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Recent Developments in Small Business Economic and Financial Conditions

Nick Harvey, Paul Hutchinson and Gulnara Nolan*



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Abstract

Economic conditions for small businesses have weakened over the past year and business confidence has fallen. Higher input cost growth, higher interest rates and weaker demand are putting pressure on profit margins as businesses are unable to fully pass through cost increases to prices. Availability of finance had improved for small businesses in recent years, driven in part by greater competition among banks and non-banks, and growth in credit for small and medium enterprises (SMEs) was strong. Despite this, some small businesses continued to report difficulties in obtaining finance that suits their needs. This article discusses recent trends in economic and financial conditions for small businesses, drawing on insights from the RBA's 34th Small Business Finance Advisory Panel.

Introduction

This article provides an update on the economic environment and availability of finance for small businesses. It draws on information from the RBA's 34th annual Small Business Finance Advisory Panel held in August 2026, the RBA's regular liaison program, economic indicators, business surveys and data from financial institutions.[1]

Understanding developments in economic and financial conditions for small businesses is important because small businesses account for a large share of output, employment and income in the Australian economy (Commonwealth of Australia 2025; Chan, Chinnery and Wallis 2023). Small businesses can also face greater challenges accessing finance, which can hamper their growth and limit their ability to innovate (Jones 2024).

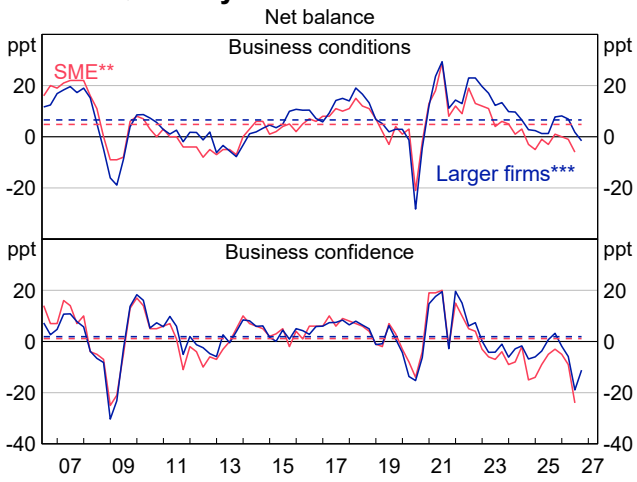
Economic conditions for SMEs

Panellists from the Small Business Finance Advisory Panel highlighted a range of challenges for small businesses in the current economic environment, consistent with information from the RBA's liaison program and broader macroeconomic trends. Panellists generally reported that customer demand had weakened over the past year, particularly in the discretionary spending and interest-sensitive sectors. They also reported broad-based input cost pressures and a limited ability to pass these on to customers amid weak demand. Instead, panellists reported absorbing higher costs through compressed margins and/or seeking to cut costs by reducing waste or cutting labour hours. Several noted that artificial intelligence (AI) had led to productivity improvements and cost savings.

Survey measures of business conditions declined this year and were below their long-run averages and much weaker for SMEs than for larger firms in the June quarter (Graph 1).[2] Weaker business conditions reflected softer profitability and trading conditions (such as turnover and gross earnings), consistent with slowing growth in domestic demand (NAB 2026a; NAB 2026b; RBA 2026a). Business confidence deteriorated to well below long-run average levels and was lower for SMEs than for larger firms. The fall in reported confidence reflected uncertainty stemming from the Middle East conflict, recent government policy changes and higher interest rates (NAB 2026a). Panellists also noted that similar factors were weighing on confidence.

Graph 1

Quarterly Business Sentiment*



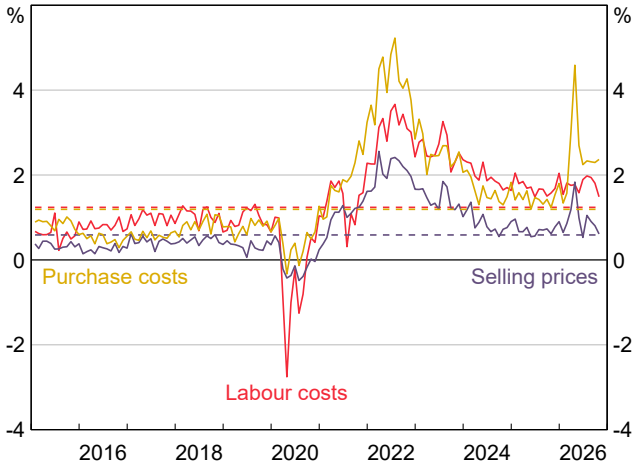
* Dashed lines represent the long-term average of each series from 2006.
** 'SME' represents small and medium enterprise responses from the NAB SME Business Survey.
*** 'Larger firms' represents larger firm responses from the NAB Quarterly Business Survey.
Sources: NAB; RBA.

Input costs and profit margins

Input cost pressures have been broadly based, reflecting both capacity pressures in the domestic economy and global cost pressures related to the Middle East conflict. Panellists noted that input cost growth had increased over the past year, particularly for freight, labour, materials and land.

Many firms in the RBA's liaison program report that higher input costs are putting pressure on profit margins (RBA 2026a).[3] Survey data suggests that selling prices have not grown as fast as labour and purchase costs (Graph 2). Similarly, panellists reported that a limited scope to pass cost increases through to customers had put pressures on their profit margins. Several had instead looked for ways to reduce costs, such as by reducing waste, tightening inventory, and cutting labour hours.

Graph 2
Purchase and Labour Costs, and Selling Prices*



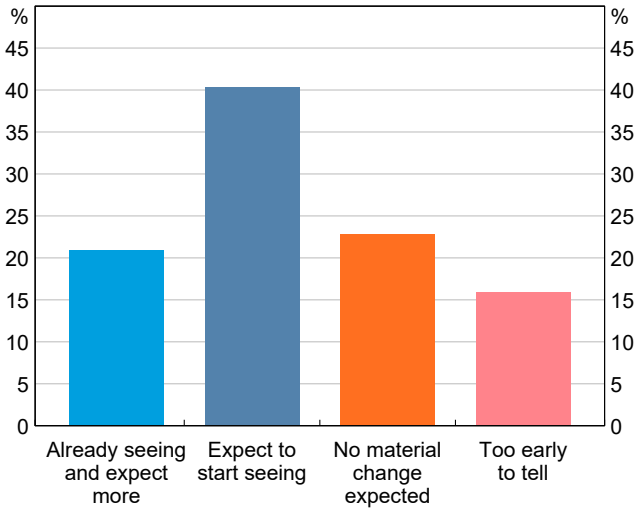
* Average of respondent's monthly per cent changes at a quarterly rate; dashed lines represent the long-term average of each series from 1997 onwards. Sample includes firms of all sizes.
Sources: NAB; RBA.

Use of AI

Several panellists noted that AI has supported cost reduction and productivity improvement in some areas of their businesses. They have used AI for some tasks previously undertaken by external contractors or permanent staff, particularly in marketing, administration, and basic legal and accounting functions.

Similarly, survey data indicate that AI use among SMEs is widespread and increasing, although its integration into business processes generally remains limited. In one recent survey, around half of SMEs reported using AI tools to assist with administrative tasks or forecast cash flows (Prospa 2026). And in Macquarie University's Business Outlook Scenarios Survey (BOSS), more than two-thirds of SMEs reported some use of AI in their operations. In that survey, around one in five SMEs reported that they have experienced material efficiency gains in their regular operations because of AI use, and a further two-fifths expected to start seeing material efficiency gains over the coming year (Graph 3). Many businesses in the RBA's liaison program (which covers businesses of all sizes) report that they are in the early stages of incorporating AI into their business processes. To date, firms have reported mixed experiences with AI's impact on productivity and most have reported no impact on their headcount (RBA 2026b). Several panellists and liaison contacts reported that implementation costs, technology requirements, and risk and governance concerns remain barriers to more extensive AI adoption.

Graph 3
Expected Efficiency Gains from AI over the Next 12 Months*
Share of SMEs



* Survey question: "Thinking about your business's current or planned use of AI, do you expect AI to deliver material efficiency gains in your regular business operations over the next 12 months?".
Sources: Macquarie University; RBA.

Financial stress for small businesses

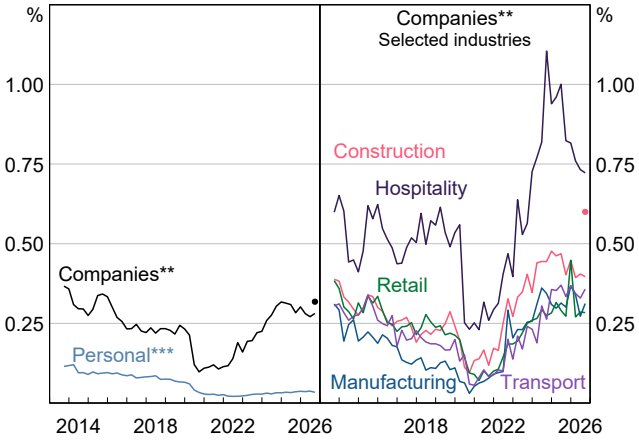
Financial stress is expected to increase for smaller businesses amid the weakening in economic conditions, increase in interest rates and pressure on profit margins (RBA 2026c). The rise in financial stress is likely to be more pronounced for smaller than larger businesses, particularly among more cyclical industries, such as construction, hospitality and retail, and energy-intensive businesses, such as those in transport and manufacturing, which are more exposed to cost increases related to the Middle East conflict.

To date, increased financial stress has not been widely evident in rates of insolvency (RBA 2026c). Rates of company insolvency generally declined a little since early 2025, after earlier increases following the pandemic, and rates of personal insolvency of business owners remain low (Graph 4). However, weaker economic conditions and pressure on margins may not yet be fully captured in current insolvency rates, since insolvency represents the final stage of severe financial stress for firms. Rates of insolvency are highest in the construction, hospitality and transport sectors, which are more exposed to recent wage and input cost pressures.

Graph 4

Business Insolvency Rates*

Quarterly; seasonally adjusted



* Latest observation is September 2026.
** Calculated as a share of total operating companies and by industry. Dots include the administration of one large builder and developer and its large number of subsidiaries, excluded from the main series.
*** Business-related personal insolvencies calculated as a share of total operating businesses.

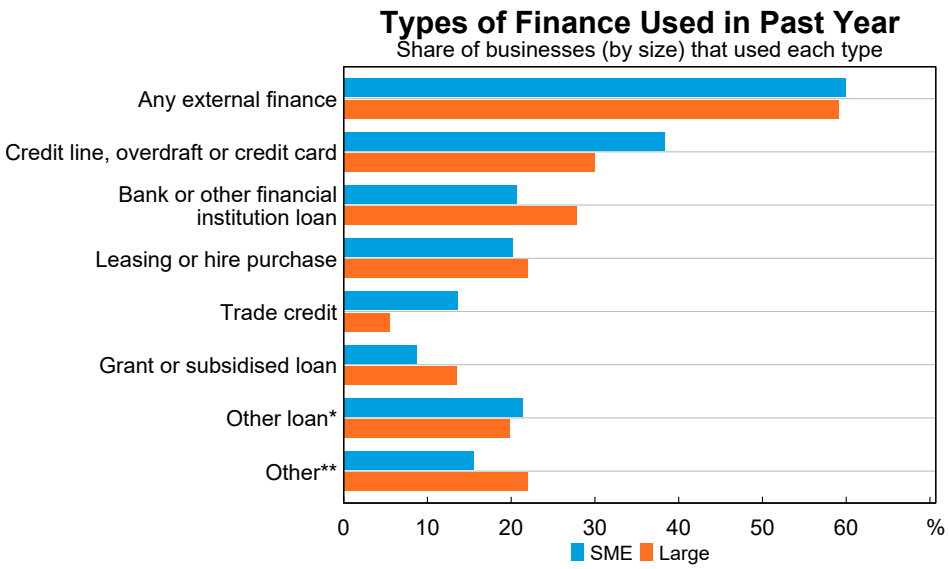
Sources: ABS (BLADE); AFSA; ASIC; RBA.

Cost, availability and use of SME finance

Demand for and use of finance

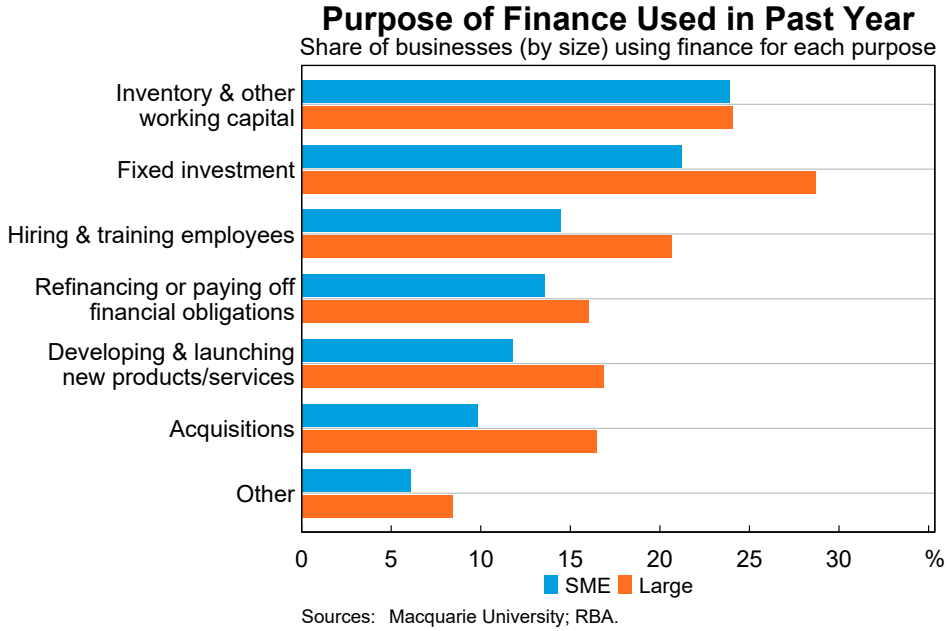
Survey data suggest that more than half of SMEs used external financing during the past year (Graph 5). The most commonly reported sources of finance were banks and other financial institutions, from which businesses borrowed fixed-term loans, lines of credit and finance leases. Many SMEs also borrowed from other sources, including family and friends. External finance was used for a range of purposes; the most frequently reported uses were for working capital and to fund fixed investment (Graph 6). Businesses also reported using external finance to refinance or pay off other financial obligations. Consistent with this, panellists and contacts in the RBA's liaison program have suggested that because the Australian Taxation Office (ATO) has resumed enforcement actions on unpaid taxes, it has become increasingly common for small businesses to borrow from financial institutions to help pay down their tax liabilities (RBA 2026d).

Graph 5



* For example from family and friends, a related enterprise or shareholders.
** Includes equity capital, debt securities, factoring and other sources of external finance.
Sources: Macquarie University; RBA.

Graph 6



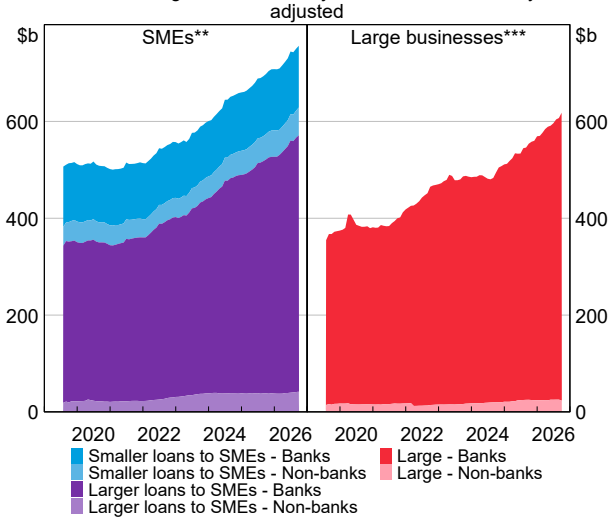
Sources: Macquarie University; RBA.

SME credit from banks and other financial institutions had grown quickly over recent years, reflecting strength in both the demand for business finance and the supply of credit from lenders (discussed below; Graph 7). Over the past year, growth in SME credit held up, though it was somewhat below its 2024 peak and slower than growth in large business credit. The growth in SME credit was led by fixed-term lending, while growth in revolving credit (which is typically used to fund businesses' ongoing operations) had also picked up in 2026 to date (Graph 8). In liaison, a few lenders noted that smaller businesses' demand for credit had moderated recently. In part, this may relate to a delay or reassessment of investment plans by some businesses, given the uncertain economic environment and sharp deterioration in small business confidence. For example, in a recent survey, SMEs reported a noticeable reduction in plans to grow through acquisition (Banjo Loans 2026).

Graph 7

Lending to Businesses*

Outstanding credit; break-adjusted but not seasonally adjusted

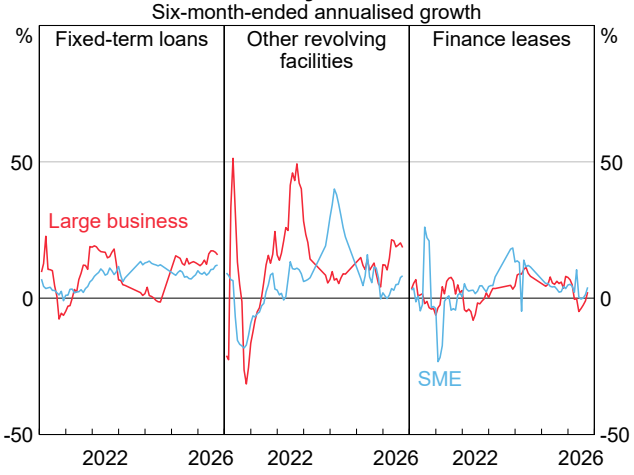


* Break-adjusted for changes in business-size definitions in April 2023 and August 2024.
** SMEs have annual turnover of less than $75 million; loans classified as 'smaller' if lender has exposure of less than $1.5 million to the business and 'larger' if lender has exposure of $1.5 million or more.
*** Businesses with annual turnover of $75 million or more.
Sources: APRA; RBA.

Graph 8

Business Credit by Size and Product*

Six-month-ended annualised growth



* Growth observations spanning business size definition changes are omitted; definitions changed in April 2023 and August 2024.
Sources: APRA; RBA.

Access to finance

SME access to credit had improved over recent years, reflecting a range of factors (Harvey, Lai and Spiller 2025). These included:

- the continued growth of specialist non-bank SME lenders, supported by generally favourable funding conditions for these lenders (Jennison, Spiller and Wallis 2026)
- greater competition among banks for business customers due, in part, to banks pivoting towards business lending as margins on housing lending declined
- an increase in broker activity for business loans, particularly for SME loans, likely supporting lender competition and helping to match borrowers with lenders that can provide suitable finance
- lender investments in technology and staff to support simpler and faster loan processing.

Panellists noted that lower barriers to accessing credit, including unsecured credit, can help to manage cash flow pressures. However, increased access can also lead to financial risks. For example, panellists noted some small businesses were less likely to seek financial advice before taking on debt that was more readily available than traditional bank loans (e.g. automated loan offers linked to a businesses' revenues). And while access to unsecured credit had improved, these facilities still attract higher interest rates reflecting the increased financial risk borne by the lender.

Despite some improvements in the availability of finance, some SMEs continued to report difficulty in accessing finance on terms that suited their needs. According to a recent survey, one in five SMEs experienced challenges in obtaining finance (Banjo Loans 2026). Strict lending requirements were the most common challenge that SMEs faced in accessing finance, and the share of businesses that reported this challenge increased from last year (Graph 9). In liaison, lenders have reported that SME lending standards have been little changed over the past year.

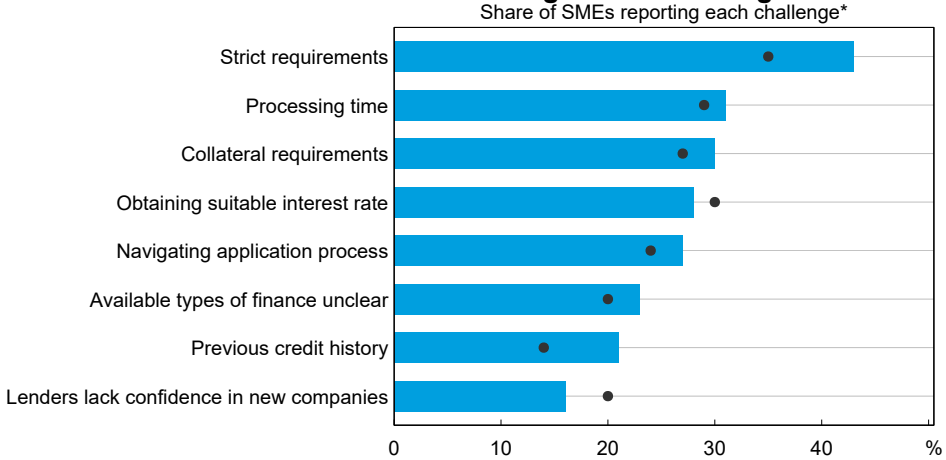
Small businesses continue to report that the requirement to provide residential property or other physical assets as collateral is a key challenge to accessing finance. While housing prices have grown strongly over recent years, the recent declines could exacerbate this challenge in the period ahead. Almost half of small business credit outstanding is secured by residential property and a similar amount is secured by other assets (such as vehicles and equipment).

While information from liaison suggests that access to unsecured finance had improved over recent years, the share of unsecured SME credit has remained below 5 per cent. This could suggest that unsecured finance has become only marginally more accessible or that demand for unsecured finance has not increased materially (Harvey, Lai and Spiller 2025). It is also possible that borrowers take out unsecured loans for relatively short periods (e.g. to manage temporary cash flow issues) given that they typically have relatively high interest rates, and rely on secured lending for larger or longer-term financing. Furthermore, some non-bank providers of unsecured lending are not well captured in official data sources.

Graph 9

Challenges to Accessing Finance

Share of SMEs reporting each challenge*



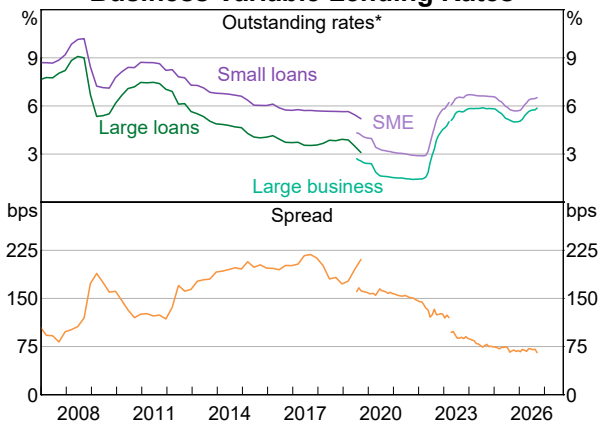
* From cohort of SMEs that experienced challenges when seeking finance. Bars show 2026 responses, dots 2025. Categories not mutually exclusive.

Source: Banjo Loans.

Cost of finance

Difficulty obtaining a suitable interest rate is another key challenge reported by SMEs (Graph 9). On average, loans to SMEs are currently about 75 basis points higher than loans to large businesses (Graph 10). However, the spread between SME and large business lending rates has narrowed over the past decade to a historical low. This trend partly reflects measurement changes, with definitions of business size changing in 2023 and 2024, resulting in some large business loans (which pay lower interest rates on average) being reclassified as SME loans. But it also reflects the increased competition for SME loans noted above and a reduction in the Australian Prudential Regulation Authority's (APRA) capital requirements for banks' SME loans in 2023. Rates on loans to SMEs have increased this year broadly in line with increases in the cash rate.

Graph 10
Business Variable Lending Rates



* Breaks for introduction of Economic and Financial Statistics in 2019 and changes to business size definitions in April 2023.

Sources: APRA; RBA.

Conclusion

Economic conditions for small businesses have weakened over the past year. Survey measures of small business confidence have deteriorated to well below long-run averages, and SMEs report worse business conditions and confidence than large businesses. Elevated growth in input costs is putting pressure on profit margins as businesses feel unable to fully pass them onto customers. Despite weaker economic conditions and pressure on margins, company insolvencies stabilised recently after earlier increases following the pandemic.

Borrowing from banks and other financial institutions grew at a fast pace over recent years, reflecting strength in both the demand for business finance and the supply of credit from lenders. The increase in the availability of credit reflected greater competition among lenders, an increase in broker activity, and favourable conditions in wholesale debt markets. However, borrowing costs have risen this year as interest rates have increased, and some SMEs continue to report difficulty in obtaining finance on terms that suit their needs.

Endnotes

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1 The 2026 Panel and most of the information considered in this article predate the removal of card payment surcharging from 1 October 2026. The Panel comprised representatives from nine SMEs across Australia, covering a range of sectors (RBA 2026e).

2 The SME series was discontinued in June 2026.

3 Contacts in the RBA's liaison program tend to be medium- to larger-sized firms (Dwyer, McLoughlin and Walker 2022).

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Uncertainty About the Stars

Leon Berkelmans and Matthew Read*



Photo: choja – Getty Images

Abstract

The non-accelerating inflation rate of unemployment, potential output and the neutral interest rate can be used to assess economic conditions and inflationary pressures. Because these 'star' variables cannot be observed directly, they must be estimated using economic models and are subject to considerable uncertainty. This article discusses the main sources of uncertainty surrounding star-variable estimates and the implications for interpretation. It shows that commonly used measures of uncertainty, such as the range of estimates across models, provide only a partial picture. Once broader sources of uncertainty are considered, estimates of the neutral rate appear particularly uncertain. Star-variable estimates are also subject to revision as new information becomes available. Despite these limitations, they remain a useful input into the RBA's broader assessment of economic and financial conditions: for example, they are integral for judging the degree of spare capacity in the economy.

Introduction

The state of the economy can be assessed by comparing observed economic outcomes with benchmarks that cannot be observed directly. This comparison can inform discussions about the degree of spare capacity in the economy and so how monetary policy should respond to achieve the RBA's objectives. For example, comparing the unemployment rate with an estimate of the rate consistent with low and stable inflation provides one input into assessing spare capacity in the labour market. The RBA routinely estimates several of these unobservable benchmarks, often referred to as 'star' variables. They are:

- the non-accelerating inflation rate of unemployment (NAIRU)
- potential output[1]
- the neutral interest rate.

Broadly speaking, these concepts refer to the levels of unemployment, real GDP and the inflation-adjusted cash rate (the RBA's policy interest rate) that are consistent with low and stable inflation.[2] Where the economy sits relative to these star variables can provide useful information about the likely path of inflation. For example, when the unemployment rate is below the NAIRU and real GDP is above potential, we might expect capacity pressures to put sustained upward pressure on inflation.

The unobservable nature of these star variables means they must be estimated from data using models of how the economy works. Estimating star variables presents substantial challenges. Even observable macroeconomic data are measured imperfectly and can be revised substantially over time. For example, real GDP in the March quarter 2011 was initially reported to have declined by 1.2 per cent relative to the previous quarter. This estimate was heavily affected by economic disruptions associated with severe flooding in Queensland and was subsequently revised to a decline of only 0.3 per cent, representing a substantial upward revision of about 0.9 percentage points. Uncertainty about input data, such as real GDP, is only one challenge in estimating star variables; using economic models to estimate these variables introduces additional uncertainty.

This article examines the main sources of uncertainty surrounding estimates of star variables and discusses how these estimates should be interpreted. It shows that commonly used measures of uncertainty, such as ranges of central estimates from different models, capture only part of the relevant uncertainty and so can give a misleading impression of precision. It also highlights that star-variable estimates can be revised substantially as new data become available. Because the models assume that star variables evolve gradually over time, new data can change not only current estimates but historical estimates too. It is crucial to account for revisions in historical estimates when interpreting new estimates in recent periods. Despite these challenges, star-variable estimates remain a useful input into the RBA's overall assessment of economic and financial conditions, alongside a wide range of other information and informed judgement.

How much uncertainty is there?

The RBA uses a suite of models to estimate each star variable because there is uncertainty about the strength of different economic relationships and which data contain the most useful information. Because these models differ in their assumptions and the information they use, they can produce different estimates of the same concepts.

There are several benefits to monitoring estimates from multiple models. First, it reduces reliance on any single set of assumptions. If a particular model provides a misleading description of the economy at a particular point in time, estimates from other models can provide a useful cross-check. Second, different models may extract information from different sources. For example, some of the RBA's neutral-rate models infer the neutral rate from macroeconomic relationships, while others use information embedded in financial-market prices. Third, differences across models can improve understanding of the economy by highlighting areas where the evidence is ambiguous or sensitive to modelling assumptions.

The range of central estimates across a model suite provides one indication of uncertainty. Graph 1 plots the range of central estimates of the NAIRU, the output gap (the difference between real GDP and potential output) and the neutral rate. For a given star variable, estimates can vary substantially across models. For example, the range of estimates of the neutral rate has often spanned

2–3 percentage points; this range is large relative to the typical variation in the real cash rate. The degree of disagreement across models can also vary over time. For instance, while the range of estimates of the NAIRU is now only 15 basis points, the range was over 60 basis points prior to the COVID-19 pandemic. However, the range of estimates across models has several limitations as a measure of uncertainty.

First, the range of central model estimates should be viewed as indicative rather than exhaustive, because it is based on a particular set of models and not *all* plausible models of the economy. In practice, it is not feasible to develop and maintain every plausible model, so the true degree of model uncertainty is likely to be greater than suggested by the range of estimates.

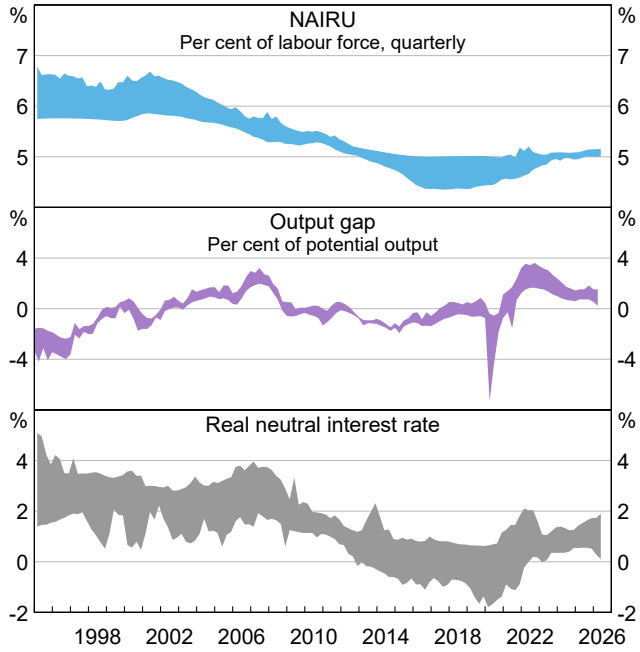
Second, the range depends only on the minimum and maximum estimates from the model suite, making it sensitive to model choice and re-estimation. Adding or removing a single model can substantially change the range. In the context of the neutral-rate model suite, Graph 2 illustrates the sensitivity of the range by removing one class of model, which is often an outlier in the suite.

Third, the range treats all models as equally informative, even though some may be viewed as more credible than others.

Finally, dispersion in estimates across models can sometimes partly reflect differences in the concepts being estimated. Some models of the neutral rate estimate the persistent component of real interest rates, whereas others estimate the expected real cash rate at a particular horizon. These conceptual differences partly explain the relatively wide range of neutral-rate estimates.

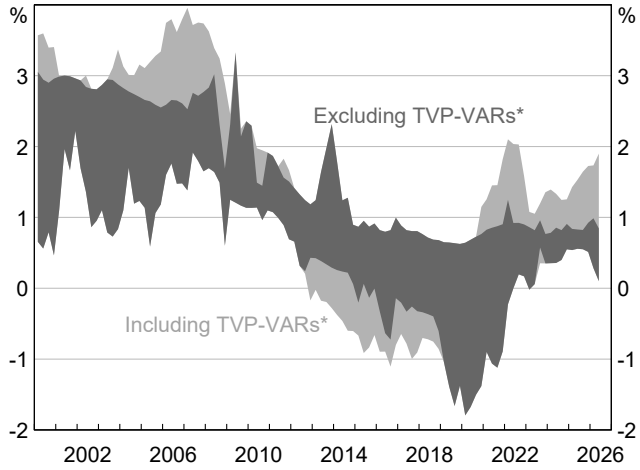
The next section discusses the additional uncertainty that arises because the variables themselves cannot be observed directly and must be inferred from economic data.

Graph 1
Range of Estimates from Model Suite*



* Shaded region shows illustrative range of central estimates from a selection of models.
Source: RBA.

Graph 2
Real Neutral Rate
Range of estimates across model suite



* TVP-VARs cover three time-varying-parameter vector autoregression models.
Source: RBA.

Additional sources of uncertainty

The range of estimates across models captures only part of the uncertainty surrounding star-variable estimates. Even within a given model, estimates are uncertain because star variables must be inferred from a necessarily limited sample of economic data, which can be measured with error and revised. Two additional sources of uncertainty are:

1. **estimation uncertainty,** which arises from the need to estimate unknown parameters ('parameter uncertainty') and extract signal about the star variables from the data ('filtering uncertainty')
2. **data uncertainty,** which arises from using input data that are measured with error and prone to being revised ('data revisions').

These sources of uncertainty are conceptually distinct, although in practice they often interact. Together they imply that the true value of a star variable may differ materially from any particular estimate and that estimates can change over time as new information becomes available.

Estimation uncertainty

Even if the appropriate model were known with certainty, the estimates would remain imprecise because star variables cannot be observed directly and must instead be inferred from economic data. Box A briefly describes how the RBA estimates star variables. The process of estimating star variables introduces additional sources of uncertainty, which can be grouped under the heading of 'estimation uncertainty'.

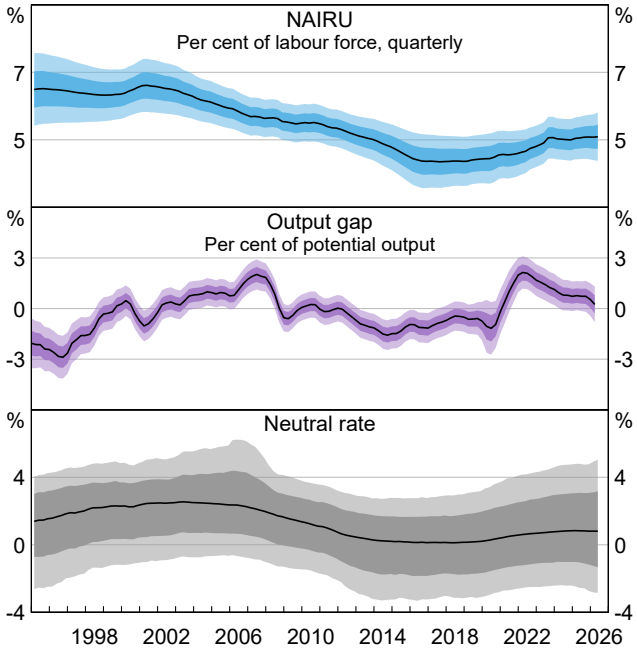
First, the models that we use to estimate the star variables require estimating unknown parameters, like the slope of the Phillips curve in the models that are used to estimate the NAIRU (see Box A for a simple example). Because models are estimated using a finite sample of data, there is always uncertainty about the true values of the model parameters. Model parameters influence how much signal is taken from the observed data when estimating the star variables. Because changes in model parameters will change estimates of the star variables, any uncertainty about model parameters will directly imply some degree of uncertainty around estimates of the star variables. This source of uncertainty can be described as 'parameter uncertainty'.

A second type of estimation uncertainty arises from attempting to estimate the unobservable star variables from observed data, acknowledging that the *true values* of the star variables could differ from the estimates. This source of uncertainty can be described as 'filtering uncertainty'. Filtering uncertainty would be present even if the true values of the model parameters were known, so this source of uncertainty is distinct from parameter uncertainty.[3]

Graph 3 plots the central star-variable estimates from selected models in the suite along with intervals that illustrate the degree of estimation uncertainty.[4] These intervals represent one and two standard errors either side of the model estimate, and can be interpreted as 68 per cent and 95 per cent confidence intervals, respectively.[5] These intervals are in general wider than the model ranges shown in Graph 1. Moreover, their width varies across the star variables appreciably. Of the three models considered, estimation uncertainty is largest for the neutral rate. Intuitively, this is because the model must first estimate spare capacity, which itself is uncertain, and then use a weak and imprecisely estimated relationship between spare capacity and the cash rate to infer the neutral rate.[6] Estimates of the neutral rate from some other models in the suite are similarly uncertain, suggesting that the high degree of estimation uncertainty for the neutral rate is not confined to a particular model framework. The difficulty in precisely estimating the neutral rate has been well documented (Kiley 2020).

Graph 3

Estimation Uncertainty for Selected Models*



* Shaded areas represent one and two standard error bands around smoothed estimates, accounting for filtering and parameter uncertainty.

Source: RBA.

Box A: How Are Star Variables Estimated?

Star variables cannot be observed directly. Instead, they must be inferred from the behaviour of observable variables, such as inflation.

To illustrate the basic idea, consider a stylised version of the 'Phillips curve' models that the RBA uses to estimate the NAIRU. The model assumes that inflation depends on the degree of spare capacity in the labour market:

$$\pi_t - \bar{\pi} = \kappa\left(u_t - u_t^*\right) + \varepsilon_t^{\pi}$$

where π_t is inflation, $\bar{\pi}$ is the inflation target, u_t is the unemployment rate and u_t^* is the NAIRU. According to this relationship, inflation tends to be higher when unemployment is below the NAIRU and lower when unemployment is above it. The NAIRU is assumed to evolve gradually over time, reflecting the idea that structural features of the labour market typically change slowly.

The model uses information on inflation and unemployment outcomes to estimate the unknown model parameters (e.g. the slope of the Phillips curve, κ) and the value of u_t^* in each period that is most consistent with the data.[7]

Though this example is simple, many of the models that the RBA uses to estimate star variables possess similar features, although the models differ in their structure and the information they use:

- The NAIRU is estimated using a suite of Phillips curve models. Different models draw signal from different measures of wages growth and inflation, and make different assumptions about the role of productivity growth in the wage- and price-setting processes.[8] One model also draws signal from a broad range of labour-market indicators, such as vacancies and job advertisements.
- Potential output is estimated using different modelling frameworks. Like the NAIRU models, some models in this suite treat potential output as an unobservable variable and infer its value given assumptions about macroeconomic relationships (including Phillips curves).[9]
- The neutral rate is estimated using three types of models: models that infer it from macroeconomic relationships (McCririck and Rees 2017); flexible time-series models (time-varying-parameter vector autoregressions) that use long-horizon forecasts of the real cash rate (following Lubik and Matthes (2015)); and a model of interest-rate term structures that uses the expected short-maturity real interest rate at a suitably long horizon (Hambur and Finlay 2018).[10]

While these models have very different structures and rely on different assumptions, they are all subject to similar sources of uncertainty.

Data uncertainty

Star-variable estimates are derived from economic data that are themselves subject to measurement error and revision. Some data are constructed from surveys of a random sample of the population, so the published estimates will differ from their true population counterparts. For example, the unemployment rate is estimated from the Australian Bureau of Statistics' monthly Labour Force Survey, which asks around 50,000 people about their participation in the labour market; the resulting estimate will differ from the unemployment rate that would be obtained by surveying the entire labour force.[11] Other data are revised as more complete, but less timely, sources of information become available. For example, to provide a timely read on economic conditions, initial estimates of GDP are published before all source data are available and are subsequently revised as more information is incorporated (Bishop, Gill and Lancaster 2013). As a result, uncertainty about the underlying data can contribute to uncertainty about the estimates.

The importance of data uncertainty varies across models and variables. For example, data from the national accounts – like real GDP – are typically subject to larger revisions than data on inflation and the unemployment rate.[12] More generally, the impact of any revision depends on both the size of the revision and the weight the model places on that particular data series.

One way to quantify this source of uncertainty is to re-estimate the star variables based on different vintages of data. Exercises of this type suggest that, for the NAIRU and potential output, data revisions are typically not a large source of uncertainty relative to the other sources of uncertainty described above (Sullivan and West 2026). This partly reflects that the star-variable models tend to take signal from multiple data sources, so unless revisions are common across multiple input variables, they are unlikely to systematically drive material changes in estimates.

Implications for interpretation and policy

The uncertainty surrounding star-variable estimates has important implications for how they should be interpreted and used. This section discusses what measures of uncertainty convey, why estimates are revised as new information becomes available, and how star variables can inform forecasting and policy discussions.

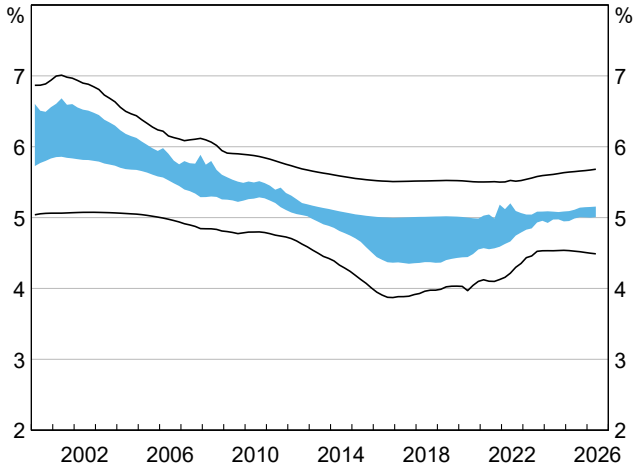
Communicating uncertainty

Estimates of star variables should be interpreted in the context of the uncertainty surrounding them, rather than in isolation. For example, an estimate of the NAIRU of 5 per cent should not be interpreted as implying that the unemployment rate consistent with stable inflation is exactly 5 per cent. Rather, the estimate should be viewed as the centre of a range of plausible values. Similarly, changes in estimates should be interpreted with caution, particularly when they are small relative to the surrounding uncertainty.

This is particularly relevant when uncertainty is communicated using the range of estimates across models. As discussed above, model ranges capture only one source of uncertainty and can therefore give a misleading impression of precision. A narrowing of the range across models does not necessarily imply that overall uncertainty has declined, just as a widening of the range does not necessarily imply that uncertainty has increased.

Graph 4 illustrates this point for the NAIRU. While the range of central estimates from the RBA's NAIRU models has narrowed considerably in recent years, substantial estimation uncertainty remains. The one-standard-error band spans about a percentage point, even though the range of central estimates is currently narrow, with a width of only 15 basis points.[13]

Graph 4
NAIRU
Model Range and Standard Errors*
Per cent of labour force, quarterly

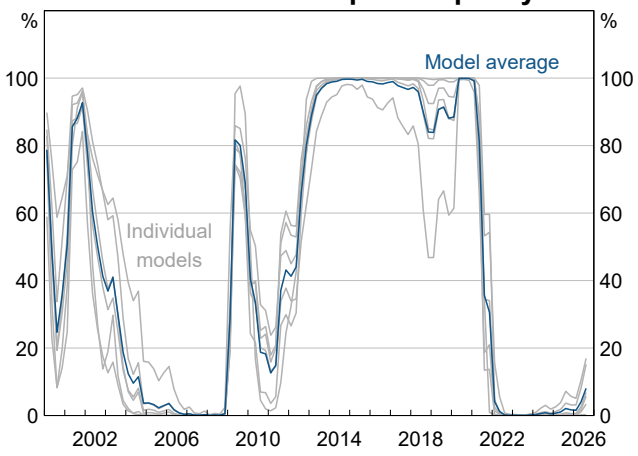


* Shaded areas represent the range between the lowest and highest NAIRU central estimate from a suite of 6 NAIRU models. Solid lines are the maximum and minimum one-standard-error bands from the 6 models.

Source: RBA.

At the same time, uncertainty about the precise level of a star variable does not necessarily imply uncertainty about broad economic conditions. Observable variables (e.g. unemployment) are often sufficiently far from their respective star-variable estimates (e.g. the NAIRU) that reasonably clear signals emerge despite uncertainty about the benchmark itself. The experience of the labour market in recent years provides an example. Graph 5 shows that, despite the estimation uncertainty around the NAIRU estimates, there was only a very small chance that the unemployment rate was above the NAIRU between 2023 and 2025. This means that whether the economy is operating above or below capacity can sometimes be assessed with reasonable confidence, even when it is difficult to determine exactly how much spare capacity exists (Ballantyne, Sharma and Taylor 2024).

Graph 5
Model Probability of Labour Market Spare Capacity*



* The probability of the unemployment rate being higher than the model estimate of the NAIRU, accounting for parameter and filtering uncertainty.
Source: RBA.

Revisions of star-variable estimates

Because star variables cannot be observed directly, estimates should be expected to change as new information becomes available. The sources of these revisions mirror the sources of uncertainty discussed above.

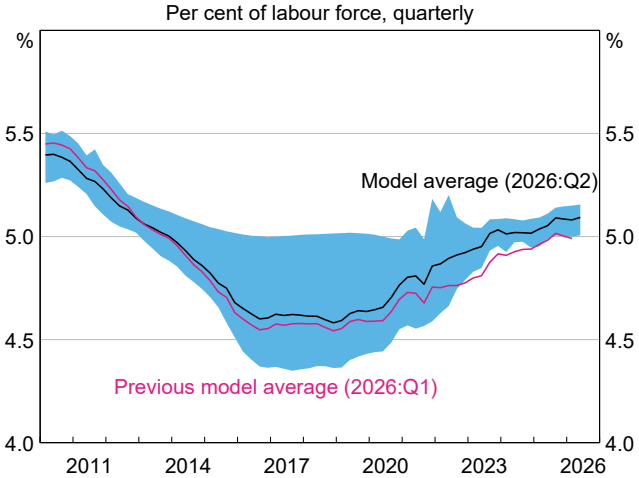
The most immediate source of revisions is the arrival of new data. Because star variables are typically modelled as evolving gradually over time, new information that changes estimates of their current values often leads to revisions in earlier periods as well. To illustrate, consider the NAIRU. Suppose new data show higher-than-expected inflation despite relatively high unemployment. A model may interpret this as evidence that the NAIRU is higher than previously thought. However, because the model assumes that the NAIRU changes only gradually, it is unlikely to attribute all this reassessment to the current period. Instead, the model will typically revise up its estimates of the NAIRU in preceding periods as well, producing a smoother path for the estimated series.

Revisions also arise through other channels. Estimates of model parameters change as additional observations become available and models are re-estimated. Historical economic data are themselves revised over time. In addition, RBA staff regularly refine modelling frameworks to incorporate new evidence, improvements in statistical methods and developments in the research literature. Each of these factors can alter estimates of star variables, including estimates for periods many years in the past. As a result, revisions can be significant. Exercises that approximate the information that would have been available to the RBA in earlier periods suggest that estimates of the NAIRU may be revised by as much as half a percentage point as additional information accumulates (Sullivan and West 2026).

These revisions have important implications for interpretation. Changes in the latest estimate of a star variable do not necessarily imply that economic conditions have changed materially since the estimates were last updated. In many cases, the new information primarily affects estimates of earlier periods rather than the assessment of recent developments. Accordingly, movements in estimates should be interpreted alongside revisions to the historical profile of the series.

A recent update to the RBA's NAIRU model estimates illustrates these ideas (Graph 6).[14] The latest central estimate from the June quarter 2026 national accounts was higher than the latest central estimate from the March quarter 2026 national accounts, reflecting new data, revisions to earlier data and some refinements to modelling assumptions. However, estimates for preceding years were also revised up, and the updated estimates suggested that the NAIRU had remained broadly unchanged over the first half of 2026. The higher estimate therefore reflected a reassessment of the NAIRU's level, rather than evidence it had increased over the quarter.

Graph 6
NAIRU Model Estimates*
Per cent of labour force, quarterly



* Shaded areas represent the range between the lowest and highest NAIRU central estimate from a suite of 6 NAIRU models.
Source: RBA.

More broadly, revisions are not a sign of model failure. They are a natural consequence of relying on imperfect and continually evolving information to learn about an unobservable variable whose value may itself vary over time.

Use in forecasting

Given the large amount of uncertainty around the star-variable estimates and the degree to which they are subject to revision, it is reasonable to ask whether they provide useful information for forecasting. Forthcoming RBA research examines the usefulness of the NAIRU and potential output in generating forecasts of inflation and wages growth (Sullivan and West 2026). In exercises that approximate the information available to the RBA at each point in time, this work finds that forecasting models based on estimates of the NAIRU and potential output tend to outperform simple benchmarks. This indicates that, despite the uncertainty inherent in estimating the star variables, they can play a useful role in the RBA's forecasting process.

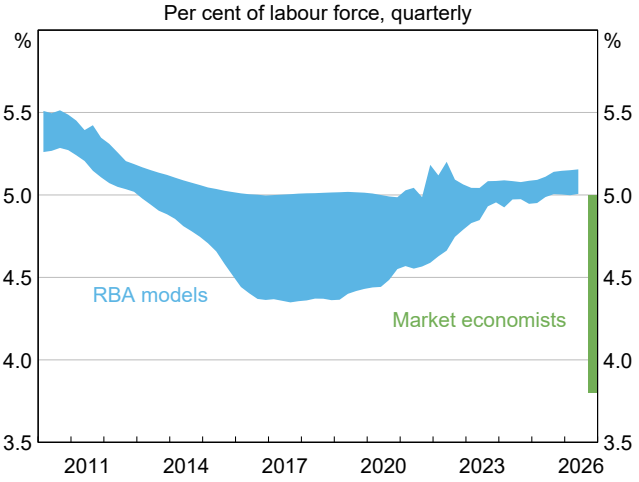
Nevertheless, the RBA's forecasting process draws on a wide range of information and does not rely solely on estimates from the star-variable model suites. These estimates provide useful quantitative signals, but each model necessarily offers only a partial view of the economy and may omit important features. Staff therefore consider the model estimates alongside other indicators and apply informed judgement when assessing current economic conditions and their likely evolution.

The assessment of labour-market spare capacity provides an illustration of this general approach. Staff monitor a range of indicators that compare current labour-market conditions with estimated benchmarks that are consistent with full employment. These benchmarks are informed not only by inflation and wages growth, but also by trends in labour-market indicators. They therefore provide alternative signals about spare capacity and an important cross-check on the NAIRU model estimates (RBA 2026a; RBA 2026b).

The role of individual star variables in the forecasting and policy process has also evolved over time. For example, recent enhancements to the RBA's modelling of potential output and the output gap have allowed estimates of these variables to play a more prominent role in the policy process (Bishop *et al* 2024).

RBA staff also monitor professional forecasters' star-variable estimates as one of several independent cross-checks on the model-based estimates. These estimates can vary widely. For example, recent estimates of the NAIRU from professional forecasters span over a percentage point, which is wider than the range of current estimates from the RBA's models (Graph 7).

Graph 7
Range of NAIRU Estimates*
Per cent of labour force, quarterly



* Shaded areas represent the range.
Source: RBA.

Role in policy formulation

Uncertainty around the star-variable estimates also has implications for how they should be used in policy formulation. Some research on monetary policymaking under uncertainty implies that policymakers should place greater weight on observed data when star variables are highly uncertain (e.g. Orphanides and Williams 2002). If a central bank treats its star-variable estimates as highly accurate when they are subject to substantial estimation error, it risks making large policy mistakes. Better outcomes may therefore be achieved, on average, by placing more weight on observed variables, such as inflation or the change in the unemployment rate.

Measures of uncertainty can also inform the relative weight placed on estimates of different star variables when assessing the policy environment. Other things equal, a less precisely estimated star variable should generally receive less weight than a more precisely estimated one. However, these weights should not be determined mechanically by the measures of uncertainty presented above, which may omit important sources of uncertainty and may not be directly

comparable across star variables.[15] The appropriate weight also depends on the relevance of each variable to the policy question at hand. Careful judgement is therefore required to weigh the estimates alongside observed economic outcomes and other indicators.

Conclusion

The NAIRU, potential output and the neutral rate are important macroeconomic concepts for assessing economic and financial conditions and inflationary pressures. However, owing to their unobservable nature, they are challenging to estimate and there is significant uncertainty about their true values at any point in time.

This article has highlighted three key messages. First, the range of estimates across models captures only part of the uncertainty surrounding star variables, and it is important to keep in mind the broader degree of uncertainty when interpreting estimates. Second, estimates can be revised substantially, including for historical periods, as new information becomes available. Third, uncertainty differs across variables and appears particularly large for estimates of the neutral rate.

Despite these challenges, star-variable estimates remain useful. While uncertainty makes it difficult to determine their precise values, the estimates can still provide valuable information about underlying economic and financial conditions. For this reason, the RBA considers star-variable estimates alongside a broad range of other indicators, model-based analysis and informed judgement when assessing economic and financial conditions.

Endnotes

* Leon Berkelmans is from Economic Analysis Department and Matthew Read is from Economic Research Department. The authors thank Willy Alanya-Beltran, Alex Ballantyne, Ben Crosbie, Patrick Hendy, Claude Lopez, Shane McMiken, Michael Plumb and many other colleagues for helpful comments and inputs.

1 Throughout the article, we focus on the output gap rather than potential output because the upwards trend in potential output makes uncertainty around its estimates harder to visualise.

2 The NAIRU, potential output and the neutral rate are commonly denoted by u^*, y^* and r^*, respectively, which is why they are often referred to as 'star' variables. For recent discussions of these concepts, see Ballantyne and Cusbert (2025) for the NAIRU, Bishop *et al* (2024) for potential output (and the output gap), and Ellis (2022) or Kent (2026) for the neutral rate.

3 Filtering uncertainty arises when the available data do not contain enough information to perfectly infer the unobservable variables. See Buncic, Pagan and Robinson (2023) for further discussion.

4 The NAIRU estimates are from a model that takes signal from growth in consumer prices and labour costs, accounting for the role of productivity growth (Ballantyne, Cusbert and Titkov forthcoming). The output gap estimates are from the small multivariate output gap (SMOG) model, which relates the output gap to the cyclical components of inflation, unemployment and GDP (Bishop *et al* 2024). The neutral-rate estimates are from a model that infers the neutral rate from the behaviour of interest rates, economic activity, the unemployment rate and inflation (McCririck and Rees 2017).

5 The interpretation of the uncertainty measures differs across models and depends on various assumptions. When the models are estimated using maximum likelihood, as is the case for the NAIRU and output gap, we use a procedure described in Hamilton (1994) to compute standard errors. When the models are estimated using Bayesian methods, as is the case for the neutral rate, we sample from the posterior distribution of the model parameters and then sample from the posterior distribution of the star variables conditional on the parameters using the 'simulation smoother' (e.g. Carter and Kohn 1994; Durbin and Koopman 2002). Importantly, both approaches capture parameter and filtering uncertainty.

6 There are many influences on the degree of spare capacity in the economy, and isolating the precise effect of the cash rate is difficult given these competing forces.

7 Many of the models are estimated using state-space methods and employ statistical filtering techniques to infer the values of unobservable variables from observed data. Some models are estimated using maximum likelihood, which finds the parameter values that make the observed data most likely, given the model. Other models are estimated using Bayesian methods, which impose prior beliefs (or judgement) about the values of model parameters prior to estimation. Bayesian methods generate a (posterior) probability distribution that reflects beliefs about model parameters after having observed the data. Star-variable estimates may be 'one-sided', using only information available up to a given quarter, or 'two-sided', using information available at the time they are produced. For example, a one-sided estimate of the NAIRU in the June quarter 2024 uses information available up to that quarter, whereas a two-sided estimate for the June quarter 2024 can use information available up to the June quarter 2026. All estimates in this article are two-sided.

8 For more information about these models, see Ballantyne, Sharma and Taylor (2024), Ballantyne and Cusbert (2025) and Ballantyne, Cusbert and Titkov (forthcoming).

9 Another approach extracts slow-moving trends in observed factors of production and inputs those trends into a standard production function. Because the trends in these input variables are uncertain, so are the resulting estimates of potential output. For information about the models that are used to estimate potential output and the output gap, see Bishop *et al* (2024).

10 Ellis (2022) and Kent (2026) also provide high-level descriptions of these models.

11 The Australian Bureau of Statistics provides estimates of the 'sampling error' that arises because the Labour Force Survey is conducted on a sample of households rather than the whole population. For example, if the estimated monthly change in the seasonally adjusted unemployment rate is zero, the 95 per cent confidence interval for that change ranges from –0.2 to 0.2 percentage points.

12 The RBA's star-variable models typically use seasonally adjusted inputs. The inflation and unemployment rate series that enter some of the models are revised only due to the updating of seasonal factors, which is typically not a major source of revisions. By contrast, real GDP is frequently revised as more information becomes available and occasionally due to conceptual changes (Bishop, Gill and Lancaster 2013).

13 Comprehensive measures of estimation uncertainty are available for the RBA's NAIRU models. For potential output and the neutral rate, uncertainty measures are available for selected models but are not currently produced on a comparable basis for every model in the suites. This partly reflects differences in model structure and estimation approach across models.

14 The central model estimate is not necessarily the same as the assumption underlying the forecasts that appear in the *Statement on Monetary Policy*; RBA staff layer judgement on top of model estimates.

15 For instance, the measures of uncertainty presented in Graphs 1–4 do not capture data uncertainty arising from the use of input data that are measured with error and prone to revision.

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