RESERVE BANK OF AUSTRALIA

RBAFOI-252609

The applicant sought documents that analyse the Non-Accelerating Inflation Rate of Unemployment (NAIRU) and the Neutral Cash Rate.

Summary of Request	Not applicable
Notes/context to any specific documents released:	Three internal research notes have been released essentially in full, with redactions made in terms of section 22 to remove staff names below deputy head of department level and material irrelevant to the request.

ESTIMATING AUSTRALIA'S NEUTRAL RATE: A POST-COVID REFRESH[1]

Purpose: *To outline recent refinements to the neutral rate models from McCririck and Rees (2017) (MR17), including improvements in the way the models handle the COVID-19 period.*

Why this matters: *These models provide an important input into SAMM's suite of estimates of the neutral rate. The extreme nature of the COVID-19 period posed challenges for the ability of the models to infer the neutral rate from the data. Previous work partly addressed these challenges by using a lockdown 'stringency index' to adjust model inputs. We build on this by introducing breaks in shock variances, consistent with international practice and treatment of the COVID-19 period in other star variable models.*

Implications: *The refined models imply a significant downward revision in the central estimate of the real neutral rate from the MR17 models (a downward revision of 1.6 percentage points in 2024Q2). This implies a smaller downward revision in SAMM's preferred central estimate, which is an average over a broader suite of models (a downward revision of 0.7 percentage points in 2024Q2). The new estimates are more closely aligned with pre-pandemic vintages, with new external estimates of the neutral rate in Australia and with estimates in some peer economies. While the new estimates suggest that the cash rate is further above neutral than previously thought, the gap between the cash rate and neutral remains smaller than the policy-rate gaps seen in other economies at the peak of their tightening cycles.*

Background and non-technical summary

The neutral rate can refer to different concepts. Most commonly, it refers to the real cash rate that would keep inflation at target and output at potential (or the labour market at full employment) in the absence of shocks (e.g. Ellis 2022). Estimates of the neutral rate are sometimes used to assess the stance of monetary policy; for example, if the real cash rate is above the neutral rate, monetary policy might be described as 'restrictive' (e.g. Ellis 2022; 2024; RBA 2024).[2] Estimates of the neutral rate are an input into MARTIN and can also be useful for considering the likelihood that monetary policy will be constrained by the effective lower bound on nominal interest rates.

The RBA uses a suite of models to estimate the neutral rate for Australia, including semi-structural models (McCririck and Rees 2017; henceforth, MR17), a vector autoregression (2021) and a financial market-based model (Hambur and Finlay 2018). Focusing on the models from MR17, this note explains recent model refinements to better account for the COVID-19 period and additional minor adjustments.

Extreme macroeconomic volatility during the COVID-19 pandemic posed challenges for the ability of the MR17 models to infer the neutral rate from the data.[3] (2022) (DT22) partly addressed these problems by controlling for the direct economic effects of COVID-related restrictions by adjusting output using a lockdown 'stringency index', following Holston, Laubach and Williams (2020). However, even with this adjustment, the COVID-19 period still led to implausibly large changes in the neutral rate estimates. To mitigate this, DT22 additionally constrained model parameters to keep them close to their pre-pandemic values, which at the time was viewed as a temporary fix in lieu of more sophisticated approaches to handling macroeconomic volatility during the pandemic.

We refine the COVID-19 adjustments from DT22 by introducing structural breaks into the variances of the model's shock processes, replacing the ad hoc constraints on the model parameters. This treatment is consistent with Holston, Laubach and Williams (2023) (HLW23) as well as some of our other star-variable models (e.g. 2023; 2024; 2024). The estimated variances are larger during the pandemic, which results in incoming data over this period being down-weighted.

1 We thank for his valuable guidance. .

2 The high degree of uncertainty about the estimates of the neutral rate (2024), along with a number of other reasons, suggests that it should not be overly relied on for setting monetary policy. Indeed, some policymakers have expressed scepticism about using neutral rate estimates as a guide to the appropriate setting of policy. For example, FOMC Chair Powell has stated that the neutral rate "doesn't really get you where you need to be to think about what appropriate policy is in the near term" (Powell 2024). Borio (2024) expresses similar sentiments.

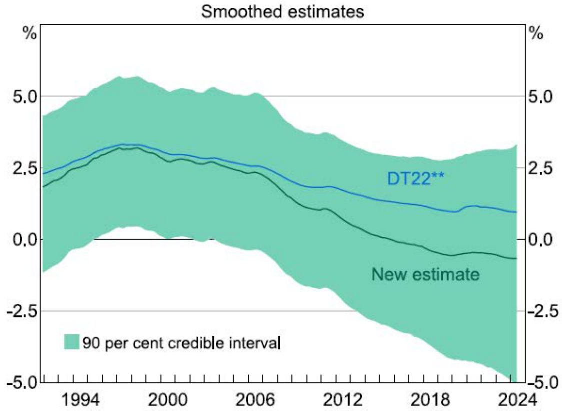
3 (2023) show how the extreme movements in GDP and inflation during the COVID-19 pandemic yield large outliers in the standard HLW model. These outliers significantly affect neutral rate estimates, even with pre-pandemic parameter values, highlighting the need for model modifications.

In addition to the COVID-19 adjustments, we introduce two further refinements to the MR17 models. First, we use an *ex-ante* real cash rate instead of an *ex-post* measure. Historically, these measures were not materially different, but they have diverged in recent years. Using an *ex-ante* cash rate is more consistent with economic theory and empirical evidence, which emphasises that expectations matter for decision-making. Second, we allow the relationship between trend output growth and the neutral rate to be estimated, consistent with HLW23. In contrast, the previous version of the model assumes that the neutral rate responds one-for-one to changes in trend growth.

Compared with DT22, our refined models deliver consistently lower neutral rate estimates after 2006 (Graph 1). The revisions are large, but:

1. The new estimates are closer to pre-pandemic estimates of the neutral rate, new external estimates of the neutral rate in Australia and estimates in some peer economies.
2. The new estimates lie within credible intervals around the previous estimates. Given the large uncertainty around the estimates, it is perhaps unsurprising that refinements to the models have large effects on estimates.
3. This is not the revision to SAMM's preferred estimate of neutral, which averages over a broader suite of models. The revision to the preferred estimate is less than a half of the revision in the MR17 models, reflecting the weight on these models in the model average.[4]

Graph 1
Real Neutral Rate*
Smoothed estimates



* Average of the smoothed estimates from the three models in McCririck and Rees (2017) with updated COVID adjustments and model refinements. The 90 per cent credible interval is an average interval from the three models.

Source: RBA.

The downward revision is mainly driven by incorporating variance breaks, slightly offset by the other two adjustments. By incorporating variance breaks, we allow for more-volatile shocks during the pandemic period. This means the model interprets less of the post-pandemic inflation as coming from a positive output gap driven by loose monetary policy. Therefore, the estimates of the neutral rate over the post-pandemic inflation are lower than before (rates were less below neutral than the prior estimates suggest). Because the neutral rate is slow moving, that lower rate persists through to current estimates.

The remainder of the note details the model refinements and their effects on estimates of the neutral rate.

Models

MR17 developed three 'semi-structural' state-space models, which differ in whether the output gap or unemployment gap is used in the Phillips Curve and whether import prices are included. We briefly summarise the model that includes the unemployment gap and describe the COVID-19 adjustments. The model economy can be summarised by the relationships between: 1) inflation and the unemployment gap (Phillips curve); 2) the unemployment and output gaps (Okun's law); and 3) the output gap and the deviation of the real cash rate from the neutral rate (IS curve). The neutral rate is driven by trend productivity growth and 'other determinants', which are unobserved variables that follow random walks. Given the model structure and model parameters, the Kalman filter and smoother are used to infer the neutral rate from the joint behaviour of inflation, output, unemployment and the cash rate. Intuitively, from the perspective of the model, unexpected weakness in macroeconomic variables tells us that the real cash rate is further above neutral than previously thought. The model parameters are estimated via Bayesian methods given prior distributions on the parameters. See Appendix I for further details.

4 The neutral rate estimates are a simple average of the smoothed estimates from the three MR17 models in the MR17 suite. The version of the model that includes the unemployment rate yields higher estimate of the neutral rate relative to the other two models and the estimates from this model are revised downwards by less when including the volatility breaks. Increasing the weight on this model would reduce the size of the overall revision.

COVID-19 adjustments

Our COVID-19 adjustments follow HLW23, combining the stringency index adjustment in DT22 with structural breaks in shock volatilities. Since the stringency index adjustment is detailed in DT22 (see also Appendix I), we focus on describing the volatility breaks. We apply scale factors to the variances of shocks to the model's measurement variables (output, unemployment and inflation) during the years 2020, 2021 and 2022.[5] In particular, we allow the scale factors to vary across different observables and years.[6] We define the scale parameters κ_t^x for each observable $(x = \mathrm{y}, \mathrm{u}, \pi)$ at time t that take the values

$$\kappa_t^x = \begin{cases} \kappa_{2020}^x, & 2020Q2 \leq t \leq 2020Q4 \\ \kappa_{2021}^x, & 2021Q1 \leq t \leq 2021Q4 \\ \kappa_{2022}^x, & 2022Q1 \leq t \leq 2022Q4 \\ 1, & \text{otherwise} \end{cases}$$

The variances of the shocks are now time-varying and are given by $(\kappa_t^x\,\sigma_x)^2$, so σ_x^2 is the variance of variable x during non-pandemic periods. The scale factors are estimated alongside the other parameters, with the constraint that each scale factor must not be smaller than one.

This approach is flexible in that it *allows* for increased volatility during the three years following the onset of the pandemic, but it does not *impose* higher volatility. By estimating the scale factors, the approach allows the data to inform the degree to which outliers during the pandemic are down-weighted when estimating model parameters.[7] The approach therefore allows us to still take some information from the COVID-19 period, rather than discarding it all (e.g. by treating the pandemic data as missing). Higher shock volatilities result in the Kalman filter taking less signal from the data when updating estimates of the neutral rate (and other state variables), because the 'signal-to-noise' ratio is lower.

We apply loose priors to most parameters, consistent with MR17. For the variance scale factors, we use the estimated parameters from HLW23 as the prior means. The posterior estimates of the scale factors differ noticeably across observables, providing support for our specification. See Appendix I for further details.

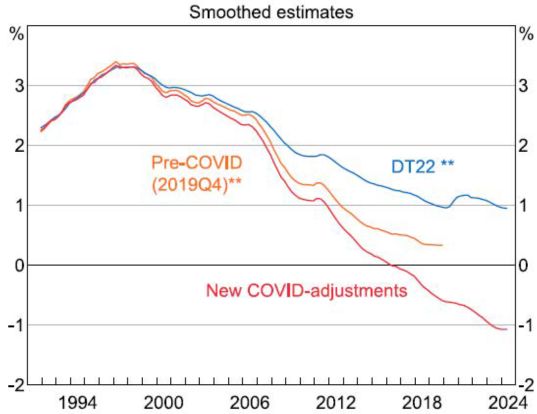
Results

We compare smoothed estimates of the neutral rate from the model with volatility breaks against those from the DT22 version and the pre-pandemic vintage (MR17) (Graph 2). To be clear, these results do not reflect the additional refinements mentioned in the Introduction (i.e. changing from an *ex-ante* to *ex-post* real cash rate and estimating the relationship between trend growth and the neutral rate). Including volatility breaks results in a large downward shift in the neutral rate estimates. Relative to the estimates from the DT22 model, the central estimate is approximately 1.5–2 percentage points lower on average since 2020. In 2024Q2, the refined model estimate is –1 per cent, compared with 0.9 per cent in the DT22 model. The new estimates align more closely with the pre-pandemic vintage (with some differences due to data revisions), and the model parameters are more consistent with pre-pandemic parameters.

Graph 2

Real Neutral Rate*

Smoothed estimates



* Average of the smoothed estimates from the three models in McCririck and Rees (2017). All models are estimated using ex-post real cash rate.

Source: RBA.

5 The idea is similar to Lenza and Primiceri (2022) in the context of estimating vector autoregressions; if the timing of increased volatility is known – as is the case for the pandemic – we can introduce volatility breaks with known timing.

6 HLW23 allow the scale factors to vary across years but assume they are the same across variables. We relax this assumption, allowing the scale factors to differ both across years and across variables to account for heterogeneity in how the pandemic affected different observables. Using the specification in HLW23 does not generate substantially different results.

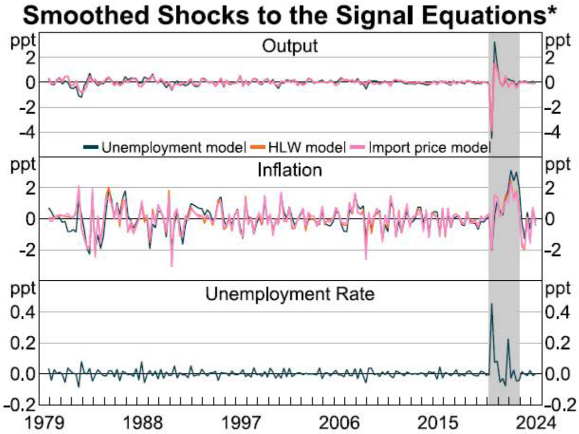
7 Higher shock volatility in a period means that data in the period receive less weight in the model's likelihood function and hence has less influence on parameter estimates.

What drives the downward revision?

By incorporating variance breaks, we allow for more of the large changes in output, inflation and unemployment during the pandemic to be driven by shocks (Graph 3). For example, post-pandemic inflation is driven more by shocks to the Phillips curve than by changes in the output gap (relative to the DT22 version). Similarly, Okun's Law also attributes less of the movement in unemployment to the output gap and more to unemployment shocks. This results in an estimated output gap that varies less and is less positive over the post-pandemic period (Graph 4). The model infers the neutral rate from the output gap, with a relation that suggests expansionary policy increases the output gap. With a lower output gap, policy appears to be less expansionary during the pandemic period. Because the neutral rate is persistent, that tightness carries over to recent periods, so the neutral rate is currently estimated to be lower.

Graph 3

Smoothed Shocks to the Signal Equations*

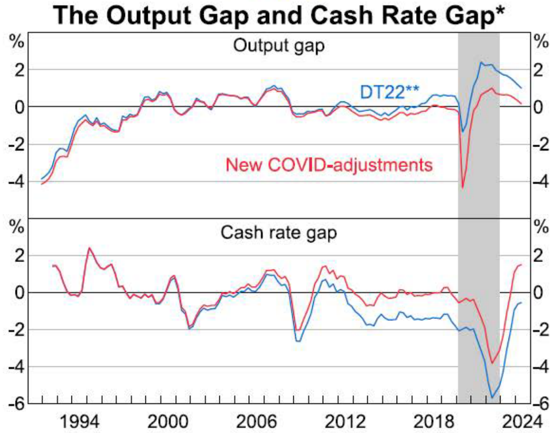


* Smoothed shocks are calculated as residuals in the IS curve, Phillips curve, and Okun's law. For output and inflation, these shocks are derived from the three models in McCririck and Rees (2017) suite. For the unemployment rate, the shocks are derived from the unemployment model only. Shaded area represents the pandemic period.

Source: RBA.

Graph 4

The Output Gap and Cash Rate Gap*



* Average of the smoothed estimates from the three models in McCririck and Rees (2017). All models are estimated using ex-post real cash rate. Shaded areas represent the pandemic period.

Source: RBA.

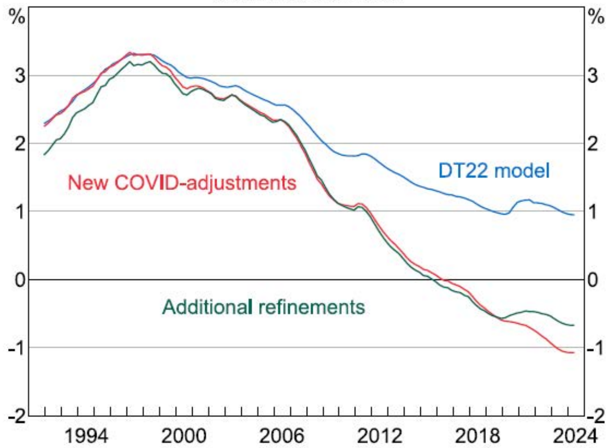
Other model refinements

In addition to the COVID-19 adjustments, we consider two further refinements to the MR17 models: 1) using an *ex-ante* real cash rate (nominal cash rate minus trend inflation expectations) instead of an *ex-post* measure (nominal cash rate minus year-ended trimmed mean inflation);[8] and 2) allowing the relationship between trend output growth and the neutral rate to be estimated (rather than calibrated), consistent with HLW23. Together, these changes slightly offset the downward revision due to incorporating variance breaks (Graph 5). As a result, the estimated neutral rate for 2024Q2 shifts up from –1 per cent to –0.7 per cent in the final refined estimates. Detailed information about each model refinement and their incremental effects on the estimates can be found in Appendix II.

Graph 5

Real Neutral Rate*

Smoothed estimates



* Average of the smoothed estimates from the three models in McCririck and Rees (2017).

Source: RBA.

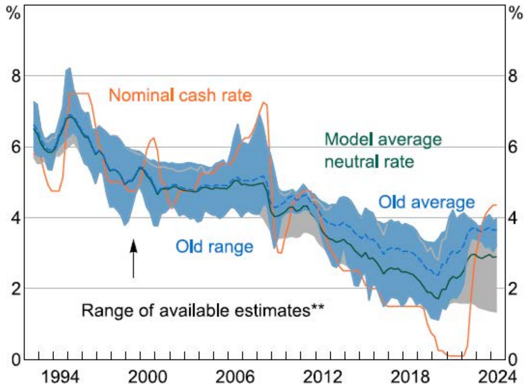
8 There are differing opinions on which horizon should be used for inflation expectations. Economic theory would suggest a shorter horizon than the 'trend' variable we use. However, in recent years the Bank has typically used trend inflation expectations when calculating *ex-ante* rates, so we follow this practice. Whether other measures of inflation expectations yield different results is an avenue for further work.

Implications for our preferred estimates

While the refined models yield substantially lower estimates than the DT22 versions, the effect on SAMM's preferred measure, which is the model average over the broader suite, is smaller; the model average for the nominal neutral rate decreases from 3.6 per cent to 2.9 per cent in 2024Q2 (Graph 6). Over most of the sample period, the range of estimates from the model suite – which we often report to convey uncertainty around the central estimate – is broadly consistent with the previous range, though the range is wider during the GFC and post-pandemic periods.

Graph 6

Nominal Neutral Rate*



* Nominal neutral rates are defined using trend inflation expectations.

** Range of central estimates corresponding to available models; this range does not reflect considerable uncertainty around the central estimates.

Source: RBA.

The refined estimates are more closely aligned with new external estimates of the neutral rate in Australia and with estimates in some peer economies.[9] While the new estimates may suggest that monetary policy is a bit more restrictive, it remains the case that monetary policy in Australia is less restrictive compared with other central banks at the peak of their tightening cycles (Table 1). However, as some central banks begin to cut rates, Australia's policy stance is converging with other advanced economies, based on a comparison of current policy rates against their nominal neutral rate estimates.

Table 1: Estimates of the neutral rate

Central bank estimates ranked by the gap between current policy rate and nominal neutral rate [(a)]

	Current policy rate (%)	Nominal neutral rate (%)	Difference (ppts)	Difference at peak rate (ppts)
Norway	4.5	2.5	2	2
New Zealand[(b)]	4.25	2.5	1.75	3
US[(b)]	4.5	2.8	1.7	2.58
Australia (new)	4.35	2.9	1.45	1.45
Euro area[(b)]	3	2	1	2
Australia (old)	4.35	3.6	0.75	0.75
Canada[(b)]	3.25	2.75	0.5	2.25
Sweden[(b)]	2.75	2.5	0.25	1.5

(a) Estimates of the nominal neutral rate for other central bank are taken from (2024). Policy rates are updated to December 2024.

(b) These jurisdictions' central banks have already cut their policy rates, by 100 basis points (euro area and US), 125 basis points (Sweden and New Zealand) and 175 basis points (Canada).

Sources: Central banks; RBA

Economic Analysis and Economic Research Departments

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9 estimate neutral rates for small open economies using a multivariate Beveridge-Nelson decomposition. Their estimate of the real neutral rate in Australia is close to zero. The nominal neutral rates for peer economies in Table 1 are also consistent with real neutral rates close to zero.

Appendix I

1. Models with updated COVID-19 adjustments

The MR17 model are based on the models from Holston, Laubach and Williams (2017) (HLW) and have three specifications:

1. The HLW model (the *lagged inflation* model).
2. The HLW model with the inclusion of an Okun's law equation and the unemployment gap (the *unemployment* model).
3. The HLW model with the inclusion of import price inflation (π_t^m) as an additional observable variable in the Phillips Curve equation (the *import price* model).

Below we describe the benchmark model that includes the unemployment gap (the *unemployment* model) with the COVID-19 adjustments (via the lockdown stringency index) from DT22. Similar adjustments are applied to the other models.

COVID-related restrictions

Following DT22, we adjust the output gap to control for the effect of the lockdowns, based on a stringency index d_t, with coefficient ϕ:

$$COVID\text{–}adjusted\ output\ gap = 100 * (y_t - y_t^*) - \phi d_t = \tilde{y}_t - \phi d_t$$

Measurement equations

IS curve:

$$\tilde{y}_t - \phi d_t = a_{y,1}(\tilde{y}_{t-1} - \phi d_{t-1}) + a_{y,2}(\tilde{y}_{t-2} - \phi d_{t-2}) + \frac{a_r}{2}\sum_{j=1}^{2}(r_{t-j} - r_{t-j}^*) + \varepsilon_t^{\tilde{y}}$$

Phillips curve:

$$\pi_t = \beta_1 \pi_{t-1} + \frac{(1-\beta_1)}{3}\sum_{i=2}^{4}\pi_{t-i} + \beta_2(\tilde{y}_{t-1} - \phi d_{t-1}) + \varepsilon_t^{\pi}$$

Okun's law:

$$u_t = u_t^* - \beta(0.4(\tilde{y}_t - \phi d_t) + 0.3(\tilde{y}_{t-1} - \phi d_{t-1}) + 0.2(\tilde{y}_{t-2} - \phi d_{t-2}) + 0.1(\tilde{y}_{t-3} - \phi d_{t-3})) + \varepsilon_t^u$$

State equations

Potential output:

$$y_t^* = y_{t-1}^* + g_t + \varepsilon_t^{y^*}$$

Potential output (trend) growth:

$$g_t = g_{t-1} + \varepsilon_t^g$$

NAIRU:

$$u_t^* = u_{t-1}^* + \varepsilon_t^{u^*}$$

The neutral rate driven by trend growth and 'other determinants' z_t which is a catch-all for all other factors that can affect the neutral rate:

$r_t^* = 4 \times g_t + z_t$The latent factor z_t is a random walk process:

$$z_t = z_{t-1} + \varepsilon_t^z$$

2. Parameter Estimates

Table A1: Parameter estimates in MR17, DT22 and with updated COVID-19 adjustments

(*Unemployment* model, with *ex-post* real rate)

Parameter	**Posterior**			**Prior**		
	Mean (MR17)	**Mean (DT22)**	**Mean (Updated COVID-19 adjustment)**	**Distribution**	**Mean**	**Std dev.**
Structural parameters						
IS curve - $\tilde{y}_{t-1}$	1.48	1.28	1.47	Normal	1.10	1.50
IS curve - $\tilde{y}_{t-2}$	-0.53	-0.35	-0.52	Normal	-0.20	1.50
IS curve - $r_t(L) - r_t^*(L)$	-0.06	-0.06	-0.06	Inverse Gamma	0.15	1.00
Phillips curve - $\pi_t(L)$	0.41	0.51	0.52	Beta	0.50	0.25
Phillips curve - $u_{t-1} - u_{t-1}^*$	-0.33	-0.35	-0.35	Normal	-0.50	0.30
Okun's law - $\tilde{y}_t(L)$	0.64	0.66	0.66	Normal	0.50	0.30
Shock processes						
IS curve	0.37	0.53	0.34	Inverse Gamma	1.00	1.00
Phillips curve	0.80	0.87	0.78	Inverse Gamma	1.00	1.00
Unemployment	0.07	0.02	0.06	Inverse Gamma	0.25	0.25
Trend output	0.55	0.46	0.52	Inverse Gamma	1.00	1.00
NAIRU	0.15	0.20	0.15	Inverse Gamma	0.40	0.25
Trend growth	0.05	0.05	0.05	Inverse Gamma	0.25	0.50
Other determinants	0.34	0.28	0.34	Inverse Gamma	0.40	0.25
COVID-19 variables						
Stringency index		-0.07	-0.05	Normal	-0.05	0.5
Variance scale factors						
κ_{2020}^{y}			10.3	Normal	9	5
κ_{2021}^{y}			2.2	Normal	3	2
κ_{2022}^{y}			2.0	Normal	3	2
κ_{2020}^{π}			4.3	Normal	9	5
κ_{2021}^{π}			2.5	Normal	3	2
κ_{2022}^{π}			4	Normal	3	2
κ_{2020}^{u}			6.9	Normal	9	5
κ_{2021}^{u}			3	Normal	3	2
κ_{2022}^{u}			2.5	Normal	3	2

Note: Estimates of the parameters of the MR17 model is drawn from . DT22 and the updated COVID-19 adjusted models are estimated using data up to 2024Q2.

Appendix II

Switching to an *ex-ante* real cash rate

The previous versions of the model use the *ex-post* real cash rate (nominal cash rate minus year-ended trimmed mean inflation) to measure the real interest rate. However, there are good reasons to use an *ex-ante* real cash rate (nominal cash rate minus trend inflation expectations), because theory and empirical evidence point to an important role for expectations in decision-making. While *ex-post* and *ex-ante* measures have typically moved together closely, they diverged significantly during the post-pandemic period of high inflation. Estimating the refined COVID-adjusted model described above (which uses an *ex-post* cash rate) with an *ex-ante* cash rate indicates a slightly higher neutral rate post-pandemic, as the *ex-ante* rate has been consistently higher than the *ex-post* rate during this period (Graph 7).

Estimating the relationship between trend output growth and the neutral rate

Finally, we follow HLW23 and relax the assumption in MR17 and DT22 of a one-for-one relationship between trend output growth and the neutral rate.[10] The process for the neutral rate is now given by

$r_t^* = c \times 4 \times g_t + z_t$where g_t is potential output growth and z_t are 'other determinants' of the neutral rate. The parameter c controls the strength of the relationship between trend growth and the neutral rate. The *unemployment* model estimates c to be around 0.9, implying a slightly weaker connection between potential output growth and the neutral rate than previously assumed. This effect of this refinement on the neutral rate estimates is very modest (Graph 8).

10 Empirical evidence suggests the relationship between the neutral rate and trend growth may not be as strong as commonly assumed (e.g., Hamilton *et al* 2016; Lunsford and West 2019; Kiley 2019).

Table A2: Parameter Estimates with Additional Model Refinements

(the *unemployment* model, with ex-ante real rate)

Parameter	Posterior		Prior		
	Mean (Ex-ante)	Mean (Final model)	Distribution	Mean	Std dev.
Structural parameters					
IS curve - $\tilde{y}_{t-1}$	1.42	1.42	Normal	1.10	1.50
IS curve - $\tilde{y}_{t-2}$	-0.46	-0.47	Normal	-0.20	1.50
IS curve - $r_t(L) - r_t^*(L)$	-0.06	-0.06	Inverse Gamma	0.15	1.00
Phillips curve - $\pi_t(L)$	0.52	0.52	Beta	0.50	0.25
Phillips curve - $u_{t-1} - u_{t-1}^*$	-0.36	-0.36	Normal	-0.50	0.30
Okun's law - $\tilde{y}_t(L)$	0.67	0.66	Normal	0.50	0.30
Shock processes					
IS curve	0.36	0.37	Inverse Gamma	1.00	1.00
Phillips curve	0.78	0.78	Inverse Gamma	1.00	1.00
Unemployment	0.06	0.06	Inverse Gamma	0.25	0.25
Trend output	0.51	0.51	Inverse Gamma	1.00	1.00
NAIRU	0.16	0.16	Inverse Gamma	0.40	0.25
Trend growth	0.05	0.05	Inverse Gamma	0.25	0.50
Other determinants	0.37	0.38	Inverse Gamma	0.40	0.25
COVID-19 variables					
Stringency index	-0.05	-0.05	Normal	-0.05	0.5
Variance scale factors					
κ_{2020}^{y}	10.6	9.9	Normal	9	5
κ_{2021}^{y}	2.2	2.2	Normal	3	2
κ_{2022}^{y}	2.0	1.9	Normal	3	2
κ_{2020}^{π}	4	3.3	Normal	9	5
κ_{2021}^{π}	2.4	2.2	Normal	3	2
κ_{2022}^{π}	3.8	3.5	Normal	3	2
κ_{2020}^{u}	7.5	11	Normal	9	5
κ_{2021}^{u}	3.7	3.5	Normal	3	2
κ_{2022}^{u}	2.5	2.4	Normal	3	2

NOTE EA: USING LABOUR MARKET INDICATORS TO SUPPORT REVISIONS TO THE NAIRU[1]

Labour market indicators other than the unemployment rate may provide corroborating evidence to support updates to our NAIRU assumption. I consider the statistical relationship between various indicators and the unemployment gap. I find that many indicators have had a reasonably tight relationship with the unemployment gap over time. I also find that in aggregate, recent levels of most indicators point to a slightly lower estimate of the NAIRU relative to our February 2025 SMP staff assumption, though there is variability across indicators. This is the first of a series of notes using labour market indicators to assess full employment.

Motivation

EC's assumption of the NAIRU is a key input into the forecasting process. The assumption is revised quarterly based on updates to model estimates from SAMM's suite of NAIRU models and staff judgement. The main labour market slack variable that is used in the model suite is the unemployment (and underutilisation) rate . [2] Yet, labour market indicators other than the unemployment rate may provide additional information about the degree of labour market tightness (RBA Review). While this information may informally feed into staff judgement, a formal approach provides a more transparent way to corroborate revisions to the NAIRU assumption.

Approach

I consider a simple way to extract information from other labour market indicators about the unemployment gap. The exercise is statistical, and largely agnostic about the underlying mechanism that links each indicator to measures of tightness.[3] I use the set of indicators used in the SMP for assessing labour market spare capacity introduced in Ballantyne, Sharma & Taylor (2024), as well as several other measures that have some predictive power in forecasting wages and inflation (Table 1)

Table 1: Indicators of labour market tightness

	Start date	Frequency	Source
Medium-term unemployment rate	January 1991	Monthly	ABS
Youth unemployment rate	February 1978	Monthly	ABS
Vacancies-to-unemployment rate[(a)]	May 1979	Quarterly	ABS
Share of firms reporting labour constraints[(a)(b)]	September 1989	Quarterly	NAB
Non-mining capacity utilisation	March 1997	Monthly[(c)]	NAB
Hires rate	August 1984	Quarterly	ABS
Quits rate	August 1986	Quarterly	ABS
Layoff rate	August 1986	Quarterly	ABS
Weekly hours per capita	July 1978	Monthly	ABS
Job ads (as share of labour force)	January 2006	Monthly	JSA
Liaison employment intentions	January 2003	Monthly	RBA

(a) Log transformation as it fits the data better, consistent with past academic work (Barnichon & Shapiro 2024).
(b) The results are similar when using the share of firms reporting *significant* labour constraints, though the fit is slightly poorer.
(c) There is a quarterly series commencing from September 1989, but it is less timely.

For each indicator, I construct the NAIRU estimate that is implied by the current level of each indicator. To do so, I regress the unemployment gap ($u_t - u_t^*$) on each indicator (x_j) and a linear time trend (t):

$$(u_t - u_t^*) = \alpha_j + \beta_j x_{jt} + \gamma_j t + \varepsilon_{jt}$$

which includes a constant (α_j), a coefficient (β_j) for the indicator, a coefficient (γ_j) for the time trend and an error term (ε_{jt}). The linear time trend is designed to account for any structural (but linear) trend in the indicator over time. I adopt a linear trend rather than a more sophisticated trend technique to keep the

1 I would like to thank and for feedback.
2 The exception is the labour slack model which also includes job ads, vacancies and labour constraints
3 See for a discussion of the theoretical basis of some measures.

approach simple and transparent, though other methods, such as state-space approaches, will be considered in future work. In the default specification, I use the unemployment gap derived from the smoothed model average of SAMM's suite.[4] I then use the fitted values from each regression to construct an implied unemployment gap ($u_t - u^*_{jt} = \hat{\alpha}_j + \widehat{\beta_j}\, x_t + \hat{\gamma}_j t$) and an implied NAIRU estimate based on each indicator ($u^*_{jt} = u_t - (\hat{\alpha}_j + \hat{\beta}_j x_t + \hat{\gamma}_j t)$).[5]

This exercise complements the approach by who use an unobservable components model to extract a common signal from a subset of these indicators (specifically job ads, vacancies and labour constraints) in a Phillips curve framework. Their approach allows for non-linear trends and directly links indicators to nominal variables. In contrast, the approach in this note considers a broader range of indicators and focuses on how each indicator individually relates to the unemployment gap.[6]

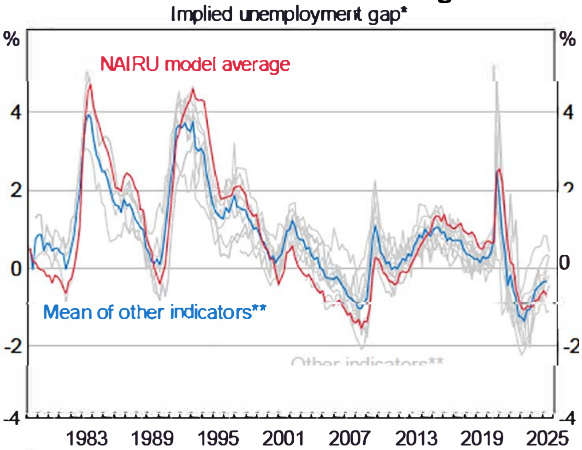
Results and assessment

There is a reasonably tight historical relationship between the unemployment gap and implied gaps using the indicators (Graph 1). The overall model fit, or R^2, is one way to gauge the appropriate weight to place on each indicator in proxying for the NAIRU. A more direct way to determine the relevance of each indicator for full employment would be based on how well each indicator explains inflation or wages, independent of the unemployment gap, which we explore in a coming note. The R^2 values suggests that alternative unemployment rate measures, job ads and average hours per capita have the strongest fit (Graph 2). However, the job ads series has a shorter back history (commencing from 2006) than other indicators, and thus has less data from which to assess model fit (Table 1). In contrast, employment intentions, non-mining capacity utilisation and the hires rate have the poorest fit. Employment intentions likely has a poor fit because it is under-weighted in its coverage of the non-market sector where there has been recent strong employment growth; when excluding the post-2020 period (blue dots), the fit is substantially better. The fit for most indicators is poorer when the time trend is excluded (red dots), particularly for the quits rate, hires rate and the vacancies-to-unemployment ratio (Graph A3). This implies that using historical benchmarks for these variables, such as the series mean, may lead to misleading conclusions about spare capacity.

Graph 1

Indicators of Labour Market Tightness

Implied unemployment gap*

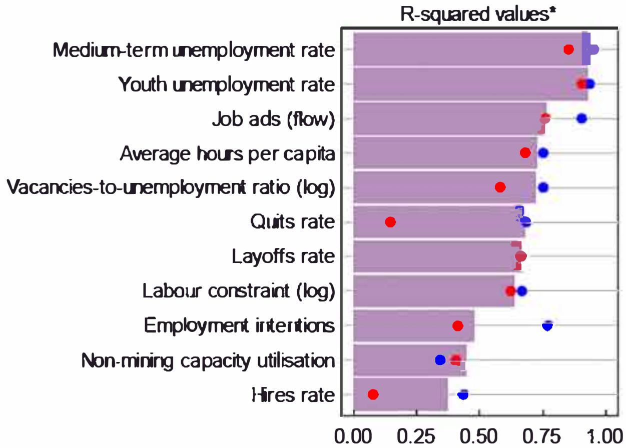


* Gaps constructed by regressing the unemployment gap on the indicator and a linear time trend.
** Other indicators include hours per capita, quits, hires, layoffs, vacancies-to-unemployment, non-mining capacity utilisation, labour constraints, youth unemployment, medium-term unemployment, job ads and employment intentions.
Source: RBA.

Graph 2

Model Fit

R-squared values*



* Blue dots use pre-2020 sample only, red dots do not use a time trend.
Source: RBA.

The most recent levels of indicators point towards a slightly lower estimate of the NAIRU relative to our February 2025 SMP staff assumption of 4.5 per cent (Graphs 3 and 4). The mean of the implied NAIRU

4 Results are similar when using the one-sided estimates (Graph A4). See Graph A5 for results using other models in SAMM's suite.

5 An intuitive way to interpret the case when an indicator-based NAIRU estimate deviates from our model-based estimates, is that either the indicator is deviating from its typical relationship with nominal outcomes and we should take no signal about tightness from the indicator, or the indicator is following its typical relationship with nominal outcomes, and we should expect the model-based estimates to revise in response to unexpected nominal outcomes. The implied estimates assume the latter.

6 An alternative approach is to include all indicators in a multivariate OLS regression. While this may provide a more accurate prediction of the unemployment gap, it raises multicollinearity concerns that makes. Future work could also consider expanding the labour gap model to capture more indicators though there are potential trade-offs to tractability and interpretability.

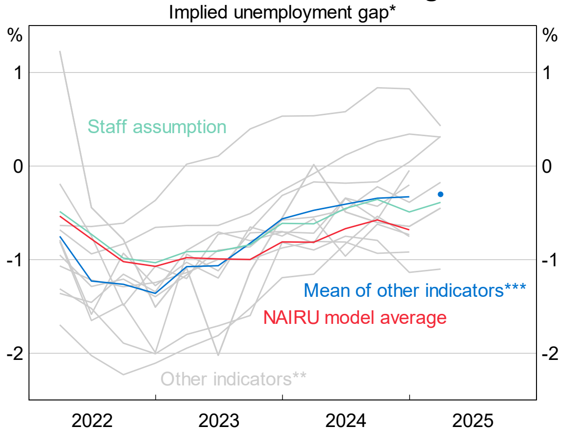
estimates is 4.3 per cent (and 4.4 per cent if weighting the series by R^2 values). The Appendix shows each individual series and the implied level consistent with full employment (Graphs A1 and A6-8). An important caveat is that the implied levels are assumed to be linear, unlike (2023) which allow for flexible structural trends.

While some indicators suggest a lower NAIRU estimate than others, these tend to be series with a poorer fit (employment intentions, hires rate and capacity utilisation) or a short back history (job ads). However, the quits rate is one exception that has a decent fit and is suggesting a lower NAIRU estimate than the staff assumption. Indeed, the recent decline in the quits rate was part of the explanation behind the risk that we have misjudged the extent of labour market spare capacity in the February 2025 SMP (see Key risk #1).

Graph 3

Indicators of Labour Market Tightness

Implied unemployment gap*



* Gaps constructed by regressing the unemployment gap on the indicator and a linear time trend.

** Other indicators include hours per capita, quits, hires, layoffs, vacancies-to-unemployment, non-mining capacity utilisation, labour constraints, youth unemployment, medium-term unemployment, job ads and employment intentions.

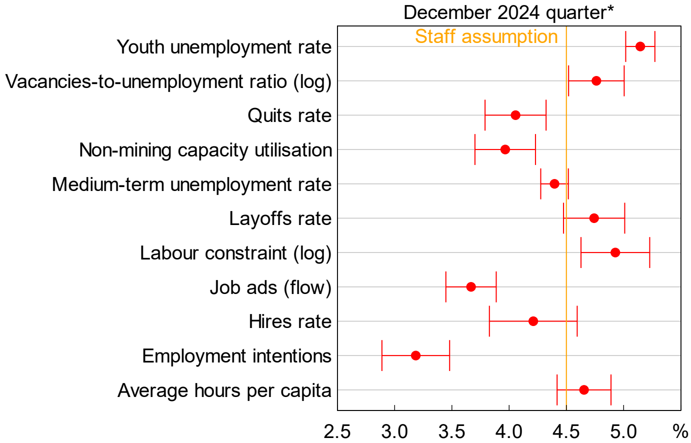
*** Dot shows the mean using the most recent value of each indicator.

Source: RBA.

Graph 4

Implied NAIRU Estimate

Based on value of indicator in December 2024 quarter*



* Range indicates 95 per cent confidence interval.

Source: RBA.

Robustness check

The default specification uses all available data to estimate the model, and thus recent outcomes affect the estimate of the model. As a robustness check, I re-run the regressions only estimating the model using data before 2020 (see Appendix). Restricting the estimation to pre-2020 acts as an out-of-sample prediction of the NAIRU using each indicator. This is particularly useful when there is uncertainty about the current level of spare capacity, which has been recently discussed in the February 2025 SMP and in

When restricting the estimation to before 2020, the implied NAIRU estimates vary for some indicators but overall, the indicators continue to imply a NAIRU estimate that is slightly below the staff assumption (Graph A2).

Conclusion and future work

The approach provides a simple and transparent way to determine if current estimates of the NAIRU are consistent with the level of other labour market indicators. This approach is useful in determining if recent periods are unusual relative to history, but *not* whether labour market indicators or the NAIRU itself is a good proxy of labour market slack. Importantly, the approach does *not* provide an independent assessment of full employment to the NAIRU suite, given that it assumes that the NAIRU series is the desired series to track on average over time. A more rigorous and independent approach to assess the relevance of each indicator for assessing full employment is by linking it directly to nominal variables (similar to

but estimating the independent signal from each variable), consistent with how we defined full employment in our mandate. This will be the focus of a coming note. A 'full-employment consistent' level or gap of an indicator can then be constructed. This approach also allows for an alternative weighting scheme to summarise the information from other indicators, such as using the root mean squared error in a Phillips curve framework, instead of the simple mean shown in the charts above.

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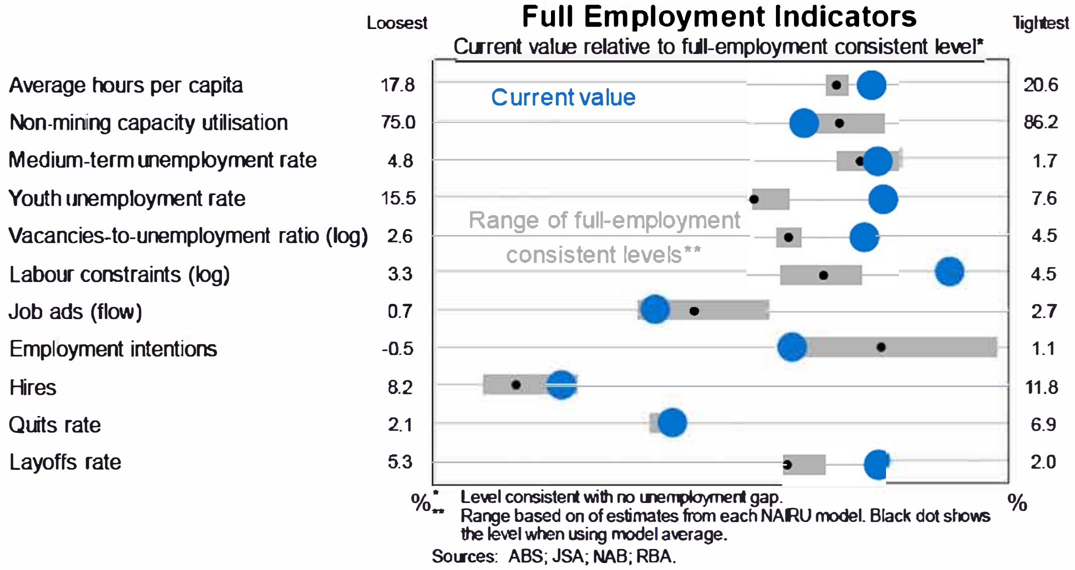
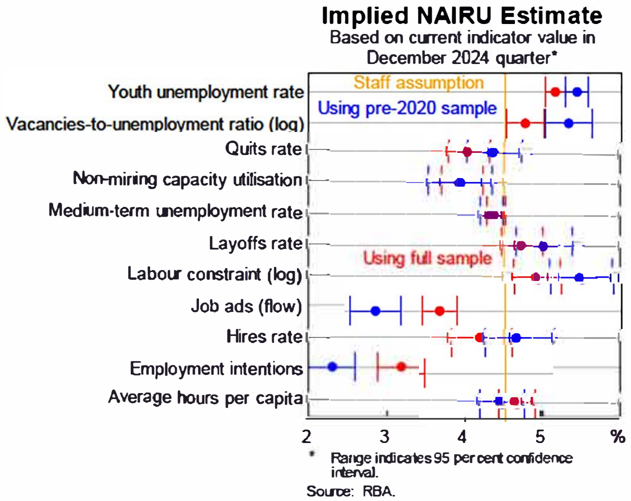
Appendix

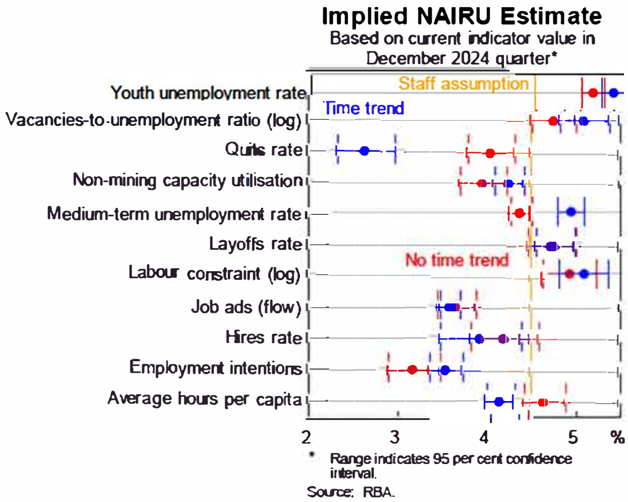
Graph A1



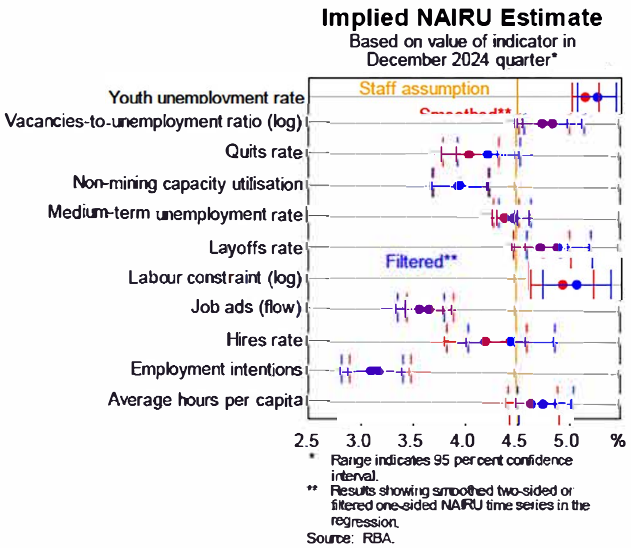
Graph A2



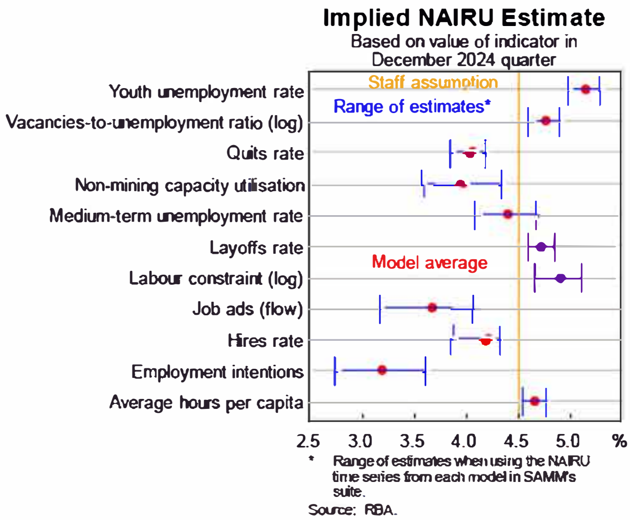
Graph A3



Graph A4



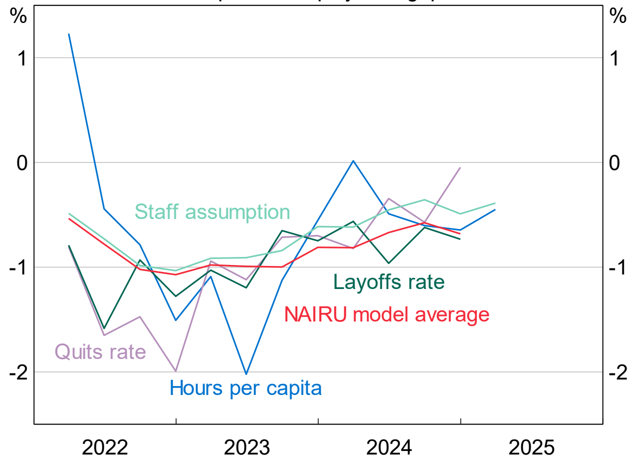
Graph A5



Graph A6

Indicators of Labour Market Tightness

Implied unemployment gap

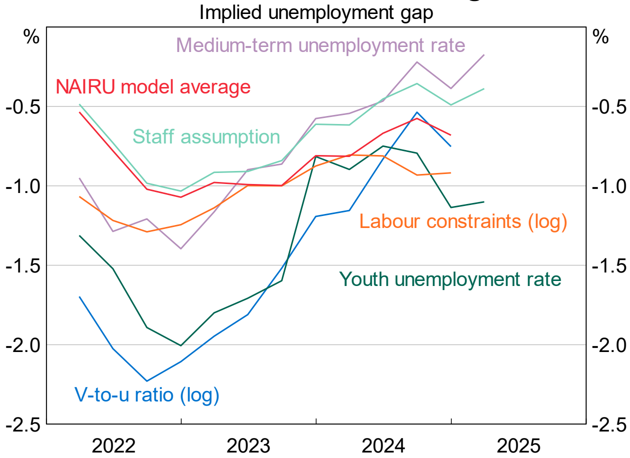


Source: RBA.

Graph A7

Indicators of Labour Market Tightness

Implied unemployment gap

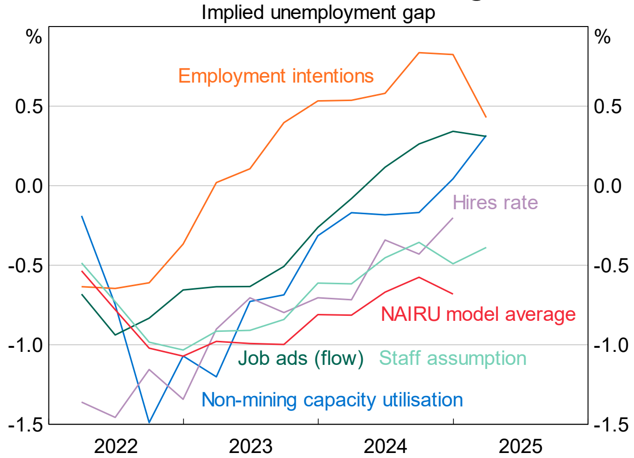


Source: RBA.

Graph A8

Indicators of Labour Market Tightness

Implied unemployment gap



Source: RBA.

FULL EMPLOYMENT UPDATE – MARCH QUARTER 2025[1]

This document details the impact of new data on the NAIRU for the March quarter 2025. The model average NAIRU estimate increased from 4.69 per cent at the time of May SMP to 4.83 per cent. The 14 bps increase reflects the flow of new data (+6 bps) and data revisions (+8 bps).

This note focuses on mechanical changes in the model estimates due to data updates and technical revisions; a more thorough update to the central estimates used in constructing the economic outlook will be provided at the start of the next forecast round.

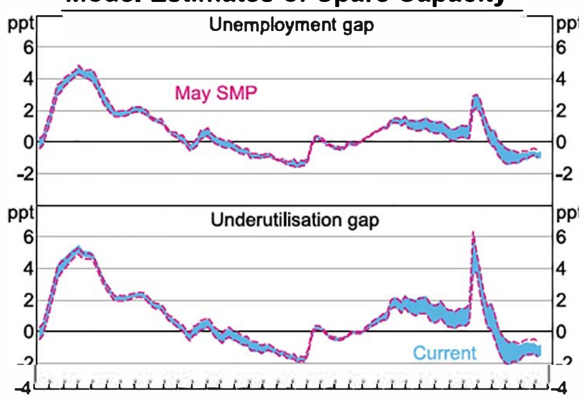
Labour gaps

Our suite of models indicates that the **unemployment gap remains negative, roughly between -1 to -0.6 per cent**, and has widened slightly relative to the May SMP (Graph 1). The widening primarily reflects upwards movement of the NAIRU estimates. The underutilisation gap also remains negative, with the range widening to roughly between -1.5 and -0.8 per cent. This was largely driven by an increase in the minimum NAIRLU estimate.

The model average NAIRU estimate, which is SAMM's preferred model-based estimate, increased from 4.69 per cent at the time of May SMP to 4.83 per cent (Graph 2). The model estimates remain high relative to estimates from the RBA survey of market economists . The 14bps increase in the model-based estimate of the NAIRU reflects new data for the March quarter (+6bps) and historical revisions (+8bps) (both capture the March quarter National Accounts release). There is no specific driver of the historical revisions; it reflects broad-based upwards revisions from data and possible parameter changes.

Graph 1

Model Estimates of Spare Capacity*

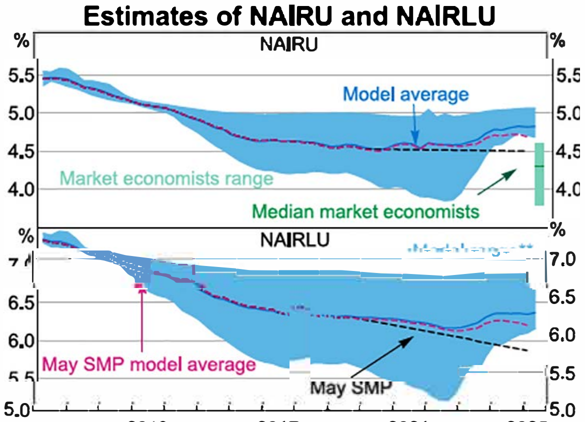


* Blue-shaded region shows illustrative range of central gap estimates from a selection of models; estimates are subject to substantial uncertainty, as well as revision due to data and model refinements.

Sources: ABS; RBA; Ruberl et al (2021).

Graph 2

Estimates of NAIRU and NAIRLU



* Using model-predicted values for the 2023Q3 observations for WPI and AENA.

** The 'Model range' refers to the range between the lowest and highest NAIRU central estimate from a suite of 6 NAIRU models.

Source: RBA.

Table 1: Model Estimates

	MAY SMP *2024Q4*	Post-National Accounts *2025Q1*
NAIRU	4.69	4.83
NAIRLU	6.20	6.36

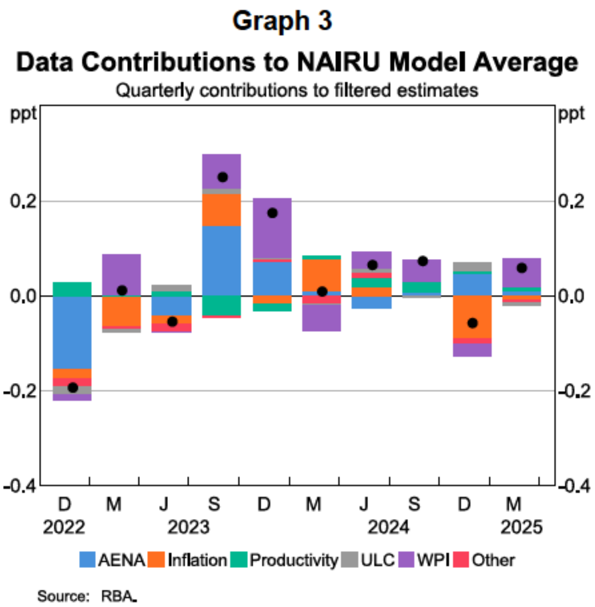
1 We would like to thank SAMM for help with the contents of this note.

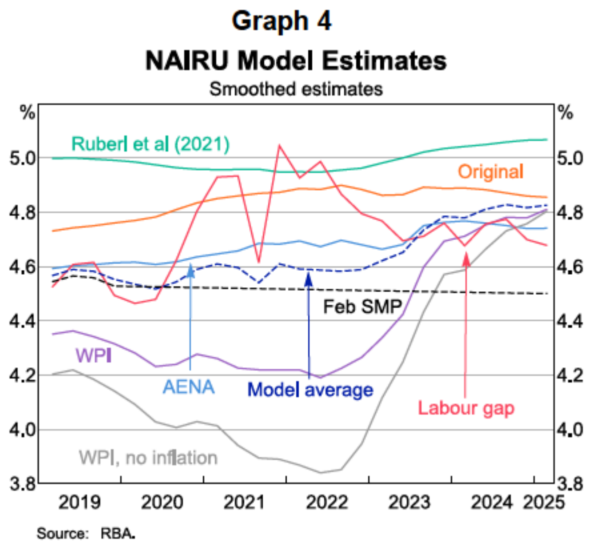
Contributions of new data

Information in the March quarter contributed to a 6 bps increase in the NAIRU model average (Graph 3). This was driven by the WPI outcome coming in above the model predictions, with other data making offsetting contributions.

The NAIRU model range for the March quarter tightened from our May SMP estimate of the December quarter. This was primarily due to an upwards revision of the labour gap model estimate – which has been one of the lowest estimate for the past couple of quarters. Over the past couple of quarters, the model range has widened due to downwards movement at the bottom of the estimates, whereas the maximum estimate has only increased marginally.

The positive contribution of new data to the NAIRU model average in the March quarter unwinds the decrease from the December quarter (Graph 3). Increases in the model average over the past two years have been primarily driven by the two WPI models (Graph 4).





SAMM
6 June 2025