as Latin America, which are characterized by distinct structural dynamics and historical shocks.

For my analysis, I apply a multivariate Beveridge and Nelson (1981) (BN) decomposition within a large Bayesian vector autoregression (BVAR) framework following Morley et al. (2023) with one key modification. Following a suggestion in Morley and Wong (2020), I place an informative prior on the signal-to-noise ratio to mitigate potential upward bias in the estimated variance of the permanent component. This selection for the signal-to-noise prior ensures the multivariate estimates remain comparable to standard univariate benchmarks while allowing the additional macroeconomic variables to identify the cyclical component more precisely. Secondly, since these countries are considered small open economies, I adopt a two-block structure that distinguishes between global and local sectors, following the approach of Zha (1999), Justiniano and Preston (2010), Kamber and Wong (2020), and Morley et al. (2023), where the global sector is treated as block-exogenous relative to these emerging Southeast Asian economies. Finally, following a Lenza and Primiceri (2022) style approach, I reweight data starting at the COVID-19 pandemic's onset to mitigate outlier effects. This adjustment corrects for the pandemic-induced volatility in macroeconomic time series.

The empirical results yield three key findings. First, traditional slack measures, such as the unemployment rate, are less informative in these emerging economies than in advanced economies. A distinctive feature of these economies is the prevalence of informal employment (Ohnsorge and Yu, 2022). In such settings labor market adjustment to demand shocks occurs largely through movements between formal and informal work, making variables like the official unemployment rate a less informative measure of slack. Capacity utilization series are likewise uninformative, as they cover mainly manufacturing and can move for supply-side reasons. I find that unemployment and capacity utilization do not Granger-cause output in these emerging economies as these indicators suffer from structural issues, contain unit roots, and are available only over relatively short sample periods. Robustness checks further show that the resulting output gap estimates remain almost unchanged when contemporaneous slack measures are included. Despite these constraints, central banks in these economies often rely on such indicators to gauge inflationary pressure; my findings suggest that a multivariate structure provides a more robust signal of the business cycle by incorporating a broader set of macroeconomic and financial

[1] Crucially, these countries also have sufficiently long and consistent macroeconomic time series required for the model estimation.

data.

Second, financial variables, are highly informative. Multivariate output gap estimates align closely with known recession periods and exhibit cyclical persistence, and attribute pre-crisis overheating, most notably before the AFC and the Global Financial Crisis (GFC), to movements in exchange rates, equity prices and international liquidity. Despite a sharp reduction in log output during 1997–98, the moderate decline in the multivariate output-gap estimates suggests a permanent downward shift in trend output, implying that policymakers should consider structural adjustments rather than solely cyclical interventions. Given the regional experience during the AFC, these results show that financial variables such as equity prices and exchange rates are essential for identifying the cyclical component of output during periods of financial stress. Contrary to earlier literature (Kose et al., 2012; Borio et al., 2013; Felipe et al., 2015), my analysis highlights that both global and domestic financial factors account for a significant share of the information that is useful to estimate the output gap, consistent with evidence that excessive financial sector growth can negatively impact real economic output beyond certain thresholds (Cecchetti and Kharroubi, 2015; Rioja and Valev, 2004).

Third, global variables play a crucial role in shaping output gaps for these open emerging economies. Variance decompositions in which global variables are treated as exogenous with respect to the emerging economies show that global factors explain a substantial share of cyclical fluctuations, often more than domestic output itself. While local variables were the primary drivers during the AFC, capital flows linked to global shocks also played a significant role. Negative output gaps during the GFC are likewise largely attributable to spillovers from global shocks. This implies that for these emerging Asian economies, the output gap is driven heavily by global demand and price shocks. Consequently, this makes the multivariate BN framework a practical alternative to more restrictive structural models in monitoring cyclical developments for small open emerging economies. Furthermore, an open-economy Phillips curve analysis reveals that while global demand is the primary driver of inflation in these economies, the multivariate BN gaps yield theoretically consistent positive signs, whereas the standard HP filter often produces counter-intuitive and statistically significant negative coefficients.

The structure of this chapter is organized as follows. Section 2.2 outlines the multivariate BN decomposition method and details on the data used. Section 2.3 presents the main estimation results. Section 2.4 evaluates the robustness of these findings, and Section 2.5 concludes.

2.2 Methods and Data

2.2.1 BN decomposition based on a Bayesian VAR

To estimate the output gap, I implement a multivariate Beveridge-Nelson (BN) decomposition (Beveridge and Nelson, 1981) based on a Bayesian vector autoregression (BVAR). The BN trend τ_t^{BN} is defined as the long-horizon conditional expectation of a time series net of any deterministic drift:

$$\tau_t^{BN} = \lim_{h\to\infty} \mathbb{E}_t[y_{t+h} - h \cdot \mu], \tag{2.1}$$

where $\mu = \mathbb{E}[\Delta y_t]$ is the unconditional mean growth rate and h denotes the forecast horizon. The cyclical component, which represents the output gap, is defined as the deviation of the current level of log real GDP from its permanent trend: $c_t^{BN} = y_t - \tau_t^{BN}$. Following Morley and Wong (2020) I operationalize this using the BVAR companion form:

$$X_t = FX_{t-1} + He_t, \tag{2.2}$$

where $X_t = [\tilde{x}_t', \tilde{x}_{t-1}', \ldots, \tilde{x}_{t-p+1}']'$ is an $Np \times 1$ vector containing the current and lagged values of the demeaned growth rates. F is the $Np \times Np$ companion matrix, and H is a matrix that maps forecast errors to the companion form. As shown in Morley (2002), the BN cycle is a linear function of this companion vector and is calculated as:

$$c_t^{BN} = -\iota_k F[I - F]^{-1} X_t, \tag{2.3}$$

where ι_k is a $1 \times Np$ selector vector with 1 as its k-th element, corresponding to the target variable, log real GDP, and zero otherwise. I estimate the parameters in F by fitting a BVAR(p) model to a demeaned $N \times 1$ vector $\tilde{x}_t = x_t - \mu$, where μ is an $N \times 1$ vector of unconditional means for x_t

$$\tilde{x}_t = \Phi_1 \tilde{x}_{t-1} + \cdots + \Phi_p \tilde{x}_{t-p} + e_t, \tag{2.4}$$

with Φ_j as autoregressive coefficient matrices. Following Morley and Wong (2020), I adopt a Minnesota-type prior where each coefficient ϕ_i^{jk}, representing the i-th lag of variable k in equation j, has mean zero and variance:

$$\mathrm{Var}[\phi_i^{jk}] = \begin{cases} \frac{\lambda^2}{i^2}, & \text{if } j = k, \\ \frac{\lambda^2}{i^2} \cdot \frac{\sigma_j^2}{\sigma_k^2}, & \text{otherwise,} \end{cases} \tag{2.5}$$

where $i \in \{1, \ldots, p\}$ denotes the lag order with σ_j^2 and σ_k^2 being residual variances from univariate AR(4) processes (Bańbura et al., 2013).

Although it is possible to estimate, rather than fix, the shrinkage hyperparameter λ (Giannone, Lenza, et al., 2015), I follow the recommendation in Morley et al. (2023) that, when the focus is on the output gap rather than forecasting the full BVAR system, fixing λ can be more appropriate. Following Evans and Reichlin (1994), the forecastability of real GDP growth is the key element in identifying the output gap. Consequently, the high dimensionality of a BVAR creates a risk of overfitting; this can lead to spurious forecastability that distorts the cyclical estimates (Morley et al., 2023). Estimating λ in such settings tends to place undue weight on fitting all variables in the system, rather than isolating the cyclical dynamics of the target variable, in this case log real GDP. This can distort the estimation of the output gap, which is more directly linked to the predictive accuracy of GDP growth itself, not to the overall system fit. Thus, I fix the shrinkage hyperparameter at $\lambda = 0.2$, following Carriero et al. (2015). This relatively tight prior provide necessary regularization in a large-scale model, ensuring that the estimated forecastability of output growth is not driven by over-fitting a large number of predictors. While lower values of λ can occasionally suppress the amplitude of the output gap, a comparison with a much looser specification of $\lambda = 0.75$ (as seen in Section 2.4) yields nearly identical results. This consistency indicates that the findings, including the significant declines in trend levels during the Asian Financial Crisis, are robustly supported by the data and are not artifacts of the prior.

2.2.2 Imposing Block Exogeneity on the Global Sector

To account for the open-economy structure, I follow Morley et al. (2023) by imposing block exogeneity on the global sector within a BVAR framework. This assumption reflects the idea that global variables, specifically the World Industrial Production (WIP) by Baumeister and Hamilton (2019), U.S. CPI, and the real price of oil, evolve independently from local macroeconomic conditions, while still influencing the local variables. Structurally, this involves enforcing zero restrictions on the autoregressive coefficient matrices such that local variables respond to lagged global variables, but global variables remain unaffected by past local developments.

Formally, the vector of endogenous variables x_t is partitioned into global x_t^g (dimension $N_g \times 1$) and local x_t^l (dimension $N_l \times 1$) components:

$$x_t = \begin{bmatrix} x_t^g \\ x_t^l \end{bmatrix}. \tag{2.6}$$

The resulting block-exogenous VAR(p) is structured as follows:

$$\begin{bmatrix} x_t^g \\ x_t^l \end{bmatrix} = \sum_{i=1}^{p} \begin{bmatrix} A_{gg,i} & 0 \\ A_{lg,i} & A_{ll,i} \end{bmatrix} \begin{bmatrix} x_{t-i}^g \\ x_{t-i}^l \end{bmatrix} + \begin{bmatrix} \varepsilon_t^g \\ \varepsilon_t^l \end{bmatrix}, \quad \varepsilon_t \sim \mathcal{N}(0, \Sigma). \tag{2.7}$$

Here, the zero restrictions explicitly enforce that global variables are unaffected by lagged local variables. Following Morley et al. (2023), I employ a Gibbs sampler combined with a Minnesota-type prior and a Normal-inverse-Wishart prior structure to estimate the model with block exogeneity.

To operationalize this framework, matrices for global (X^g) and local (X^l) equations are separately constructed. The global equations exclusively incorporate lags of global variables, whereas local equations include lags of both global and local variables. Consequently, prior covariance matrices and parameter vectors differ across equations:

$$a_{\text{prior}} = \begin{bmatrix} a_{\text{prior}}^g \\ a_{\text{prior}}^l \end{bmatrix}, \quad V_{\text{prior}} = \begin{bmatrix} V_{\text{prior}}^g & 0 \\ 0 & V_{\text{prior}}^l \end{bmatrix}. \tag{2.8}$$

Because the imposed block exogeneity removes the ability to solve the posterior analytically, Bayesian inference relies on Gibbs sampling, which works with conditional conjugacy. In each iteration of the sampler, VAR parameters are sequentially drawn from conditional posterior distributions, with VAR coefficients drawn conditional on the covariance matrix Σ (assuming normality), and Σ subsequently drawn from an inverse-Wishart distribution conditional on VAR parameters. Iterations continue until convergence is established after a burn-in period. This approach aligns closely with standard practices in the open-economy BVAR literature (see e.g., Zha, 1999; Justiniano and Preston, 2010; Kamber and Wong, 2020; Morley et al., 2023).

2.2.3 Prior on the Signal-to-Noise Ratio

To improve the estimation of the cyclical component in small samples, I impose a prior on the signal-to-noise ratio, defined as the relative variance of trend shocks to forecast errors. This is similar to Kamber, Morley, et al. (2018), and is implemented in the multivariate BN decomposition setting by Morley and Wong (2020). In particular, under a basic Minnesota prior, the log of real GDP in levels is shrunk toward a random walk, which assumes a signal-to-noise ratio of one. While this balances flexibility and parsimony in large samples, in shorter samples, as is common across Southeast Asia, it risks mistaking noise for signal, leading to an upward bias in the implied signal-to-noise ratio. I address this by shrinking toward a pre-specified lower signal-to-noise ratio instead of the random walk case ($\delta = 1$) under a standard Minnesota prior, thus tempering the model's tendency to shrinking towards a random walk and improving cyclical inference.

The prior is implemented via dummy observations appended to the Y_d and X_d matrices. For a given target variable indexed by l, I impose:

$$\mathbb{E}\left[\sum_{i=1}^{p} \beta_i^{ll}\right] = \rho(\bar{\delta}), \tag{2.9}$$

$$\text{Var}\left[\sum_{i=1}^{p} \beta_i^{ll}\right] = \chi^2, \tag{2.10}$$

where β_i^{ll} denotes the autoregressive coefficients of the l-th variable in the BVAR, representing the target variable's own lags. $\rho(\bar{\delta}) = 1 - 1/\sqrt{\bar{\delta}}$ and χ are scaled relative to the overall shrinkage parameter λ. While Morley and Wong (2020) propose $\chi = \lambda/10$, I use $\chi = \lambda/5$ to place a bit weaker shrinkage towards the specified signal-to-noise ratio. Dummy rows are constructed as:

$$[0_{1,l-1}, \frac{\rho}{\chi}, 0_{1,n-l}] \quad \text{for } Y_d, \qquad 1_{1,n} \otimes [0_{1,l-1}, \frac{1}{\chi}, 0_{1,n-l}] \quad \text{for } X_d,$$

encoding the prior belief about the persistence of the target variable.

I set country-specific values of $\bar{\delta}$ based on univariate BN filter output gap decompositions. This embeds prior knowledge from simpler models while maintaining the benefits of multivariate estimation. As discussed in the online appendix to Morley and Wong (2020), the prior has little influence in large samples but plays an important role in smaller samples where the risk of shrinking towards a random walk is greater.

2.2.4 Treatment of COVID-19 Outlier Observations

To address substantial outlier observations arising from the COVID-19 pandemic, I employ a reweighting strategy following the approach outlined in Lenza and Primiceri (2022) and adapted for the multivariate BN decomposition by Morley et al. (2023). This method mitigates the disproportionate influence of pandemic-induced volatility on the Bayesian VAR estimates by introducing a scaling factor that explicitly downweights observations during the COVID-19 period. Intuitively, this approach allows the residual covariance matrix to scale up during the pandemic quarters. By allowing the variance of the structural shocks to expand, the model effectively absorbs the extreme volatility, preventing these outlier observations from distorting the VAR coefficients and ensuring that the estimated trends and cycles remain representative of long-run historical relationships.

Specifically, let Y and X represent the original data matrices composed of demeaned variables:

$$Y = \begin{bmatrix} y_{p+1} \\ \vdots \\ y_T \end{bmatrix}, \quad X = \begin{bmatrix} x_p & \dots & x_1 \\ \vdots & \ddots & \vdots \\ x_{T-1} & \dots & x_{T-p} \end{bmatrix}.$$

I then estimate a vector of pandemic-specific scaling parameters, ψ, for the error variance-covariance matrix Σ via Maximum Likelihood Estimation (MLE):

$$\hat{\psi} = \arg\min_{\psi} -\mathcal{L}(\psi \mid Y, X, T_{covid}),$$

where $\mathcal{L}(\psi \mid Y, X, T_{covid})$ denotes the log-likelihood function conditioned on the observations impacted by COVID-19. Following Morley et al. (2023), I estimate three distinct parameters to cover 2020Q1, 2020Q2, and 2020Q3. This specific window is necessary because the data at the time were characterized by different magnitude changes across all three quarters, with significantly larger drops in 2020Q2 than in 2020Q1, followed by large rebounds in 2020Q3. No parameters are estimated for 2020Q4 as variation typically returns to pre-pandemic levels thereafter. Given these estimated parameters, I construct a time-dependent scaling factor, ψ_t, defined as:

$$\psi_t = \begin{cases} \hat{\psi}_t, & t \in \{T_{covid}, \dots, T_{covid} + n_{covid} - 1\} \\ 1, & \text{otherwise} \end{cases}$$

This scaling factor generates reweighted data matrices by dividing the observations by ψ_t, which effectively downweights the pandemic quarters in the estimation:

$$Y^* = \text{diag}\left(\frac{1}{\psi_t}\right) Y, \quad X^* = \text{diag}\left(\frac{1}{\psi_t}\right) X.$$

The VAR coefficients' posterior mode is then computed analytically using these scaled matrices via penalized least squares:

$$\hat{A} = (X^{*\prime} X^*)^{-1} X^{*\prime} Y^*,$$

and the posterior covariance matrix is estimated accordingly. This two-step approach, estimating pandemic-specific parameters via MLE and then estimating a standard BVAR with reweighted data, is more computationally efficient than a fully Bayesian approach while yielding nearly identical output gap estimates (Morley et al., 2023). This procedure mirrors the approach in Morley et al. (2023) and Lenza and Primiceri (2022), allowing for a correction of the extreme volatility observed across the selected quarters.

2.2.5 Data

I consider quarterly data sourced from CEIC's Key Variables Indicator dataset, spanning Indonesia, Malaysia, the Philippines, and Thailand for the period from 1993Q1 to 2024Q4.[2] Because these Southeast Asian countries are small open economies, I adopt a standard two-block model structure, global and local, where the global block is treated as block-exogenous with respect to the local economies.

Model variable selection is motivated by Evans and Reichlin (1994), specifically recognizing that direct Granger causality with the target variable Δx_t is sufficient but not a necessary condition for inclusion. Variables indirectly influencing the target via another predictor are also included if excluding them changes the BN cycle estimate for y_t. As noted by Morley and Wong (2020), multivariate BN decomposition models should include all variables that carry useful forecasting information for output growth directly or indirectly. Omitting variables with relevant information would alter the estimated output gap, while redundant variables have no effect. Thus, I set a benchmark with 8 variables to broadly capture relevant forecasting information. Due to limited data availability over the full sample period, the baseline model includes eight variables, most or all of which Granger-cause GDP growth at the 10% significance level. For robustness, I extend the analysis to a larger 15-variable model, where each variable similarly satisfies the 10% Granger causality criterion.

The specific set of local variables differs across these four countries for several reasons. First, variables are selected only if data are available for the entire sample period starting in 1993. Second, the variation in the local blocks reflects the unique economic characteristics of each country. What constitutes a relevant leading indicator for output in one economy may not hold the same predictive value in another due to differences in industrial structure, trade dependencies, and domestic institutions. For instance, factors such as oil production in Malaysia or specific export destinations for the Philippines are highly country-specific and may not be relevant for the other economies in the sample. The complete variable list and specific transformations for each series are provided in the Appendix.

The global block includes the World Industrial Production (WIP) by Baumeister and Hamilton (2019), U.S. CPI and the real price of oil. WIP is a volume-based index aggregating industrial activity across OECD and major non-OECD economies, including China. It captures the cyclicality of the global industrial sector and the demand for industrial commodities. By accounting for the shifting centers of global production, WIP provides a more comprehensive proxy for external shocks and regional trade integration than U.S. output would alone.

The local block consists of country-specific variables. For Indonesia, these local variables are domestic GDP, Malaysian GDP, motor vehicle sales, market capitalization, international liquidity, spot FX rate, real effective exchange rate (REER), and imports from the U.S. Both the spot rate and REER are included to distinguish between immediate financial-sector sentiment and real-sector price competitiveness, as both provide non-negligible information for the output gap. For Malaysia, the local block includes domestic GDP, Thai GDP, newly registered companies, employment

[2] The CEIC Key Variables dataset provides a comprehensive suite of indicators that are systematically tracked by national policymakers and central banks in these jurisdictions.

index, consumer sentiment index, equity market index, REER, FX rate, and oil production. For the Philippines, the local variables are domestic GDP, Indonesian GDP, stock market index, exports to China, exports to the Netherlands, net international reserves, government revenue, number of financial institutions, and industrial production index (IPI).[3] Finally, for Thailand, the local block includes domestic GDP, Malaysian GDP, money market rate, FX rate, electricity generation, stock market index, business sentiment index, minimum wage, motor vehicle production, and government debt.[4] Neighboring GDP series (e.g., Malaysian GDP in the Indonesian model) are included because they Granger-cause domestic output, reflecting regional ASEAN links and supply-chain dependencies that the global block does not fully capture.

Data are transformed to ensure stationarity, required for BN decomposition as outlined in Section 2.2.1. I take logarithms of variables when appropriate and difference them if either an Augmented Dickey-Fuller (ADF) test fails to reject a unit root or a Chow test indicates a change in mean between sample halves at the 5% significance level. Furthermore, I apply seasonal adjustments to the series where necessary. If official seasonally adjusted data are not available, the X-13ARIMA-SEATS methodology is used. No structural breaks are detected in these variables based on the Bai and Perron (2003) structural break test. The lag length is set to $p = 4$, consistent with quarterly data analysis.

2.3 Results

2.3.1 Baseline Estimates

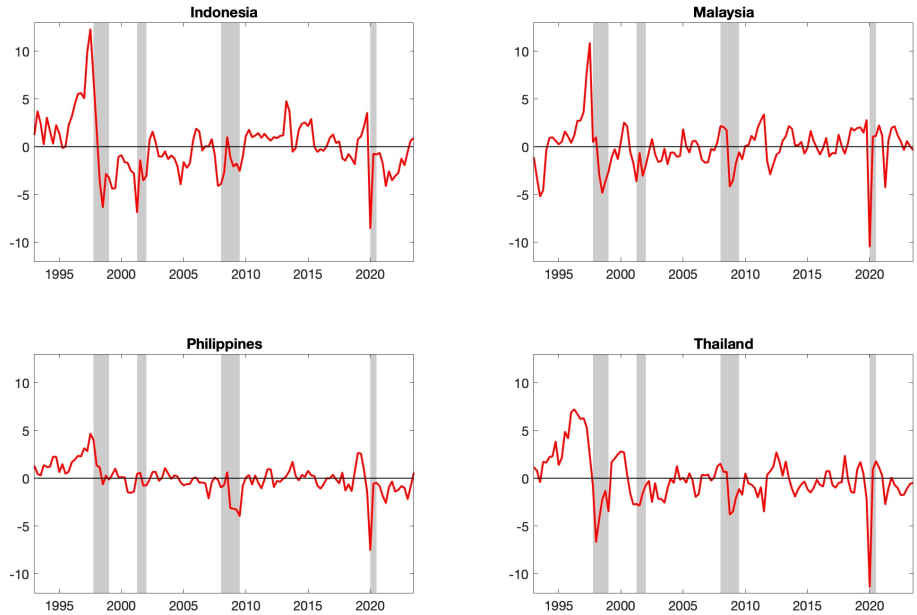
Figure 2.1 presents the baseline multivariate output gap estimates for these emerging Southeast Asian economies. The shaded bars in the figures represent recession dates as identified for the United States by the National Bureau of Economic Research (NBER). It is important to note that for the emerging Asian economies in this study, there are no official, standardized recession chronologies provided by national authorities or institutional bodies. In the absence of country-specific dating, US recession periods are utilized as a proxy for global business cycle downturns. This approach is valid given the high degree of economic openness and trade integration within these emerging Asian economies, where domestic business cycles are often reasonably synchronized with global economic conditions and major external shocks.

These output gap estimates align closely with known recessions and exhibit significant deviations from zero, positive at the peaks of booms and negative during recessions. This suggest that these output gaps are highly persistent. My results also reveal distinct cross-country heterogeneity both in the amplitude and duration of cyclical

[3] Exports to the Netherlands is included to capture the significant trade linkage in the semiconductor and electronics sector; as the Netherlands is a primary destination and a central European distribution node for Philippine electronic components. Moreover, this series carries significant informational content and statistically Granger-causes domestic real GDP growth at the 10% level.

[4] While the minimum wage is not adjusted frequently, its changes serve as a proxy for structural shifts in labor costs and institutional shocks. The variable was selected based on the criteria that it Granger-causes domestic GDP growth at the 10% significance level, suggesting that even infrequent adjustments carry relevant information for estimating output growth.

Figure 2.1: Baseline output gap estimates for Emerging Southeast Asia



Note: Units are 100 times natural log deviation from trend. Shaded areas denote major crisis periods and recession dates as identified by the NBER: the Asian Financial Crisis (1997–1998), the Dot-com Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020).

fluctuations. However, similar to the findings of Gerlach and Yiu (2004), I find that these Southeast Asian economies all experienced a cyclical boom preceding the AFC, suggesting overheating prior to the crisis. Furthermore, the relatively moderate decline in the multivariate output gap estimate during 1997–98, despite a sharp reduction in log output, implies a permanent downward shift in trend output given larger falls in real GDP. After 1998, gradual recovery ensued, but the pace differed by country. For instance, Indonesia's recovery was the most protracted, in part due to political instability following President Suharto's resignation in 1998. In contrast, the Philippines exhibited a relatively smaller negative output gap during the crisis, likely due to less significant overheating in the Philippine economy prior to the crisis relative to its neighbours.

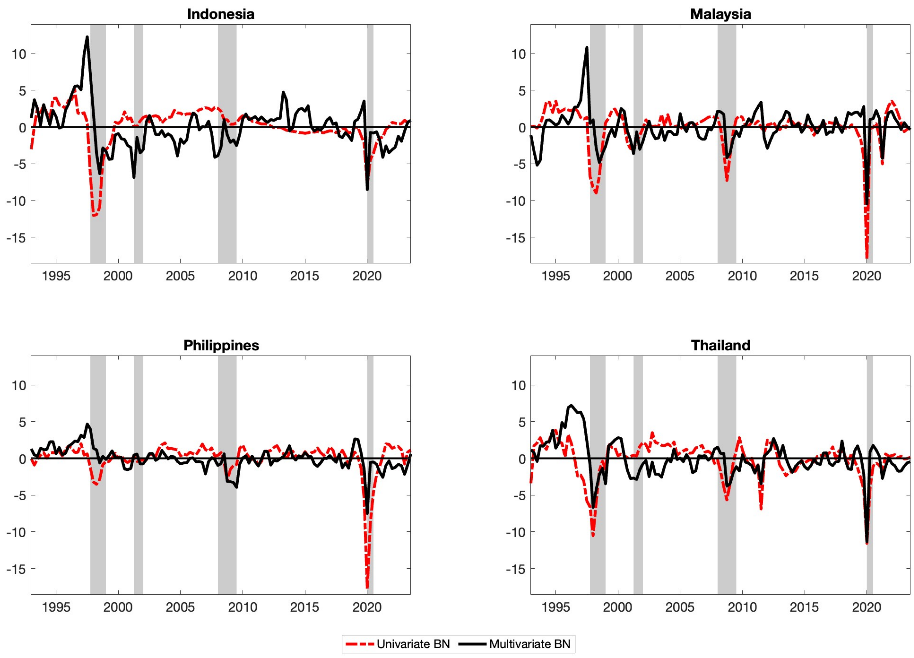
A decade later, the GFC spread to Southeast Asia through collapsing export demand and volatile capital flows. Output gaps turned negative as growth faltered, however these gaps were shallower than in the AFC. Several factors help explain why the GFC impact was not as severe for these economies. By the late 2000s, many Southeast Asian economies had implemented structural reforms and prudent macroeconomic policies in the wake of the AFC, such as building foreign exchange reserves, reducing debt, and strengthening financial oversight. Moreover, China's rapid stimulus-driven recovery buoyed Asian exports and moderated cyclical fluctuations during the GFC period. The post-GFC decade was characterized by relatively smaller output gaps and sustained growth.

My estimates capture a large common drop in output during the COVID-19 pandemic.

Among the hardest hit, the Philippines endured a particularly prolonged contraction. This was exacerbated by one of the world's most stringent and extended COVID-19 lockdowns, which shut down large swathes of its economy. Even after the strict restrictions were eventually relaxed and the economy rebounded, the estimated output gap remained negative, suggesting that actual output was still below the pre-pandemic trend. For Indonesia, Malaysia, and Thailand, these economies saw sharp output declines in the immediate aftermath of the pandemic's onset, but also recovered relatively quickly once restrictions were eased. Each experienced a rapid rebound in economic activity after mid-2020 as lockdown measures were lifted. By 2021, their output gaps had narrowed significantly (closer to zero), implying that most of the pandemic-induced shortfall in output was temporary rather than permanent.

Comparison against other estimates

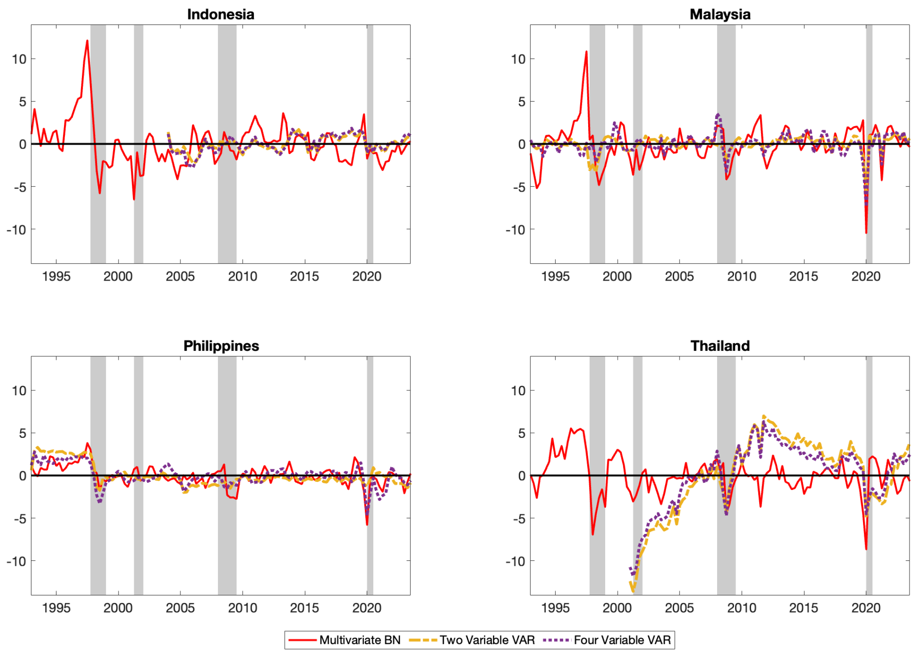
Figure 2.2: Output gap estimates from univariate and multivariate BN decompositions.



Note: Units are 100 times natural log deviation from trend. Units are 100 times natural log deviation from trend. Shaded areas denote major crisis periods and recession dates as identified by the NBER: the Asian Financial Crisis (1997–1998), the Dot-com Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020).

A common approach to validating output gap estimates is to compare results against official benchmarks from institutional bodies such as the IMF, OECD, or national central banks. However, for the emerging Asian economies in this sample, consistent and publicly available institutional estimates for the output gap do not exist in a standardized format. While central banks in these countries have significantly increased transparency and frequently reference output gaps or spare capacity in their communications to signal policy stances (see e.g., Bangko Sentral ng Pilipinas, 2026; Bank of Thailand, 2026), they typically do not publish the underlying official

Figure 2.3: Comparison of the baseline estimated multivariate output gap with those from other Bayesian VAR models



Note: "Two variable VAR" is based on a Bayesian bivariate VAR(4) model using output growth and the unemployment rate. "Four variable VAR" employs a Bayesian four-variable VAR(4) model that additionally incorporates IPI growth and quarterly CPI. Units are 100 times natural log deviation from trend. Shaded areas denote major crisis periods and recession dates as identified by the NBER: the Asian Financial Crisis (1997–1998), the Dot-com Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020).

time-series used in their internal models.[5]

In the absence of these benchmarks, the reliability of the multivariate BN approach is instead assessed through a comparative analysis of revision properties against established univariate filters. Evidence from Chapter 1 shows that for Indonesia, Malaysia, Philippines, and Thailand, the univariate BN filter consistently outperforms the Hamilton, HP, and CF filters in terms of revision stability.[6] In Indonesia and Malaysia, the Hamilton filter tends to produce mechanically large spikes following recessions, likely due to predictable base effects from the 8-quarter-ahead forecast of log real GDP (De Gorostiza-Roudnitski, 2026). This is consistent with what Kamber, Morley, et al. (2025) found for the United States. Furthermore, the requirement to drop the first eight quarters of data poses a challenge for economies with shorter time series (Quast and Wolters, 2022).[7]

To further motivate this approach, I follow Morley et al. (2023) by also comparing my estimates against the univariate BN filter estimate, a bivariate VAR model comprising output growth and a slack variable (either the unemployment rate or capacity utilization, depending on data availability), and a four-variable VAR model consisting of output growth, the slack variable, CPI inflation, and industrial production growth. Figure 2.2 compares the multivariate BN estimates to that of the univariate BN estimates based on the BN filter (Kamber, Morley, et al., 2018; Kamber, Morley, et al., 2025). This comparison assesses the effects of incorporating multivariate information on estimating the output gap. I find that the multivariate output gaps broadly aligns with the univariate estimates, though distinct differences emerge during crisis episodes. Notably, during the AFC, both approaches identify a comparable magnitude of impact on the change in the output gap, but the univariate BN estimates suggest this leads to a larger negative output gap, whereas the multivariate BN estimates suggests the change was from a larger positive output gap due to overheating prior to the crisis. Additionally, during the pandemic, the univariate estimates suggest a more negative output gap compared to the multivariate estimates. This divergence likely arises because the multivariate estimates incorporate additional sources of information beyond real GDP alone, such as from the financial sector, whereas the univariate approach relies solely on GDP data and explicitly

[5]While the Bangko Sentral ng Pilipinas (BSP) employs a "suite-of-models" approach, averaging results from various statistical filters (i.e. HP and Kalman filters) and structural models, it does not disclose the specific weights or historical revisions applied to these estimates (Bangko Sentral ng Pilipinas, 2026). Bank Negara Malaysia (BNM) and Bank Indonesia (BI) on the other hand, utilize multivariate filters and manufacturing surveys to gauge slack (Bank Negara Malaysia, 2026; Bank Indonesia, 2025). However, these assessments are typically presented as qualitative charts or short-term forecasted ranges. Consequently, they do not constitute a continuous historical dataset suitable for direct quantitative benchmarking in longitudinal studies.

[6]To benchmark the performance of the BN filter for these emerging Asian economies, De Gorostiza-Roudnitski (2026) employs three alternative detrending methods: the boosted Hodrick–Prescott (HP) filter of Phillips and Shi (2021), the refined Hamilton filter of Quast and Wolters (2022), and the Christiano and Fitzgerald (2003) (CF) filter. Each method represents a modified version of standard approaches, chosen to address known weaknesses such as excessive smoothing, endpoint bias, and spurious high-frequency fluctuations. These refinements ensure that comparisons with the BN-based estimates reflect differences in methodology rather than suboptimal parameterization.

[7]It is important to note that the multivariate BN decomposition considered in this chapter is not directly comparable to the Hamilton filter or other univariate detrending methods, as the multivariate BN decomposition incorporates a broader information set from slack variables and financial indicators whereas the univariate filters do not.

imposes a trend smoothness assumption.

Looking at Figure 2.3 for the comparisons of the benchmark multivariate estimates to that of the two-variable and four-variable VAR estimates, output gaps derived from VAR models generally align with known recession periods and are roughly similar to the benchmark estimates but exhibit smaller amplitudes. In particular, the smaller-order VAR estimates tend to imply a less negative and relatively flat output gap during known recession periods. Although the literature on the U.S. economy (see Fleischman and Roberts, 2011; Berge, 2018; Morley and Wong, 2020; Barbarino et al., 2024; González-Astudillo and Roberts, 2022) emphasizes slack variables, such as unemployment rates and capacity utilization, as critical for accurately capturing output gaps, data constraints, particularly in countries like Indonesia and Thailand, limit their application due to shorter sample periods.

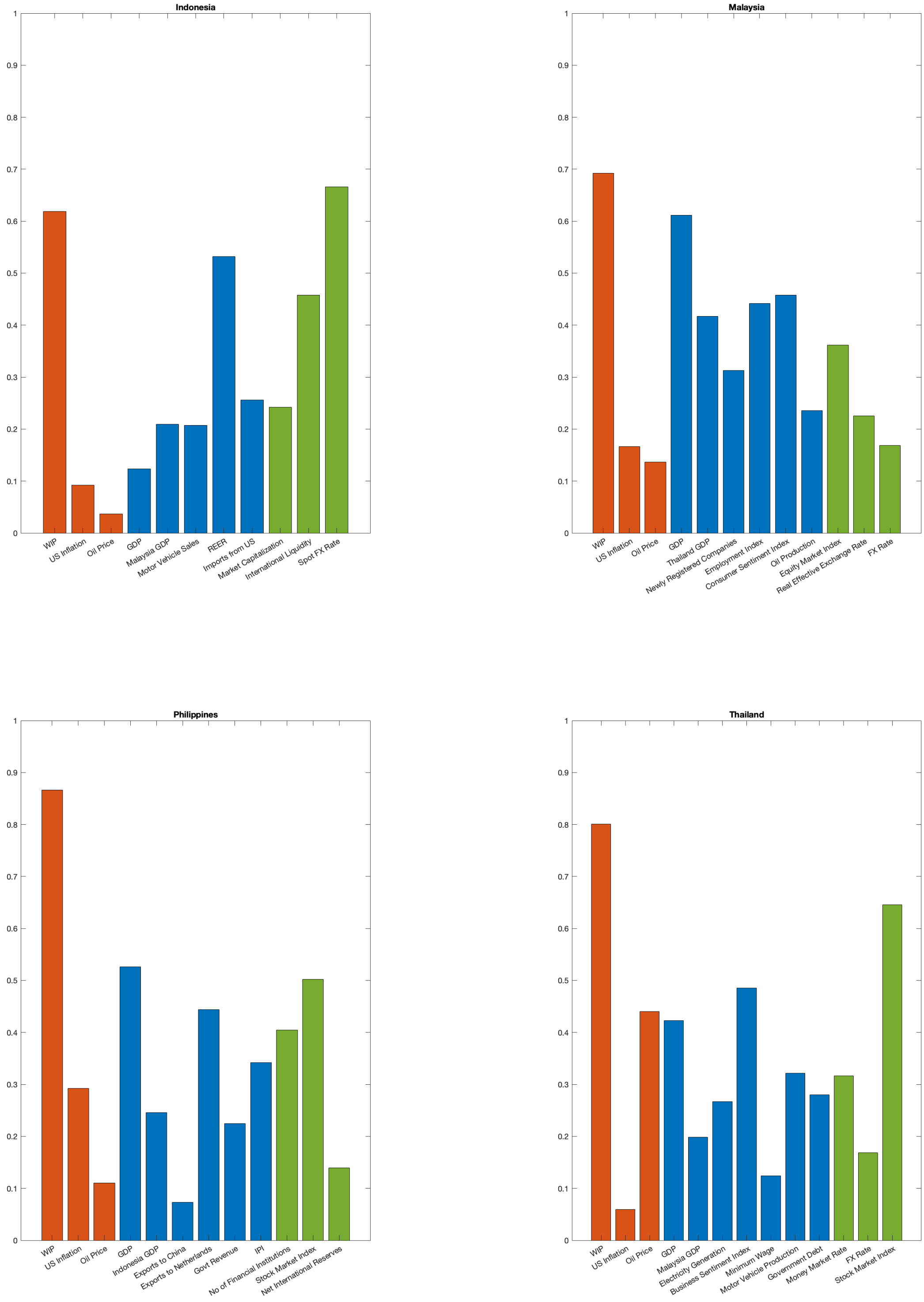
2.3.2 Information Decompositions

A key advantage of the multivariate framework adopted in this study compared to a univariate approach is that it allows for more interpretation of the output gap by decomposing it into various sources of forecast errors, or potentially identified structural shocks, as discussed in Morley and Wong (2020). Although my results from Figure 2.3 and the findings of Morley and Wong (2020) and Morley et al. (2023) show that these estimates do not always deviate substantially from their univariate counterparts, the ability to isolate components of the output gap associated with possible explanatory factors remains a distinct benefit of the multivariate approach.

An immediate concern is whether each variable in the benchmark model contributes relevant information for estimating the output gap. To address this, I examine the relative contributions of forecast errors for each variable. Figure 2.4 reports the standard deviations of these contributions in the baseline specification. The most important conditioning variables across the Philippines, Thailand, Malaysia, and Indonesia include those related to external economic conditions, most notably WIP. Other macroeconomic factors, such as industrial production, international trade, and cross-country GDP within the region, are also relevant. Additionally, financial variables, particularly exchange rates, equity market indices, and international liquidity, play key roles in accounting for cyclical fluctuations in these economies. My results show that almost every included variable makes a non-negligible contribution, implying they capture information beyond what is contained in output growth alone. This observation also helps explain why multivariate output gap estimates differ from univariate ones, such as those as shown in Figure 2.2.

Three main insights emerge from this informational decomposition. First, while there is no single domestic indicator that overwhelmingly dominates in explaining the estimated output gap, financial variables appear to play a particularly important role in conveying information about the output gap, consistent with impacts of the AFC and GFC. During the AFC, for example, substantial currency depreciations and the fall in equity prices occurred alongside the contraction in real activity. These financial shocks may have contributed to a widening of the output gap, as disruptions in credit markets and increased debt-servicing costs likely pushed actual output below its potential level. Similarly, during the GFC, the reduction in international liquidity and increased equity market volatility signaled a decline in output before

Figure 2.4: Relative informational contribution of each variable.



Note: The relative informational contribution of each variable is measured as the ratio of the standard deviation of the variable-specific component to the standard deviation of the BN cycle for real GDP. Block exogenous global variables are in orange, financial variables are in green, while all other macroeconomic variables are in blue.

it was fully reflected in national accounts data. These observations suggest that financial variables contain relevant forecasting information for output gap dynamics, as financial stress is often associated with a persistent deviation of GDP from its long-run trend.

Second, contemporaneous measures of slack like unemployment and capacity utilization do not explain the estimated output gap.[8] Indeed, no slack indicators were included in the baseline because they do not appear to Granger-cause output in these economies. This result may be attributable to structural issues, unit roots, or relatively short sample periods for these slack measures for these emerging Asian economies.

Beyond data length, several structural features of emerging Asian labor markets likely contribute to this result. Unlike advanced economies, these markets are often characterized by significant rigidities in the formal sector, including stringent employment protection legislation and high severance costs (Forteza and Rama, 2006; Betcherman, 2012). These institutions incentivize firms to adjust hours or wages rather than headcount during downturns, which can lead to "jobless" recoveries and a decoupling of formal unemployment from the business cycle (Duval and Loungani, 2021). Furthermore, the limited informational content of capacity utilization may stem from its narrow coverage. In these economies, these series are predominantly manufacturing-based and often derived from business tendency surveys with low response rates or limited sectoral scope. Such measures are frequently influenced by supply-side idiosyncratic shocks—such as energy shortages, infrastructure bottlenecks, or export-oriented inventory cycles—rather than aggregate demand-side slack. Consequently, these indicators may provide a poor signal for the aggregate output gap in economies where the services and informal sectors represent a substantial share of total activity. As documented in De Gorostiza-Roudnitski (2026), while these narrow measures of slack do display some correlation with the univariate BN filter output gaps, they are frequently dominated by secular trends and exhibit reduced amplitude compared to benchmarks like the United States. In the case of Indonesia, specifically, the unemployment rate may capture more structural rather than cyclical movements due to its biannual frequency and shorter historical coverage.

Another plausible explanation is the prevalence of large informal sectors. Informal employment accounts for roughly two-thirds of total employment in Indonesia and the Philippines and remains above one-half in Malaysia and Thailand (Ohnsorge and Yu, 2022). With a sizeable informal sector, labor market adjustment to demand shocks occurs mainly through transitions between formal jobs, informal self-employment and own-account work rather than through unemployment, thus the official unemployment rate becomes a poor barometer of economic slack. Empirically, unemployment-output correlations decline with informality (Horvath and Yang, 2022; Coşkun, 2022), and DSGE models featuring formal–informal segmentation reproduce this dampening mechanism by showing that unemployment volatility falls as informality rises (Lambert et al., 2020). Although incorporating the informal sector is crucial,

[8] Capacity utilization in these countries is typically measured through manufacturing or business tendency surveys conducted by central banks or national statistics agencies. For instance, Bank Indonesia's Business Survey reports manufacturing capacity utilization quarterly; Malaysia's Department of Statistics collects similar data via industrial performance surveys; Thailand and the Philippines also rely on manufacturing-sector surveys to compute this metric.

informality itself is difficult to observe and typically employs either survey-based or model-based measures. Survey-based approaches can capture various aspects of informality but often suffer from limited data availability across countries and periods, reporting biases, and methodological inconsistencies (Ohnsorge and Yu, 2022). Conversely, model-based measures provide broader and more consistent coverage with clear economic interpretations, however they depend heavily on strong assumptions (Ohnsorge and Yu, 2022).

To explore further the limited informational content of unemployment in these economies, I compare each measure with electricity consumption.[9] Electricity usage is a widely accepted proxy for aggregate economic activity because it responds to changes in industrial output, commercial services, and household demand, and can capture formal as well as informal production. Conceptually, electricity consumption should rise when the economy is operating above potential, yielding a positive correlation with the output gap; and fall when labor market slack widens, implying a negative correlation with unemployment. Table 2.1 shows that electricity demand co-moves positively with the multivariate output gap in all three countries, as anticipated: higher utilization of productive capacity boosts electricity usage. The link is moderate in Malaysia (ρ = 0.53) and Thailand (ρ = 0.47) but stronger in the United States (ρ = 0.66). In contrast, unemployment is essentially uninformative in the two emerging economies, correlations with electricity are near zero or mildly negative. This pattern is consistent with large informal sectors muting labor market signals while electricity demand continues to track aggregate activity. For the United States, where unemployment rate is largely informative, the correlation with electricity consumption (ρ = -0.90) is quite strong.

Table 2.1: Contemporaneous correlations of 100 times natural log of electricity consumption with alternative slack indicators.

Country	Output gap	Unemployment
Malaysia	**0.53**	−0.15
Thailand	**0.47**	0.06
United States	**0.66**	**-0.90**

Note: The first column reports the correlation between electricity usage and the multivariate BN output gap estimate; The second column reports the correlation between electricity usage and the unemployment rate. Positive values signal co-movement with economic activity, whereas negative values indicate an inverse relationship.

It is important to note that quarterly electricity data are only available for Malaysia and Thailand. While the lack of comparable series for Indonesia and the Philippines prevents a similar quantitative correlation exercise for these cases, the results for

[9] Electricity usage is the sum of consumption by the different end-use sectors (industry, transport, residential, commercial, and agriculture). It excludes energy used by the energy sector itself (e.g., for power plant operations) and losses incurred during the transformation and distribution of energy (e.g., grid transmission losses). Quarterly data on total electricity consumption are available only for Malaysia and Thailand among the four emerging Asian economies analysed; hence the correlation exercise is limited to these two cases. The United States is included solely as a benchmark for comparison. Data is sourced from International Energy Agency (IEA).

Malaysia and Thailand provide a suggestive benchmark for the region. Given that Indonesia and the Philippines possess even larger informal employment shares, estimated at approximately two-thirds of total employment (Ohnsorge and Yu, 2022), the dampening effect of informality on formal slack measures is likely at least as significant in these economies. Using the cross-country database of Elgin et al. (2021), the size of the informal economy as a percentage of official GDP in 2020 is estimated at 45.0% for Thailand, 43.1% for Indonesia, 32.0% for the Philippines, and 26.8% in Malaysia which are substantially larger than in high-income countries like the United States, where the informal economy is estimated at approximately 8.5% of GDP.

This characteristic is further supported by sensitivity analysis across the full country sample. As discussed in the section 2.4, the inclusion of unemployment or capacity utilization results in near-identical output gap estimates to the baseline multivariate BN model. The fact that the estimated gaps remain virtually unchanged across all four countries despite the addition of these variables implies that the BN filter identifies formal slack measures as statistically uninformative for output dynamics. This finding reinforces the argument that large informal sectors decouple formal labor market indicators from aggregate activity, as the estimated gaps remain robust to the exclusion of these measures even in the cases of Indonesia and the Philippines where electricity consumption data is unavailable.

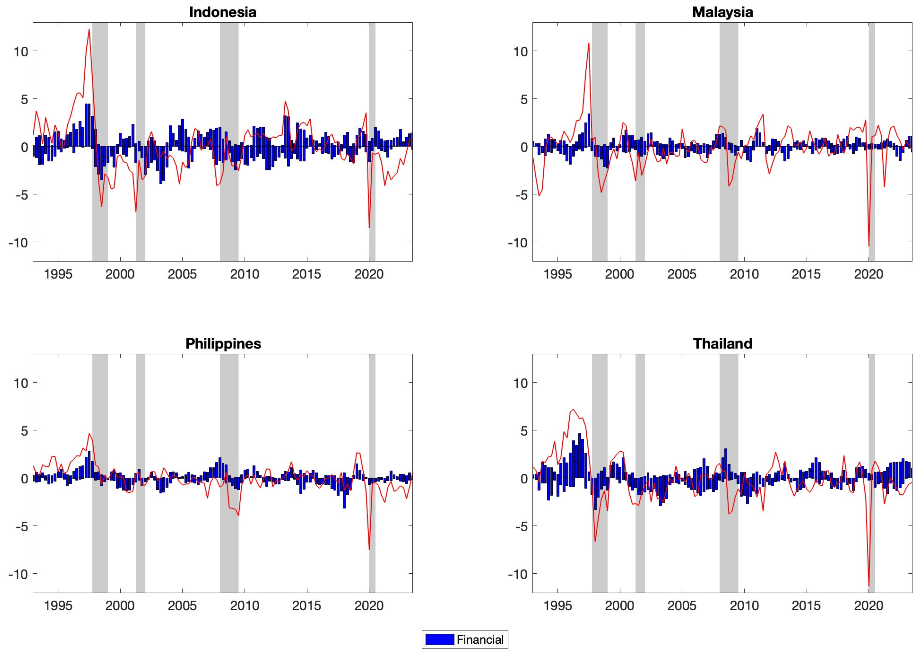
Lastly, despite consisting of only three variables, the global sector block collectively accounts for a sizable portion of the information used to estimate the output gap. Moreover, given the limitations of traditional slack measures, external variables may be more informative for assessing output gaps in these economies, suggesting a susceptibility of business cycles to global forces. I discuss the specific channels and historical impact of these global forces in further detail in Section 2.3.2.

The Historical Role of the Financial Sector

A clear similarity across the Philippines, Thailand, Malaysia, and Indonesia is the prominent role of financial factors in explaining output gaps. Unlike the global-versus-local decomposition, which relies on a structural identification scheme discussed later in Section 2.3.2, the contributions here are derived from a historical informational decomposition of the output gap, showing the proportion of its variation explained by the forecast errors of financial sector variables, grouped together. As the estimated output gap is a linear function of the historical forecast errors (e_{t-i}) of the variables in the system, this approach allows us to back out the contribution of each specific variable's information to the BN cycle (Morley et al., 2023). It is important to note that because these forecast errors are correlated, their total sum does not necessarily add up to the total variance of the output gap (Morley et al., 2023) and is not necessarily causal. This differs from the structural identification of global and local shocks in Section 2.3.2, where the variances of orthogonalized structural shocks do add up to the total output gap variance and are meant to be causal.

In all four economies, variables capturing financial conditions (stock market indices, foreign exchange rates, market capitalization, etc.) provide substantial informational content for the output gap. This suggests a region-wide phenomenon: as these economies have developed and integrated financially, the financial cycle has become tightly coupled with the business cycle. When credit is abundant and financial

Figure 2.5: The role of the financial sector.

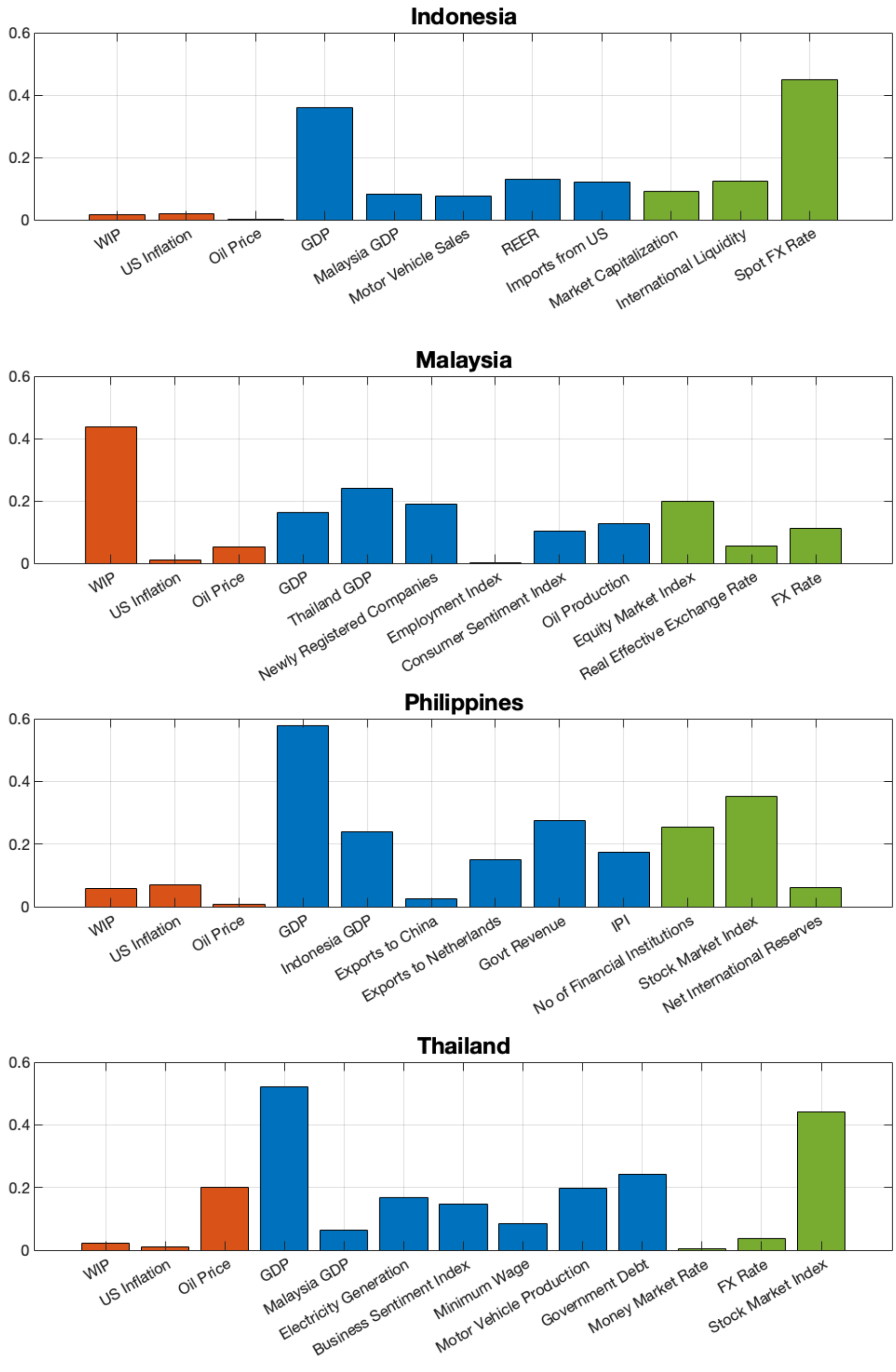


Note: Contributions are derived from an informational decomposition of the output gap, showing the proportion of its variation explained by the forecast errors of financial sector variables, grouped together. Shaded areas denote major crisis periods and recession dates as identified by the NBER: the Asian Financial Crisis (1997–1998), the Dot-com Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020).

markets buoyant, actual output tends to rise above potential; when credit conditions tighten or financial stress emerges, output falls below potential. Contrary to earlier findings for different sample periods of data (e.g., Kose et al., 2012; Borio et al., 2013; Felipe et al., 2015), my results suggest that financial variables provide a sizable portion of the information used to calculate the output gap in emerging Southeast Asian economies. A closer look at the historical decomposition in Figure 2.5 reveals that these financial factors were especially significant in explaining the downturn in real output during both the AFC and the GFC. These episodes highlight the increasing importance of financial sector developments as economies progress, in line with the argument that financial conditions become more influential for real activity over time (Rioja and Valev, 2004; Cecchetti and Kharroubi, 2015).

This inclusion is justified by the presence of financial frictions that create a wedge between actual and efficient levels of output (Furlanetto et al., 2021). While standard models focus on nominal rigidities, Furlanetto et al. (2021) demonstrate that credit market imperfections, such as borrowing constraints and time-varying risk premia, act as a distinct source of inefficiency. An examination of the informational contributions to the trend component as seen in Figure 2.6 reinforces this view. While real GDP remains the primary driver of trend identification, the contributions of financial variables are non-negligible. These frictions imply that the natural level of output is an insufficient benchmark; instead, an "efficient" level must be considered that accounts for financial distortions. Under this framework, financial shocks can fundamentally shift the supply-side capacity of the economy. For instance, an easing of financial

Figure 2.6: Information Decomposition of the Trend



Note: Relative informational contribution of each variable to the trend, measured as the ratio of the standard deviation of the variable-specific component to the standard deviation of the BN trend for real GDP. Block exogenous global variables are in orange, financial variables are in green, while all other macroeconomic variables are in blue frictions reduces the cost of capital and stimulates potential output in the short run, while a crisis tightening these constraints leads to a persistent decline in productive capacity. This resonates with the "finance-neutral" output gap literature, which argues that traditional measures fail by ignoring the procyclical nature of the financial cycle (Borio et al., 2013). By incorporating indicators like credit conditions and asset prices, the multivariate BN filter captures these financial distortions and identifies cyclical movements that remain invisible to real-side approaches (Filardo, 2004; Borio et al., 2013).

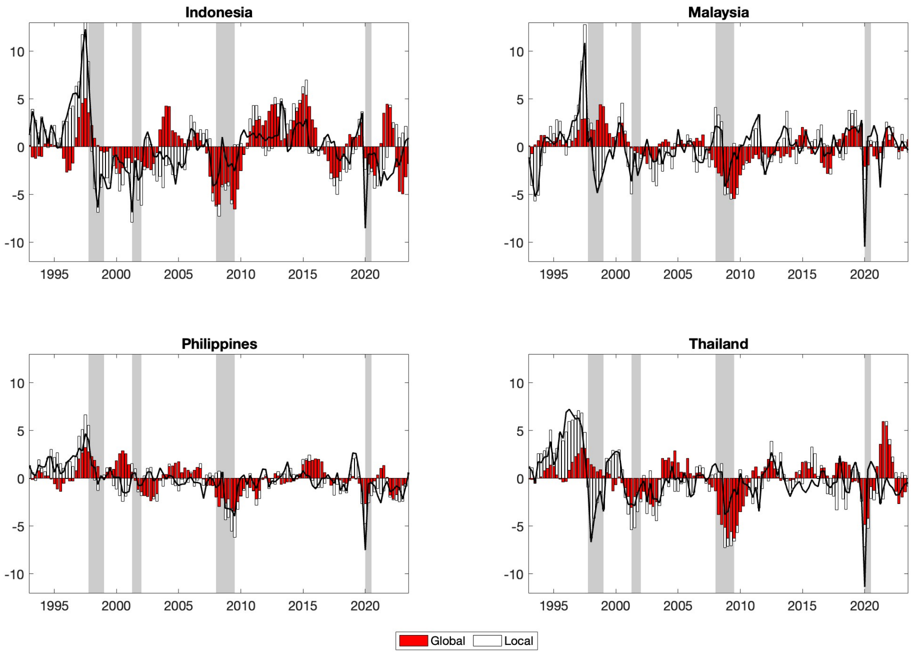
Moreover, the results support the notion that excessive expansion in the financial sector can drive resource misallocation, thereby reducing potential output gains (Cecchetti and Kharroubi, 2015). Consistent with Law and Singh (2014), finance exerts a positive influence on growth only up to a certain threshold, after which it tends to crowd out the very investments needed for sustainable real output. In addition, elevated inflation can undermine the benefits of financial development (Rosseau and Wachtel, 2002), limiting finance's ability to foster productivity once prices begin accelerating. This analysis also resonates with the view that ample credit availability during economic booms loosens supply-side constraints in the short term, leading to a surge in investment and output, but can also stimulate unsustainable asset price inflation and real exchange rate appreciation, ultimately harming longer-term stability. These findings reinforce the argument of Borio et al. (2013) that incorporating financial factors into models of potential output and the output gap yields a more comprehensive understanding of economic dynamics than approaches that tended to focus on real-sector slack and often assumed financial effects were secondary. Furthermore, my results indicate that policymakers in these Southeast Asian economies should pay close attention to financial indicators when assessing economic slack or overheating, as they are important determinants of the output gap and capture imbalances that pure real-side measures might miss.

The Historical Role of the Global Shocks

Following the two-block structure with block exogeneity for the foreign block, as advocated by Zha (1999), Justiniano and Preston (2010), Kamber and Wong (2020), and Morley et al. (2023), I separate the model into global and local sectors, treating the global sector as block-exogenous relative to these emerging Southeast Asian economies. Under this assumption, I impose that shocks from these small open economies do not feed back into major global indicators such as World Industrial Production, U.S. CPI, or real oil prices. This restriction helps mitigate the risk of overfitting in a relatively small sample, while also reflecting the likely limited influence that these economies actually exert on global aggregates.

Figure 2.7 presents an historical decomposition of the baseline estimated output gap into global and local shocks. Following Kamber and Wong (2020) and Morley and Wong (2020), this is more of a structural decomposition than the information decomposition for financial variables given the block exogeneity assumption for the foreign block. By utilizing a Cholesky decomposition to orthogonalize the reduced-form errors into domestic and foreign blocks, the global and local components sum to the total output gap at each period. Furthermore, while individual informational variance shares do not sum to the total due to correlations, the variances of these orthogonalized structural shocks do add up to the total output gap variance. The

Figure 2.7: Decomposition of the output gap estimates into global versus local shocks.



Note: Contributions are derived from an informational decomposition of the output gap, showing the proportion of its variation explained by the forecast errors of global vs local sector variables. Shaded areas denote major crisis periods and recession dates as identified by the NBER: the Asian Financial Crisis (1997–1998), the Dot-com Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020).

results indicate that global factors often have a substantial impact on the output gaps for all four of the economies, at times exceeding the influence of local shocks. This high explanatory power reflects the high degree of openness characterizing these emerging economies, where domestic conditions are closely tied to international trade and financial cycles. Specifically, shocks to World Industrial Production capture broad shifts in global demand which impact domestic output through export channels while shocks to the real price of oil impact production costs and the terms of trade. Furthermore, U.S. price shocks may influence local price-setting behavior and real interest rate differentials, potentially causing actual output to deviate from potential.

For example, although local variables largely determined output gap fluctuations during the AFC, capital reversals and shifting global investor sentiment also played a key role. During this period, the tightening of global financial conditions interacted with domestic vulnerabilities, suggesting that even crises primarily characterized by local structural issues are exacerbated by external financial volatility. Similarly, much of the negative output gap observed during the GFC stemmed from spillovers originating in the global sector. The collapse in aggregate demand in advanced economies translated into a sharp contraction in export-oriented manufacturing across Southeast Asia. This shows that global trade shocks can drive domestic output significantly below potential even in the absence of a systemic domestic banking crisis. During the COVID-19 pandemic, approximately half of the decline in the output gap can be ascribed to the direct effects of external shocks. This finding captures the worldwide fallout from the virus, including the synchronized halt in global tourism and the disruption of international supply chains. Meanwhile, domestic factors, especially those associated with lockdown policies, account for the remaining half. This decomposition highlights the importance of local policy decisions in shaping macroeconomic outcomes. Although the pandemic was a global event, the scope and severity of its impact on each economy were strongly influenced by the specifics of local containment measures. For instance, the Philippines imposed one of the most stringent lockdowns and experienced a protracted contraction, whereas Indonesia, Malaysia, and Thailand recovered relatively quickly after easing restrictions.

The significant role of external shocks suggests that traditional output gap estimates, which often rely on purely domestic indicators, may be insufficient for guiding policy in small open economies. While central banks in the region already monitor global developments, these findings suggest that formally incorporating global macroeconomic factors and commodity price shocks into the estimation of the output gap can provide a more informative measure of potential output. By utilizing a multivariate framework that accounts for these global linkages, policymakers can better distinguish between transitory external shocks and structural domestic shifts. This allows for a more calibrated policy response to deviations from potential that are driven by factors originating outside of domestic control.

2.3.3 Open-Economy Phillips Curve

To evaluate the economic relevance of the estimated output gaps, I examine their relationship with inflation through an open-economy Phillips curve framework. Following the literature on small open economies, I regress the inflation gap on its own lag, the domestic output gap, and a foreign output gap proxied by the cyclical component of the WIP. The foreign output gap is proxied by the WIP gap; both the WIP and inflation gaps are estimated via univariate BN decomposition. For the comparison case, the inflation, foreign, and domestic gaps are all derived using the two-sided HP filter. This exercise compares the performance of the multivariate BN output gaps against those derived from a standard two-sided HP filter.

Table 2.2 presents the results. A consistent finding across both specifications is the high degree of inflation persistence and the dominance of global factors. The foreign output gap is positive and statistically significant for almost all countries, confirming that inflation in these emerging Southeast Asian economies is primarily driven by international demand and global output cycles. This finding is consistent with (Auer et al., 2018) which suggests that external slack often overshadows domestic conditions in highly open economies.

The lack of statistical significance for domestic output gaps suggests that inflation dynamics in these emerging economies are primarily governed by international rather than domestic demand pressures. However, the multivariate BN decomposition yields coefficients with signs that are broadly consistent with economic theory, contrasting with the statistically significant, counter-intuitive negative slopes produced by the HP filter. These results imply that the multivariate BN approach provides a more theoretically coherent identification of the domestic business cycle.

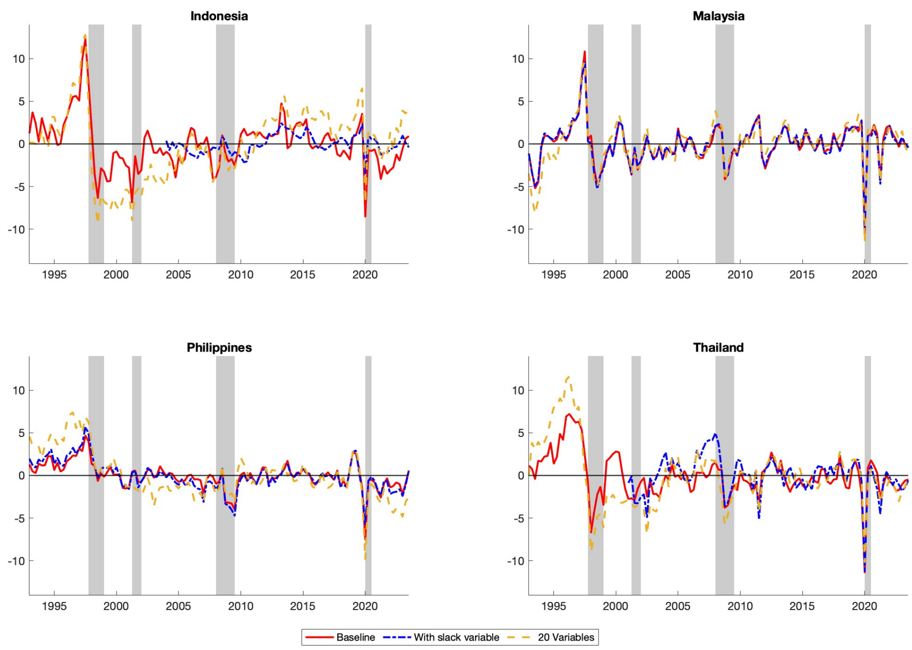
Table 2.2: Phillips Curve Regression Results

	Multivariate BN				Two-Sided HP Filter			
Dep. Var: Inflation Gap	INO	THA	MAL	PHI	INO	THA	MAL	PHI
Lagged Inflation Gap	0.853***	0.674***	0.641***	0.719***	0.507***	0.651***	0.695***	0.714***
	(0.051)	(0.063)	(0.066)	(0.062)	(0.058)	(0.063)	(0.059)	(0.064)
Domestic Output Gap	0.068	0.0003	0.028	-0.051	-0.909***	-0.048	-0.010	-0.009
	(0.126)	(0.043)	(0.040)	(0.066)	(0.115)	(0.034)	(0.026)	(0.039)
Foreign Output Gap	0.145	0.271***	0.206***	0.168***	0.293***	0.212***	0.154***	0.087*
	(0.209)	(0.064)	(0.052)	(0.057)	(0.109)	(0.052)	(0.041)	(0.050)
R-squared	0.714	0.611	0.522	0.565	0.840	0.618	0.585	0.520

Notes: Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The foreign output gap is proxied by the WIP gap. In Panel A both WIP and inflation gaps are estimated via univariate BN decomposition. In Panel B, the inflation, domestic and foreign output gaps are derived using the two-sided HP filter ($\lambda = 1600$).

2.4 Robustness

Figure 2.8: Estimated output gaps for various-sized models



Note: Units are 100 times natural log deviation from trend. Shaded areas denote major crisis periods and recession dates as identified by the NBER: the Asian Financial Crisis (1997–1998), the Dot-com Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020).

In this section, I examine the robustness of the output gap estimates in these emerging Southeast Asian economies. Given the relatively brief historical data availability for these countries, I conduct several robustness exercises to assess the sensitivity of output gap estimates to the choice of indicators. As seen in Figure 2.8, I first compare multivariate estimates that include and exclude slack variables such as the unemployment rate or capacity utilization.[10] The resulting output gaps for most

[10]Unemployment data are included for the Philippines (available from 1993:Q1) and Thailand (from 2001:Q1) Capacity utilization data are included for Malaysia (from 1993:Q1) and Indonesia (from 2004:Q1). In Indonesia, unemployment data are excluded from the baseline specification due to their biannual frequency and limited historical coverage.

Figure 2.9: Effects of changing the shrinkage hyperparameter

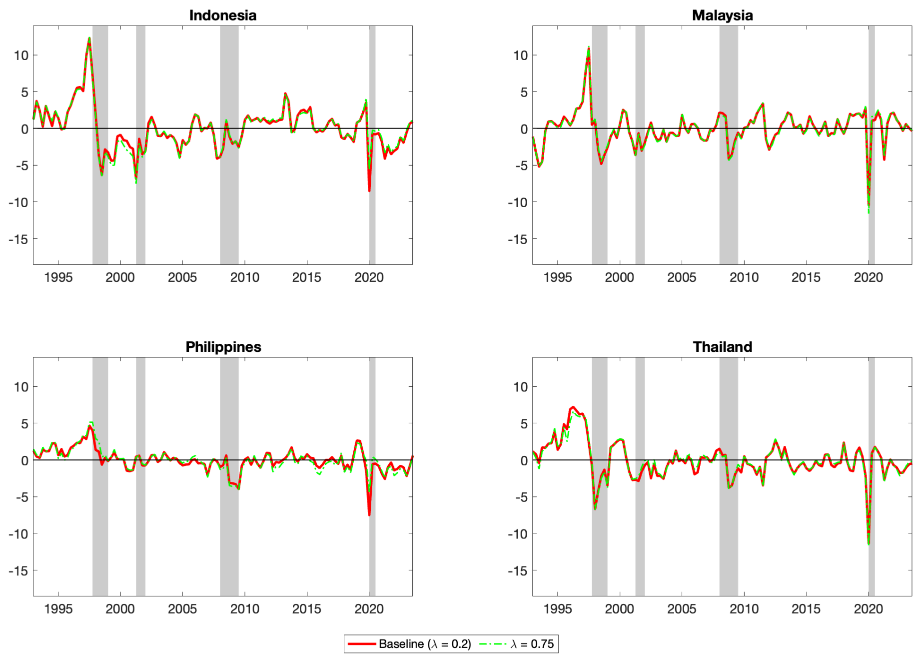
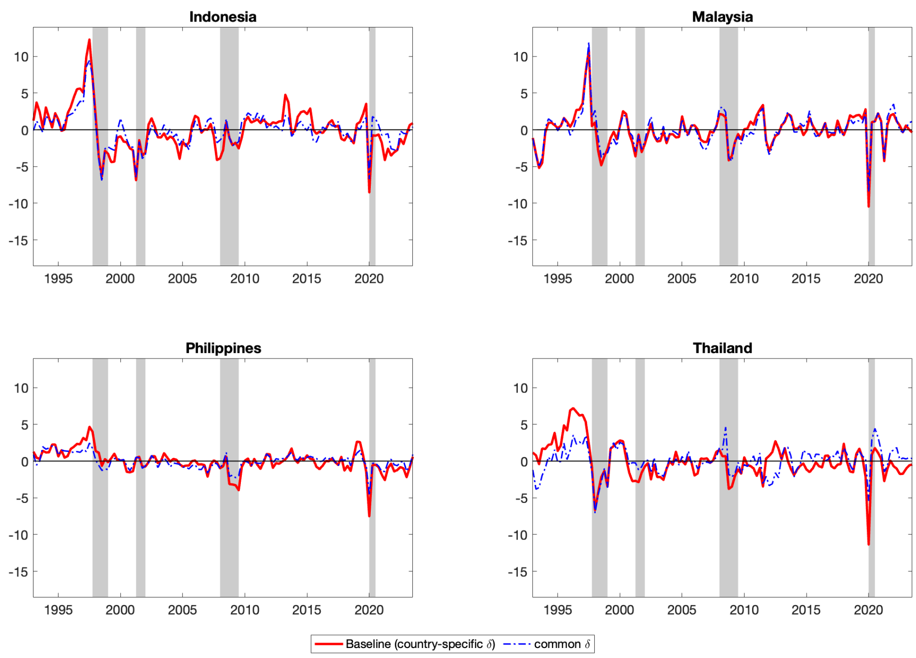


Figure 2.10: Effects of changing the Signal-to-Noise ratio



economies are nearly identical to the baseline estimates, suggesting that contemporaneous slack measures in Southeast Asian economies add little new information. Standard unemployment metrics may underestimate labor market slack in these emerging countries due to high levels of informal employment. Many individuals engage in informal work not by choice but due to the lack of formal employment opportunities, thus rendering traditional unemployment rates less informative of actual economic conditions. This also likely reflects the fact that these series often exhibit unit roots, structural breaks, and are only available over relatively short sample spans, which limits their usefulness in informing output gap estimates.

Second, I investigate whether expanding the information set by adding more macroeconomic series alters the estimated output gap. As Morley and Wong (2020) and Evans and Reichlin (1994) highlight, if the excluded variables do not offer additional predictive content for output growth, then the estimated output gap remains unchanged, as the baseline model still captures the full informational content. Conversely, when the omitted variables contain relevant forecasting information, incorporating them alters the estimated output gap, bringing it closer to the true "output gap." Thus, the objective of a multivariate BN decomposition is to specify a model that encompasses all relevant predictors of output growth, such that, the inclusion of additional variables no longer affects the gap estimate. My results show that once key cyclical indicators are included, further additions do not appreciably change output gap estimates. Even when additional variables, selected based on Granger causality at the 10% significance level compared to the baseline variables significant at the 5% level, are introduced, the output gap estimates closely tracks that obtained from the baseline model. Domestic inflation and short-term interest rates were found not to Granger-cause output growth in the sample countries. This indicates that the relevant information to estimate the output gap are already captured by the baseline model. Similar to Morley and Wong (2020) and Morley et al. (2023), I find that the inclusion of relevant informational variables in estimating multivariate output gap is more important than the size of the model. While using the Industrial Production Index (IPI) as a target variable yields cyclical profiles that are positively correlated with the baseline, it is less suitable for measuring aggregate slack due to its high volatility and exclusion of the service and agricultural sectors. A detailed comparison is provided in Appendix B.

I further assess the sensitivity of the estimates to the choice of Bayesian hyperparameters. Following Carriero et al. (2015), the baseline model employs a shrinkage hyperparameter of $\lambda = 0.2$. As shown in Figure 2.9, the results are highly robust to a looser specification ($\lambda = 0.75$), supporting that the posterior is well-informed by the data. Regarding the signal-to-noise ratio (δ), Figure 2.10 demonstrates that while the timing of the business cycle is robust, the magnitude of the gaps is sensitive to the level of δ. This necessitates a motivated selection for the signal-to-noise prior; I calibrate δ to match the ratio used in the univariate Beveridge-Nelson filter for each country. This ensures the multivariate estimates remain comparable to standard univariate benchmarks while the additional macroeconomic variables serve to identify the cyclical component more precisely.

2.5 Conclusion

This chapter contributes to the output gap literature by applying a multivariate Beveridge-Nelson decomposition within a large Bayesian VAR framework to emerging Southeast Asian economies, specifically Indonesia, Malaysia, Thailand, and the Philippines. The focus on these countries is motivated by their exposure to significant external shocks as small open economies, notably during the Asian Financial Crisis, the Global Financial Crisis, and the COVID-19 pandemic. The approach addresses the limitations of univariate filters by incorporating additional macroeconomic indicators and accounting for the block-exogenous influence of global factors. To address potential overfitting and signal distortion in small samples, particularly in emerging markets with shorter data, I impose a signal-to-noise prior to mitigate upward bias and prevent excessive shrinkage toward a random walk.

I find that multivariate output gap estimates for these four emerging economies align closely with known recession periods and exhibit cyclical persistence. Traditional slack measures add little information in these emerging economies. High levels of informal employment mean that adjustment to demand shocks occurs mainly through shifts between formal and informal work, weakening the link between unemployment and output gap. Moreover, unemployment and capacity utilization series in these economies suffer from structural breaks, unit roots, and are available only over relatively short sample periods. Despite these data constraints, central banks in these economies currently rely on slack indicators to gauge inflationary pressure. My findings suggest that by incorporating a broad set of macroeconomic and financial indicators, the multivariate structure provides a more informative view of the output gap compared to those of traditional univariate filters.

More importantly, financial and global sector variables account for a substantial share of output gap fluctuations, particularly during systemic crises such as the AFC and the GFC. These findings emphasize the importance of extending output gap estimation beyond domestic GDP measures and highlight the value of financial and external conditions as early warning signals in emerging markets. My results suggests that central banks could incorporate financial and global variables as leading indicators within their economic monitoring frameworks. Since these external factors drive a significant portion of the cyclical fluctuations in emerging Southeast Asia, they can serve as proxies for impending shifts in domestic demand. For instance, policymakers can use the transmission of global shocks to adjust their economic assessments, treating a tightening of global financial conditions or energy price spikes as direct signals of a projected contraction in the domestic output gap.

More broadly, my results suggests that the multivariate BN decomposition is well-suited for environments with limited data. Unlike structural DSGE models that require complex calibration or long historical series for identification, the Bayesian framework utilizes shrinkage priors to maintain estimation stability in shorter samples. This makes the approach a computationally efficient alternative for policymakers in these economies to monitor macro-financial risks without the data requirements of more restrictive structural models.

This framework also opens several avenues for future research. One practical extension involves extending the model to accommodate mixed-frequency data as in Berger, Morley, et al. (2023). In many emerging markets, key indicators such as trade measures, consumer sentiment, or financial market conditions are available monthly, while GDP is reported quarterly. A mixed-frequency VAR could allow such high-frequency data to inform more timely and accurate nowcasts of the output gap. Another promising direction is to jointly estimate the output gap alongside other latent cycles, such as a financial cycle, within the same multivariate system, similar to Berger, Richter, et al. (2022) for the US economy. Given the prominent role of financial factors found in this study, a joint detrending approach could offer a more comprehensive view of macro-financial dynamics for these emerging economies. Such an approach would be particularly valuable for investigating the decoupling of financial and real cycles, especially during periods of significant overheating. My findings show sharp increases in the output gap immediately preceding the Asian Financial Crisis (AFC), particularly for Indonesia and Malaysia. While this likely reflects the informational role of financial sector variables in identifying cycles, it also raises questions about whether such spikes represent genuine business cycle fluctuations or asset price movements that have decoupled from the real economy. Future work could investigate whether traditional real-side indicators, such as wage growth or hours worked, accelerated alongside these financial signals. Furthermore, incorporating risk-premium data, such as the spread between corporate and safe bonds, could help refine the distinction between financial-side shocks and real output gaps.

B Appendix to Chapter 2

Sensitivity to the Choice of Output Measure

To address concerns regarding GDP measurement issues and volatility in emerging market economies, I examine the sensitivity of the output gap estimates to the choice of the target variable by re-estimating the baseline model using the Industrial Production Index (IPI).[11] As shown in Table B.1, the resulting IPI gaps exhibit positive correlations with the baseline Output-based gaps, ranging from 0.307 for Indonesia to 0.660 for Malaysia. Looking at Figure B.1, the general cyclical profile remains consistent across both measures. The IPI-based gaps are significantly more volatile, particularly for Thailand. This volatility likely reflects idiosyncratic supply-side shocks, such as energy price fluctuations, global trade shifts, or labor strikes, that do not necessarily correspond to aggregate domestic demand or overall economic slack.

There are several structural reasons why real GDP remains the more appropriate measure for estimating the aggregate output gap. First, IPI focuses exclusively on manufacturing and mining, ignoring the service and agricultural sectors which constitute the largest shares of GDP in Southeast Asian emerging markets. Second, the prevalence of large informal economies means formal manufacturing indices can quickly become unrepresentative of total economic slack. Third, outdated weighting schemes in many EME industrial indices often fail to capture new, high-growth industries, leading to biased trend estimations. Consequently, while the IPI provides a useful cross-check, it is a less reliable proxy for the aggregate output gap than a comprehensive real GDP measure.

Table B.1: Correlation Coefficients: Output Gap vs. IPI Gap

Country	**Correlation**
Malaysia	0.660
Philippines	0.433
Thailand	0.386
Indonesia	0.307

Data and Data Transformations

Note that 'x' in the 'Baseline' column indicates that a variable is included in the benchmark BVAR and that 'x' in the 'Block Exo' column refers to the block exogenous variables. 'Transformation' column refers to any data transformations: 0 denotes data in levels, '1' indicates 100 $\times$ natural logarithms have been taken, '2' is percentage growth rate, and '3' indicates the variable has been first differenced. Subsequent differencing is conducted if a Chow test for a change in mean from the first half to

[11] For this robustness exercise, only the target variable is changed; the set of candidate informational variables and the model structure remain identical to the baseline specification. The informational variables to explain the IPI gap may as well differ from those in the baseline GDP specification as the drivers of industrial activity, often tied to specific global supply chains, do not fully align with the broader macroeconomic factors influencing aggregate output.

[htbp]

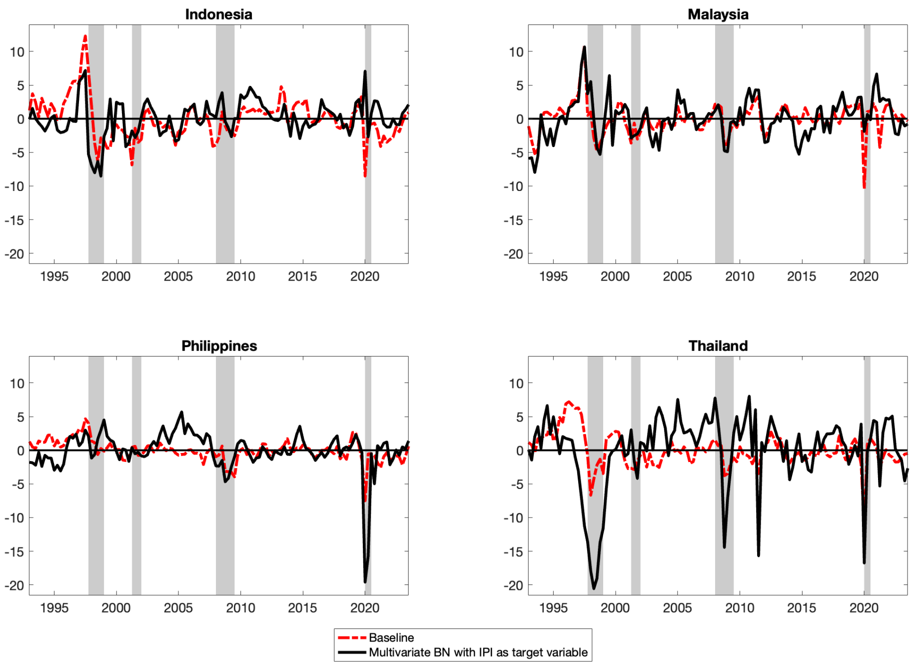


Figure B.1: Estimated Multivariate BN Output Gaps with IPI as the target variable

the second half of the sample is significant at the 10% level and/or an augmented Dicky-Fuller test rejects a unit root at the 5% level.

Table B.2: Data and Data Transformations for Indonesia

Series	**Transformation**	**Baseline**	**Block Exo**
Gross Domestic Product: United States, Seasonally Adjusted (sa)	1	x	x
Crude Oil: United States: Brent	1	x	x
US Consumer Price Index	1	x	x
Gross Domestic Product: Indonesia, sa	1	x	
Gross Domestic Product: Malaysia, sa	1	x	
Motor Vehicle Sales: PT Astra: Local	1	x	
IDX: Market Cap: Total	1	x	
International Liquidity: Foreign Exchange	1	x	
Spot FX Rate: Bank Indonesia: Rupiah to US Dollar	1	x	
Real Effective Exchange Rate Index: CPI Based	1	x	
Total Imports from USA: USD mn, sa	1	x	
Total Imports from China: USD mn, sa	1	x	
Loans Disbursed: Real Estate Sector	1	x	
Jakarta Composite Index: Return	2	x	
Interest Rate: Bank Indonesia: 7-Day Reverse Repo Rate	0	x	
Bank Indonesia: FX Reserves	1	x	

Source: CEIC Key Indicators dataset.

Table B.3: Data and Data Transformations for Philippines

Series	**Transformation**	**Baseline**	**Block Exo**
Gross Domestic Product: United States, Seasonally Adjusted (sa)	1	x	x
Crude Oil: United States: Brent	1	x	x
US Consumer Price Index	1	x	x
Gross Domestic Product: Philippines, sa	1	x	
Gross Domestic Product: Malaysia, sa	1	x	
Vehicle Sales: Passenger Cars	1	x	
Philippine Stock Exchange Index: Market Capitalization	1	x	
Net International Reserves: Bangko Sentral ng Pilipinas	1	x	
Spot FX Rate: PHP to USD	1	x	
Real Effective Exchange Rate: CPI Based	1	x	
Total Imports from USA: USD mn, sa	1	x	
Total Imports from China: USD mn, sa	1	x	
Construction: Value of Building Permits	1	x	
PSE Index Daily Return	2	x	
Philippines Policy Rate: Overnight Borrowing Rate	0	x	
Gross International Reserves: BSP	1	x	

Source: CEIC Key Indicators dataset.

Table B.4: Data and Data Transformations for Malaysia

Series	Transformation	Baseline	Block Exo
Gross Domestic Product: United States, Seasonally Adjusted (sa)	1	x	x
Crude Oil: United States: Brent	1	x	x
US Consumer Price Index	1	x	x
Gross Domestic Product: Malaysia, sa	1	x	
Vehicle Sales: Passenger Vehicles	1	x	
KLSE Composite Index: Market Capitalization	1	x	
International Reserves: Bank Negara Malaysia	1	x	
Exchange Rate: MYR to USD	1	x	
Real Effective Exchange Rate Index: CPI Based	1	x	
Total Imports from USA: USD mn, sa	1	x	
Total Imports from China: USD mn, sa	1	x	
Loans Outstanding: Residential Property	1	x	
KLSE Index Daily Return	2	x	
Policy Interest Rate: OPR	0	x	
BOP: Reserves	1	x	

Source: CEIC Key Indicators dataset.

Table B.5: Data and Data Transformations for Thailand

Series	Transformation	Baseline	Block Exo
Gross Domestic Product: United States, Seasonally Adjusted (sa)	1	x	x
Crude Oil: United States: Brent	1	x	x
US Consumer Price Index	1	x	x
Gross Domestic Product: Thailand, sa	1	x	
Car Sales: Domestic Vehicles	1	x	
SET Index: Market Capitalization	1	x	
International Reserves: Bank of Thailand	1	x	
Exchange Rate: THB to USD	1	x	
Real Effective Exchange Rate Index: CPI Based	1	x	
Total Imports from USA: USD mn, sa	1	x	
Total Imports from China: USD mn, sa	1	x	
Construction Permits Issued	1	x	
SET Index Daily Return	2	x	
BOT Policy Interest Rate	0	x	
FX Reserves (USD)	1	x	

Source: CEIC Key Indicators dataset.

Chapter 3

What does a Mixed-Frequency Multivariate Beveridge-Nelson Decomposition tell us about the Australian Output Gap?

3.1 Introduction

Economic monitoring frequently necessitates the assessment of mixed-frequency data, as policymakers and professional forecasters must analyze a range of monthly, weekly, and even daily indicators to evaluate current economic activity. Within this context, the output gap serves as a primary metric for gauging economic slack for central banks and policy institutions. Given that potential output is unobserved, the gap must be estimated through structural production functions or filtering techniques. However, traditional approaches face significant limitations in a policy setting; they are often unreliable in contemporaneous estimates and typically yield only retrospective insights due to the substantial reporting lags of quarterly GDP data (Orphanides and van Norden, 2002). For small open economies, these monitoring challenges are compounded by the need to distinguish between domestic cyclical developments and spillovers from global shocks.

A wealth of information related with economic activity, including labor market indicators, trade statistics, retail sales, housing data, and business surveys, are released well before the quarterly GDP figure. Theoretically, this timeliness allows for the prediction of the present and very near future, a process known as nowcasting, to provide a contemporary view of the output gap. Yet, integrating these indicators into analysis introduces new challenges, as high-frequency data is often noisy and its predictive content can be highly context-dependent. For a small open economy, this requires effectively weighting domestic signals against timely global indicators to obtain a consistent view of the business cycle. Contemporary econometric developments have introduced various statistical techniques to incorporate high-frequency data into frameworks designed for lower-frequency indicators such as output growth. These methodologies include linear bridge equations to map monthly data into quarterly frequencies (Parigi and Schlitzer, 1995; Corrado and Greene, 1988), dynamic factor models (Giannone, Reichlin, et al., 2008; Blasques et al., 2016; Hartigan and Rosewall, 2025), and vector autoregressions (VAR) that utilize state-space representations to treat lower-frequency data as a missing value problem (Zadrozny, 1990; Mittnik and Zadrozny, 2005). Within this state-space framework, researchers have employed both maximum-likelihood estimation via Kalman filtering and Bayesian approaches to bridge disparate data frequencies (Eraker et al., 2014; Schorfheide and Song, 2015; Brave et al., 2019). Ghysels (2016) and McCracken et al. (2021) utilize a mixed-frequency VAR that treats high-frequency observations as distinct series at the lowest sampling frequency to obtain intra-quarter forecasts and rely on Bayesian shrinkage to mitigate the parameter proliferation.

The estimation of the Australian output gap has been a central focus of domestic macroeconomic research, evolving from simple filtering techniques to models designed to address real-time uncertainty. Gruen, Robinson, et al. (2005) provided the first comprehensive study of these issues in Australia, using over a hundred vintages of GDP data to demonstrate that robust real-time estimates could be generated despite data revisions and end-point problems. An advancement in the domestic data infrastructure was the development of the Australian Real-Time Database by Lee, Olekalns, et al. (2012). This provided the first systematic compilation of historical data vintages for Australia—including GDP, prices, and labor statistics—thereby allowing researchers to evaluate the macroeconomic environment as it was published and revised in real time. Building on these foundations, more recent work by the Reserve Bank of Australia, such as Bishop et al. (2024), has refined these measures by incorporating labor market indicators and expectations to assess spare capacity. While these benchmarks are subject to historical revisions, they provide a standard ex-post reference for evaluating model performance. Despite these advancements, existing Australian models often do not incorporate data tracking global conditions or do not fully integrate the high-frequency data flows available in a modern monitoring environment.

This chapter provides a novel contribution to the Australian literature by adapting the mixed-frequency Bayesian vector autoregressive (MF-BVAR) framework to a small open economy setting and applying a multivariate Beveridge–Nelson (BN) decomposition. The modeling setup builds upon the foundation established by Berger, Morley, et al. (2023) in their application to the U.S. economy, but introduces three distinct contributions designed to adapt the framework to a small open economy setting. First, I incorporate an open-economy assumption by including monthly and quarterly block-exogenous foreign sector variables, acknowledging the role of external shocks in a small open economy like Australia. By accounting for external spillovers, a dimension typically omitted in existing output gap models for the Australian economy, this framework provides a more robust tool for the contemporaneous monitoring of domestic slack. Second, the model explicitly accounts for outlier observations during the COVID-19 pandemic. Finally, while the existing literature typically bridges monthly and quarterly frequencies, I refine this specification by incorporating a weekly indicator. Furthermore, as in Berger, Morley, et al. (2023), I utilize the conditional forecasting approach of Waggoner and Zha (1999) to produce within-quarter updates that revise the output gap estimate as each higher frequency data point arrives.

I find that the estimated output gap based on the mixed-frequency Bayesian VAR aligns with known expansions and recessions and is broadly consistent with the revised Reserve Bank of Australia (RBA) output gap estimates. The informational decomposition results reveal that every variable in the model contributes non-negligibly to this estimate. In particular, foreign variables provide a significant share of the information needed to estimate the Australian output gap. Domestically, the Trade Weighted Index (TWI) emerges as the most informative individual indicator, as it captures the domestic impact of terms-of-trade shocks. Furthermore, aggregate hours worked provides a more significant informational contribution than the headline unemployment rate, suggesting that the intensive margin more effectively captures cyclical labor market adjustments. The sectoral aggregation highlights the labor sector as the primary source of timely information for the output gap. Notably, the TWI alone provides informational value nearly equivalent to the entire financial or macroeconomic sectors combined. These findings offer a practical framework for policymakers to assess the specific informational contributions of domestic and foreign indicators throughout the quarter.

When decomposing the Australian output gap into foreign and domestic shocks, I find that while domestic shocks drive the majority of cyclical fluctuations, foreign shocks play a substantial role through terms-of-trade and global demand channels. Historically, the 1990s recession and the post-pandemic recovery were predominantly driven by domestic factors. In contrast, the movements in the output gap during Global Financial Crisis—while not a technical recession in Australia—were largely attributable to external spillovers.

The MF-BVAR framework utilizes timely data arrivals to provide frequent updates to the Australian output gap nowcast, which is finalized only once quarterly GDP completes the information set. Between monthly updates, specifically from weeks one through three, the model relies exclusively on weekly indicators before the information set expands at the end of each month when monthly vectors are integrated in weeks four, eight, and thirteen. Monthly releases provide particularly useful new information about the final estimate of the output gap. I evaluate the predictive accuracy of these updates using the Mean Absolute Error (MAE), using the beginning of the quarter as the benchmark, where the initial MAE stands at 0.48 percentage points before within-quarter information is integrated. Diebold-Mariano tests reveal that sequential informational gains are substantial, with first month of the quarter improvements driven by labor market intentions and household sentiment, followed by global demand shocks and domestic credit in the second month.[1] Finally by the third month of the quarter, "hard" indicators like commodity prices and dwelling approvals, further reduces the MAE of the output gap nowcasts, compared to final estimates, to 0.16 percentage points.

Regarding the weekly TWI, the MAE remains largely flat during most weeks, implying that the TWI provides limited new information for the nowcast when viewed in isolation. Diebold-Mariano tests for the TWI are significant only at monthly boundaries, suggesting that the index is most valuable when interpreted alongside monthly data releases.

[1] While the Diebold-Mariano test is a standard measure of relative forecast performance, its results are interpreted here as evidence of predictive accuracy within this specific modeling context rather than a definitive test of model specification (Diebold, 2015)

Finally, I assess whether a three-frequency (3F) BVAR is necessary or if a two-frequency (2F-BVAR) model is preferable for the purposes of nowcasting. Estimates for a mixed frequency model with monthly TWI suggest no benefit in terms of nowcasting accuracy from using the higher-frequency weekly TWI. The comparison between the 2F-BVAR and 3F-BVAR specifications reveals a trade-off between accuracy and timeliness. While the 2F-BVAR is more accurate at the end of the quarter, with a final MAE of approximately 0.10 percentage points compared to 0.16 in the 3F-BVAR, it provides no new information between monthly releases. Testing under different data arrival sequences shows that the TWI does not drive MAE reduction independently. However, the 3F-BVAR specification allows the model to reflect timely information revealed between monthly data arrivals. Despite these differences, both mixed-frequency models produce broadly similar estimates and capture identical cyclical turning points.

The remainder of this chapter is organized as follows: Section 3.2 lays out the model specification and discusses the data. Section 3.3 discusses the empirical results when applied to Australian data. Finally, Section 3.4 concludes.

3.2 Methodology

The econometric literature on forecasting and nowcasting is generally divided into partial (single-equation) models and full system approaches (Bańbura et al., 2013). Partial frameworks, such as Bridge Equations and Mixed-Data Sampling (MIDAS), are widely employed for their flexibility in handling data with differing sampling frequencies. However, these approaches typically do not explicitly model the joint dynamics of all variables in the system, limiting their utility for structural interpretation or identifying system-wide shocks.

Alternatively, "parameter-driven" state-space models treat high-frequency data as the baseline and view low-frequency realizations as missing observations, recoverable via the Kalman filter (Schorfheide and Song, 2015). While theoretically attractive, these models can be computationally intensive to estimate.

Therefore, I adopt the "stacked" vector autoregressive approach following Ghysels (2016), Brave et al. (2019), McCracken et al. (2021), Berger, Boll, et al. (2022), and Berger, Morley, et al. (2023). This framework specifies the model at the lowest observed frequency but preserves high-frequency information by treating intra-period data releases as distinct variables within the system. This approach essentially functions as a system-wide extension of the Unrestricted MIDAS (U-MIDAS) concept, estimated via Bayesian methods to handle the resulting parameter proliferation.

3.2.1 Data Structure and Model Specification

My empirical strategy extends the mixed-frequency Bayesian vector autoregression framework established by Berger, Boll, et al. (2022) and Berger, Morley, et al. (2023). While the existing literature typically bridges monthly and quarterly frequencies, I refine this specification by also incorporating weekly indicators.

Let $w_{i,t-1+v}$ be the i^{th} weekly variable, assuming 13 weeks per quarter, where $v \in \{1/13, 2/13, \ldots, 1\}$ corresponds to the week within the quarter. Similarly, let

$m_{j,t-1+u}$ be the j^{th} monthly variable where $u \in \{1/3, 2/3, 1\}$ corresponds to the month within the quarter.

To incorporate high-frequency information for the purposes on model estimation, I first stack the k_w weekly indicators for the entire quarter into the vector $\tilde{\boldsymbol{w}}_t$.[2] Specifically, the intra-quarterly observations are arranged as:

$$\tilde{\boldsymbol{w}}_t = \begin{bmatrix} \boldsymbol{w}_{t-1+1/13} \\ \vdots \\ \boldsymbol{w}_t \end{bmatrix}, \tag{3.1}$$

where $\boldsymbol{w}_{t-1+v} = [w_{1,t-1+v}, \ldots, w_{k_w,t-1+v}]'$ is the vector of indicators for a specific week v.

A similar stacking procedure is applied to the k_m monthly variables. The vector $\tilde{\boldsymbol{m}}_t$ is constructed by stacking the observations for the first, second, and third months of the quarter:

$$\tilde{\boldsymbol{m}}_t = \begin{bmatrix} \boldsymbol{m}_{t-1+1/3} \\ \boldsymbol{m}_{t-1+2/3} \\ \boldsymbol{m}_t \end{bmatrix}, \tag{3.2}$$

where $\boldsymbol{m}_{t-1+u} = [m_{1,t-1+u}, \ldots, m_{k_m,t-1+u}]'$.The vector process $\boldsymbol{Y}_t$ is assumed to have a VAR(p) structure at the quarterly frequency given by:

$$\boldsymbol{Y}_t = \boldsymbol{\Phi}_1 \boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{Y}_{t-p} + \boldsymbol{e}_t, \quad \boldsymbol{e}_t \sim \mathcal{N}(0, \boldsymbol{\Sigma}). \tag{3.3}$$

Given the large dimension of the state vector $\boldsymbol{Y}_t$, which is inflated by the stacking of weekly and monthly indicators, I restrict the lag length to $p = 2$ quarters. While standard quarterly VARs typically utilize $p = 4$ lags, this more parsimonious specification is necessary to mitigate the parameter proliferation inherent in the stacked mixed-frequency approach with weekly variables. Furthermore, a lag order of two captures dynamics over a six-month window, which, when combined with the intra-quarterly high-frequency provides sufficient persistence for the nowcasting analysis.

3.2.2 Treatment of Outlier Observations around the COVID-19 Pandemic

A significant challenge in estimating the model over the recent sample is the presence of extreme outliers associated with the COVID-19 pandemic. As noted by Lenza and Primiceri (2022), such observations can induce nontrivial distortions in the estimated autoregressive parameters and the error covariance matrix of a BVAR. To address

[2] To be clear, the order of variables for estimation does not matter, at least in principle, and this order is only for convenience in presentation and estimation of the model. When considering within-quarter nowcasts, the order that information is revealed does matter and I discuss this ordering later when discussing nowcasting.

this, I adopt a pragmatic approach to handle the COVID-19 data, following the stochastic volatility scaling suggestion of Lenza and Primiceri (2022).

Formally, the standard VAR specified in Equation 3.3 is rewritten to include a time-varying stochastic volatility term s_t:

$$\boldsymbol{Y}_t = \boldsymbol{\Phi}_1 \boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{Y}_{t-p} + s_t \boldsymbol{e}_t, \quad \boldsymbol{e}_t \sim \mathcal{N}(0, \boldsymbol{\Sigma}). \tag{3.4}$$

Here, s_t serves as a scalar scaling factor that allows the residual covariance matrix to scale up by a factor of s_t^2 during the pandemic period. Conditional on s_t, the model can be normalized by dividing both sides of the equation by s_t:

$$\boldsymbol{Y}_t / s_t = \boldsymbol{\Phi}_1 (\boldsymbol{Y}_{t-1} / s_t) + \cdots + \boldsymbol{\Phi}_p (\boldsymbol{Y}_{t-p} / s_t) + \boldsymbol{e}_t. \tag{3.5}$$

While the original implementation by Lenza and Primiceri (2022) specifies parameters for individual months followed by a decay factor, it is necessary to adjust their approach to suit the quarterly frequency of the stacked model used here. Since the MIDAS-U approach specifies the VAR at the lower frequency, the error covariance matrix is defined only at the quarterly level. Therefore, following the specific adaptation employed by Morley et al. (2023), I estimate three distinct volatility scaling parameters: one each for 2020Q1, 2020Q2, and 2020Q3. That is, s_t is set to 1 for all periods except these three quarters.

Consistent with Morley et al. (2023), a decay parameter is not modeled for subsequent periods because the variation in the data appears to have returned to pre-pandemic levels post-2020Q3. However, estimating distinct parameters for the first three quarters of 2020 is essential to capture the magnitude changes of differing scales characterized by this period.

Following Morley et al. (2023), the estimation follows a two-step hybrid approach. First, the COVID-19 scaling parameters ($s_{2020Q1}, s_{2020Q2}, s_{2020Q3}$) are estimated by maximizing the likelihood function of the re-weighted VAR. Second, the data are re-weighted using these estimates as per Equation 3.5, and the BVAR parameters are estimated using the standard Bayesian methods described in Section 3.2.5.

3.2.3 Trend-Cycle Decomposition and Nowcasting

To recover the output gap, the model is cast into companion form following Morley (2002). Let $\boldsymbol{X}_t$ be the $np \times 1$ state vector:

$$\boldsymbol{X}_t = \boldsymbol{F} \boldsymbol{X}_{t-1} + \boldsymbol{H} \boldsymbol{e}_t, \tag{3.6}$$

where $\boldsymbol{F}$ is the companion matrix containing the $\boldsymbol{\Phi}$ coefficients, and $\boldsymbol{H}$ maps the forecast errors to the companion form. The multivariate Beveridge-Nelson (BN) trend is defined as the long-horizon forecast of the level of output. Consequently, the BN cycle (output gap), c_t, is obtained as:

$$c_t = -\mathbf{s}'_{np,n} \boldsymbol{F} (\boldsymbol{I} - \boldsymbol{F})^{-1} \boldsymbol{X}_t, \tag{3.7}$$

where $\mathbf{s}'_{np,n}$ is a selector vector that isolates the element corresponding to real GDP growth within the state vector $\boldsymbol{X}_t$.

A key advantage of the weekly specification is its ability to incorporate timely signals from high-frequency indicators such as the TWI. This index captures rapid fluctuations in the external sector through import and export cycles, which often move more quickly than standard domestic macroeconomic indicators. This reduces the informational lag between monthly data releases and provides a more granular information set for policymakers to monitor cyclical developments in a small open economy context. Adopting the conditional forecasting framework of Waggoner and Zha (1999) and the iterative approach of Berger, Boll, et al. (2022), I derive a "nowcast" of the cycle $c_{T+1|T+\omega}$ given information available up to fraction ω of the quarter.

Let $\omega \in (0,1)$ represent the timing of a specific weekly data release. The conditional expectations are modeled by decomposing the error covariance $\boldsymbol{\Sigma} = \boldsymbol{B}\boldsymbol{B}'$, where $\boldsymbol{B}$ is the lower-triangular Cholesky decomposition of the error covariance matrix. If the first i variables are observed at time $T+\omega$, I denote the observed forecast errors as $\boldsymbol{\varepsilon}_{T+1|T+\omega}$. The updated cycle is calculated as:

$$c_{T+1|T+\omega} = -\mathbf{s}'_{np,n}\boldsymbol{F}(\boldsymbol{I}-\boldsymbol{F})^{-1}\left[\boldsymbol{F}\boldsymbol{X}_T + \boldsymbol{H}\boldsymbol{e}_{T+1|T+\omega}\right], \tag{3.8}$$

where $\boldsymbol{e}_{T+1|T+\omega}$ represents the vector of innovations where unobserved elements are replaced by their conditional expectations derived from $\boldsymbol{B}$. This formulation allows the cycle estimate to evolve dynamically as each new data point is released week by week.

3.2.4 Block Exogeneity and Variable Ordering

Given that the Australian economy is a small open economy, it is standard practice to impose a block-exogenous structure to separate foreign and domestic dynamics (e.g., Hendy and Beckers, 2024). In a standard quarterly VAR, this involves restricting the coefficients such that domestic variables do not affect foreign variables, while foreign shocks are allowed to impact the domestic economy contemporaneously and with lags.

In the mixed-frequency framework employed here, the imposition of block exogeneity is complicated by the presence of high-frequency monthly foreign indicators alongside quarterly and weekly domestic variables. Specifically, the model includes N^* foreign variables observed at a monthly frequency and one foreign variable observed at a quarterly frequency (US Real GDP). To ensure the structural identification remains valid within the stacked vector representation, the variables should be carefully ordered and the corresponding blocks of the transition matrix $\boldsymbol{\Phi}$ restricted.

The vector of observables $\boldsymbol{Y}_t$ is constructed by placing the foreign block first, followed by the domestic block. Within the quarterly partition, the foreign variable is ordered prior to the domestic quarterly variables. Consequently, the full state vector is defined as:

$$
\boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{q}_t^* \\ \boldsymbol{m}_t^* \\ \boldsymbol{q}_t \\ \boldsymbol{m}_t \\ \boldsymbol{w}_t \end{bmatrix}, \tag{3.9}
$$

where $\boldsymbol{m}_t^*$ denotes the vector of stacked intra-quarterly observations of the foreign monthly variables, and q_t^* represents the foreign quarterly variable. The domestic block follows, consisting of the domestic quarterly variables $\boldsymbol{q}_t$, the domestic monthly indicators $\boldsymbol{m}_t$, and the stacked domestic weekly series $\boldsymbol{w}_t$.

This ordering $\boldsymbol{Y}_t = [\boldsymbol{Y}_t^{*\prime}, \boldsymbol{Y}_t^{dom\prime}]'$ ensures that the block-exogenous restrictions are consistently applied across the different frequencies. While the model is estimated in a reduced-form framework, the block structure is strictly imposed on the vector-autoregressive coefficients to ensure that domestic dynamics do not influence the foreign sector. The transition matrices $\boldsymbol{\Phi}_l$ are restricted such that the domestic variables do not Granger-cause the foreign variables. Partitioning the coefficient matrix conformably with $\boldsymbol{Y}_t$, the restricted transition matrix takes the following structure:

$$
\boldsymbol{\Phi}_l = \begin{bmatrix} \boldsymbol{\Phi}_{\boldsymbol{m}^*\boldsymbol{m}^*} & \boldsymbol{\Phi}_{\boldsymbol{m}^*q^*} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{\Phi}_{q^*\boldsymbol{m}^*} & \phi_{q^*q^*} & \boldsymbol{0}' & \boldsymbol{0}' & \boldsymbol{0}' \\ \boldsymbol{\Phi}_{\boldsymbol{q}\boldsymbol{m}^*} & \boldsymbol{\Phi}_{\boldsymbol{q}q^*} & \boldsymbol{\Phi}_{\boldsymbol{q}\boldsymbol{q}} & \boldsymbol{\Phi}_{\boldsymbol{q}\boldsymbol{m}} & \boldsymbol{\Phi}_{\boldsymbol{q}\boldsymbol{w}} \\ \boldsymbol{\Phi}_{\boldsymbol{m}\boldsymbol{m}^*} & \boldsymbol{\Phi}_{\boldsymbol{m}q^*} & \boldsymbol{\Phi}_{\boldsymbol{m}\boldsymbol{q}} & \boldsymbol{\Phi}_{\boldsymbol{m}\boldsymbol{m}} & \boldsymbol{\Phi}_{\boldsymbol{m}\boldsymbol{w}} \\ \boldsymbol{\Phi}_{\boldsymbol{w}\boldsymbol{m}^*} & \boldsymbol{\Phi}_{\boldsymbol{w}q^*} & \boldsymbol{\Phi}_{\boldsymbol{w}\boldsymbol{q}} & \boldsymbol{\Phi}_{\boldsymbol{w}\boldsymbol{m}} & \boldsymbol{\Phi}_{\boldsymbol{w}\boldsymbol{w}} \end{bmatrix}, \tag{3.10}
$$

where each sub-matrix $\boldsymbol{\Phi}_{ij}$ captures the lagged effect of variable block j on variable block i, and $\boldsymbol{0}$ denotes a null matrix of appropriate dimension. The upper-right blocks of zeros explicitly restrict the feedback from the domestic sector variables $(\boldsymbol{q}_t, \boldsymbol{m}_t, \boldsymbol{w}_t)$ to the foreign sector variables $(\boldsymbol{m}_t^*, q_t^*)$, thereby enforcing the small open economy assumption.

The imposition of the block-exogenous structure complicates the posterior calculation. As noted in the context of the euro area by Morley et al. (2023), the zero restrictions on the transition matrix result in the loss of the natural-conjugacy of the Normal-Inverse Wishart prior. This loss is non-trivial as it precludes an analytical solution for the posterior moments. Consequently, I utilize a Gibbs sampling algorithm to simulate the posterior distribution of the parameters. While this imposes a higher computational cost compared to conjugate models that allow for direct analytical calculation, it is necessary to strictly enforce the small open economy assumption and ensure that domestic shocks do not influence the foreign sector.

3.2.5 Estimation and Prior Specification

Given the high dimensionality of $\boldsymbol{Y}_t$ introduced by the weekly partitions, estimating the model via standard ordinary least squares is infeasible due to parameter proliferation. Therefore, I employ Bayesian estimation methods with a Minnesota-type shrinkage prior consistent with the approach in Morley and Wong (2020) and Berger, Morley, et al. (2023). This prior specification shrinks the parameter estimates toward a parsimonious random walk representation in levels, reducing the risk of overfitting while preserving the signal in the data.

The tightness of the shrinkage is determined by the error variance σ_i^2 of each variable i. Consistent with the stacked structure of the data, the scaling factors σ_i^2 are estimated from auxiliary univariate autoregressive models. For the high-frequency variables (weekly and monthly), these auxiliary regressions are estimated on the stacked vector of all intra-quarterly observations to capture the appropriate variance at the quarterly frequency. Crucially, the resulting variance estimate is replicated across the constituent partitions of the variable. This imposes symmetry on the prior, ensuring that the shrinkage intensity is identical for all high-frequency partitions of the same underlying economic indicator.

The variance of the prior distribution for the coefficient on lag l of variable j in equation i, denoted as $V(\phi_{i,j}^l)$, is specified as:

$$V(\phi_{i,j}^l) = \begin{cases} \frac{\lambda^2}{l^2} & \text{if } i = j, \\ \frac{\lambda^2 \sigma_i^2}{l^2 \sigma_j^2} & \text{if } i \neq j. \end{cases} \tag{3.11}$$

The construction of the prior covariance matrix strictly enforces the block-exogeneity restrictions defined previously. The parameter vector is partitioned into two distinct blocks during estimation. For the N_{exo} equations corresponding to the foreign variables, the prior is defined only over the coefficients of the foreign regressors. This implies that the prior variance for any domestic coefficient in a foreign equation is effectively zero. Conversely, for the domestic equations, the prior is defined over the full set of N system variables, allowing for foreign spillover effects.

The shrinkage hyperparameter λ is set to a baseline value of 0.20, following Carriero et al. (2015) as a typical level of shrinkage in the Bayesian VAR literature. While it is possible to select λ using out-of-sample forecast performance as in Morley and Wong (2020), optimizing the hyperparameter in this manner presents a substantial computational burden given the use of a Gibbs sampler, which is further complicated by the relatively short sample period available. However, the baseline output gap estimates are robust to alternative hyperparameter selections; using a tighter shrinkage value of 0.075, as adopted by Morley and Wong (2020) for a similar-sized BVAR system for the U.S. economy, yields nearly identical results. As shown in Figure C.1 of the Appendix, the output gap series remains robust to the choice of the shrinkage parameter.

To address concerns regarding dimensionality, the information set is restricted to a parsimonious subset of indicators selected for their predictive content for Australian real GDP, as detailed in Section 3.2.6. This pre-selection of variables ensures that the most informative indicators for the output gap are retained while mitigating parameter proliferation.

3.2.6 Data Description and Transformation

The model is estimated using a mixed-frequency dataset comprising quarterly, monthly, and weekly indicators for the Australian economy. To estimate the output gap, I consider Australian quarterly log real Gross Domestic Product (GDP) as the target variable. The indicators used in this analysis are final-revised series sourced from the RBA, ABS, and FRED. The sample period covers 1985Q1 to 2024Q4.

Table 3.1: Variable description, release timing, and reference period

Block	**Freq**	**Variable**	**Source**	**Release Timing**	**Reference Period**
Dom	W	Nominal Trade-weighted Index	RBA	Daily / Weekly	Current Month
For	M	Brent Crude Oil	FRED	Daily / Month End	Current Month
Dom	M	Yield Spread (10y - 3m)	FRED	Daily / Month End	Current Month
Dom	M	Overnight Cash Rate	RBA	1st Tuesday	Current Month
For	M	Commodity Prices Index	RBA	1st Business Day	Previous Month
For	M	US Job Losers (U2)	FRED	1st Friday	Previous Month
Dom	M	ANZ-Indeed Job Ads	ANZ	7th of Month	Previous Month
Dom	M	Consumer Confidence[a]	OECD	15th of Month	Previous Month
Dom	M	Unemployment Rate	ABS	3rd Thursday	Previous Month
Dom	M	Employment	ABS	3rd Thursday	Previous Month
Dom	M	Hours Worked	ABS	3rd Thursday	Previous Month
Dom	M	Part-time Employment	ABS	3rd Thursday	Previous Month
Dom	M	Retail Sales	ABS	28th of Month	Previous Month
Dom	M	Housing Credit	RBA	Last Business Day	Previous Month
Dom	M	Dwelling Approvals	ABS	2nd of Month + 2	Previous Month
Dom	M	Private Non-residential Approvals	ABS	2nd of Month + 2	Previous Month
For	Q	US Real GDP	BEA	30 Days post-qtr	Previous Qtr
Dom	Q	Trimmed Mean Inflation	ABS	30 Days post-qtr	Previous Qtr
Dom	Q	AUS Real GDP	ABS	65 Days post-qtr	Previous Qtr

[a]While the Consumer Confidence data is sourced from the OECD (code CSCICP02AUM460S), the underlying series is the Westpac-Melbourne Institute Consumer Sentiment Index. Although the OECD reports this with a one-month lag, the survey is conducted early in the current month, meaning it potentially contains more timely information than the release date suggests.

The variables are selected to retain a parsimonious subset that manages parameter proliferation while satisfying two criteria: (1) they possess a sufficiently long time series, and (2) they exhibit significant predictive content for Australian real GDP growth. This selection is drawn from the broad database of Australian macroeconomic indicators utilized by Hartigan and Rosewall (2025).

Variable selection follows the approach outlined by Morley and Wong (2020). As noted by Evans and Reichlin (1994), direct Granger causality with the target variable is sufficient but not strictly required for inclusion; variables that influence GDP indirectly via transmission through other predictors are also retained. Furthermore, consistent with Morley and Wong (2020), the multivariate Beveridge-Nelson decomposition must incorporate all variables that contain distinct predictive content for output growth. Thus, the final specification retains those indicators whose exclusion would materially alter the estimated output gap, ensuring the information set is comprehensive without including redundant series.

The resulting information set, summarized in Table 3.1, includes domestic macroeconomic activity indicators, labor indicators (i.e., employment, hours worked, and ANZ-Indeed Job advertisement), and financial variables (i.e., the overnight cash rate and yield spreads). The foreign block includes US Real GDP, BRENT Crude oil prices, and the Index of Commodity Prices. Regarding the foreign labor market, I employ the U-2 unemployment rate—defined as job losers as a percentage of the civilian labor force—rather than the headline unemployment rate. As noted by

Van Zandweghe (2012), Erceg and Levin (2014), and Fujita (2014), the standard unemployment measure is often confounded by persistent structural shifts in labor force participation, which can obscure the true cyclical position of the economy. By focusing strictly on job losers, the U-2 rate serves as a more robust proxy for global slack, consistent with the specification in Berger, Boll, et al. (2022).

To capture high-frequency global commodity movements, I include the RBA's Index of Commodity Prices and the Nominal Trade-weighted Index (TWI) of the Australian dollar, with the latter serving as the model's weekly indicator. While the Index of Commodity Prices is available on a monthly basis, the nominal TWI is available at a higher weekly frequency, providing more timely information. The selection of the TWI is further motivated by the fact that the Australian dollar is frequently characterized as a commodity currency, and a significant literature suggests the exchange rate co-integrates with the terms of trade, which are primarily driven by commodity prices (Ballantyne et al., 2020). Thus, the TWI serves as a high-frequency proxy for these broader foreign influences and external shocks in a small open economy. In principle, some other variables such as interest rates could be included at a higher weekly (or higher) frequency. But including even one variable as weekly massively increases parameterization.

The inclusion of foreign variables such as US Real GDP and global oil prices allows the model to control for external shocks, consistent with the small open economy assumption.

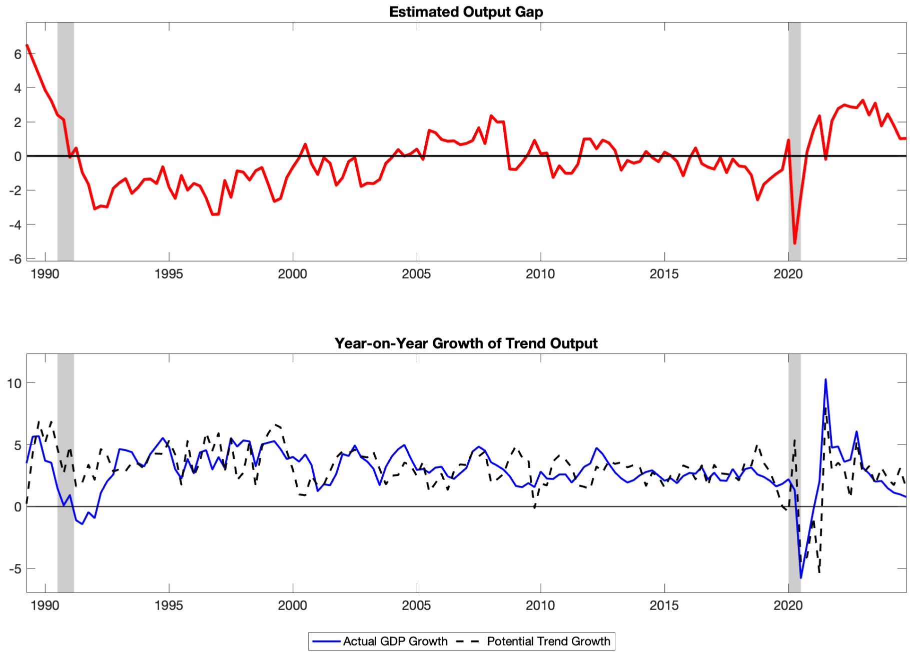
Given that the BN decomposition calculation (see equation 3.7) requires inversion of the companion matrix for a VAR, appropriate transformations are applied to ensure the stationarity of every time series prior to estimation. Following Berger, Boll, et al. (2022) and Morley and Wong (2020), I take natural logarithms of variables in levels (e.g., retail sales, employment) while keeping rates (e.g., US Job Losers, interest rates) in their original units. As the target variable, real GDP is differenced by construction to enter the model as an annualized growth rate. For the remaining non-target variables, I test for unit roots and structural breaks using Augmented Dickey-Fuller (ADF) and Chow tests, respectively. These variables are differenced if the null hypothesis of a unit root cannot be rejected or if a break in the mean is detected. In general, real activity and price series enter the model as annualized growth rates, while interest rates enter as first differences. The specific transformations for each series are detailed in the Table C.1 of the Appendix.

3.3 Empirical results

3.3.1 The estimated MF-BVAR output gap

Figure 3.1 presents the MF-BVAR output gap estimates for Australia. The results demonstrate that the estimated gap aligns closely with historical turning points and suggests that output gaps in Australia are persistent. To identify periods of economic contraction, I utilize the business cycle dates produced by the Melbourne Institute. These dates are derived using the Bry-Boschan Quarterly (BBQ) algorithm developed by Harding and Pagan (2002), which identifies turning points in the level of economic activity. It should be noted that while these represent "classical" business cycle

Figure 3.1: Baseline MF-BVAR output gap and potential trend growth estimates for Australia.



Note: The shaded gray bars correspond to the Melbourne Institute Business Cycle dates, determined using the Bry-Boschan Quarterly (BBQ) algorithm (Harding and Pagan, 2002)

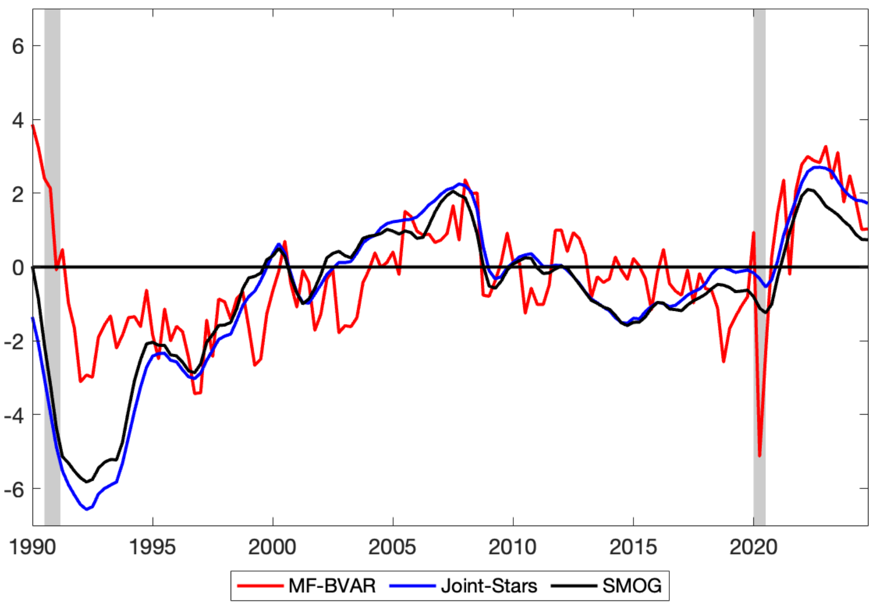
dates, the MF-BVAR estimates the output gap; however, the BBQ dates provide a valid standard domestic benchmark. The estimates captures the steep contraction of the early 1990s, a period consistent with aggressive disinflationary monetary policy. Following this downturn, the estimates reveal a period of persistent slack between 1993 and 2005, where the output gap remained negative despite positive GDP growth. This observation aligns with the "productivity boom" narrative, suggesting that structural reforms expanded potential GDP rapidly enough to allow for a prolonged period of non-inflationary growth (Gruen and Stevens, 2000; Parham, 2002). Following the productivity-driven expansion, the economy shifted toward a period of heightened activity driven by the terms-of-trade boom. By the mid-2000s, the output gap moved into positive territory, coinciding with the start of the mining investment boom. This upward trend indicated that the economy was beginning to encounter capacity limits resulting from the exogenous terms-of-trade shock (Plumb et al., 2013). Crucially, the strongly positive output gap estimates in the pre-GFC period coincide with a phase of strong inflation and accelerating unit labor cost growth in Australia.

The most recent portion of the sample is defined by the downturn during the COVID-19 pandemic. The MF-BVAR estimate records a sharp contraction in 2020, with the gap reaching approximately -5%, which reflects the immediate cessation of economic activity during lockdowns. Unlike the recovery following the 1990s recession, the pandemic era exhibits high volatility characterized by a V-shaped trajectory rather than longer term persistence. The subsequent recovery saw the output gap swing rapidly from a position of significant slack to an inflationary gap exceeding 2%. This positive gap implies that the economy is overheating where demand, bolstered by expansionary policy, outstripped a supply side constrained by global supply chain disruptions. These results provide empirical support for the view that an exceptionally tight labor market and excess demand drove the recent inflationary surge, necessitating the subsequent monetary policy tightening by the RBA (Beckers et al., 2023).

Looking at the implied behavior of potential output growth during the recession of the early 1990s and the GFC, potential growth remained resilient and stayed in positive territory even as actual output growth contracted or slowed sharply. This implies that the MF-BVAR estimates interpret these historical episodes primarily as transitory demand-side contractions rather than permanent reductions in productive capacity. In contrast, the COVID-19 pandemic induced a simultaneous and severe drop in both actual and potential growth, reflecting an immediate, supply-side shock to the economy's potential capacity during government-mandated lockdowns. Reflecting the rapid nature of this crisis, potential growth experienced an equally swift rebound as containment measures eased and resource allocation normalized.

3.3.2 Comparison to central bank estimates

Figure 3.2: Comparison to the central bank output gap estimates



Note: MF-BVAR refers to the baseline output gap estimates. The small multivariate output gap (SMOG) and 'Joint-stars' refer to RBA's output gap estimates (source: RBA).

Figure 3.2 compares the MF-BVAR output gap with the output gap estimates from the RBA: the Small Multivariate Output Gap (SMOG) and the 'Joint-stars' model.[3]

[3]The SMOG is a multivariate filtering model that links the output gap to observable variables including non-farm GDP, trimmed-mean inflation, wages, and unemployment (Bishop et al., 2024). The 'Joint-stars' model is a more complex multivariate unobserved components framework that jointly estimates potential output alongside other unobserved 'star' variables, such as the natural rate of interest (r^*) and the non-accelerating inflation rate of unemployment (u^*) (Bishop et al.,

It is important to note that all series presented here are based on revised (ex-post) data rather than real-time data vintages. The MF-BVAR output gap estimate broadly align with the RBA's output gap estimates, with some differences in amplitude. A primary distinction is that the MF-BVAR output gap estimates exhibits considerably more volatility than the RBA estimates. This is a characteristic of the Beveridge-Nelson decomposition. As noted by Morley, Nelson, et al. (2003), while one can estimate a parameter such that true innovations are strongly negatively correlated, the estimated innovations themselves are perfectly negatively correlated. This results in a more volatile cyclical component compared to unobserved components models that utilize an irregular term or assume zero correlation between shocks.

During the early 1990s recession, the MF-BVAR suggests a much less negative contraction than the central bank's output gap estimates. However, it is important to note that the MF-BVAR estimates generally imply a more positive output gap prior to the recession, suggesting a higher degree of capacity utilization than implied by the RBA's output gap measures. This difference could be driven by the fact that the MF-BVAR estimates incorporate a broader set of information, such as the TWI and the Index of Commodity Prices. During the late 1980s, strong terms-of-trade and elevated commodity prices provided a significant stimulus to the Australian economy; the MF-BVAR identifies this as a period of high capacity utilization. In contrast, RBA estimates may attribute this to potential growth.

All three series capture the period of weak activity during the Global Financial Crisis (GFC). However, the downturn appears less severe than other historical contractions in the sample. This likely reflects the combined effects of substantial fiscal stimulus, aggressive monetary easing by the RBA, and sustained commodity demand from China, which effectively cushioned the Australian economy from the worst of the global shock (Hartigan and Rosewall, 2025).

Finally, another divergence occurs during the COVID-19 pandemic. The MF-BVAR identifies a more negative output gap compared to both the 1990s recession and the RBA's own pandemic-era output gap estimates. The smaller output gap reported by the RBA is primarily due to a correction they apply, which effectively treats a portion of the pandemic-induced volatility as an irregular component (Bishop et al., 2024). Moreover, while domestic indicators were heavily influenced by fiscal interventions such as JobKeeper, foreign variables, specifically global demand and energy prices, provided a more direct signal of the contraction in economic activity. By explicitly modeling these foreign channels, the MF-BVAR identifies a deeper cyclical contraction that may be partially reclassified as a negative supply-side shock in models with a closed-economy assumption.

These differences between estimates likely stem from the fact that the MF-BVAR incorporates a broader set of information, specifically including foreign shocks, which are not explicitly accounted for in the RBA's current suite of models. This does not necessarily suggest that the MF-BVAR estimates are more accurate or represent the "true" output gap; rather, given an open-economy assumption, it provides an alternative interpretation of the Australian output gap that accounts for foreign

2024). Notably, both RBA estimates are derived from models that utilize only quarterly domestic data. I thank the RBA for providing data on their output gap estimates.

shocks. These differences are important as they would suggest a different policy response in a Taylor rule compared to estimates derived from a closed-economy assumption.

Table 3.2: Correlations with Future Output Growth

Output Gap Measure	**Correlation**	***p*-value**
3MF_BVAR	-0.377^{***}	0.000
SMOG	-0.134	0.117
Joint-Stars	-0.143^{*}	0.096

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, based on the reported p-values.

To evaluate the economic plausibility of the MF-BVAR output gap, Table 3.2 presents the correlations between the output gap measures and future output growth. The negative sign for all output gap measures aligns with standard macroeconomic expectations of mean reversion given deviations from trend. Notably, the MF-BVAR output gap exhibits a stronger and highly significant negative correlation (-0.377, $p = 0.000$) compared to the RBA's SMOG and Joint-stars estimates. This result is particularly noteworthy given that the RBA measures are smoothed estimates that incorporate two-sided information, whereas the MF-BVAR yields filtered estimates using a one-sided information set.

3.3.3 Information decomposition

To investigate the primary drivers of information in the estimated MF-BVAR output gap, I employ an informational decomposition framework based on the methodology developed by Morley and Wong (2020) where they show that the estimated output gap via the multivariate BN decomposition is a linear function of the historical forecast errors contained in e_{t-i}. Consequently, one can back out the specific contribution of each variable's forecast error to the cycle.

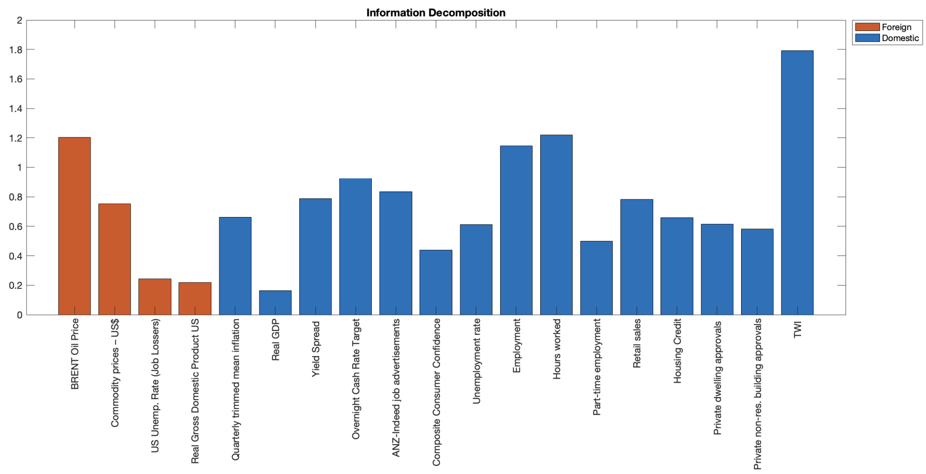
I extend the framework by Berger, Morley, et al. (2023) to a mixed-frequency setting that incorporates weekly and monthly indicators alongside the quarterly target variable. Based on Equations (3.6) and (3.7), the informational contribution of a j^{th} indicator is determined by aggregating forecast error contributions across the specific sub-periods of each variable. To formalize this, recall that $\mathbf{F}$ is the companion matrix, $\mathbf{H}$ is the mapping matrix for forecast errors, and $\mathbf{s}_{np,n}$ is the selector vector for the n^{th} variable (output growth) from the $np \times 1$ state vector. For a monthly indicator, the contribution $c_{j,t}$ is calculated by summing the forecast error contributions over the three months within a quarter. I extend this logic to the weekly indicator by aggregating its contributions across the weeks corresponding to the quarterly period. Following Morley and Wong (2020), the contribution is expressed as:

$$c_{j,t} = -\sum_{i=1}^{m}\sum_{l=0}^{t-1} \mathbf{s}'_{np,n}\mathbf{F}^{l+1}(\mathbf{I}-\mathbf{F})^{-1}\mathbf{H}\mathbf{s}_{n,j+(i-1)k}\mathbf{s}'_{n,j+(i-1)k}\mathbf{e}_t \tag{3.12}$$

where $\mathbf{e}_t$ is the vector of forecast errors, k represents the number of indicators at a given frequency, and m denotes the number of sub-periods (e.g., $m = 3$ for monthly indicators). The term $\mathbf{s}_{n,j+(i-1)k}$ serves as a selection vector that identifies the j^{th} indicator's innovation within the i^{th} sub-period. The total number of variables in the mixed-frequency VAR is defined as $n = mk + 1$, such that output growth is the n^{th} variable. Following Morley and Wong (2020), the standard deviation of $c_{j,t}$ is used to quantify the j^{th} variable's informational contribution. I note that the individual variance shares do not aggregate to the total variance of the output gap; this is due to the presence of non-zero correlations between specific forecast errors, which introduces covariance terms into the decomposition (Morley et al., 2023).

Information content of mixed-frequency variables

Figure 3.3: Informational decomposition of the Australian output gap



Note: Contributions are measured in standard deviations and reflect the decomposition of the estimated output gap according to the underlying forecast errors of each indicator.

The informational decomposition results, illustrated in Figure 3.3, quantify the standard deviations of the informational contributions for each mixed-frequency indicator within the estimated output gap. I observe that every variable in the system contributes non-negligibly to the estimated output gap, with most indicators providing more information beyond that contained in output itself. Foreign variables, in particular, contribute a significant share of useful information needed to estimate the Australian output gap, highlighting the necessity of an open-economy framework. This finding aligns with Sheen et al. (2015) and Yamout (2022), who find that external factors are important for determining domestic conditions given Australia's status as a small open economy. Within the foreign block, Brent crude oil prices function as a proxy for global demand shocks and inflationary pressures, providing the most substantial contribution of useful information among the foreign variables.

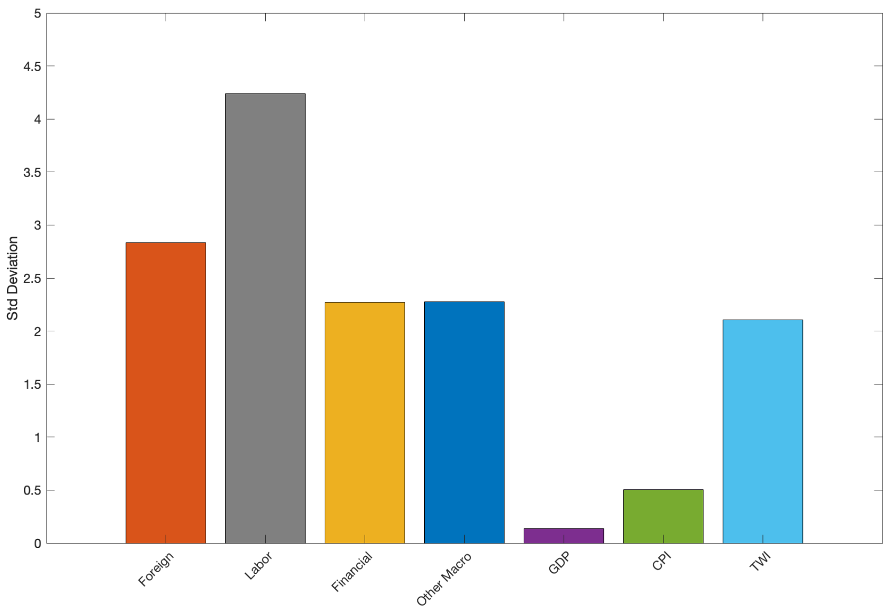
Among all domestic variables, the TWI emerges as the single most informative indicator for the output gap estimate. The TWI functions as a high-frequency proxy for the Terms of Trade; while the model explicitly controls for global commodity prices in the foreign block, the TWI captures the domestic valuation of those external price shocks and acts as a buffer for national income. This is consistent with Yamout

(2022), who emphasizes that for a commodity-exporting economy, fluctuations in the terms of trade are a primary driver of potential output and the output gap. As an asset price, the TWI reacts instantaneously to changes in the economic outlook, allowing it to provide a timelier signal of cyclical turning points than "sticky" variables like employment or inflation. Furthermore, the TWI also serves as a proxy for the exchange rate channel of monetary policy. For instance, during the 2022–2023 tightening cycle, the relative stability of the TWI does not imply the channel was inactive; rather, it indicates that RBA rate hikes successfully maintained interest rate differentials, preventing the inflationary depreciation that would have occurred under a more neutral policy stance.

Among the domestic labor variables, the decomposition reveals that the intensive margin, measured by aggregate hours worked, contributes significantly more useful information needed to estimate the output gap than the headline unemployment rate, similar to what Morley et al. (2023) find for the Euro Area. This suggests that the MF-BVAR model captures cyclical adjustments through reduced shifts or overtime before layoffs occur.

Sectoral Informational Decomposition

Figure 3.4: Sectoral information decomposition



Note: Units are standard deviations. Bars represent the summed standard deviation contributions of variables within each sector. GDP, CPI, and the TWI are treated separately because they represent quarterly and weekly variables, respectively.

To further evaluate the relative importance of different 'sectors', I aggregate the informational contributions into sectoral groupings.[4] The results, illustrated in Figure

[4]The sectors are aggregated as follows: the **Foreign** sector includes Brent oil prices, index of commodity prices, US unemployment rate (job losers), and US GDP; the **Labor** sector comprises job advertisements, unemployment, employment, hours worked, and part-time employment; the **Financial** sector includes the yield spread, the official cash rate (OCR), and housing credit; and

3.4, display the summed standard deviation contributions of variables within each sector with GDP, CPI, and the TWI are treated separately because they represent quarterly and weekly variables, respectively.

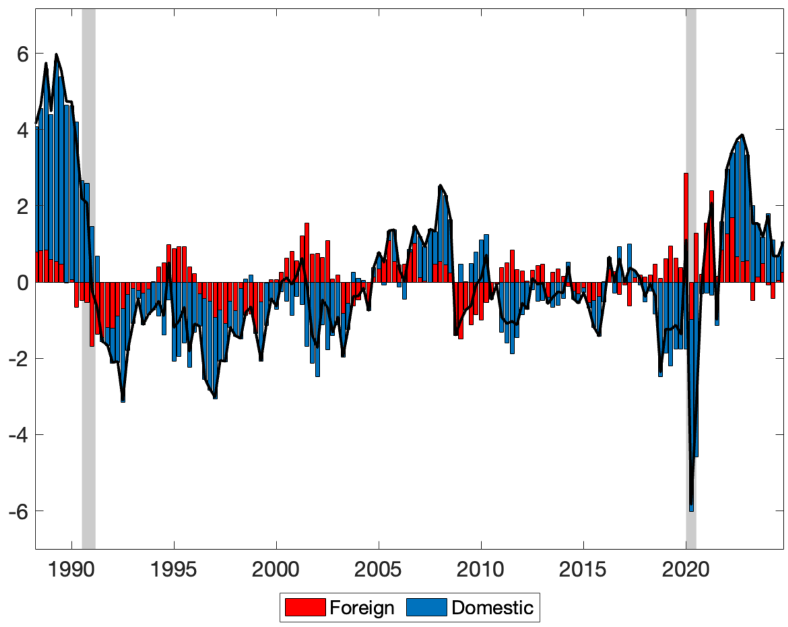
There are two key insights from this decomposition. First, the labor sector constitutes the most important source of useful information needed to estimate the output gap. The model relies on the intensive and extensive margins of the labor market, specifically hours worked and employment levels, as the main indicators of domestic economic activity. Second, the TWI alone provides nearly as much information as the entire financial sector or the other macro sectors combined. This result shows the role of high-frequency exchange rate movements in tracking the economy compared to broader domestic data sources.

The foreign sector emerges as the next most important grouping, outweighing domestic financial or broader macroeconomic variables. This confirms that Australian business cycles cannot be accurately estimated in isolation from global shocks and supports the use of an open-economy framework.

Notably, all sectors have much higher contributions to the output gap than output growth forecast errors themselves.

3.3.4 Foreign vs domestic shocks

Figure 3.5: Decomposition of the Australian output gap into foreign versus domestic shocks.



Other Macro consists of consumer confidence, retail trade, and building approvals. **GDP**, **CPI**, and the **TWI** are treated as individual categories.

The decomposition of the Australian output gap into foreign and domestic shocks based on block exogeneity reveals that while domestic shocks drive the majority of cyclical fluctuations, global shocks still play a substantial role (see Figure 3.5). These foreign shocks transmit through terms of trade fluctuations and foreign demand channels, which is consistent with the small open economy framework where external variables are important for determining domestic conditions. The finding that domestic shocks explain the bulk of output gap variation is consistent with Hendy and Beckers (2024), who argue that while global shocks drive significant variation in the exchange rate and the cash rate, they account for a smaller proportion of the variance in real economic variables. This suggests that the exchange rate and domestic monetary policy have historically functioned as a buffer, insulating the real economy from the full weight of external volatility (Hendy and Beckers, 2024).

Historically, the overheating observed prior to the 1990s recession and the subsequent contraction were predominantly driven by domestic shocks. While the foreign contribution to the output gap was substantial during this period, the empirical results suggest that domestic factors remained the primary driver for the downturn during this period. In contrast, foreign shocks transitioned from a negative to a positive shock during the mid-2000s mining boom, aligning with the exogenous surge in commodity prices and global demand. The negative output gap experienced during the Global Financial Crisis was largely attributable to spillovers originating from these foreign shocks, a result that matches the finding by Sheen et al. (2015) that the 2008 crisis in Australia was fundamentally driven by external factors.

During the COVID-19 pandemic, approximately a quarter of the decline in the output gap can be attributed to foreign shocks, which reflects the impact of the virus on the global economy. However, the majority of the contraction is explained by domestic shocks. Unlike the experience of the Global Financial Crisis, the post-pandemic overheating from 2022 onwards is predominantly driven by domestic factors. This suggests that local policy actions and pent-up demand outweighed the pressures stemming from global supply chain disruptions.

3.3.5 Sources of information for within-quarter output gap estimates

The MF-BVAR framework leverages data that arrives in a more timely manner than the standard quarterly BVAR. This section examines the informational content contained in each monthly and weekly release for the final output gap estimate. Because the BN decomposition functions as a one-sided filter based on conditional expectations, the estimate is only finalized once the release of real GDP for a given quarter completes the required information set (Berger, Morley, et al., 2023). This structure allows for an assessment of the general reliability of within-quarter nowcasts as new data are integrated.

The arrival of information within a reference quarter t is organized into stacked vectors, $\tilde{\boldsymbol{w}}_t$ and $\tilde{\boldsymbol{m}}_t$, to reflect the staggered release schedule. Weekly vectors, $\boldsymbol{w}_{t-1+v}$, enter the model sequentially at intervals $v \in \{1/13, 2/13, \ldots, 1\}$. During the periods between monthly updates, such as Weeks 1 through 3, the model relies exclusively on these weekly indicators to update the output gap nowcast. Monthly data arrives in batches at $u \in \{1/3, 2/3, 1\}$, incorporating both timely estimates for the current

Figure 3.6: Timing of data releases.

Quarter		t		
Month		t − 2/3	t − 1/3	t
Week	1	$\mathrm{w}_{t-12/13}$	$\mathrm{w}_{t-8/13}$	$\mathrm{w}_{t-4/13}$
	2	$\mathrm{w}_{t-11/13}$	$\mathrm{w}_{t-7/13}$	$\mathrm{w}_{t-3/13}$
	3	$\mathrm{w}_{t-10/13}$	$\mathrm{w}_{t-6/13}$	$\mathrm{w}_{t-2/13}$
	4	$\mathrm{w}_{t-9/13}$	$\mathrm{w}_{t-5/13}$	$\mathrm{w}_{t-1/13}$
		$\mathrm{m}_{1,t-2/3}$	$\mathrm{m}_{2,t-1/3}$	
		$\mathrm{m}_{1,t-1}$	$\mathrm{m}_{2,t-2/3}$	
	5			w_{t}
				$\mathrm{m}_{3,t}$
				$\mathrm{m}_{3,t-1/3}$
				q_{t-1}

Note: This figure shows how information arrives within a reference quarter t. The vector $\boldsymbol{w}_{t-1+v}$ represents weekly indicators observed at week $v \in \{1/13, 2/13, \ldots, 1\}$, and $\boldsymbol{m}_{t-1+u}$ represents monthly indicators for month $u \in \{1/3, 2/3, 1\}$. q_{t-1} denotes the quarterly GDP for the previous period, which is only available at the end of the current quarter ($u = 1$)

period and updates for lagged indicators. As illustrated in Figure 3.6, these batches include releases such as $m_{1,t-2/3}$, representing the first month's estimate of the current period, and $m_{1,t-1}$, which denotes variables whose reference month is the previous period but for which data is received in the first month.

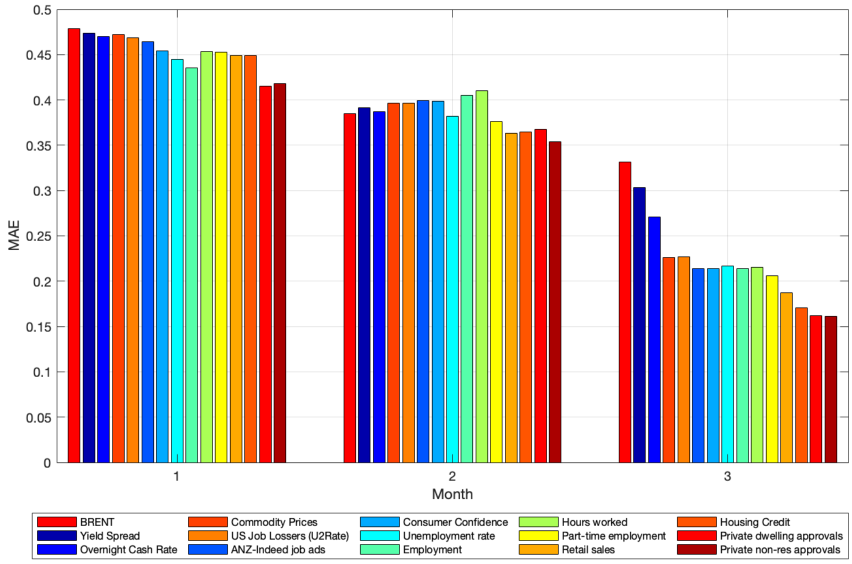
Informational Gains from Monthly Data Releases

Figure 3.7 displays the Mean Absolute Error (MAE) of the within-quarter output gap nowcast for each data release point compared to the final estimate.[5] This approach allows for a specific identification of which variables within each month drive the improvement between intra-quarter nowcasts and the final output gap estimation. To evaluate the statistical significance of these results, Table 3.3 reports p-values for two-tailed Diebold-Mariano tests based on MAE. These tests assess the null hypothesis of equal predictive accuracy between the current nowcast and the nowcast produced at the immediately preceding data release point. I utilize an absolute error loss function to evaluate these marginal informational gains, following the approach in Berger, Boll, et al. (2022) and Berger, Morley, et al. (2023). However, as noted earlier, DM statistics evaluate relative predictive performance within a specific modeling environment; thus, significant results should be interpreted as evidence of incremental informational value rather than a rejection of the underlying model specification.[6]

[5]The choice to evaluate the accuracy of the output gap revisions using MAE is motivated by the presence of extreme outliers in the recent sample, particularly during the COVID-19 pandemic, which can disproportionately distort Root Mean Squared Error (RMSE) metrics. Using MAE ensures that the evaluation of the model's performance remains robust to these high-volatility episodes.

[6]See Diebold (2015) for a detailed discussion on the interpretation and potential over-application of DM tests in model comparison.

Figure 3.7: Average percentage point deviation from final estimate with each monthly data release.



The results for the first month of the quarter indicate that given an initial mean absolute error of 0.48 percentage points before within-quarter information is integrated, observing financial variables such as the yield spread or the cash rate has relatively little impact on improving the nowcast. However, Consumer Confidence ($p = 0.001$), Employment ($p = 0.015$), and Job Ads ($p = 0.028$) are statistically significant at the 5% level. This suggests that early-quarter information is primarily derived from household sentiment and labor market intentions. Since these indicators are released early, for instance, Job Ads on the seventh of the month, they provide the first signals of economic activity before official ABS data accumulates.

During the second month, the results show a further reduction in mean absolute error. This improvement is driven by information in Housing Credit ($p = 0.002$), Brent Crude Oil ($p = 0.003$), and the Yield Spread ($p = 0.022$), suggesting that global shocks and domestic credit conditions provide intermediate signals before hard activity data arrives. Financial variables are particularly useful at this stage because they are available immediately. While the model waits for real data, such as sales or approvals which are delayed by publication lags, it relies on timely financial pricing to fill the information gap.

By the third month, most variables contribute to improving the reliability of the nowcasts. The reduction in forecast error is determined by Commodity Prices ($p = 0.001$) and Private Dwelling Approvals ($p = 0.037$), which serve as direct proxies for the income and construction components of the National Accounts. The statistical significance of approvals emerges only in the third month due to a two-month publication lag; this represents the first instance in which the model observes hard construction data for the start of the reference quarter.

Table 3.3: Diebold–Mariano test p-values for monthly variables.

Variable	Month 1	Month 2	Month 3
Brent Crude Oil	0.345	**0.003**	0.376
Yield Spread (10y - 3m)	0.063	**0.022**	0.101
Overnight Cash Rate Target	0.255	0.126	**0.026**
Index of Commodity Prices	0.693	0.092	**0.001**
US Job Losers (U2RATE)	**0.035**	0.280	0.641
ANZ-Indeed Job Ads	**0.028**	0.324	0.390
Composite Consumer Confidence	**0.001**	0.647	0.435
Unemployment Rate	0.448	**0.047**	0.329
Employment	**0.015**	0.238	0.668
Hours Worked	0.365	0.896	0.388
Part-time Employment	0.207	**0.002**	0.507
Retail Sales	0.833	0.206	0.406
Housing Credit	0.366	**0.002**	**0.044**
Private Dwelling Approvals	0.174	0.078	**0.037**
Private Non-Res Approvals	0.182	**0.031**	0.847

Note: Significant p-values ($p < 0.05$) are in bold.

Informational Gains from Weekly Data Releases

The reduction in forecast error associated with the weekly TWI is closely linked to the staggered release schedule of the model. During the periods between monthly updates, such as Weeks 1 through 3, the model relies exclusively on these weekly indicators to update the output gap nowcast. The information set expands at the end of each month—specifically in Weeks 4, 8, and 13—when the monthly vectors are integrated into the system. I evaluate these weekly updates using the MAE metric, where the Diebold-Mariano tests in Table 3.4 compare the current week's nowcast against the nowcast from the immediately preceding week. As with the monthly analysis, these statistics serve as a relative measure of predictive accuracy and are subject to the same interpretative cautions regarding model specification and data noise at high frequencies. The MAE remains flat during most weeks, implying that standalone weekly exchange rate volatility provides little new information for the nowcast. Diebold-Mariano tests in Table 3.4 confirm this, showing that the TWI is statistically insignificant for the majority of the quarter, as seen in Week 1 ($p = 0.640$) and Week 7 ($p = 0.750$).

Statistical significance for the TWI emerges primarily at the monthly boundaries, such as Week 5 ($p = 0.002$) and Week 9 ($p = 0.030$). This timing suggests that the information contained in the TWI is most valuable when interpreting simultaneous monthly data releases. While standalone TWI movements offer limited improvements to the nowcast in isolation, the TWI serves as a mechanism for the model to react to global shocks in a timely manner. Despite the lack of continuous significance, including the TWI is valuable because it reacts instantaneously to global shocks. This allows the model to update its view immediately during major events, whereas waiting for monthly indicators, such as employment, would introduce a lag of four to five weeks.

Figure 3.8: Average percentage point deviation from final estimate with each weekly data release.

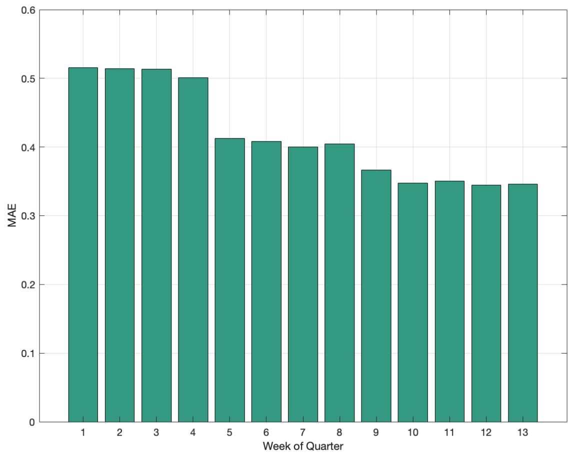


Table 3.4: Diebold–Mariano test p-values for weekly TWI.

Trade Weighted Index (TWI)	
Week	**P-value**
1	0.640
2	0.878
3	0.143
4	0.192
5	**0.002**
6	0.650
7	0.750
8	0.274
9	**0.030**
10	0.343
11	0.833
12	0.901
13	0.318

Note: Significant p-values ($p < 0.05$) are in bold.

3.3.6 Is the weekly TWI helpful?

Naturally, the question arises whether a three-frequency BVAR is necessary or if the two-frequency model is preferable for nowcasting purposes. The comparison between the two-frequency (2F-BVAR) and three-frequency (3F-BVAR) specifications reveals a trade-off between final estimate accuracy and the timeliness of informational updates.

Looking at Figure 3.9, the 2F-BVAR is more accurate at the end of the quarter, yielding a final mean absolute error of approximately 0.10 percentage points compared to approximately 0.16 percentage points in the 3-frequency model. However, because it lacks weekly variables, the 2F-BVAR provides no new information between monthly releases. This leads to a nowcast that remains flat until the end of each month, effectively ignoring any economic developments that occur within that interval. While the 3F-BVAR has a higher MAE, this specification allows the model to reflect timely information revealed between monthly data arrivals.

To evaluate the specific informational role of the TWI in improving the nowcasts, I examine the 3F-BVAR model under two different data arrival sequences. The first, denoted as sequence A, utilizes the staggered release schedule illustrated in Figure 3.6, whereas sequence B treats the information set by processing all weekly indicators before integrating the monthly and quarterly data blocks at the conclusion of the period. I evaluate these results using MAE as the performance metric. Table 3.5 reports p-values for Diebold-Mariano tests, where the benchmark for each week is the nowcast produced in the immediately preceding week

A comparison between these two specifications confirms that the weekly TWI provides almost no information when observed in isolation (see Figure 3.10a and 3.10b). Looking at Table 3.5, the TWI remains statistically insignificant for all thirteen

Figure 3.9: Average percentage point deviation from final estimate with each monthly data release for the 2F-BVAR specification

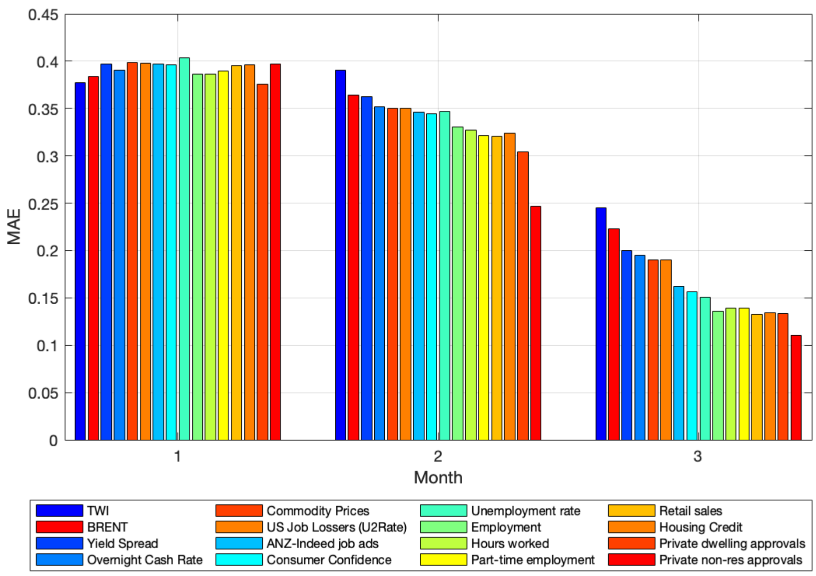
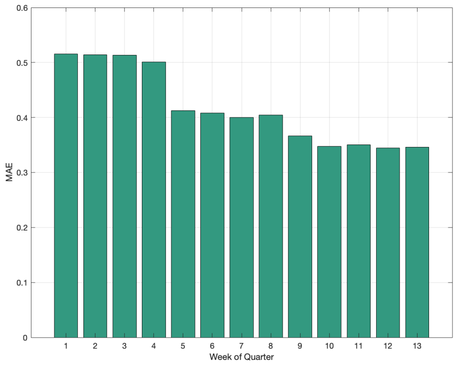


Table 3.5: Diebold–Mariano test comparison for marginal TWI contribution

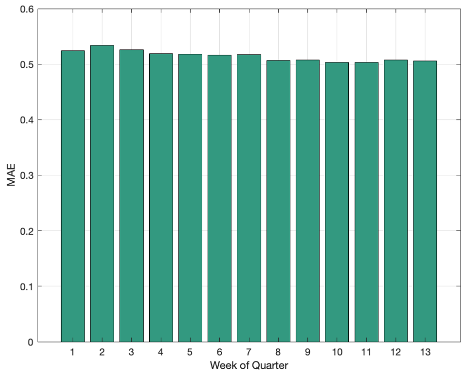
Week	**Data Release Schedule Sequence A**	**Weekly-First Schedule Sequence B**
1	0.640	0.149
2	0.878	0.457
3	0.143	0.791
4	0.192	0.871
5	**0.002**	0.475
6	0.650	0.788
7	0.750	0.193
8	0.274	0.119
9	**0.030**	0.351
10	0.343	0.303
11	0.833	0.410
12	0.901	0.932
13	0.318	0.819

Note: Sequence follows the staggered release schedule in Figure 3.6.
Sequence B observes all weekly indicators first, followed by monthly and quarterly blocks only at the end of the period.
Bold values indicate significance at the 5% level.

Figure 3.10: Comparison of weekly MAE by information sequence.



(a) Weekly MAE following the staggered release schedule in Figure 3.6.



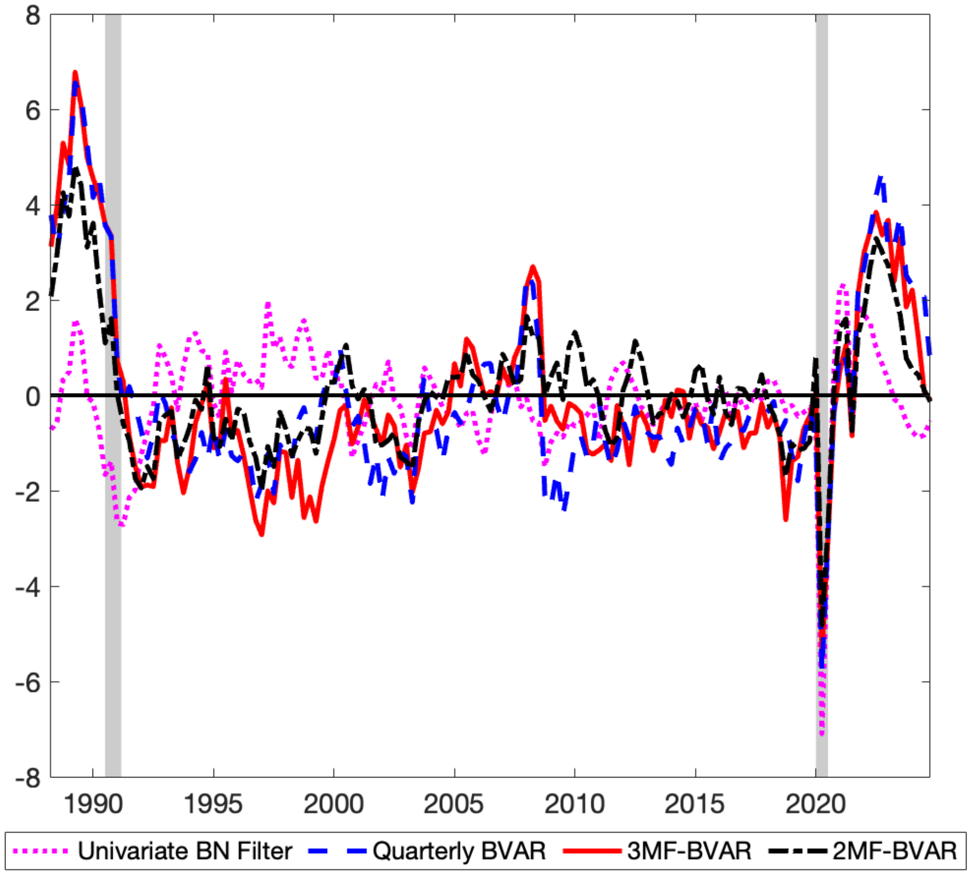
(b) Weekly MAE where weekly indicators are observed first, with monthly/quarterly blocks at period-end.

weeks of the quarter in sequence B. In contrast, under sequence A, the TWI gains statistical significance only at the end of the month—specifically in Weeks 5 and 9—concurrent with the release of monthly data. These results imply that the TWI is most useful for its interaction with simultaneous monthly observations, rather than as a standalone predictor given that TWI does not drive the reduction in mean absolute error independently.

An important consideration is how the output gap estimates vary across the different frequencies and whether these differences are substantial. Figure 3.11 illustrates the output gap estimates derived from the quarterly BVAR alongside the 2F-BVAR and 3F-BVAR specifications, as well as the univariate BN decomposition based on the BN Filter (Kamber, Morley, et al., 2018; Kamber, Morley, et al., 2025). All four models produce broadly similar estimates and capture identical cyclical turning points throughout most of the sample period. However, the univariate output gap estimates a deeper contraction during the recession of the early 1990s compared to the other output gap estimates. A notable difference among the specifications occurs between 1995 and 2000, where the univariate BN estimates a positive output gap, whereas all the multivariate alternatives indicate a negative gap. Another difference in the estimates occurs in the post-GFC period between 2009 and 2012. While the quarterly BVAR suggests a persistent negative output gap, the mixed-frequency models and univariate estimates a gap near zero or positive. This latter estimation matches the capacity constraints observed during the peak of the mining boom. Finally, during the COVID-19 pandemic, the univariate output gap identifies the most severe cyclical contraction among all specifications, while during 2022–2023, the quarterly BVAR indicates a higher peak of excess demand (exceeding 4%) than the mixed-frequency specifications, which estimate a peak of approximately 3%.

The 3-frequency and 2-frequency estimates track each other closely, sharing a high correlation of 0.917. Their respective correlations with the quarterly BVAR are lower, at 0.853 and 0.843, while their correlations with the univariate baseline are lower still, at 0.137 for the 3-frequency and 0.247 for the 2-frequency specification. The high degree of comovement between the two mixed-frequency models confirms

Figure 3.11: Comparison of quarterly BVAR estimates against mixed-frequency BVAR estimates.



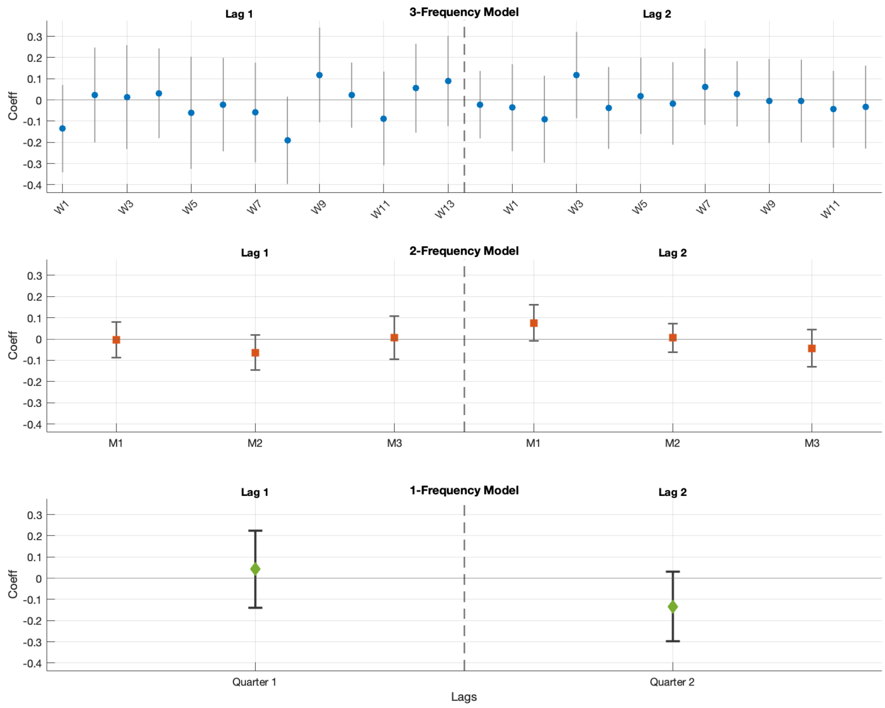
that monthly data arrivals drive the bulk of the nowcast revisions, with weekly data providing only marginal refinements to the estimates.

Furthermore, the precision of the parameters varies across specifications. As shown in Figure 3.12, the quarterly BVAR is characterized by wider credible intervals, possibly reflecting parameter instability on monthly variables within a quarter. In contrast, the 2F-BVAR produces narrower error bands for the TWI coefficients that can vary by month. In the context of Bayesian estimation, these tighter posterior distributions suggest that the 2F-BVAR specification provides a more precise signal of the underlying parameter values. The credible intervals are fairly wide for the 3F-BVAR, suggesting possible small sample issues given parameter proliferation.

3.4 Conclusion

This chapter extends the mixed-frequency Bayesian vector autoregressive (MF-BVAR) framework to the Australian economy by applying a multivariate Beveridge–Nelson (BN) decomposition. By adapting the methodology to a small open economy setting, accounting for COVID-19 outliers, and refining the model to include a weekly indicator, this study provides an approach to tracking the Australian output gap

Figure 3.12: Estimates of TWI coefficients across frequencies.



Note: The figure displays the estimated coefficients for TWI in the 3F-BVAR (top), 2F-BVAR (middle), and Quarterly BVAR (bottom). Error bars represent 95% credible intervals.

contemporaneously. The methodology utilizes the conditional forecasting approach to produce within-quarter updates that revise the output gap estimate as high-frequency data arrives. This framework demonstrates how the Berger, Morley, et al. (2023) approach can be modified to remain robust in an open-economy environment where external shocks are a key driver of domestic fluctuations. Moreover, this adaptation provides a template for researchers to isolate domestically-originating cyclical movements from global spillovers by utilizing a block-exogenous foreign sector.

The empirical findings indicate that the MF-BVAR output gap aligns with Australian recessions and expansions and remains broadly consistent with the revised Reserve Bank of Australia's estimates. The results highlight the importance of the open-economy assumption, as informational decomposition results show that every variable in the model contributes to the estimate, with foreign variables and TWI providing significant shares of useful information. For policymakers, this highlights an important advantage over standard output gap models with closed-economy assumption. Domestically, aggregate hours worked emerges as a more vital indicator than the headline unemployment rate, as the intensive margin more effectively captures cyclical adjustments. Furthermore, the sectoral aggregation identifies the labor sector as the primary source of timely information and that TWI alone provides informational value nearly equivalent to the entire financial or macroeconomic sectors combined.

The decomposition of the Australian output gap into foreign and domestic shocks reveals that while domestic shocks drive the majority of cyclical fluctuations, foreign shocks play a substantial role through terms-of-trade and global demand channels. Furthermore, I find that the 1990s recession and post-pandemic recovery were predominantly attributed to domestic shocks, whereas the output gap in the Global Financial Crisis was largely driven to foreign shocks. This demonstrates that explicitly modeling the foreign sector is essential to correctly distinguish between domestic and foreign drivers of the output gap in a small open economy.

To answer whether a three-frequency (3F) BVAR is necessary or if a two-frequency (2F-BVAR) model is preferable for nowcasting, I compare both specifications and find a trade-off between accuracy and the timeliness of the final output gap estimates. While the 2F-BVAR is more accurate at the end of the quarter with a lower final mean absolute error, it provides no new information between monthly releases. In contrast, the 3F-BVAR specification allows the model to reflect timely information revealed between monthly data arrivals. Despite these differences, both mixed-frequency models produce broadly similar estimates and capture identical cyclical turning points.

Finally, this chapter offers several avenues for future research. While the current framework utilizes a U-MIDAS approach, future work could explore alternative functional forms, such as an R-MIDAS specification, especially for coefficients on higher-frequency weekly variables, to assess whether more parsimonious parameterizations improve nowcasting performance of a model with weekly frequency variables. Given such an extension, the scope of high-frequency monitoring could be expanded by incorporating a broader set of weekly or daily indicators. While the TWI serves as a important signal for the external sector, the value-add of the 3F BVAR could be extended by including other timely variables such as Brent Oil prices or the Yield Spread to better capture global and financial conditions. Additionally, one could incorporate the World Industrial Production (WIP) index from Baumeister and Hamilton (2019) within the block-exogenous framework, as this monthly index tracks global economic activity. Future research might also consider other domestic high-frequency proxies, such as electricity usage or automotive sales, or the integration of fiscal spending data to better isolate potential domestic drivers of the output gap. Alternatively, rather than relying on interpolation, future work could integrate higher-frequency latent indicators directly; for instance, the mixed-frequency BVAR framework by Trinh and Cross (2026) could be utilized to first generate a monthly GDP index for Australia, which could subsequently be used to enhance the mixed-frequency nowcasting performance of the output gap. Such expansions would help clarify the trade-off between model parsimony and the informational gains provided by moving beyond a single weekly indicator. A further extension of this work could involve taking advantage of the Australian Real-Time Database hosted at the University of Melbourne (Lee, Olekalns, et al., 2012) to conduct a recursive estimation using historical real-time data vintages, thereby evaluating model performance under the exact information sets available to policymakers at each point in time. This approach would facilitate the estimation of Taylor-type rules using the real-time output gap to formally assess the stance of monetary policy throughout the sample period.

C Appendix to Chapter 3

Table C.1: Data Description and Transformation Codes

Variable	Source	Frequency	Transformation
Trade-weighted Index	RBA	Weekly	Log difference
Brent Crude Oil	FRED	Monthly	Log difference
Commodity Prices	RBA	Monthly	Log difference
US Job Losers (U2RATE)	FRED (BLS)	Monthly	No change
Yield Spread (10y - 3m)	FRED	Monthly	No change
Overnight Cash Rate Target	RBA	Monthly	Differenced
ANZ-Indeed Job Ads	ANZ	Monthly	Log difference
Composite Consumer Confidence	FRED (OECD)	Monthly	Differenced
Unemployment Rate	ABS	Monthly	Differenced
Employment	ABS	Monthly	Log difference
Hours Worked	ABS	Monthly	Log difference
Part-time Employment	ABS	Monthly	Log difference
Retail Sales	ABS	Monthly	Log difference
Housing Credit	RBA	Monthly	Log difference
Private Dwelling Approvals	ABS	Monthly	Log difference
Private Non-Residential Approvals	ABS	Monthly	Log difference
US Real GDP	FRED (BEA)	Quarterly	Log difference
Trimmed Mean Inflation	ABS	Quarterly	No change
AUS Real GDP	ABS	Quarterly	Log difference

Table C.2: Australian Output Gap (3MF_BVAR)

Quarter	3MF_BVAR	Quarter	3MF_BVAR
1988.25	3.161979605	2006.50	0.889399059
1988.50	4.276854347	2006.75	0.662091127
1988.75	5.903752311	2007.00	0.735288042
1989.00	5.306142073	2007.25	0.905494426
1989.25	6.542362309	2007.50	1.658796597
1989.50	5.638934359	2007.75	0.728186128
1989.75	4.754284510	2008.00	2.361906279
1990.00	3.863619226	2008.25	1.985188068
1990.25	3.238784266	2008.50	2.007000157
1990.50	2.403053775	2008.75	-0.762928017
1990.75	2.127546651	2009.00	-0.793529497
1991.00	-0.077198632	2009.25	-0.373160196
1991.25	0.471921188	2009.50	0.125091413
1991.50	-0.972114120	2009.75	0.918186267
1991.75	-1.661354810	2010.00	0.134352216
1992.00	-3.103271042	2010.25	0.174207841
1992.25	-2.926087685	2010.50	-1.252602334
1992.50	-2.987594937	2010.75	-0.574013320
1992.75	-1.894770979	2011.00	-1.012836274

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Table C.2 – Continued from previous page

Quarter	3MF_BVAR	Quarter	3MF_BVAR
1993.00	-1.568240462	2011.25	-1.013644177
1993.25	-1.325696942	2011.50	-0.481150714
1993.50	-2.191018824	2011.75	0.993650507
1993.75	-1.843756657	2012.00	1.001792314
1994.00	-1.372618720	2012.25	0.421938340
1994.25	-1.344677169	2012.50	0.934676556
1994.50	-1.613833675	2012.75	0.771021536
1994.75	-0.627179789	2013.00	0.328677295
1995.00	-1.829936911	2013.25	-0.828773805
1995.25	-2.484755525	2013.50	-0.261136906
1995.50	-1.134569597	2013.75	-0.417287243
1995.75	-1.999170882	2014.00	-0.319333788
1996.00	-1.604800788	2014.25	0.269315597
1996.25	-1.756927347	2014.50	-0.086364170
1996.50	-2.461512892	2014.75	-0.334552148
1996.75	-3.428581161	2015.00	0.228508723
1997.00	-3.405062684	2015.25	0.025003525
1997.25	-1.435796919	2015.50	-0.321871438
1997.50	-2.422174613	2015.75	-1.159517861
1997.75	-0.867065545	2016.00	-0.152695555
1998.00	-0.947215017	2016.25	0.474951709
1998.25	-1.410158773	2016.50	-0.448907394
1998.50	-0.861195285	2016.75	-0.650599449
1998.75	-0.670252751	2017.00	-0.765733243
1999.00	-1.636118579	2017.25	-0.084287611
1999.25	-2.661912216	2017.50	-0.976386877
1999.50	-2.492939010	2017.75	-0.178335742
1999.75	-1.268430867	2018.00	-0.583968398
2000.00	-0.648558307	2018.25	-0.632955425
2000.25	-0.109646927	2018.50	-1.116365573
2000.50	0.698292150	2018.75	-2.573036367
2000.75	-0.445530967	2019.00	-1.668526698
2001.00	-1.081918216	2019.25	-1.339956169
2001.25	-0.096997255	2019.50	-1.048082230
2001.50	-0.421757008	2019.75	-0.802211934
2001.75	-1.711921520	2020.00	0.938400803
2002.00	-1.275948814	2020.25	-5.121882083
2002.25	-0.320028224	2020.50	-2.316978341
2002.50	-0.093193265	2020.75	0.263958988
2002.75	-1.780572360	2021.00	1.484486648
2003.00	-1.589704696	2021.25	2.356911204
2003.25	-1.617205805	2021.50	-0.197869707
2003.50	-1.374229001	2021.75	2.055841688
2003.75	-0.428051243	2022.00	2.775565399
2004.00	-0.079679316	2022.25	2.995454553
2004.25	0.380880322	2022.50	2.882045455
2004.50	-0.008830548	2022.75	2.826036842
2004.75	0.127367672	2023.00	3.271350465

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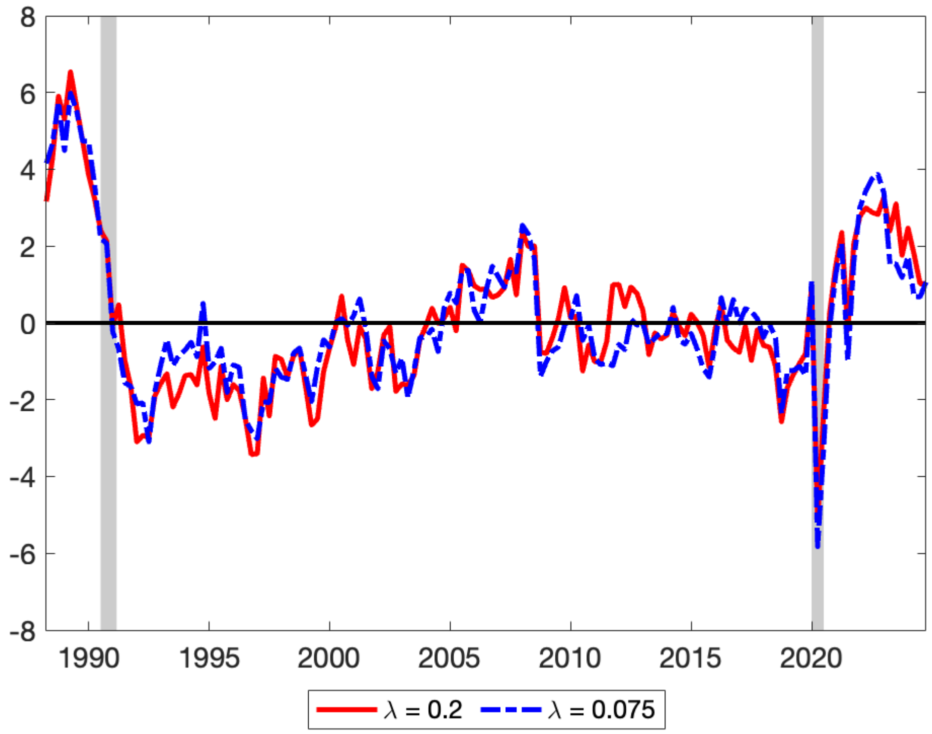
Table C.2 – Continued from previous page

Quarter	3MF_BVAR	Quarter	3MF_BVAR
2005.00	0.405531666	2023.25	2.398945791
2005.25	-0.204549065	2023.50	3.100657891
2005.50	1.504870969	2023.75	1.759515435
2005.75	1.369038622	2024.00	2.469811237
2006.00	0.968438841	2024.25	1.790069760
2006.25	0.867376794	2024.50	1.012668022
		2024.75	1.032371168

Figure C.1: Sensitivity of MF-BVAR Output Gap Estimates to the Shrinkage Hyperparameter λ



Note: The figure above compares the baseline output gap estimates ($\lambda = 0.20$) against an alternative specification using a tighter shrinkage parameter ($\lambda = 0.075$) as in Morley and Wong (2020).

Concluding Chapter

The three substantive chapters of this dissertation examine the estimation and drivers of economic slack across small open economies. By applying and extending the Beveridge-Nelson decomposition within various econometric frameworks, I address the challenges of data limitations, the influence of global and financial factors on the output gap, and reporting lags.

In Chapter 1, I apply the Beveridge-Nelson (BN) filter to address the challenges of estimating output gaps in emerging Asian economies. The results demonstrate that the BN filter provides more reliable and informative estimates than alternative methods such as the Hodrick-Prescott, Christiano-Fitzgerald, and Hamilton filters. When benchmarked against narrower indicators of slack, the findings show that BN filter output gap estimates provide a more informative indicator than capacity utilization and unemployment, given longer data coverage and controlling for long-run structural changes. I also document two systematic results for these economies: cyclical consumption is more volatile than the output gap, and decomposing GDP growth volatility shows that less than one-third of growth fluctuations is accounted for by movements in trend growth, with most variation attributed to the cyclical component. Taken together, these findings contrast with the interpretation in Aguiar and Gopinath (2007) that shocks to the trend are the primary driver of fluctuations in emerging economies and departs from their view that the "cycle is the trend." Crucially, the BN filter estimates are subject to smaller and less frequent revisions when faced with large changes in economic conditions, which benefits real-time policy decision-making.

In Chapter 2, I use a multivariate Beveridge-Nelson decomposition within a Bayesian vector autoregression framework to examine the influence of financial and global factors on the Southeast Asian emerging economies of Indonesia, Malaysia, Thailand, and the Philippines. There are three key findings. First, traditional slack measures are largely uninformative for these economies, likely due to structural issues, limited coverage, and, more importantly, the prevalence of informal employment which weakens the link between labor market indicators and the business cycle. Second, financial variables are highly informative and were particularly influential during the Asian and the Global Financial Crisis. Third, external variables explain a substantial share of cyclical fluctuations, often exceeding the contribution of domestic output, suggesting the susceptibility of these emerging market economies to global forces.

In Chapter 3, I find that the estimated output gap produced by the mixed-frequency Bayesian vector autoregressive (MF-BVAR) framework is broadly consistent with central bank estimates. Informational decomposition results reveal that every variable in the model contributes non-negligibly to the overall estimate, with foreign variables and the Trade Weighted Index (TWI) providing significant shares of useful information. Domestically, aggregate hours worked provides a more significant informational contribution than the headline unemployment rate, suggesting more information from the intensive margin of the Australian labour market than its extensive margin. Furthermore, the sectoral aggregation highlights the labor sector as the primary source of information for the output gap, while TWI alone provides informational value nearly equivalent to the entire financial or macroeconomic sectors combined. Shock decompositions reveal that while domestic shocks drive the majority of cyclical fluctuations, the Global Financial Crisis was largely attributable to foreign shocks. Finally, while the weekly TWI indicator allows for more timely updates, it does not lead to an improvement in estimates compared to a model utilizing a monthly TWI instead.

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