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An Empirical Take on the 'Plucking' Model

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Abstract

Traditional estimates of the potential output are prone to retrospective revisions after sharp fluctuations. The alternative 'Plucking' view offers a possible headway. While straightforward, empirical frameworks fit for economic analysis are yet to be developed. This paper has three parts. The first proposes a computationally simple estimation flow for the 'Plucking' output ceiling. The second analyses empirical regularities with respect to inflation, and unemployment, against a quantitative boom-bust estimate based on a production function with Hodrick Prescott (HP)-filtered inputs, and a Neo-Keynesian Phillips Curve with a Kalman Filter, which takes in HP-filtered output trend and cycle. Both two-sided and one-sided recursive versions of the time series filters are used. The third uses a vector autoregression (VAR) to compare responses to supply and demand shocks. This paper finds that the boom-bust estimates, except when one-sided recursive time series filters are used, are prone to large retrospective revisions. The 'Plucking' estimates are insensitive. Both estimates do not support a Phillips Curve relationship. The boom-bust estimates do not track the unemployment rate, an observable measure of slack, but the 'Plucking' estimates do. Moreover, consistent with 'potential output' and 'output ceiling' as measures of supply, the 'Plucking' estimates are responsive only to supply (global oil price) shocks, and not demand (interest rate). Responses of the boom-bust estimates vary across methodology, but generally do not conform to this definition. Policymakers should consider alternatives, such as this paper, alongside pre-existing methods of the boom-bust view.

Keywords: Potential Output, Business Cycle Asymmetry, Turning Points, Time Series
JEL Codes: E00, E30, E32

† Any views expressed are solely mine and should not be taken to represent those of the Central Bank of Malaysia, or the Government of Malaysia.

1 Introduction

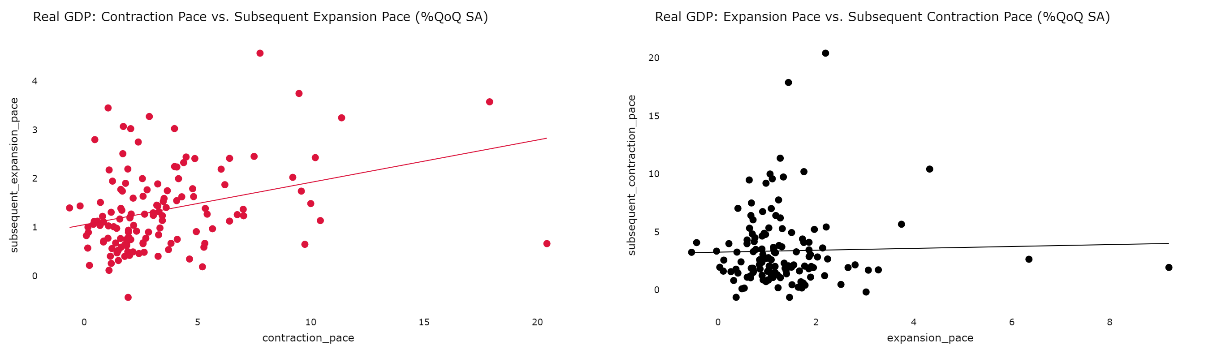
Friedman (1993) first proposed an alternate view of the business cycle, specifically that output hovers at, or below its potential, and is occasionally ‘plucked’ far down by adverse economic shocks, before rebounding towards that potential over time. The analogous description was that output behaves ‘like a guitar string’. The prevailing view, in contrast, then and now, was that output follows a boom-bust cycle, such that it fluctuates around, i.e., above and below, its potential. That bi-directional difference between output and its potential is the output gap. While they appear to be competing theories, there are subtle differences that indicate otherwise. The output ceiling, or potential in the ‘Plucking’ view, indicates a theoretical maximum, whereas the potential in the traditional boom-bust view indicates efficient, non-inflationary accelerating, allocation of resources. Without further verification from data, both of these can indeed correspond to the same, or different levels of output.

The empirical basis for both theories also differ. The ‘Plucking’ view is motivated by two empirical regularities — (1) that the pace of ongoing expansions are predicted by the pace of preceding contractions, but (2) the pace of ongoing contractions are unrelated to the pace of preceding expansions. A variety of papers have replicated this, particularly the US economy, such as in Dupraz et al. (2019). This, in essence, is diametrically opposed to the boom-bust view, where ongoing expansions and contractions are predicted, respectively, by preceding contractions and expansions. A simple tabulation of quarter-on-quarter seasonally adjusted (QoQSA) growth rates of real Gross Domestic Product (GDP) of 84 countries [1] between 2Q 1947 and 4Q 2022, where available, in figure 1 indicates that the two empirical bases of the ‘Plucking’ view hold globally.

[1] 84 countries: Albania, Armenia, Australia, Austria, Azerbaijan, Bahrain, Belgium, Botswana, Brazil, Brunei, Bulgaria, Canada, Chile, China, Colombia, Croatia, Cyprus, Czech Republic, Ecuador, Egypt, Estonia, European Union, Finland, France, Georgia, Germany, Ghana, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Jordan, Kazakhstan, Kenya, Kuwait, Latvia, Lithuania, Luxembourg, Macau, Malaysia, Malta, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Netherlands, New Zealand, Nigeria, North Macedonia, Norway, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Serbia, Singapore, Slovakia, Slovenia, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Tunisia, Turkey, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay

Figure 1

(a) Contraction Against Subsequent Expansion (b) Expansion Against Subsequent Contraction



On grounds of estimation and policy use case, the comparison between the two views becomes practical. Time series filters, and occasionally in tandem with structural vector autoregressions (SVARs), and structural equation models, such as the production function, are often used to estimate the potential output in the boom-bust view. Álvarez & Gómez-Loscos (2018), and Cerra & Saxena (2000) summarised a suite of these estimation methods. Probst (2022) also covered a production function approach by the Congressional Budget Office (CBO) that uses structural equations mimicking Okun's Law, instead of time series filters. However, due to the use of primarily two-sided time series filters, popularly the Hodrick-Prescott (HP) filter, multivariate filters such as the Kalman Filter and Smoother, boom-bust estimates of the potential output are prone to large retrospective revisions post-shock, briefly noted in Fernald (2015). This susceptibility to retrospective revision renders the policy use case of these estimates nil, as the model-consistent optimal policy action, within reasonable bounds, can only be observed ex post the observation of shocks, and cannot be rectified. Doing so requires travelling back in time knowing the ex post estimates. The scale of retrospective revisions in an estimate that is useful for real-time policy ought to be minimal. The one-sided recursive HP filter, which is used in estimating credit-GDP gaps, and described in Alfaro & Drehmann (2023), Drehmann & Yetman (2018), and Borio & Lowe (2002) offer some promise. However, ex post information may still be informative, insofar as retrospective revisions are not substantial. Moreover, they violate the conceptual characterisation of a structural, or long-term measure of supply — to be responsive only to supply shocks, and not demand shocks of a cyclical nature. Coibion et al. (2017) analysed this using VARs on estimates of potential output in the United States (US), including the Congressional Budget Office (CBO)'s estimates, and attributed the unexpected response to demand shocks to reflect potential incorporation of shocks when estimates are revised by analysts in respective institutions. The 'Plucking' view, on the other hand, has not been afforded serious estimation attempts. Friedman (1993) interpolated the peaks of the US GNP, and Probst (2022) did the same for illustrative purposes. Recent literature, primarily

Dupraz et al. (2019) used the empirical basis of the 'Plucking' view observed in the US labour market to propose a theoretical framework with downward nominal wage rigidity in a search model that reproduces the 'Plucking' dynamics in the observed data.

These issues, just as they are applicable across policymakers and economic settings, are pertinent to Malaysia. Shahrier & Lian (2019) documents the common tools to estimate potential output and the output gap in the Central Bank of Malaysia, which are reminiscent of those surveyed across the literature, particularly the boom-bust approach based on time series filters. The technical, and conceptual issues described above similarly apply to the Malaysian setting. Moreover, unlike most major and advanced economies, open-accessible estimates of potential output, or the output gap by international organisations, such as the International Monetary Fund (IMF), are unavailable for emerging economies, including Malaysia. Hence, there is a policy case to not only document estimation approaches, and the macroeconomic behaviour of potential output, and output gap estimates for Malaysia, but also provide a comparative against the nascent discussion of the 'Plucking' model in the US. Malaysia provides a microcosm of emerging economies, given its upper-middle-income stature, extensive trade linkages with regional, and major economies, and specialisation in both electronic components, and commodities. A brief application to US data will also be provided, but the main analytical sections will focus on the Malaysian application.

Given these debates on grounds of empirics, methodology, and policy practicality, this paper proposes a tractable, computationally simple, framework to estimate the output ceiling, based on the 'Plucking' view. Data from Malaysia will be used to generate the proof of concept, and for analysis of other important empirical regularities, primarily the Phillips Curve, and their responsiveness to monetary policy and price shocks. Comparisons will be made against potential output estimates generated from a production function approach, with input variables filtered using the HP filter, and estimates from a Kalman Filter. Both the two-sided and one-sided versions are used. These act as a purely methodological representation of the baseline, i.e., the boom-bust view, for comparison.

2 Estimating the 'Ceiling'

This section proposes a framework to estimate the output ceiling, or the potential output, based on the 'Plucking' view in Friedman (1993), Probst (2022), and Dupraz et al. (2019). Output is proxied by seasonally adjusted real GDP. Computational steps are summarised below. All input data are from 1995 Q4 to 2022 Q4. An adaptation of the framework to the unemployment rate is provided in the appendix, both for Malaysia, and for the US, which provides qualitatively consistent estimates of the unemployment rate floor (analogous to the output ceiling) as the main analysis. An application on US real GDP, with the same parameters as for Malaysia described below, is also shown in the appendix, but only for steps 1 to 3, given limited official data on real net capital stock.

1. Identify peaks in observed output, based on the algorithm developed by Dupraz et al. (2019), and modified for variables other than unemployment rate; do the same for labour force, and real net capital stock.
2. Apply quadratic spline interpolation for a first estimate of the ceiling; apply linear spline interpolation if the quadratic application is impossible, and do the same for labour force, and real net capital stock.
3. Update the initial output ceiling estimates so that the ceiling is always above or at the observed output.
4. Update the estimates with fluctuations in observed labour force, and net capital stock relative to their respective ceiling estimates, scaled by their relative long-run income shares; this is essentially an augmented Cobb-Douglas production function specified by gaps.
5. Apply a Cobb-Douglas production function decomposition for the contribution of labour force, net capital stock, and total factor productivity (TFP; residual) to ceiling year-on-year (YoY) growth.
   (a) First, compute TFP using the difference between observed output, and output inferred from the production function, excluding the TFP term.
   (b) Second, estimate the TFP ceiling using the difference between the output ceiling estimates, and the capital and labour force ceilings adjusted for income shares.
   (c) Third, compute the contribution of the YoY growth of capital and labour ceilings to the ceiling growth, and then back out the contribution of TFP ceiling growth.

For the baseline, a model average from estimates based on a production function with inputs filtered using the HP filter, and estimates from a Neo-Keynesian Phillips Curve with a Kalman Filter, which also takes in HP filtered trends and cycles as input. A similar approach is documented in Shahrier & Lian (2019). Both the two-sided, and one-sided recursive HP filters, described in Alfaro & Drehmann (2023), Drehmann & Yetman (2018), and Borio & Lowe (2002), are used. The estimation steps are summarised below.

1. Use the two-sided HP filter to estimate the trend components of seasonally adjusted real GDP, net capital stock, and labour stock (proxied by the labour force).
2. Compute TFP using the difference between observed output, and output inferred from the production function, excluding the TFP term.

3. Compute the potential output using two-sided HP-filtered trend components of TFP, capital and labour stocks, adjusted for income shares. This is the estimate from the production function approach in the boom-bust baseline.
4. Construct a state-space model containing a Phillips Curve equation and a IS equation, with the production function estimates of potential output and output gap, the two-sided HP-filtered trend component of real GDP, core CPI, and the 2-quarter moving average of brent crude oil prices as input variables.
5. Take a simple average of the production function, and the Kalman Filter estimates as the baseline for the boom-bust approach.
6. Repeat all previous steps using the one-sided recursive HP filter, and with a one-sided recursive Kalman Filter.

The 'Plucking' and boom-bust baseline estimates are subsequently analysed for susceptibility to retrospective revisions, before and after periods of large fluctuations in real GDP.

2.1 Interpolating the Ceiling

Peaks in the base series, de-seasonalised real GDP, are first identified. A typical preference is to use business cycle dating algorithms, such as NBER's approach in Hall et al. (2003), and econometric model-based approaches discussed in Chauvet & Piger (2008), Harding & Pagan (2003), and Hamilton et al. (2003). However, for macroeconomic surveillance and timely policy decisions, simple analytical rules that do not require long lags for deliberations, and to account for end-point biases, may be preferred. In this application, Dupraz et al. (2019)'s algorithm is adapted for variables other than the unemployment, specifically real GDP Y, labour force N, and real net capital stock K. We differ in three steps. Firstly, while the original identified peaks and troughs with inequalities of unemployment rates in different periods, this paper compares the log difference (hence, growth rates) of real GDP, labour force, and real net capital stock. These inequalities are reframed to reflect that definitions of peaks and troughs are tied to their underlying levels, rather than growth rates. Secondly, the different input variables used means that the direction of inequalities are flipped. Thirdly, the tolerance threshold used to declare peaks and troughs, are different, and selected based on ability to declare correctly commonly known shocks in Malaysia, that is the Asian Financial Crisis 1997-99, Global Financial Crisis 2007-09, and the COVID-19 pandemic 2020-22. The exact steps are described below, with deviations from Dupraz et al. (2019) bolded (steps 2-3, and steps 6-7). For consistency of notation, y_t is the log-level, Δy_t the log-difference of a variable in time t, while cp denotes a candidate for a peak, and ct a candidate for a trough. X is the tolerance threshold when determining peaks, and troughs. In this application, $X = 0.23 * \sigma$ is used, that is 0.23 times the standard deviation of real GDP, labour force, and real net capital stock, respectively. While troughs are required to identify consecutive peaks, only peaks are necessary in estimating the output ceiling. An alternative computational method, which is able to identify similar turning points, is provided in the appendix, together with its ceiling estimates. The main analysis will only use the algorithm modified from Dupraz et al. (2019).

1. $cp = t, t = t + 1$
2. **If $y_t > y_{cp}$, go back to previous step**
3. **If $\Delta y_t < 0 + X$, then $t = t + 1$, and go back to previous step;** $X = 0.23 * \sigma$
4. Add cp to the set of peaks
5. $ct = t$, and $t = t + 1$
6. **If $y_t < y_{ct}$, go back to previous step**
7. **If $\Delta y_t > 0 - X$, then $t = t + 1$, and go back to previous step;** $X = 0.23 * \sigma$
8. Add ct too the set of troughs

With the peaks identified, quadratic spline interpolation as in Marsden (1974), summarised as function $q(\mathbf{x})$ for a vector of known interval markers x, is applied between the identified peaks ($\mathbf{peak^Y}$) for initial estimates of the output ceiling $Y_t^{p,0}$, as in equation 1. At the tail end of the time series, the initial ceiling is estimated by extrapolating using the last peak-to-peak (referred to as 'episode') gradient $\Delta Y^p_{t \in episode=E}$. Likewise, the starting end of the time series is extrapolated using the next peak-to-peak gradient $\Delta Y^p_{t \in episode=1}$. Equations 2, and 3 describe the procedure for the first and last 'episodes', respectively. In instances where quadratic spline interpolation is not possible, linear spline may be used in place.

$$Y_t^{p,0} = q(\mathbf{peak^Y}) \tag{1}$$

$$\Delta Y^{p,0}_{t \in episode=0} = \Delta Y^p_{t \in episode=1} \tag{2}$$

$$\Delta Y^{p,0}_{t \in episode=E} = \Delta Y^p_{t \in episode=E-1} \tag{3}$$

2.2 Updating the Ceiling

The complete, initial, set of output ceiling estimates are then updated with movements in the labour force N_t and net capital stock K_t relative to their ceiling, which is estimated in the same way as the initial output ceiling estimate, i.e., the labour, and capital gaps (N_t^g and K_t^g), respectively. Equations 4 and 5 describe the labour and capital gaps. For ease of computation, small letters denote natural logarithms.

$$N_t^g = \frac{N_t - N_t^p}{N_t^p} \approx n_t - n_t^p \tag{4}$$

$$K_t^g = \frac{K_t - K_t^p}{K_t^p} \approx k_t - k_t^p \tag{5}$$

Equations 6 and 7 describes the updating process in levels, and natural logarithms, respectively. The initial ceiling estimate $Y_t^{p,0}$ is updated with the labour force and net capital stock gaps (N_t^g and K_t^g), but scaled by their respective income shares (α and $1-\alpha$, respectively). This is essentially an augmented production function, with α computed from the national accounts. In this application, $\alpha = 0.5842$, which is the 2010-22 output share of gross operating profits in Malaysia.

$$Y_t^p = Y_t^{p,0} * K_t^{g\alpha} * N_t^{g1-\alpha} \tag{6}$$

$$y_t^p = y_t^{p,0} + \alpha k_t^g + (1-\alpha) n_t^g \tag{7}$$

Similarly, the contribution of the natural log of labour force and net capital stock gaps to the difference between the initial and final output ceiling estimates ($\delta^k_{y^p,update}$ and $\delta^n_{y^p,update}$) can be computed from the augmented production function in equations 8 and 9, respectively.

$$\delta^k_{y^p,update} = \alpha * k_t^g \tag{8}$$

$$\delta^n_{y^p,update} = (1-\alpha) * n_t^g \tag{9}$$

Figure 2 displays the revisions between the initial estimate in the previous subsection, and the estimate updated with labour force and net capital stock gaps, alongside with contributions attributed to respective gaps. Figure 3 plots the output ceiling estimate with observed real GDP between 1Q 1995 and 3Q 2022. Figure 4 and 5 plot the estimated ceilings of labour force, and net capital stock, and the respective observed series underlying the output ceiling estimates.

Figure 2

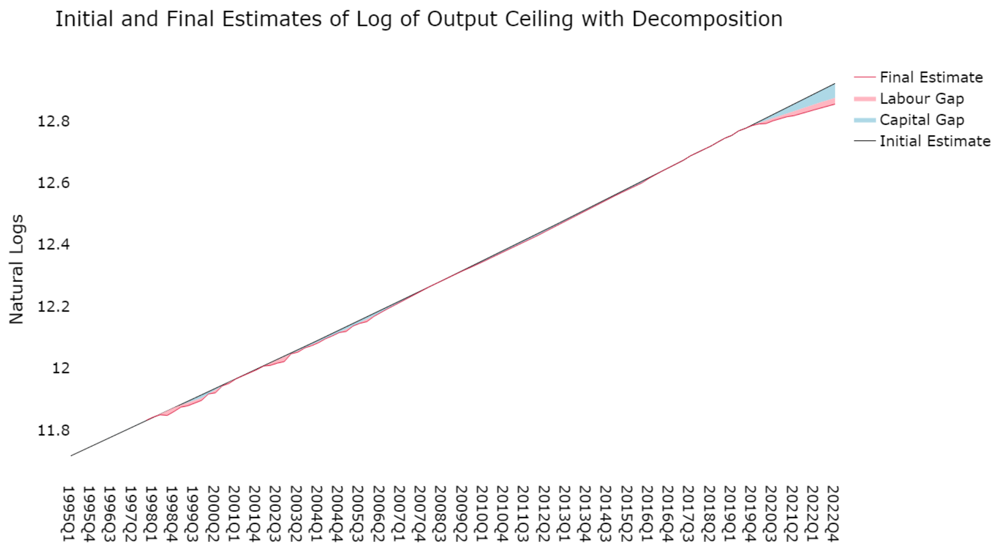


Figure 3

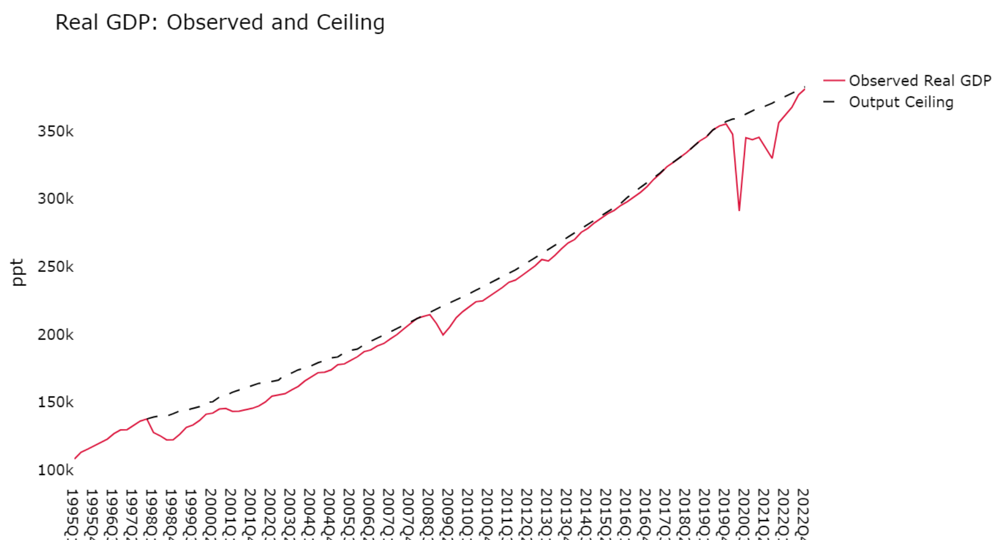


Figure 4

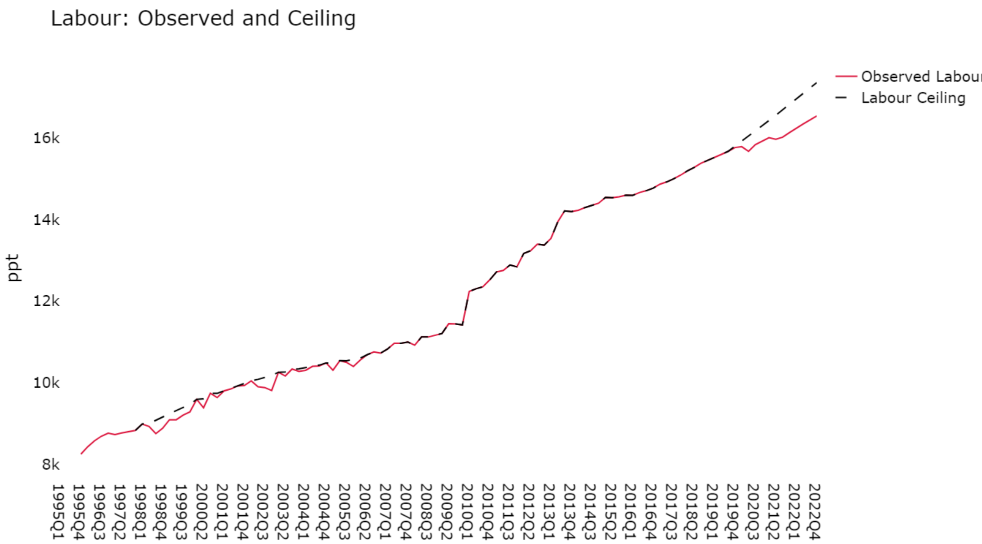
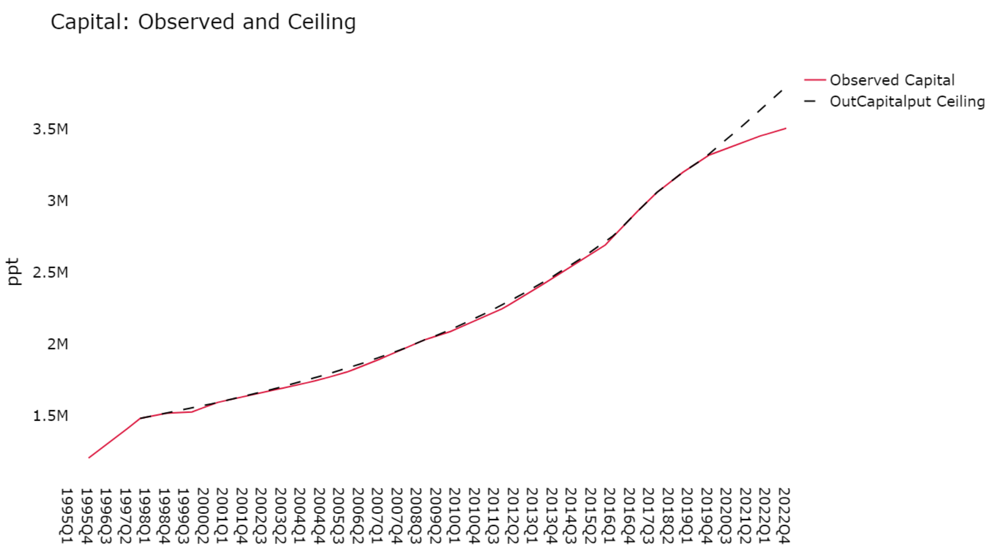


Figure 5



2.3 Production Function Decomposition

Important to policymakers with mandates geared at structural, long-term, policies is 'what underpinned growth in the output ceiling, or the potential output?'. A production function offers a useful tool, as the potential output can be decomposed structurally into changes in factors of production in the economy, e.g., labour and capital. This method yields narrative benefits compared to most other tools, e.g., time series filters, or regression-based approaches described in Álvarez & Gómez-Loscos (2018), and Cerra & Saxena (2000), that cannot account for the entirety of the estimate, akin to a semi-black box. The production function decomposition here aims to decompose output ceiling growth into growth in the labour force ceiling, the capital ceiling, and residual growth, commonly labelled conveniently in the broader literature, and policy economists as total factor productivity (TFP) growth.

Equation 10 computes the natural log of implied residual / TFP based on observed output, and the output implied by observed labour force, and net capital stock. Next, the residual / TFP ceiling is computed by rearranging the production function with output, labour force, and capital ceilings as input variables, as in equation 10. Equations 11, 12, and 13 then compute the contribution of capital, labour force, and residual / TFP, respectively. Figures 6 and 7 show the production function decomposition of the ceiling estimate YoY growth, and observed real GDP YoY growth, respectively.

$$a_t = y_t - (\alpha k_t + (1-\alpha) n_t) \tag{10}$$

$$\delta^{\Delta\%Y^p}_{\Delta\%K^p,t} = \alpha \Delta\%K^p_t \tag{11}$$

$$\delta^{\Delta\%Y^p}_{\Delta\%N^p,t} = (1-\alpha) \Delta\%N^p_t \tag{12}$$

$$\delta^{\Delta\%Y^p}_{\Delta\%A^p,t} = \Delta\%Y_t - \delta^{\Delta\%Y^p}_{\Delta\%K^p,t} - \delta^{\Delta\%Y^p}_{\Delta\%N^p,t} \tag{13}$$

Figure 6

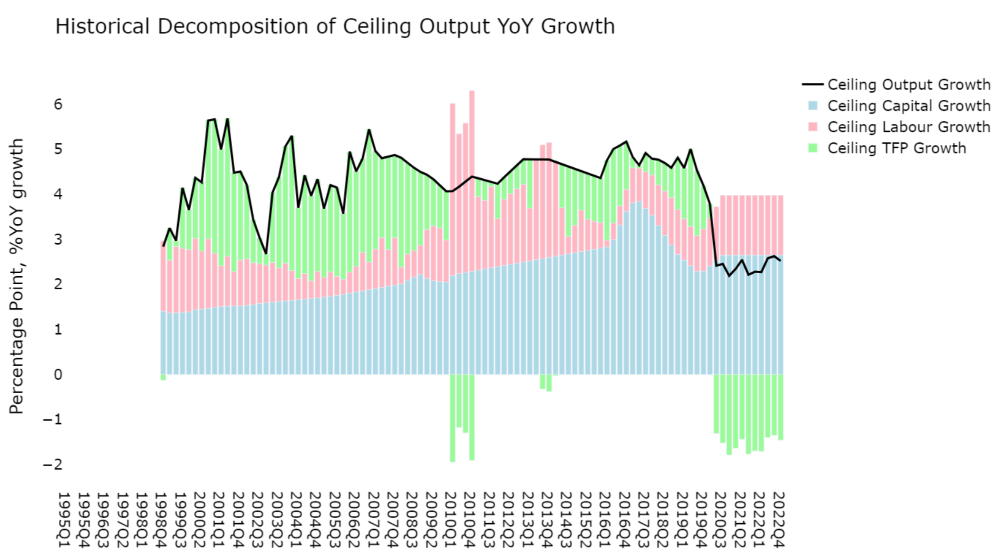
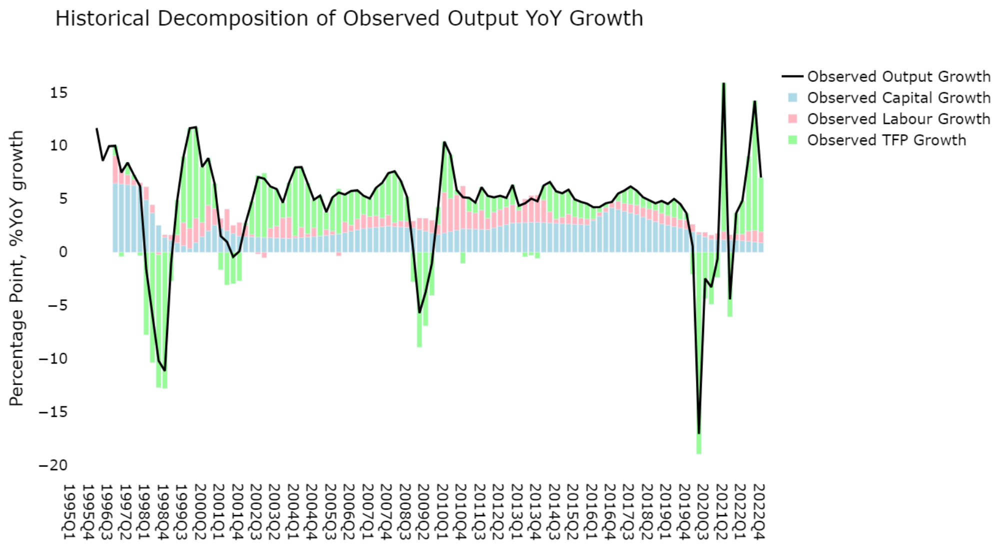


Figure 7



2.4 Introducing the Baseline Boom-Bust Estimate

The baseline estimate stems from the traditional view of the potential output, both conceptually, and methodologically. While one consideration is to use official estimates, such as from the IMF, or Malaysian government agencies, there are two issues. Firstly, as at the point of writing, neither the IMF, Malaysian government agencies, nor other international economic agencies publish estimates of potential output for Malaysia. Secondly, these external estimates may not be purely representative of the methodology, as judgment may be involved, hence could deviate occasionally from a purely data-driven approach guided by a consistent framework, such as during staff changes, managerial direction, or behavioural biases. Given that, this baseline represented by (1) estimates from a production function, with input variables filtered using a one-sided recursive HP filter, also used in Alfaro & Drehmann (2023), Drehmann & Yetman (2018), and Borio & Lowe (2002), (2) estimates from a one-sided recursive Kalman filter with Neo-Keynesian Phillips Curve equations, which also takes in as input the one-sided recursive HP filtered output trend and cycle components, and (3) an average of the two estimates. A second set of baseline instead uses the two-sided versions both time series filters. Using one-sided recursive time series filters is a common solution offered to the retrospective revision problem in estimating the boom-bust view of the output gap, as, mechanically, estimates cannot be updated retrospectively. However, considering that ex post information may also be useful in backing out the latent potential output, and that two-sided filters are common tools in estimating latent gap variables, both one-sided and two-sided versions are considered.

2.4.1 Production Function Estimate

Aggregate output Y_t is determined by labour N_t, and capital K_t as factors of production, each scaled by their income shares, α and $1-\alpha$, respectively, and total factor productivity A_t. The potential output analogue Y_t^p is determined instead by HP-filtered trend TFP A_t^{trend}, labour N_t^{trend}, and capital K_t^{trend}, scaled by income shares. $\lambda = 11200$ is used in lieu of Ravn & Uhlig (2002)'s recommendation of $\lambda = 1600$, reflecting Franke et al. (2022)'s comparison between the HP filter with the Ravn-Uhlig rule, the Hamilton filter by Hamilton (2018), and a HP filter with λ at 7 to 12 times higher than Ravn-Uhlig rule. With the same λ setting, both the one- and two-sided HP filters are used in separate iterations. Equation 14 describes the production function decomposition of observed output, equations 15 to 17 the breakdown of TFP, labour, and capital into trend and cycle components, of which the trend components are used as input for the potential output described in equation 18.

$$Y_t = A_t {K_t}^{\alpha} {N_t}^{1-\alpha} \tag{14}$$

$$A_t = Y_t^{trend} + A_t^{cycle} \tag{15}$$
$$K_t = Y_t^{trend} + K_t^{cycle} \tag{16}$$
$$N_t = N_t^{trend} + N_t^{cycle} \tag{17}$$

$$Y_t^p = A_t^{trend} {K_t^{trend}}^{\alpha} {N_t^{trend}}^{1-\alpha} \tag{18}$$

Labour input, capital input, and observed output are used to compute TFP A, shown in equation 19. This step is identical to 10 in the 'Plucking' model's production function decomposition. Subsequently, trend TFP is extracted using the HP filter, as in equation 15, and the potential output computed using equation 18. The same steps can be implemented either fully in levels multiplicatively, or in natural logarithms additively. A production function decomposition similar to equations 11 to 13 for the 'Plucking' model can be implemented, but is not pertinent to the analysis.

$$a_t = y_t - (\alpha k_t + (1 - \alpha) n_t) \tag{19}$$

2.4.2 Neo-Keynesian Phillips Curve Estimate

This setup contains five structural equations — the evolution of the (i) potential output in equation 20, (ii) potential output growth in equation 21, and the (iii) output gap in equation 22, (iv) the identity equation of output in equation 23, and (v) the Phillips Curve in equation 24. ε_t^X denotes the random shock for variable X in period t, g_t^{Yp} the growth rate of potential output in period t, π_t the inflation rate, and P_t^{com} the two-quarter moving average of the price level of global commodities, proxied by brent crude oil, and $\widetilde{P^{com}}$ its long-term average.

$$Y_t^p = Y_{t-1}^p * (1 + g_{t-1}^{Yp}) + \varepsilon_t^{Yp} \tag{20}$$

$$g_t^{Yp} = \beta_1 g_{t-1}^{Yp} + (1 - \beta_1) g_{trend}^{Yp} + \varepsilon_t^{g^{Yp}} \tag{21}$$

$$Y_t^g = \beta_2 Y_{t-1}^g + \beta_3 Y_{t-2}^g + \varepsilon_t^{Yg} \tag{22}$$

$$Y_t = Y_t^p + Y_t^g \tag{23}$$

$$\pi_t = \beta_4 \pi_{t-1} + \beta_5 \pi_{t-2} + \beta_6 Y_t^g + \beta_7 (P_t^{com} - \widetilde{P^{com}}) + \varepsilon_t^{\pi} \tag{24}$$

Before implementing the Kalman Filter to estimate the potential output, the initial values of parameters β are taken from the ordinary least squares (OLS) estimated-parameters γ in the following linear regressions. x_t^{pf} refers to the natural logarithm of estimates of x from the production function approach for period t, and ε_t white noise. Equation 25 estimates the initial values of the parameters in equation 20 (potential output), equation 26 for equation 21 (potential output growth), equation 27 for equation 22 (output gap), equation 28 for equation 24 (Phillips Curve).

$$y_t^{pf} = \gamma_1 y_{t-1}^{pf} + \varepsilon_t \tag{25}$$

$$(\Delta y_t^{pf} - \widetilde{\Delta y^{pf}}) = \gamma_2 (\Delta y_t^{pf} - \widetilde{\Delta y^{pf}}) + \varepsilon_t \tag{26}$$

$$y_t^{g^{pf}} = \gamma_3 y_{t-1}^{g^{pf}} + \gamma_4 y_{t-2}^{g^{pf}} + \varepsilon_t \tag{27}$$

$$(\Delta \pi_t - \Delta \pi_{t-2}) = \gamma_5 (\Delta \pi_{t-1} - \Delta \pi_{t-2}) + \gamma_6 (P_t^{com} - \widetilde{P^{com}}) + \varepsilon_t \tag{28}$$

Initial states of the potential output and output gap are calculated using the trend and cycle components of observed output, estimated using the HP filter. The initial state of potential output is HP-filtered trend output from the second earliest period, that of potential output growth is average trend growth. The initial states of earliest, and contemporaneous output gaps are the HP-filtered cyclical component of output from the earliest, and second earliest periods, respectively. Equations 29 to 32 summarise these relationships. A burn-in period of 26 quarters is applied. One- and two-sided versions of HP, and Kalman Filter are used in separate iterations.

$$y^{p}_{t,\mathbf{0}} = y^{trend,hp}_{t=1} \tag{29}$$

$$\Delta y^{p}_{t,\mathbf{0}} = \widetilde{\Delta y^{trend,hp}} \tag{30}$$

$$y^{g}_{t,\mathbf{0}} = y^{cycle,hp}_{t=1} \tag{31}$$

$$y^{g}_{t,\mathbf{0}} = y^{cycle,hp}_{t=0} \tag{32}$$

2.4.3 Model Average

Both estimates from the production function approach $\mathbf{y^{pf}}$, and from the Neo-Keynesian Phillips Curve approach $\mathbf{y^{pc}}$ are averaged, as in equation 33. Averages of the estimates using one-sided, and two-sided versions of the HP, and Kalman Filters, are computed separately. During the Kalman Filter's burn-in period (first 26 quarters), only estimates from the production function approach are used. This acts as the baseline estimate for the boom-bust view $\mathbf{y^{bb}}$ to be compared against the 'Plucking' estimates $\mathbf{y^{p}}$. While more complex model averaging methods can be considered, this is not necessarily pertinent to the findings. Granted, the literature does note merits of structural methods, especially the production function approach, such as in Álvarez & Gómez-Loscos (2018). However, the two-sided filters applied to input variables do assume that output fluctuations around a latent trend, hence could still be prone to pitfalls associated with this view of the potential output. Hence, this model average aims to account for both popular methods in the policy sphere in the boom-bust view of the economy.

$$y^{bb}_{t} = \frac{y^{pf}_{t} + y^{pc}_{t}}{2} \tag{33}$$

2.5 Retrospective Revisions

One major criticism, especially on the use of HP and Kalman Filters, noted in Hamilton (2018) and Probst (2022), is that they are simply arbitrary moving averages, which can produce trend-cycle decomposition on even variables that do not have intrinsic business cycle-like properties. Underpinning this, hence, is the susceptibility to retrospective revisions after major fluctuations, such as the onset of an economic crisis, noted in Fernald (2015). As a purely academic exercise, this is not entirely problematic, suppose that the ex post estimates obtained during stable periods. However, for policymakers, this type of estimates are policy-irrelevant, as decisions based on 'incorrect' information obtained pre-shocks, cannot be corrected post-shocks, which will require policymakers to travel back in time with ex post information. Figure 8 shows estimates from vintages around major economic crises — pre-GFC (2007Q2), mid-GFC (2008Q2, and 2009Q3), post-GFC (2015Q4), pre-COVID-19 (2019Q4), and mid- / post-COVID-19 (2022Q4). Figures 9 to 11 show the vintages of boom-bust output gap estimates with the recursive one-sided filters. Figures 12 to 14 show that of the version with the two-sided filters. By construction, as the recursive filters will not revise estimates for all earlier time periods, there is no retrospective revision in figures 9, 10, and 11. A fair comparison, therefore, is if the 'Plucking' output gap estimate exhibits minimal degree of retrospective revision closer to the one-sided boom-bust estimate, and far from the two-sided version, which is demonstrated in figure 8.

Figure 8

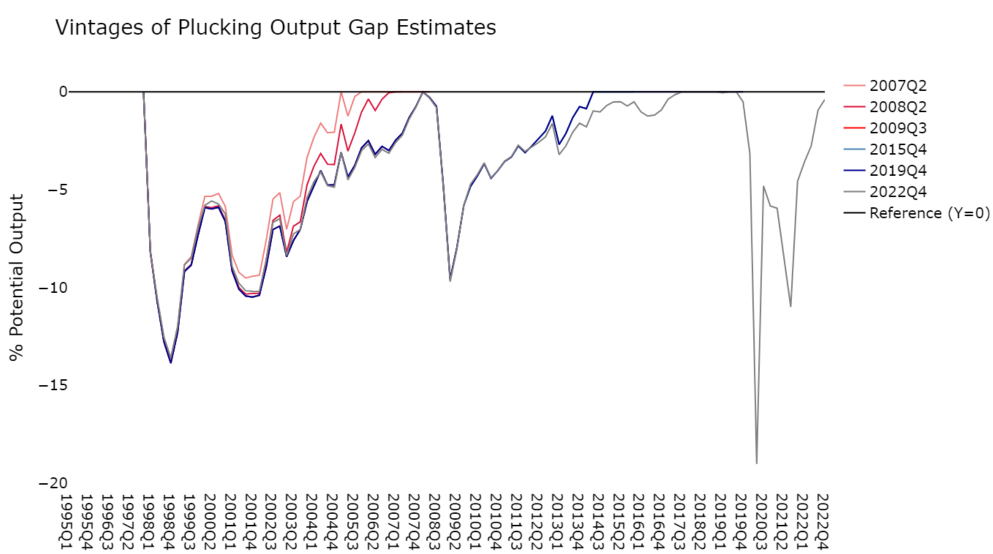


Figure 9

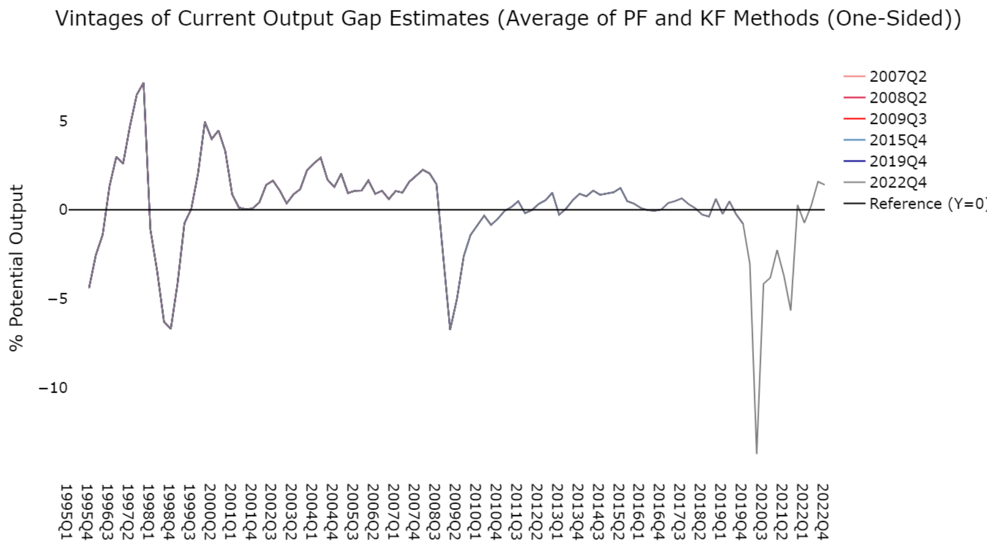


Figure 10

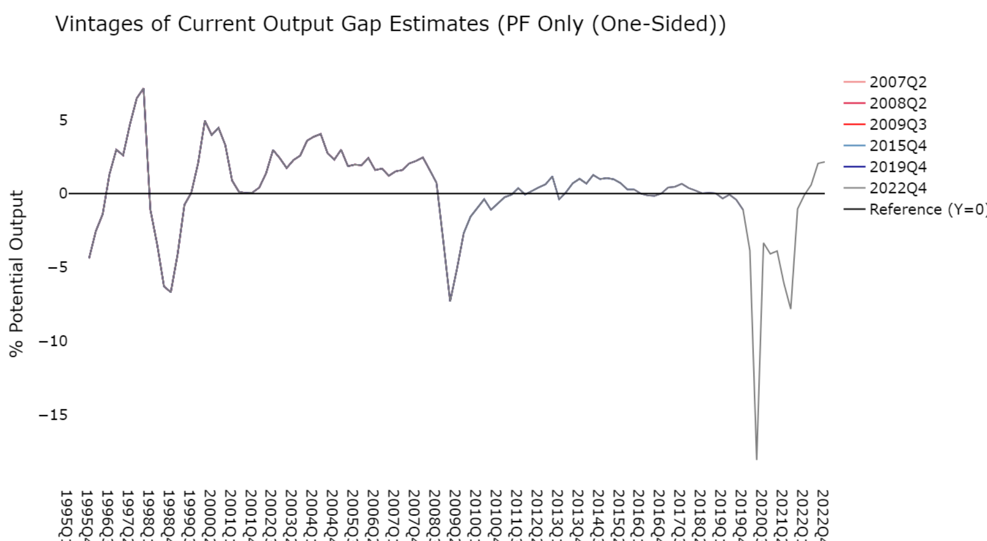


Figure 11

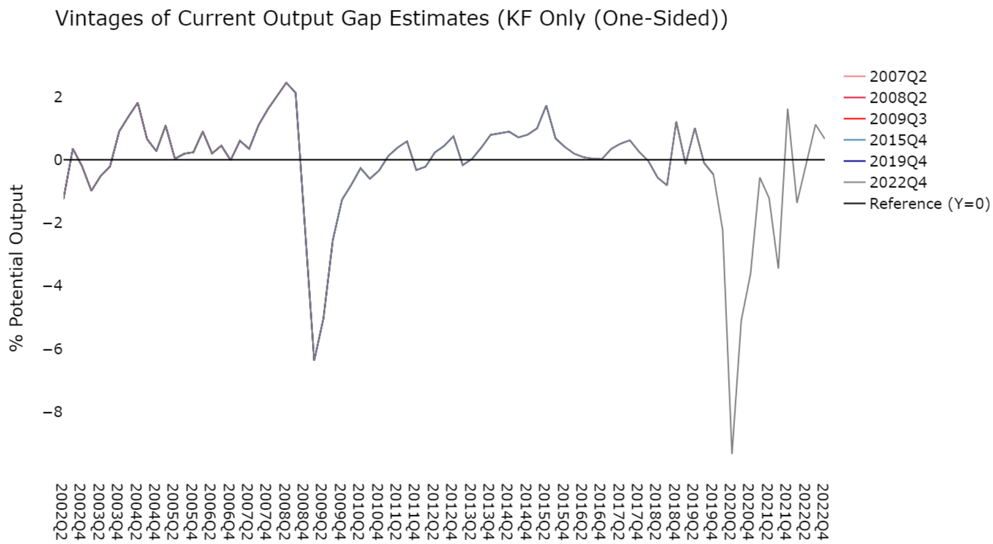


Figure 12

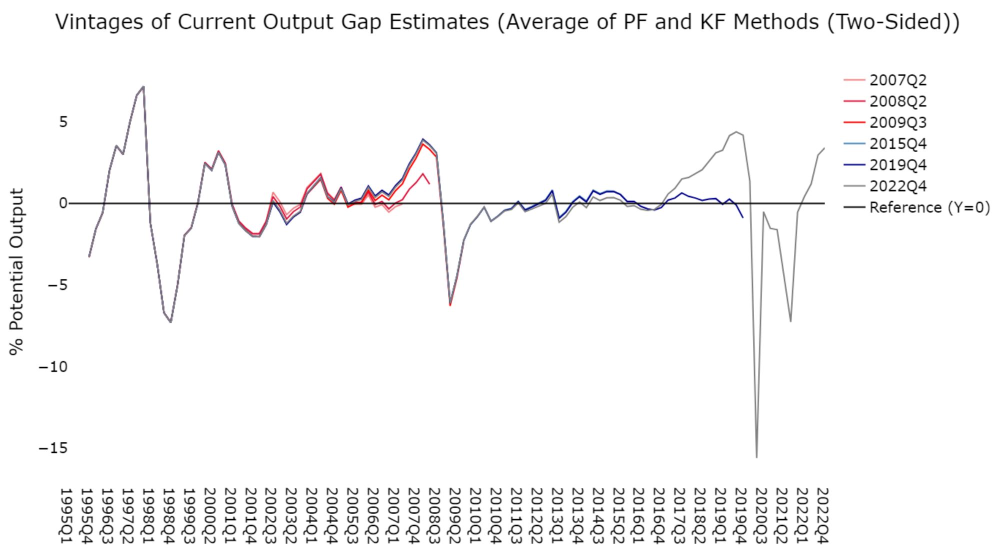


Figure 13

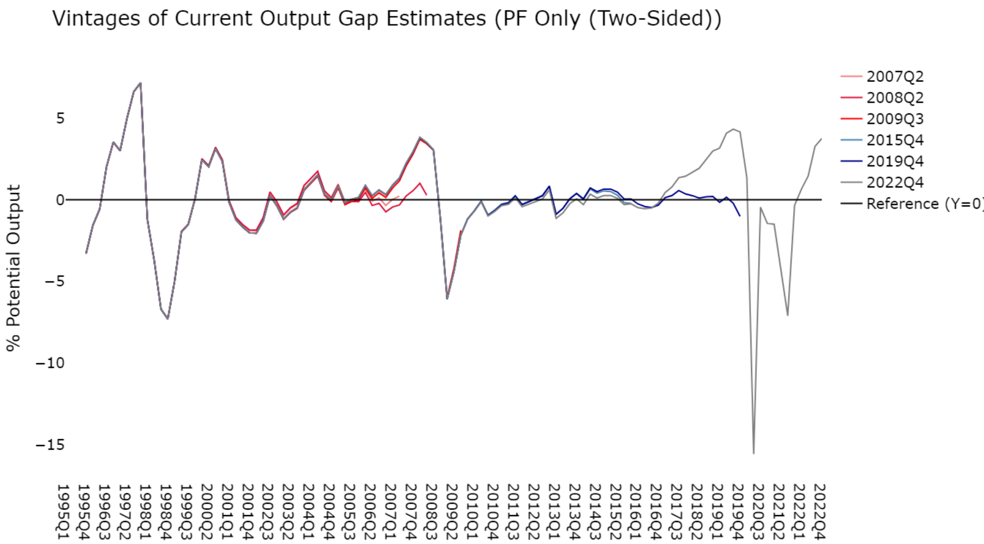
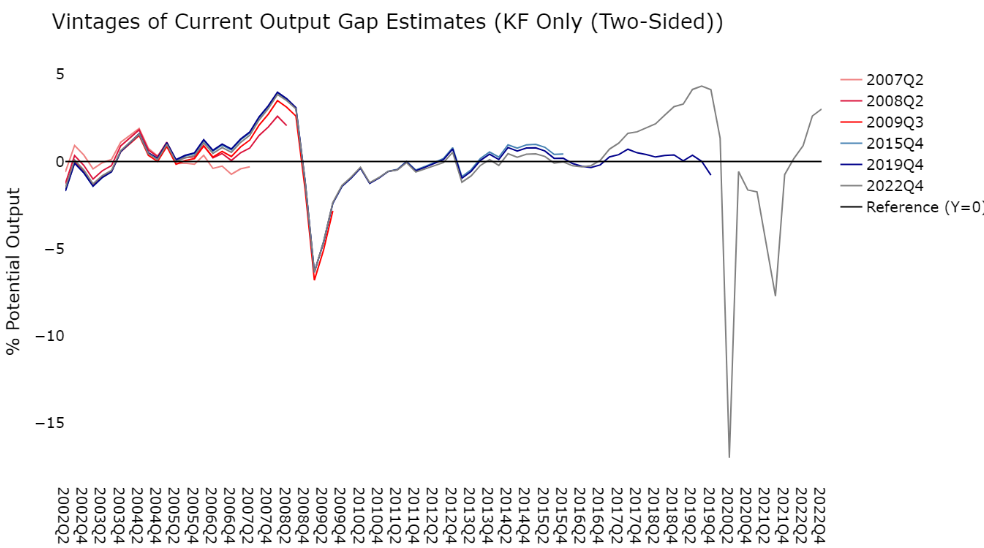


Figure 14



3 Empirical Regularities

Central to the discussion of potential output and the output gap is its link with inflation, and economic slack. For typical central banks with price stability mandates, this is conceptually central to policy considerations. For instance, Shahrier & Lian (2019) noted that policymakers derive information on expected long-term economic growth, and demand-driven inflationary pressures. This element is often reflected in estimation methodologies. For instance, Álvarez & Gómez-Loscos (2018) describes one option of using a Kalman smoother to estimate potential output using a Phillips Curve equation, another based on a Neo-Keynesian Phillips Curve, which also includes an Okun's Law equation. In essence, this take of the boom-bust output gap requires an ex post link with inflation, and some measure of the state of the economy. Recent analysis on state-level price indices by Hazell et al. (2022) confirms the absence of the Phillips Curve in the US, and the supposed steepness observed in some historical periods reflects dis-anchoring of expectations. Granted, EMEs such as Malaysia may differ. Indeed, empirical studies on Malaysia, notably Furuoka et al. (2007), Tang & Lean (2007), and Furuoka & Harvey (2015), using a mixture of stylised statistics, time series model estimation, and structural model estimate, argued the existence of a long-run and short-run Phillips Curve relationship.

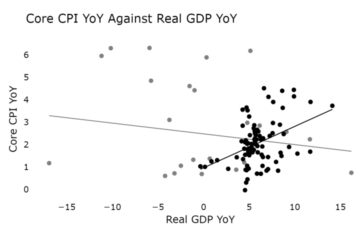
This section describes the stylised relationships in Malaysia between estimates of output gap, both the 'Plucking' estimate and boom-bust baseline, and core inflation, and the unemployment rate. All charts in this section have grey dots denoting observations from crisis periods, namely the AFC, GFC, and COVID-19, with the grey line indicating the line of best fit of all data points including crisis periods. The coloured lines indicate the line of best fit excluding crisis periods, colour coded by measure of output (red for 'Plucking' model estimates, blue for the baseline boom-bust estimates, and black for observed real GDP).

3.1 Phillips Curve Relationship

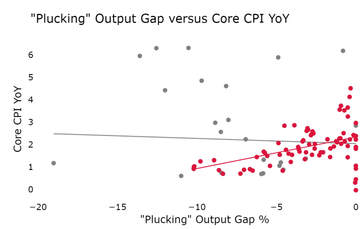
Figure 15 plots the three measures of output, the 'Plucking' output gap, the baseline boom-bust output gap, and observed real GDP growth against core inflation between 1Q 1995, and 3Q 2022. The stylised relationship between real GDP growth and core inflation is heavily clustered, with its upward sloping relationship indicative of a Phillips Curve mainly shaped by tail ends. When crisis periods are included, the relationship reverses. The one-sided boom-bust estimates show vague, and mixed relationships with core inflation. Despite the inclusion of a Phillips Curve block in the estimation flow, the one-sided Kalman Filter estimate shows an upward sloping, but unclear, and clustered, relationship with core inflation. The two-sided boom-bust estimates show clustered, but mildly upward sloping relationships with core inflation. Across the estimates, when crisis periods are included, the relationship reverses once crisis periods are included, indicating potential instability, and sensitivity to outliers. This is an important consideration when reading output gap and potential output estimates of similar methodologies, such as those in Álvarez & Gómez-Loscos (2018), and indeed used commonly across policy settings globally. The 'Plucking' model exhibits only a relatively stronger, but mild, upward slope, but is insufficient to determine if a Phillips Curve relationship is unambiguously present. These plots depart from recent research on Malaysia, namely Furuoka et al. (2007), Tang & Lean (2007), and Furuoka & Harvey (2015), and align closer with recent ones in the US noting the absence of a Phillips Curve relationship empirically, e.g., Hazell et al. (2022). Importantly, the primary purpose of this exercise is not to assert the validity of the 'Plucking' model through the presence or absence of a Phillips Curve relationship. Rather, it highlights that even if the traditional boom-bust view is premised upon the presence of a non-inflation accelerating level of output, a Phillips Curve relationship cannot be observed ex post. As the 'Plucking' model does not require a Phillips Curve relationship ex ante, its validity is not conditional on observing a Phillips Curve ex post, even if there is indication in support, as shown in 15.

Figure 15: Core Inflation Against Output Gaps

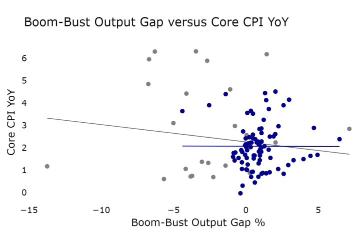
(a) Real GDP



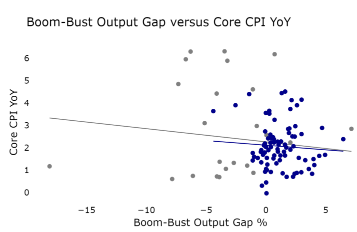
(b) 'Plucking'



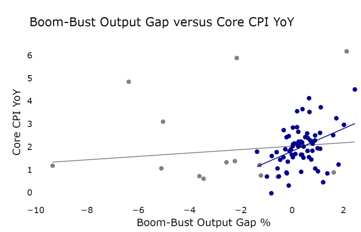
(c) Boom-Bust (One-Sided (Average))



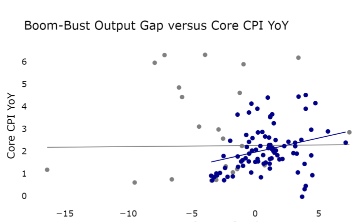
(d) Boom-Bust (One-Sided (PF Only))



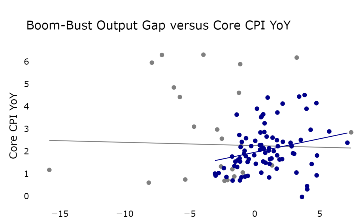
(e) Boom-Bust (One-Sided (KF Only))



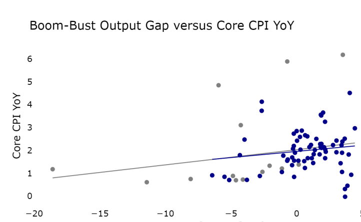
(f) Boom-Bust (Two-Sided (Average))



(g) Boom-Bust (Two-Sided (PF Only))



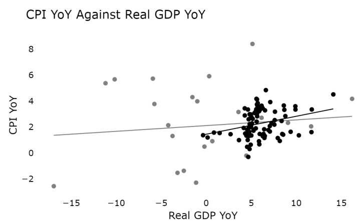
(h) Boom-Bust (Two-Sided (KF Only))



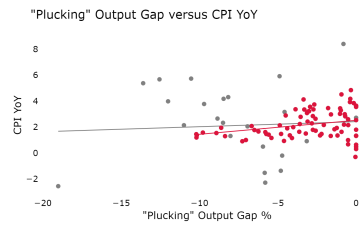
As a sensitivity check, the output measures are plotted against headline inflation in figure 16. Here, both the 'Plucking' output gap, and real GDP growth are similarly correlated with headline inflation, i.e., almost flat with a slight positive slant, irrespective of the inclusion of crisis periods. The clustering observed across the boom-bust estimates persist, irrespective of whether the one- or two-sided filters are used. Again, these stylised empirical findings support more recent takes on the Phillips Curve relationship.

Figure 16: Headline Inflation Against Output Gaps

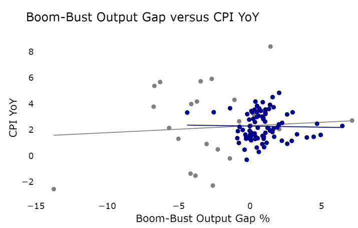
(a) Real GDP



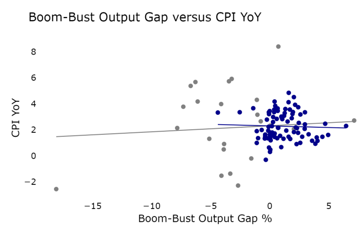
(b) 'Plucking'



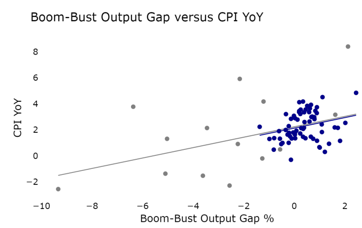
(c) Boom-Bust (One-Sided (Average))



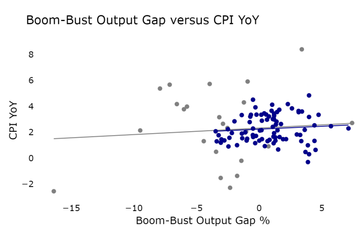
(d) Boom-Bust (One-Sided (PF Only))



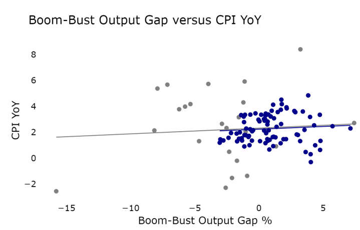
(e) Boom-Bust (One-Sided (KF Only))



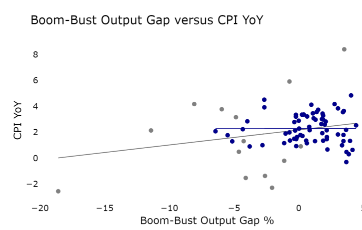
(f) Boom-Bust (Two-Sided (Average))



(g) Boom-Bust (Two-Sided (PF Only))



(h) Boom-Bust (Two-Sided (KF Only))



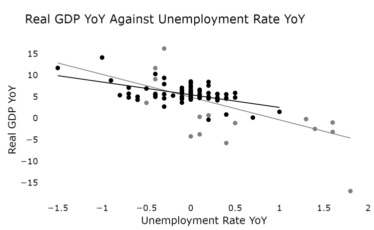
3.2 Unemployment

As the output gap is intended to be a measure of economic slack, one simple acid test is to check if it correlates well with other non-output observable measure of slack. The stylised Okun's Law, as in Okun (1963), is one framework to emulate, which posits a negative relationship between real GDP growth and unemployment rate. If a measure is a good proxy of economic slack, then the hypothesis is that it should correlate similarly, or better than real GDP growth, with the unemployment rate. Figure 17 plots the three output measures against the annual change in unemployment rate. As a baseline, there is indeed an Okun's Law relationship in Malaysia, although weaker than what is previously conceived for the

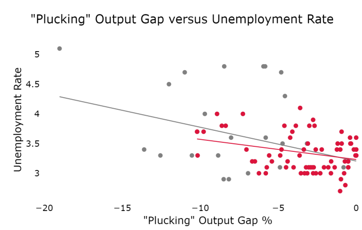
US. Ball et al. (2013) documents one such estimate. The ‘Plucking’ output gap measures a stronger downward sloping relationship with unemployment rate, irrespective of the inclusion of crisis periods, indicating stability in the methodology vis-à-vis outliers. However, amongst the baseline boom-bust output gap measures, only the two-sided average, the one-, and two-sided NKPC-Kalman Filter estimates demonstrated a mildly downward sloping relationship with unemployment rate, but with clustering observed. Other permutations of the boom-bust estimates showed no discernable relationship with the unemployment rate, and are sensitive to the inclusion, and exclusion of crisis periods.

Figure 17: Unemployment Rate Against Output Gaps

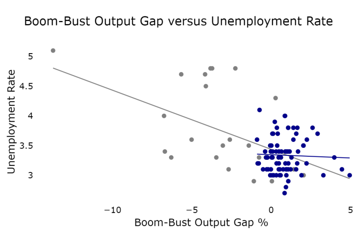
(a)



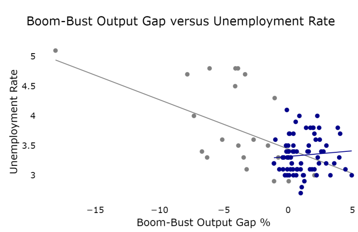
(b)



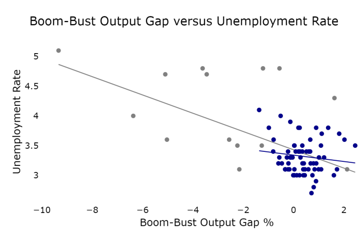
(c) Boom-Bust (One-Sided (Average))



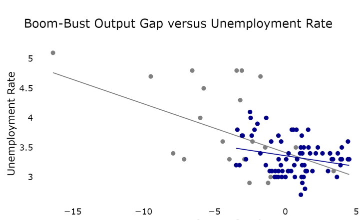
(d) Boom-Bust (One-Sided (PF Only))



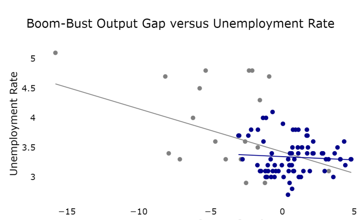
(e) Boom-Bust (One-Sided (KF Only))



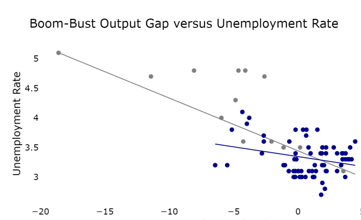
(f) Boom-Bust (Two-Sided (Average))



(g) Boom-Bust (Two-Sided (PF Only))



(h) Boom-Bust (Twone-Sided (KF Only))



4 Responses to Supply and Demand Shocks

Both concept and methodological choices suggest that potential output is a ‘long-term’ and structural measure, meaning that cyclical, short-term, factors are excluded. For instance, in Álvarez & Gómez-Loscos (2018), Cerra & Saxena (2000), and Shahrier & Lian (2019), time series filters are often used, from which trend components are used. Some structural equation methods, though some still apply time series filters, explicitly describe potential output as a long-term measure. The commonly used production function approach used in Epstein & Macchiarelli (2010), and Proietti et al. (2007), for instance intends to measure a theoretical maximum implied by factors of production available in the economy. The seminal paper of the modern view of potential output, Okun (1963), extends this description with a 'non-inflation accelerating' condition.

These definitions point to a simple analytical outcome. Potential output should be sensitive to supply shocks, but not demand shocks. Coibion et al. (2017) premised their VAR analysis of US potential output responses to supply and demand shocks similarly, that cyclical shocks that are temporary in nature should have no bearing on potential output estimates. Deviations from this expected results may indicate methodological issues in the estimation. Coibion et al. (2017) found that all potential output estimates analysed, e.g., CBO, violate this premise, and attributed this finding to possible incorporation of cyclical factors when potential output estimates are being revised by respective analysts or forecasters.

Similar to Coibion et al. (2017), this section estimates a VAR containing a measure of output (either observed real GDP, the 'Plucking' estimate, or one of the 6 permutations of the boom-bust baseline), interest rate to proxy for monetary policy (MP), global brent crude oil price to proxy for a global cost-push / supply shock, core CPI to proxy for domestic price pressures, and global economic policy uncertainty (EPU). The impulse response functions for the MP, and supply shocks will be of focus. Global EPU, introduced in Baker et al. (2016), and Davis (2016), is included on the basis of the recent plethora of empirical evidence that uncertainty shocks affect output and prices, hence exclusion may introduce non-trivial omitted variable bias, e.g., Suah (2022) using a panel of advanced and emerging economies, and Nilavongse et al. (2020) on the UK.

4.1 Methodology and Data

A VAR of output measures (real GDP, 'Plucking' output ceiling, or the boom-bust potential output, estimated separately), interest rate (KLIBOR 1-month rate), global commodity prices (Brent crude oil price), domestic prices (core CPI), and global economic uncertainty (global EPU) is estimated, as in equation 34. $\mathbf{y}$ is a vector of the variables above, β the vector of coefficients on the lags in each set of equation in the VAR, and $\varepsilon_{\mathbf{t}}$ the vector of errors. An alternate specification that excludes domestic prices (core CPI) is also estimated, whose estimated orthogonalised impulse response functions (OIRFs) are reported in the appendix. Equations 35 and 36 summarise the Cholesky Ordering implemented to estimated the OIRFs.

All level variables are transformed into first differences of natural logarithms, and interest rate into its first difference. The number of lags included in the VAR, k, is selected using the Hannan-Quinn information criterion (HQIC), as in Hannan & Quinn (1979).

$$\mathbf{y_t} = \mathbf{y_{t-k}}\beta_{\mathbf{t-k}} + \varepsilon_{\mathbf{t}} \tag{34}$$

$$\text{Global EPU} \rightarrow \text{Oil Price} \rightarrow \text{Output} \rightarrow \text{Core CPI} \rightarrow \text{KLIBOR (1M)} \tag{35}$$

$$\text{Global EPU} \rightarrow \text{Oil Price} \rightarrow \text{Output} \rightarrow \text{KLIBOR (1M)} \tag{36}$$

In the appendix, additional models without core CPI, using the base lending rate (BLR), the Malaysian Government Securities (MGS) 10-year yields, and the MGS 1-year yields as the interest rate / MP variable are also estimated, shown in figures D.1 to D.7. Two reasons underscore why the KLIBOR 1-month rate is used as the preferred proxy for MP. Firstly, the interbank rate is closely tied to the central bank's main policy rate, the overnight policy rate (OPR), but is not flat between policy changes. Fluctuations are present, possibly reflecting money market developments, and noise, like the difference between the effective Fed Funds Rate (EFFR) and the FFR range in the US. Secondly, the KLIBOR lacks the systemic deviation found in the MGS yields, and indeed other bond yields, that may also capture risk behaviour amongst investors to economic and financial events.

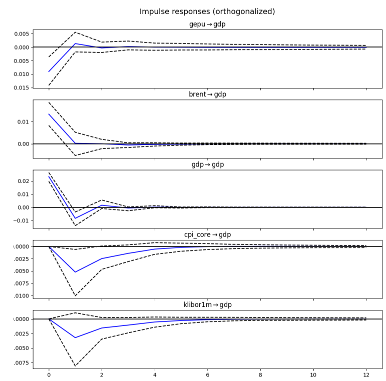
For the following subsection, charts portraying the OIRFs show the responses of observed real GDP first on the top left, 'Plucking' output ceiling on the top right, followed by the two-sided boom-bust potential output in the middle row, and the one-sided version in the last row. Within each rows corresponding to the boom-bust potential output, the average of the HP-filtered production function, and the NKPC-Kalman Filter will be on the left, followed by only the HP-filtered production function in the middle, and the NKPC-Kalman Filter on the right. The discussion will focus on the responses to oil price, core CPI, and interest rate shocks.

4.2 Findings

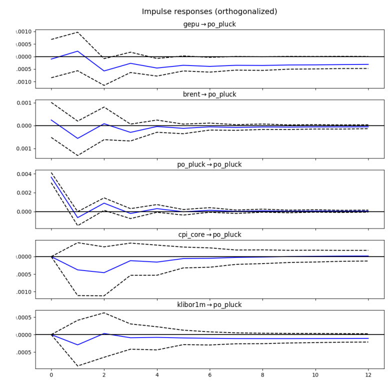
The OIRFs from the full model with core inflation included are shown in figure 18. Similar to Coibion et al. (2017), the response of real GDP offers an operational baseline for interpreting the OIRFs of the 'Plucking' ceiling, and the various permutations of the boom-bust potential output.

Figure 18

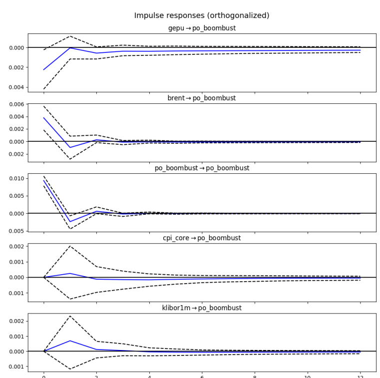
(a) Real GDP



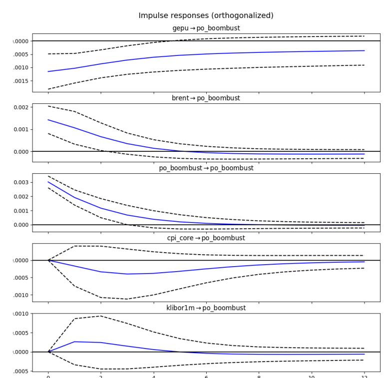
(b) ‘Plucking’ Ceiling



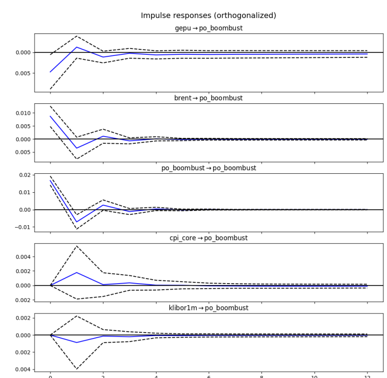
(c) Boom-Bust Potential Output (One-Sided (Average))



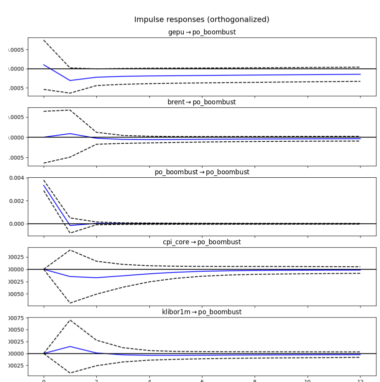
(d) Boom-Bust Potential Output (One-Sided (PF Only))



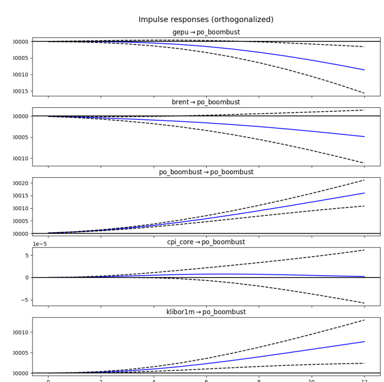
(e) Boom-Bust Potential Output (One-Sided (KF Only))



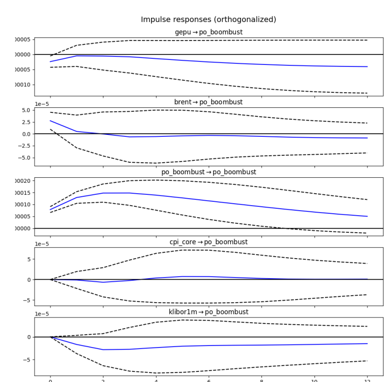
(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))



Real GDP increases briefly in response to a positive global oil price shock, reflecting Malaysia’s net oil exporter status, decreases for about a year in response to a positive domestic price shock, decreases in response to a positive interest rate shock. These estimates are not surprising, given economic conventions that a price shock increases cost, resulting in lower output, as a result of lower effective demand and supply. Interest rate hikes increases cost of borrowing, and debt service burden for agents with variable interest debt, hence weigh on agents whose expenditure are credit-dependent.

The 'Plucking' ceiling responds negatively to a positive global oil price shock for 1-2 quarters. As Malaysia has, throughout the time period studied, and in recent times, implemented price controls via subsidies on production-use, and consumer-end fuel oil, the minimal impact of global oil prices on a measure of supply is expected. Hence, the degree to which oil price shocks shift supply could be smaller than in a setting without such price controls, and subsidies, where a stronger negative response to positive global oil price shocks may be expected. Interest rate shocks, which affect primarily demand, and are cyclical in nature, are not determinants of potential output. As expected, the 'Plucking' ceiling's estimated response to unanticipated interest rate movements is miniscule, close to zero, and limited to only the first two quarters. This fits well with the conceptual definition of 'potential output', or the 'ceiling', as a measure of optimal, maximum, or sustainable supply. Response to domestic price shocks is similar to that of observed real GDP in duration, but smaller in magnitude, and demonstrates a gentler return to its steady state.

The responses of the one-sided boom-bust potential output to shocks are in similar directions as that of real GDP. Across the average measure, HP-filtered production function, and NKPC-Kalman Filter, the responses to an uncertainty shock, domestic price (core CPI) shock, and a shock from itself are in the same direction as that of real GDP. However, the response of the production function estimate persists beyond 1-2 years. They differ in the response to domestic price, and interest rate shocks. The average measure showed minute response to domestic price shocks, while the production function estimate demonstrated a sustained negative response. The response of the average measure, and production function estimate to an interest rate shock are positive for 1 year, the opposite that of the NKPC-Kalman Filter estimate.

The two-sided versions differ further. The two-sided NKPC-Kalman Filter exhibits a more persistent response similar to that of the one-sided production function estimate, but inherits the positive response to global oil price shocks demonstrated by the one-sided versions. The response to global oil prices is positive in the first quarter, and nil for the remaining, hence similar to that of observed real GDP. The HP-filtered production function demonstrates explosive responses. This may be expected, but problematic as a measure of potential output, as the two-sided HP filter smooths out substantial variation over the long term in the estimated potential output, essentially a combination of smooth trend components. The average two-sided measure is similar to its one-sided counterpart, but with longer-lived response to domestic price shocks.

The persistent, non-zero, response a cyclical demand shock in select iterations of the boom-bust potential output estimate, in particular the two-sided NKPC-Kalman Filter, and the two-sided HP filtered production function, indicate departure from its theoretical understanding, a point noted strongly in Coibion et al. (2017). While the one-sided recursive HP-filtered potential output comes close to the conceptual definition of 'potential output', the positive, statistically significant, response to global oil prices does not fit this definition. A negative response is expected. Importantly, this study boils the comparison between the 'Plucking' model, and the boom-bust model, and between different iterations of the boom-bust model to methodology in application. Expanding on Coibion et al. (2017), this study benefits from using purely quantitative measures, as opposed to official estimates from policy agencies, whose estimation process may have been moderated heavily by judgment.

In general, the responses to global economic policy uncertainty shocks, measured as per Baker et al. (2016), and Davis (2016), are as expected. An uncertainty shock leads to a slowdown in output, as documented in recent empirical work, such as Suah (2022). An extension this paper provides to the empirical literature is its impact on potential output, especially for the 'Plucking' model estimate, and a method-to-method comparison against the boom-bust estimates. The 'Plucking' ceiling estimate demonstrates a persistent negative response to uncertainty shocks, likewise the one-sided production function, two-sided NKPC-Kalman Filter estimate, and the two-sided average measure. The one-sided average measure, and the one-sided NKPC-Kalman Filter demonstrate similar response to uncertainty shocks as real GDP. The OIRF estimates from the smaller model that excludes core CPI are indistinguishable, both qualitatively, and quantitatively, as shown in figure D.1 in the appendix. However, excluding core CPI, which proxies for domestic prices, may bias the magnitude, and convergence of the remainder OIRFs.

These findings underscore a fundamental issue, already highlighted by Coibion et al. (2017) — "are estimates of potential output really measuring what they are intended to measure?". Conceptually, the potential output in the boom-bust view, and the output ceiling in the 'Plucking' view are not completely antithetical. However, this exercise highlights that a simple computational approach to estimating the 'Plucking' output ceiling is conceptually closer to the definition of 'potential output', as a supply measure absent of cyclical response than the commonly used methodologies in the boom-bust view. These differences, importantly, are methodological. Policy users ought to evaluate both methodologies side-by-side, granted that dynamically updated empirical estimates have merits in providing insights to the state of the economy alongside direct observables.

5 Conclusion

This paper demonstrated that a computational and empirical take of the 'Plucking' model, introduced and discussed in Friedman (1993), Dupraz et al. (2019), and Probst (2022), respectively, that resolves three common issues in estimating potential output estimates based on the traditional boom-bust view — (i) susceptibility to retrospective revisions post-shocks, noted in Fernald (2015), (ii) inconsistent link with observable measures of slack, and (iii) responsiveness to demand shocks, which are cyclical and near-term, with the latter analysed previously by Coibion et al. (2017) for the US.

A three-step analysis was conducted, using Malaysian data from 1995 to 2022 as proof of concept.

Firstly, an easy-to-implement, computational, and tractable estimation flow was proposed. The flow uses directly observable measures of output (real GDP), labour (labour force), and capital (net capital stock) to estimate an output ceiling using interpolation techniques on peaks identified through a modified version of the algorithm in Dupraz et al. (2019). An augmented Cobb-Douglas production function is applied to reflect labour, and capital fluctuations over time. Further decomposition of ceiling and observed output growth into TFP, labour, and capital components was also showcased. Drawing from Álvarez & Gómez-Loscos (2018), Cerra & Saxena (2000), and Shahrier & Lian (2019), (i) a structural model estimate using a Cobb-Douglas production function with HP-filtered inputs, and (ii) a Kalman Filter estimate built around a Neo-Keynesian Phillips Curve model, which also takes in HP-filtered output trend and cycle, act as baseline for the boom-bust view. Two-sided, and one-sided recursive HP filters, described in Alfaro & Drehmann (2023), Drehmann & Yetman (2018), and Borio & Lowe (2002), were also implemented separately. A comparison indicates that the 'Plucking' estimate of the output gap is not susceptible to retrospective revisions during, and after crises, whereas the boom-bust estimate generally is, except for one-sided recursive estimates, which are mechanically unalterable ex post. For the other boom-bust estimates, suppose ex post information is correct, the 'Plucking' model is policy-actionable, but the non-recursive boom-bust approaches are generally not. Policymakers cannot travel back in time to correct policies that are ex post model-inconsistent. The 'Plucking' model methodology proposed in this paper has several merits, including its flexibility to use alternative business cycle dating algorithms, both computational, and estimation-based, flexibility in structural form applied for historical decomposition, and the lack of 'black boxes', or semi-'black boxes', where all steps are purely computational.

Secondly, a review of stylised statistics was conducted, visualising the link between various output gap estimates, and inflation, and with unemployment rate, an observable non-output measure of economic slack. Both measures of the output gap do not provide basis for the existence of a Phillips Curve relationship in Malaysia, which the boom-bust view of potential output as non-inflationary level of output requires ex ante. The 'Plucking' output gap is mildly positively related to core inflation, while the boom-bust output gap estimates flat, and sensitive to outliers. This is in line with recent discussion on the Phillips Curve in the US, notably Hazell et al. (2022), who analysed state-level price data, and posited the absence of a Phillips Curve in the US. This paper departs from pre-COVID-19 empirical findings in Malaysia, notably Furuoka et al. (2007), Tang & Lean (2007), and Furuoka & Harvey (2015). The Okun's Law relationship is clearer when the 'Plucking' output gap is plotted against unemployment rate, and is comparable to the observed Okun's Law between real GDP, and the unemployment rate. However, the slopes of unemployment rate against the boom-bust estimates are highly sensitive to outliers. There may be deep conceptual and methodological issues with the boom-bust view of the output gap and potential output. As an aside, this may illustrate that the Okun's Law relationship is weaker in Malaysia than in the US, documented by Ball et al. (2013). A main limitation is that adjusted empirical analysis with more granular data, such as in Hazell et al. (2022), is warranted, but is beyond the scope of this study, and constrained by data limitations. Nevertheless, these stylised facts suffice in illustrating the lack of a basis for the Phillips Curve thesis, which the 'Plucking' view does not necessitate both ex ante and ex post, and the boom-bust view's link with observable slack.

Thirdly, a VAR analysis on Malaysia is implemented to analyse the behaviour of the 'Plucking' and boom-bust estimates of potential output to supply and demand shocks. This drew from Coibion et al. (2017), who used a similar approach to analyse estimates of US potential output. The estimated OIRFs suggest that the 'Plucking' ceiling is better aligned with the conceptual description of 'potential output', that is as a measure of supply, hence exhibits a negative response to global oil price shocks (supply), and nil, or near-nil response to interest rate shocks (demand). The boom-bust estimates, however, deviate from this characterisation. In general, when the one-sided recursive filters are used, responses of the boom-bust potential output estimates to shocks are generally more persistent than that of real GDP, but in similar directions. The two-sided versions differ further analytically. Responses of the production function estimates are explosive. The two-sided NKPC-Kalman Filter exhibits a more persistent response similar to that of the one-sided production function estimate, and responds negatively to interest rate shocks, but inherits the positive response to global oil price shocks demonstrated by the one-sided versions, and real GDP. This underscores Coibion et al. (2017)'s point that cyclical components that are not supposed to be captured by measures of potential output are indeed encapsulated in the boom-bust estimates. A contribution from this paper is the effort made to ensure that both output gap measures are purely quantitative, hence judgment is entirely absent. Hence, difference in the analytical results are underscored by conceptual, and methodological flaw in the conventional ways of estimating potential output, which are addressed in the proposed flow in estimating the 'Plucking' output ceiling. Nevertheless, extrapolation to other economic settings may require further examination on the behaviour of output gap estimates to supply, and demand shocks in a variety of emerging, and advanced economies. The Malaysian application here, and the root analysis in Coibion et al. (2017) offers a starting point for comparing the boom-bust view against the 'Plucking' view in a conceptual, but empirically-founded, manner.

Going forward, further research is needed to understand better alternate options of decomposition, potential application of highly non-linear filters, and potential extrapolation to other macroeconomic variables. Importantly, policymakers ought to consider alternative views and estimation techniques of potential output that are foremost data-founded, less prone to retrospective revisions, correlates well with observed indicators of economic slack, does not rely on the presence of a Phillips Curve, and satisfy the analytical properties of a supply measure. The 'Plucking' estimation flow introduced here is one such candidate, which ought to be at least considered alongside pre-existing methods typically in the boom-bust view. Further, one could examine the implications for optimal policy strategy, be it monetary or fiscal authorities, from a 'Plucking' view of the output gap, and if these optimal policy prescriptions differ meaningfully from the traditional boom-bust view.

Data and replication statement

All data sources used in this study are open access. Data vintages and codes are available at github.com/suahjl/plucking-ceiling.

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A Alternate Peak-Trough Identification Algorithm

In this algorithm, an output trough, $trough_t^Y$, is declared in quarter t when observed real GDP Y_t (1) contracted, (2) expanded in the subsequent quarter, and (3) the scale of contraction is at least $\tau_{trough} = 0.8$ standard deviation. An output peak, $peak_t^Y$, is then declared in quarter t when real GDP Y_t (1) expands, (2) contracted in the subsequent quarter, and (3) a trough occurs within the next $\theta_{peak} = 4$ quarters. Both parameters τ_{trough} and θ_{peak} can be variable, and tuned accordingly to the economist's judgment, and country characteristics. This procedure can also be extended to other variables, e.g., labour N_t and capital K_t for their respective ceilings (N_t^p and K_t^p). Equations 37 and 38 summarise the procedure.

$$trough_t^Y = \begin{cases} 1, & \text{if } \Delta Y_t < 0 \text{ and } \Delta Y_{t+1} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{37}$$

$$peak_t^Y = \begin{cases} 1, & \text{if } \Delta Y_t > 0 \text{ and } \Delta Y_{t+1} < 0 \text{ and } \sum_{k=1}^{4} trough_{t+k}^Y \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{38}$$

Figures A.1 to A.3 show observed output, labour force, and capital stock, and their respective estimated ceilings using the alternate algorithm described above. The timing of peaks, and troughs correspond similarly to that of the main analysis. Specifically, the Asian Financial Crisis, Global Financial Crisis, and COVID-19 Pandemic were called correctly. Beyond the identification of peaks and troughs, the estimation methodology is identical to that of the main analysis, hence the estimated ceilings are virtually identical. For ease of comparison to the nascent literature, the modified version of Dupraz et al. (2019) is retained for the main analysis. This supplementary exercise illustrates that alternative computational methods remain feasible in achieving real-time identification of peaks and troughs, as opposed to traditional business cycle dating algorithms, which typically require observations well after the supposed turning points.

Figure A.1

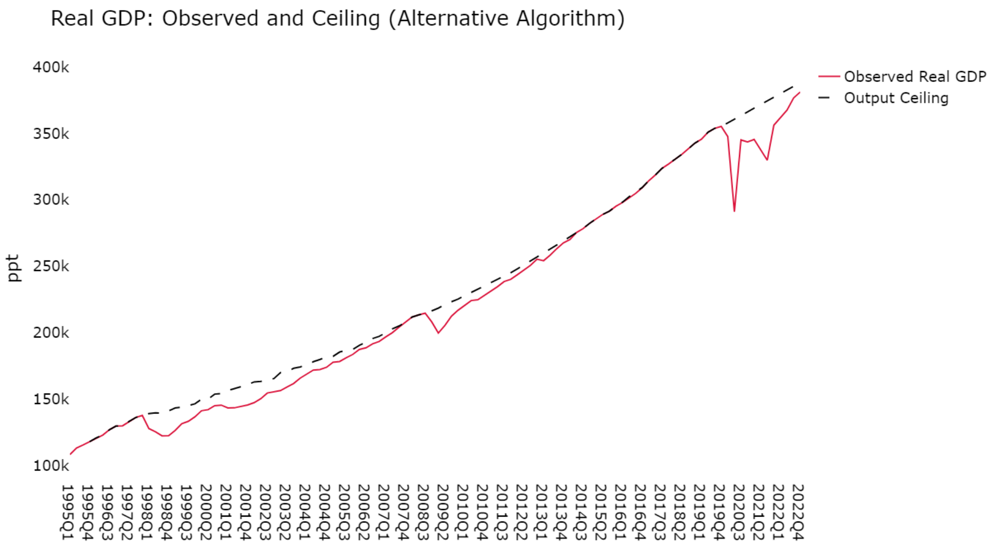


Figure A.2

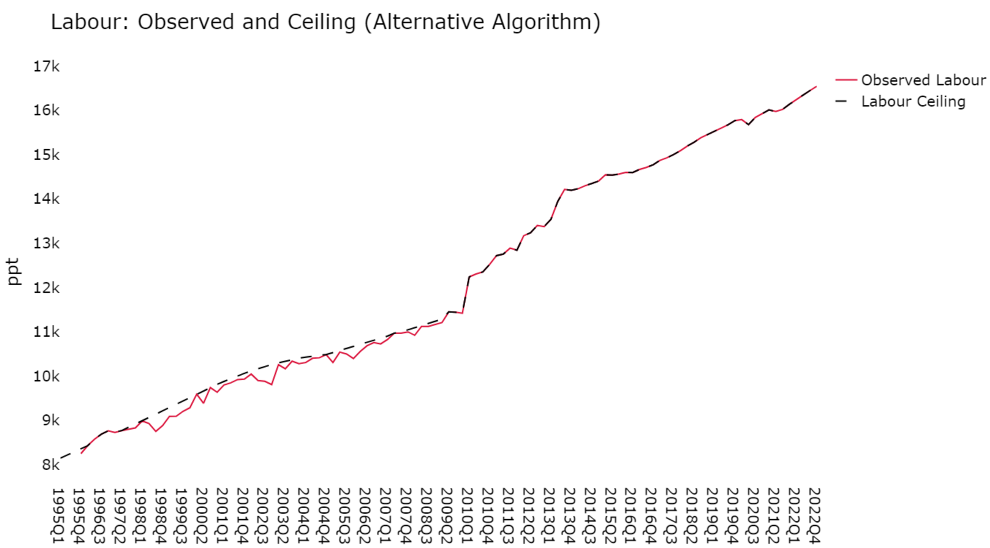
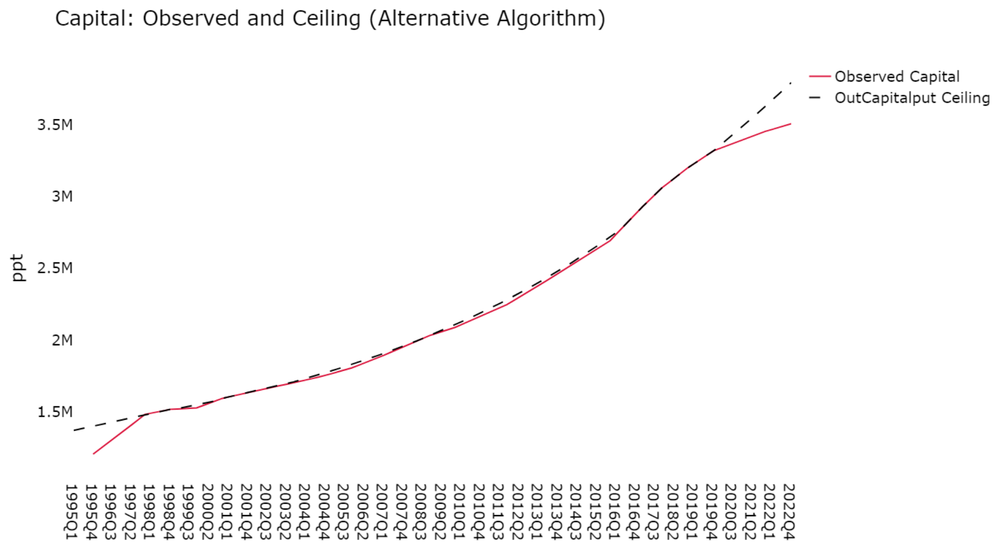


Figure A.3



B Estimating the Unemployment Rate Floor

B.1 Application to Malaysian Data

Recent empirical analysis from Dupraz et al. (2019) on the 'Plucking' model was built on behaviour exhibited by the unemployment rate. Even if the focus of this paper is on estimating output 'ceiling', there remains merit in applying the framework on the unemployment rate as a sensitivity, or informal validity, check. An acid test is if the algorithm proposed here is able to identify peaks, and troughs that are aligned with the main analysis, and comparable unemployment rate floors, analogous to the output 'ceiling'. Malaysia's monthly unemployment rate data from January 2015 is used for this analysis. Data before this date were discarded, reflecting a potential change in methodology that led to less volatile observations, and a trend shift from 2015 onwards.

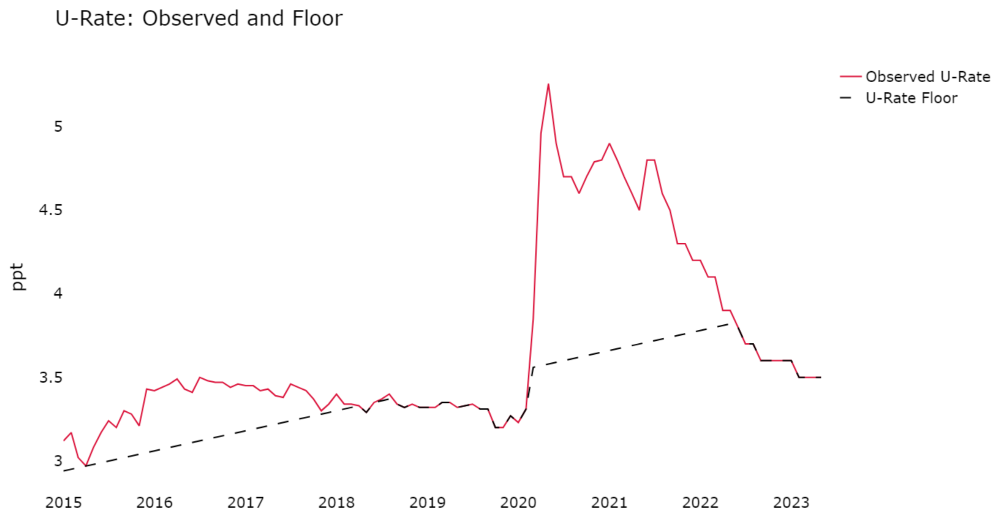
The estimation flow described in the main analysis in section 2 requires modifications before applying to the unemployment rate for two reasons. Firstly, interpretation of directions is reversed. Where output drops are associated with downturns, and output increases upturns, the opposite is true for unemployment rate. Secondly, rates require different treatment than level, or growth variables. The main departures from the framework in section 2 are (i) the peak-trough identification algorithm is identical to that of Dupraz et al. (2019), without modifications, and with $X = 0.29$, (ii) linear spline is used in lieu of quadratic spline due to shorter coverage, (iii) the unemployment rate floor cannot be higher than observed unemployment rate, whereas output ceiling cannot be lower than observed output, and

(iv) linkages with the augmented production function, and subsequent production function decomposition are omitted. The modified steps are as follows.

1. **Identify peaks in observed unemployment using the algorithm developed by Dupraz et al. (2019), with a threshold $X = 0.29$, which correctly identifies the pre-COVID peak, and the COVID-19 pandemic trough.**
2. Apply linear spline interpolation between peaks for a first estimate of the floor
3. Update the initial unemployment rate floor estimates so that the floor is always below or at observed unemployment rate.

Figure 4 shows the estimated unemployment rate floor, and observed unemployment rate. There are two key departures from the output ceiling estimates in the main analysis. The first is the timing of the pre-COVID peak. Where the output ceiling estimate pins the peak at 3Q 2019, and the COVID-19 trough at 2Q 2020, the unemployment floor estimates pins the pre-COVID peak at April 2018. The timing of the COVID-19 trough overlap at April 2020. This departure is reasonable, as early 2018 corresponds to around when US-China trade tensions first escalated. Moreover, Malaysia's unemployment rate tends to be gentle, and stable, hence departs from the analysis on output during the period corresponding to US-China trade tensions. The findings suggests that the labour market was at its peak since early 2018, before being dislocated when the first COVID-19 lockdown was implemented in March 2020. The unemployment rate then remained above the floor until June 2022. The estimated unemployment rate floor is qualitatively consistent with the main analysis, where output and output ceiling departed during the first COVID-19 lockdown, and re-converged in 2022, affirming the usability of the proposed framework on estimating the 'Plucking' output ceiling.

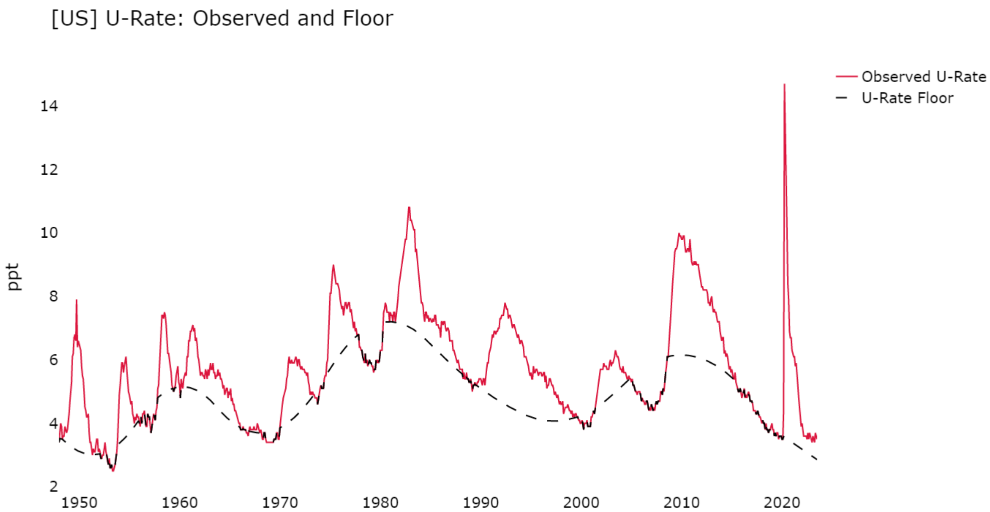
Figure B.1



B.2 Application to US Data

There are two major benefits of visualising US data. The first is the extensive data coverage at a monthly frequency, and the second the analysis by Dupraz et al. (2019) provides an anchor to assess provenance of the proposed estimation flow here. In this application, the threshold harmonised to $X = 1.5$, identical to Dupraz et al. (2019). Figure B.2 shows US unemployment rate, and the estimated floor. US unemployment rate appears to be above the estimated floor for most time periods, which fluctuates over longer cycles than the duration of a typical business cycle. Moreover, observed rate and the floor converge typically only at the end of each expansion phase, close to the peak of the corresponding cycle.

Figure B.2



C US Output Ceiling

Following the exercise on US unemployment rate, a natural follow-up is to verify if the proposed algorithm is able to generate intuitive output ceiling estimates from US real GDP. Only steps 1 to 3 are reproduced, given the absence of up-to-date (post-COVID-19) official data on real net capital stock in the US, unlike Malaysia. Nevertheless, the Malaysia-specific analysis on the influence of step 4, as illustrated in figure 2, is minimal for most parts. The executed steps are reproduced below from the main text.

1. Identify peaks in observed output, based on the algorithm developed by Dupraz et al. (2019), and modified for variables other than unemployment rate.
2. Apply quadratic spline interpolation for a first estimate of the ceiling.
3. Update the initial output ceiling estimates so that the ceiling is always above or at the observed output.

Figure C.1 shows the estimated output ceiling, and observed real GDP for the US, while figure C.2 shows the estimated 'Plucking' output gap. The timing of peaks and troughs, demonstrated by where the output gaps are largest, and when observed output, and the ceiling converged in figure C.2, are similar to the unemployment rate application in figure B.2. In all expansions, except for the 'jobless recovery' in the 1990s, and post-GFC in the 2010s, output converged to the estimated ceiling in well under a decade.

Figure C.1

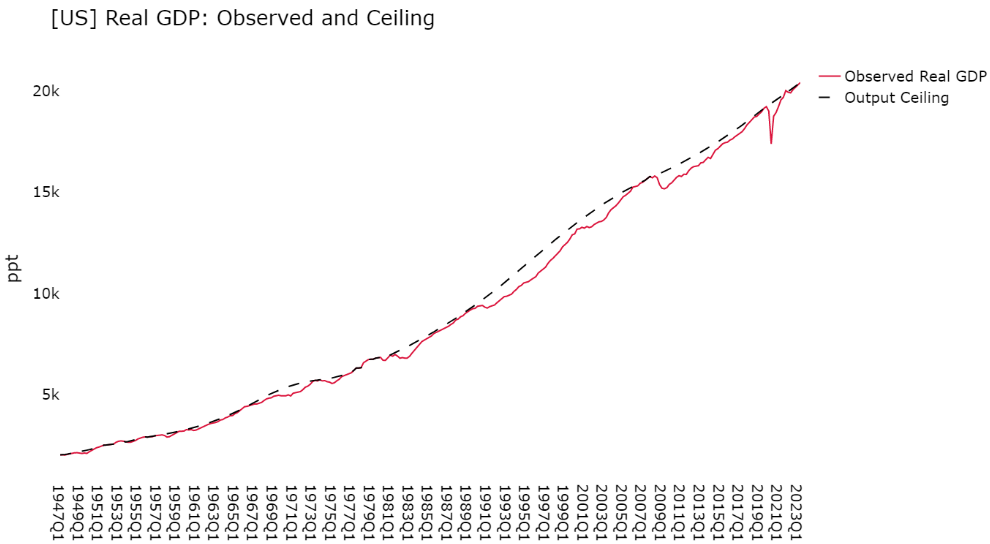
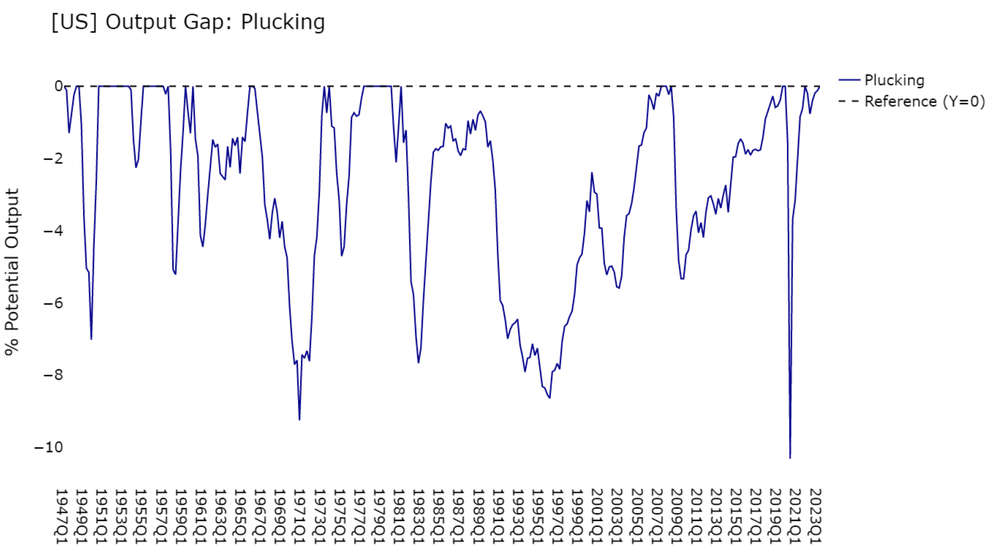


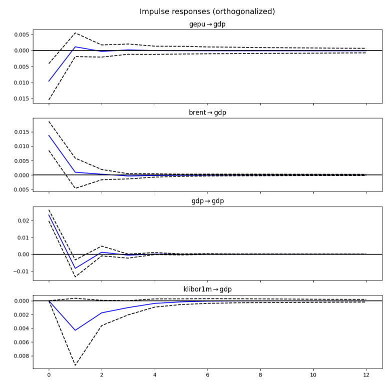
Figure C.2



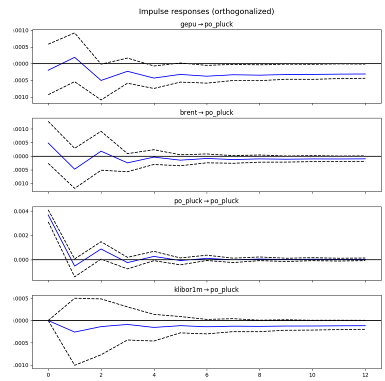
D Responses to Supply and Demand Shocks: Additional Findings

Figure D.1

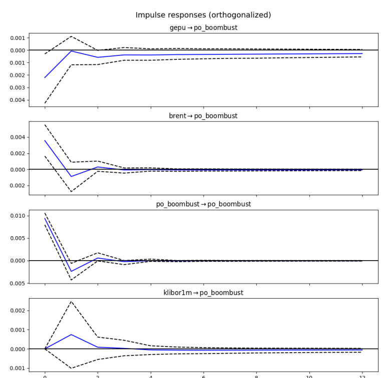
(a) Real GDP



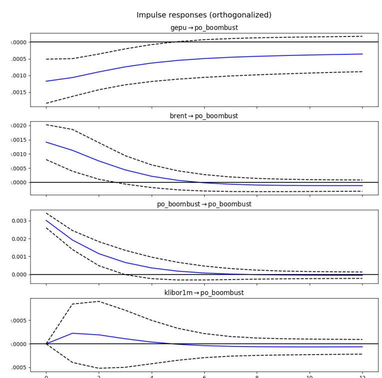
(b) 'Plucking' Ceiling



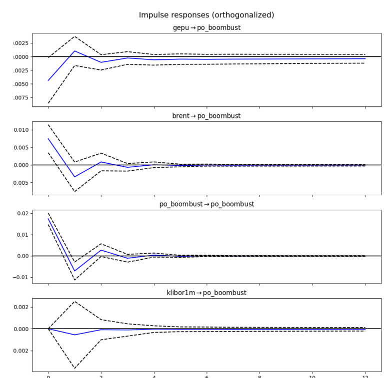
(c) Boom-Bust Potential Output (One-Sided (Average))



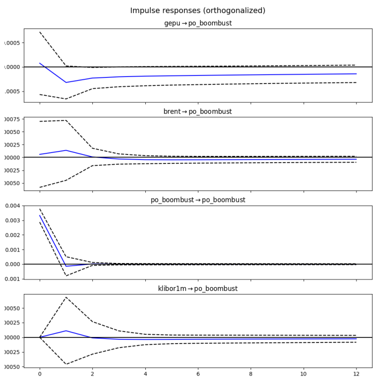
(d) Boom-Bust Potential Output (One-Sided (PF Only))



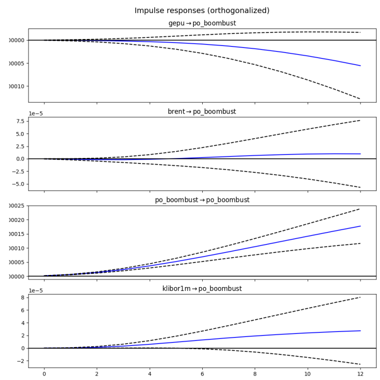
(e) Boom-Bust Potential Output (One-Sided (KF Only))



(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))

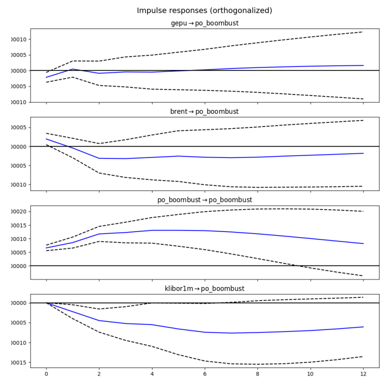
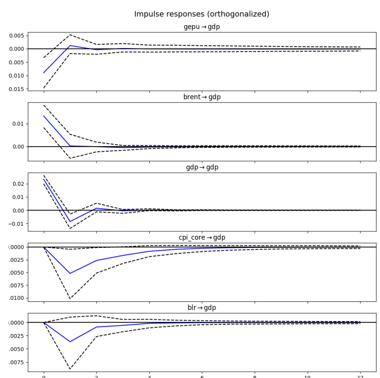
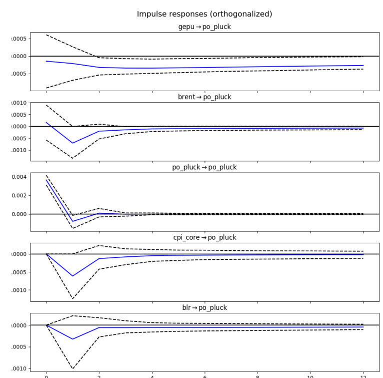


Figure D.2: Full Model with BLR

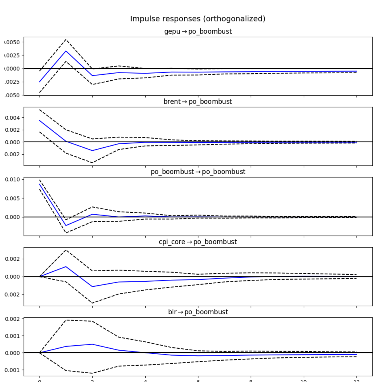
(a) Real GDP



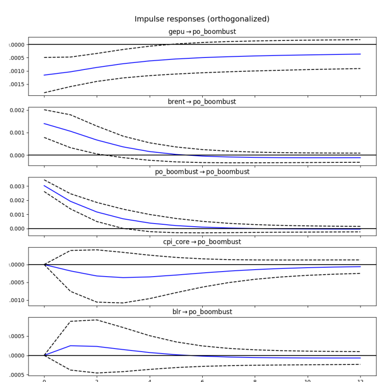
(b) 'Plucking' Ceiling



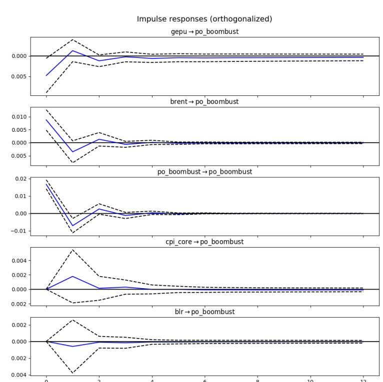
(c) Boom-Bust Potential Output (One-Sided (Average))



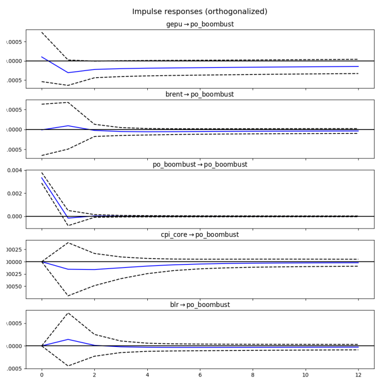
(d) Boom-Bust Potential Output (One-Sided (PF Only))



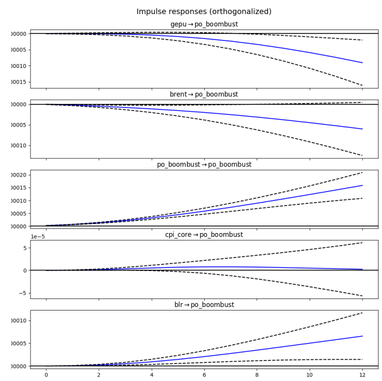
(e) Boom-Bust Potential Output (One-Sided (KF Only))



(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))

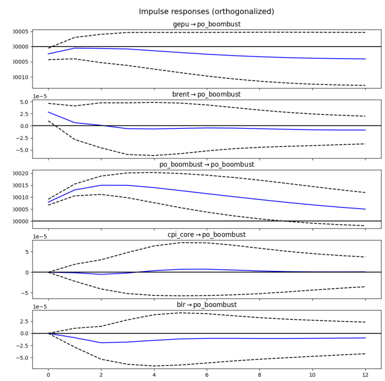
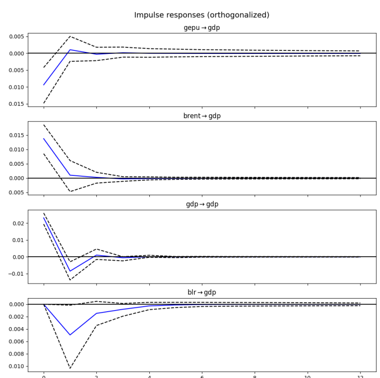
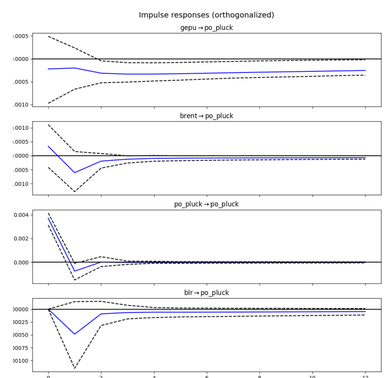


Figure D.3: Short Model with BLR (Excluding Core CPI)

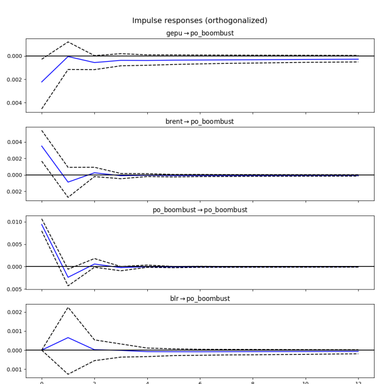
(a) Real GDP



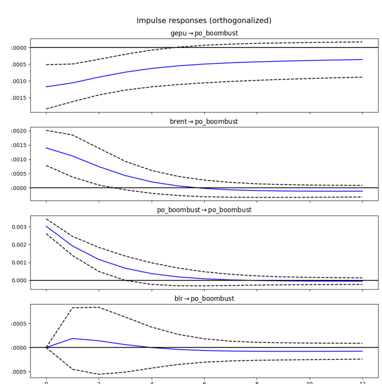
(b) ‘Plucking’ Ceiling



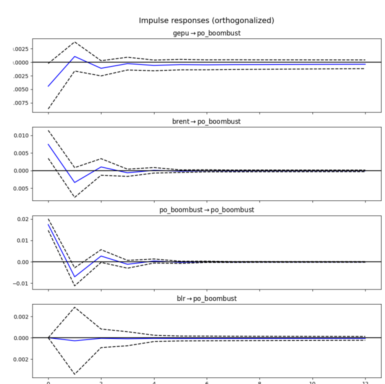
(c) Boom-Bust Potential Output (One-Sided (Average))



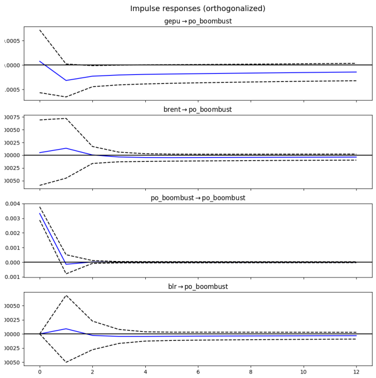
(d) Boom-Bust Potential Output (One-Sided (PF Only))



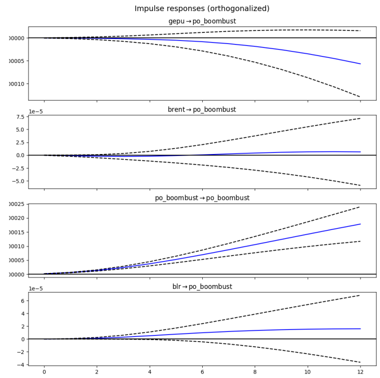
(e) Boom-Bust Potential Output (One-Sided (KF Only))



(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))

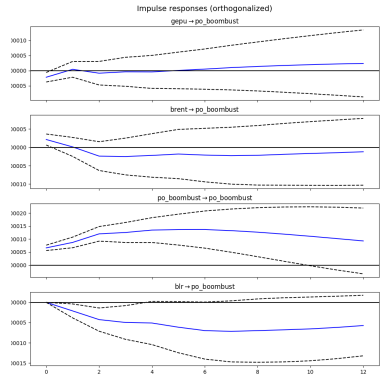
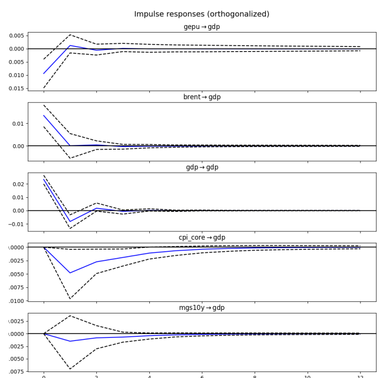
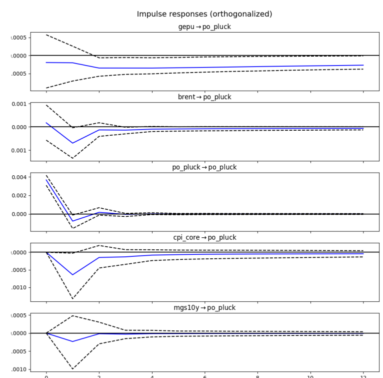


Figure D.4: Full Model with MGS10Y

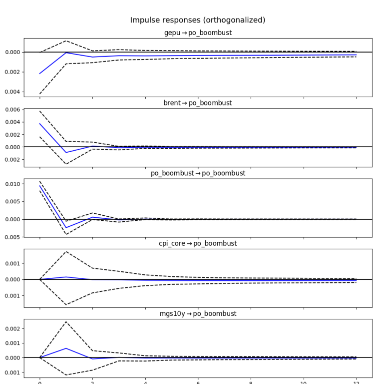
(a) Real GDP



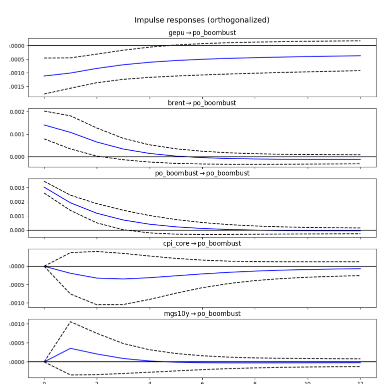
(b) 'Plucking' Ceiling



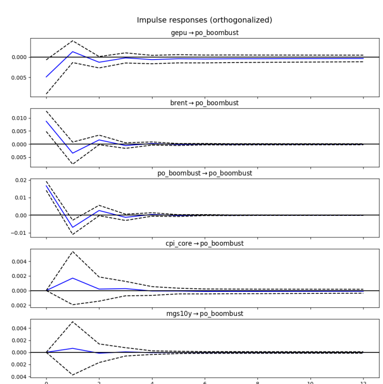
(c) Boom-Bust Potential Output (One-Sided (Average))



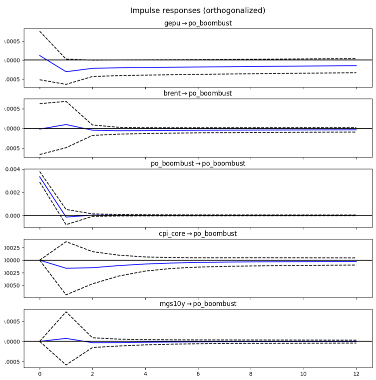
(d) Boom-Bust Potential Output (One-Sided (PF Only))



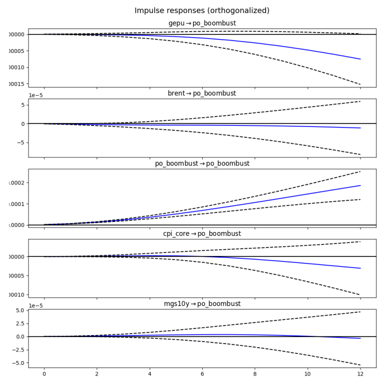
(e) Boom-Bust Potential Output (One-Sided (KF Only))



(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))

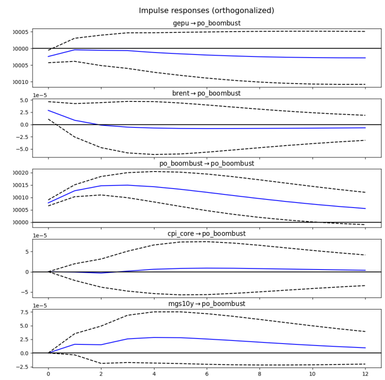
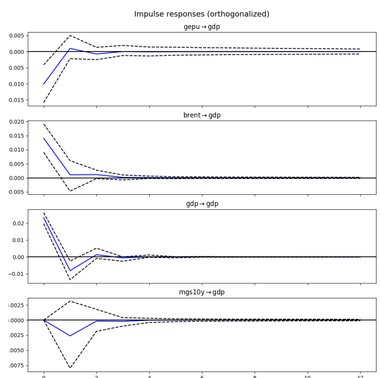
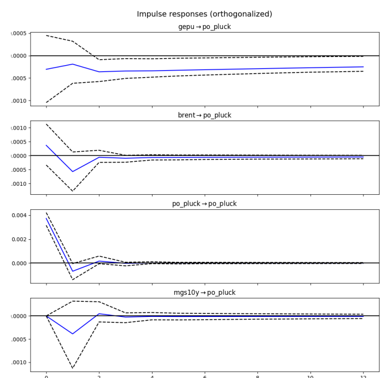


Figure D.5: Short Model with MGS10Y (Excluding Core CPI)

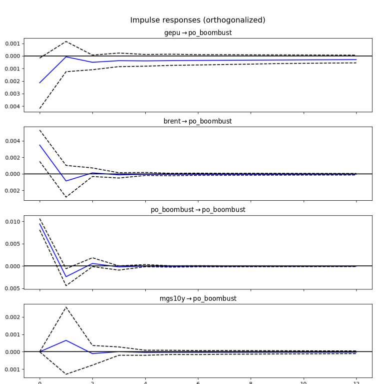
(a) Real GDP



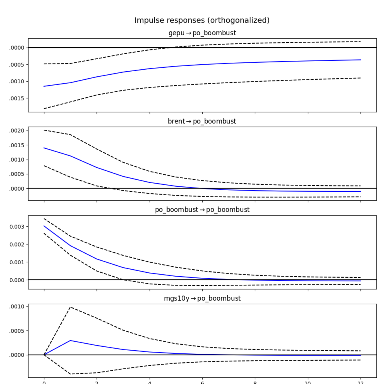
(b) 'Plucking' Ceiling



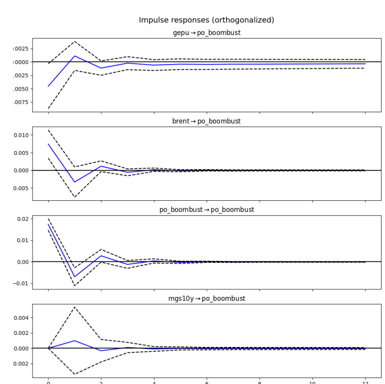
(c) Boom-Bust Potential Output (One-Sided (Average))



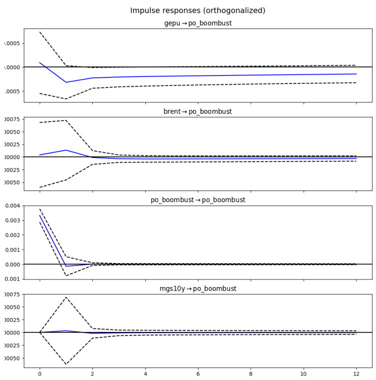
(d) Boom-Bust Potential Output (One-Sided (PF Only))



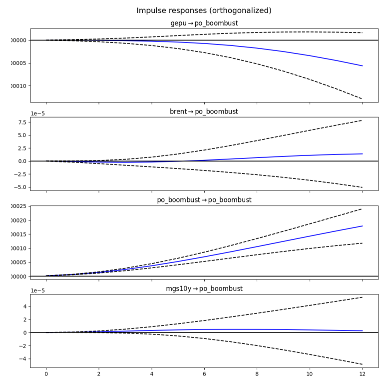
(e) Boom-Bust Potential Output (One-Sided (KF Only))



(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))

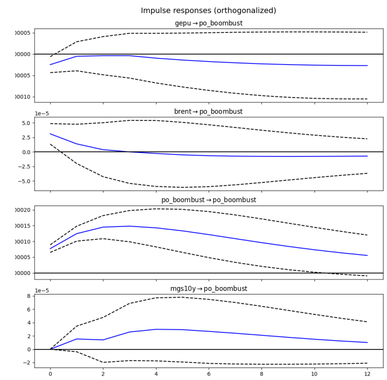
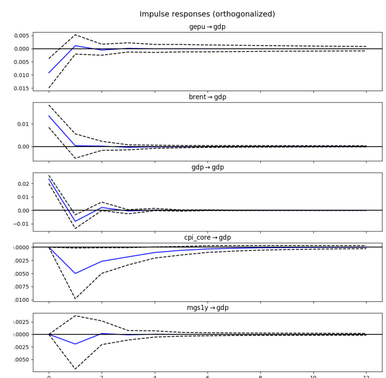
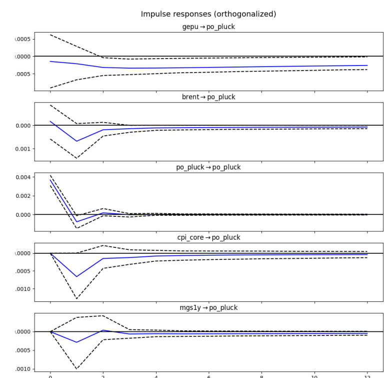


Figure D.6: Full Model with MGS1Y

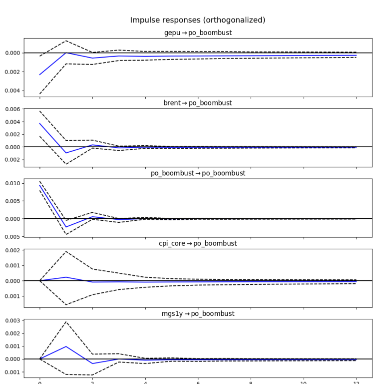
(a) Real GDP



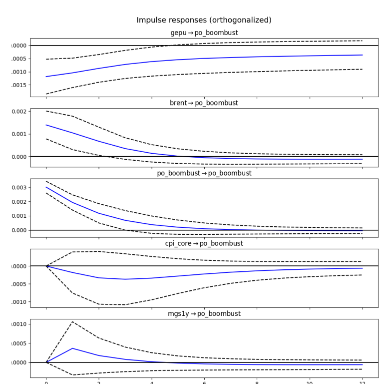
(b) ‘Plucking’ Ceiling



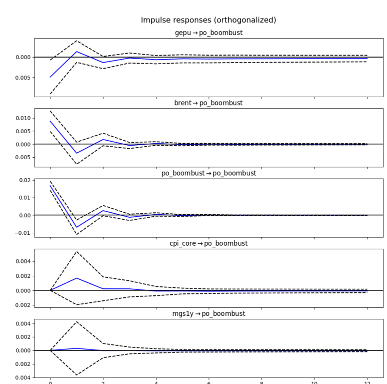
(c) Boom-Bust Potential Output (One-Sided (Average))



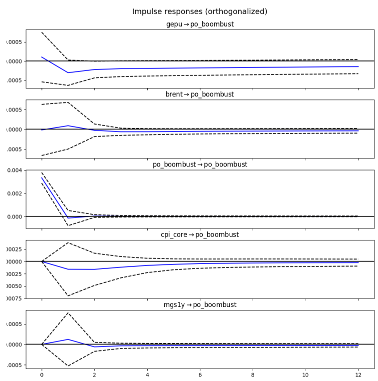
(d) Boom-Bust Potential Output (One-Sided (PF Only))



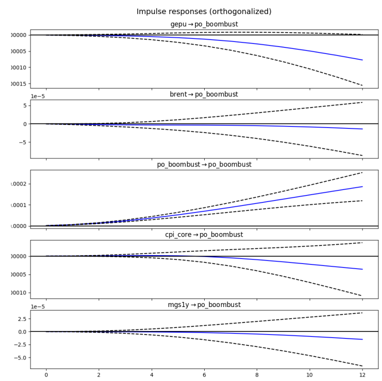
(e) Boom-Bust Potential Output (One-Sided (KF Only))



(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))

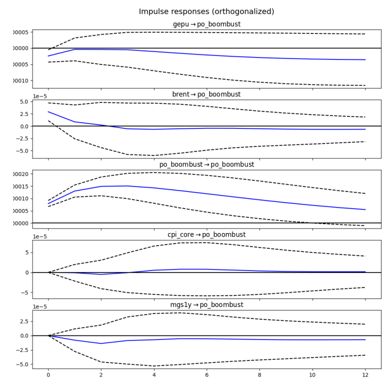
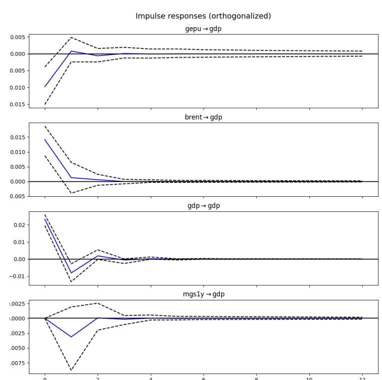
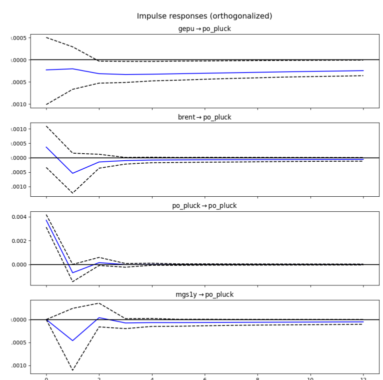


Figure D.7: Short Model with MGS1Y (Excluding Core CPI)

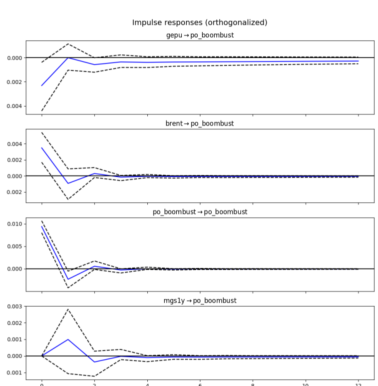
(a) Real GDP



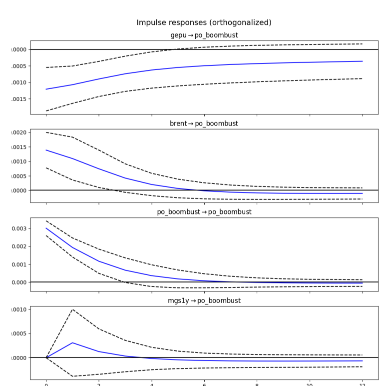
(b) ‘Plucking’ Ceiling



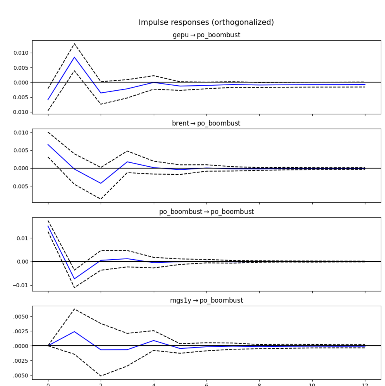
(c) Boom-Bust Potential Output (One-Sided (Average))



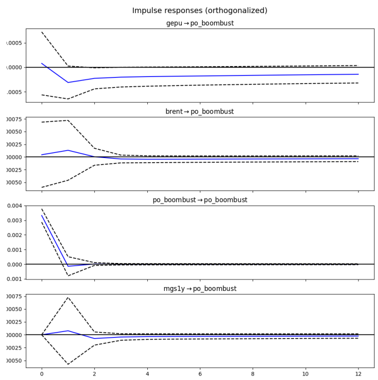
(d) Boom-Bust Potential Output (One-Sided (PF Only))



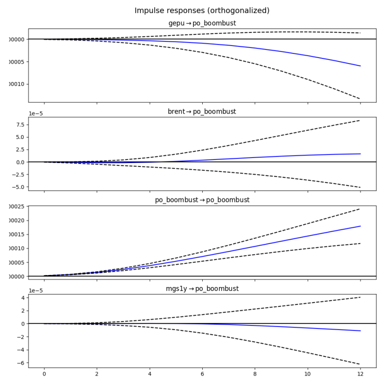
(e) Boom-Bust Potential Output (One-Sided (KF Only))



(f) Boom-Bust Potential Output (Two-Sided (Average))



(g) Boom-Bust Potential Output (Two-Sided (PF Only))



(h) Boom-Bust Potential Output (Two-Sided (KF Only))