A NEW LOOK AT COMPONENT-LEVEL FORECASTS FOR INFLATION

This note introduces new processes for the bottom-up inflation model and uses them to construct illustrative scenarios for rents and consumer durables. The baseline of these scenarios is a new version of the bottom-up forecasts which are adjusted to add up exactly to the overall inflation forecast. The modelling also uses a novel method for calculating trimmed mean which simulates EC outcomes by each component. A scenario with stronger rents inflation leads to higher headline outcomes but has a limited impact on trimmed mean inflation, because rents inflation is currently already close to being trimmed out. In contrast, a scenario featuring widespread declines in consumer good prices would lead to weaker outcomes for both headline and trimmed mean.

Making bottom-up forecasts that are consistent with the headline forecast

Over the last year there has been stronger appetite to formally present component-level inflation forecasts as part of the board and forecasting process. Component level forecasts can help to communicate our overall narrative, and also serve as a cross check against it. They can also guide our expectations and assess the nature of surprises later on as new CPI data and related information is received. While the existing bottom-up models produce forecasts for the major components of inflation, historically their use has been limited by the fact that their weighted sum is inconsistent with the aggregate inflation forecast (which also includes information from other independent models and judgement).

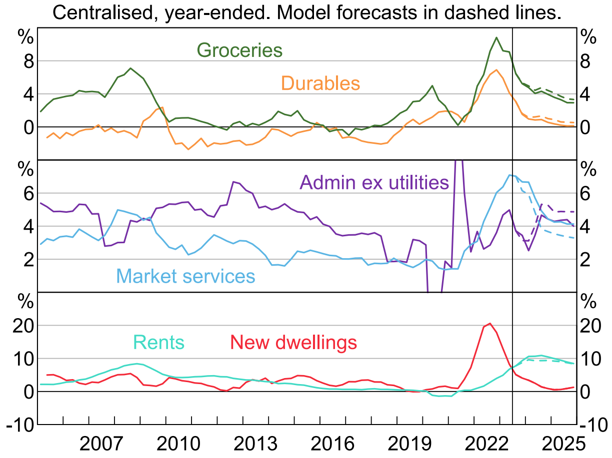
To solve this problem, I have recently developed and implemented a new approach to impose consistency on the aggregate forecast from the bottom-up model: this creates the 'centralised' component-level forecasts.

- The starting point is the original bottom-up model forecasts, with a few smaller components replaced with assumptions used elsewhere in the Statement forecasts. (Notably for electricity, where we are informed by assessments from RIA).
- A flat adjustment is made across the larger components, in order for the weighted sum of each component to match PWL's headline forecast exactly (see Appendix A for a diagram of how this fits into the rest of the forecasting process).[1]
- Some additional rebalancing is added to reflect any strong convictions we have about certain components, while maintaining the aggregate outcome.

Graph 1

Inflation Forecasts By Component

Centralised, year-ended. Model forecasts in dashed lines.



Sources: ABS; RBA.

Graph 1 shows these 'centralised' forecasts from the current, i.e. November, preliminary forecasting round. The main adjustment to the original 'bottom-up' model forecasts is to take some strength out of groceries, consumer durables and administered inflation in order to bring the sum of the component forecasts down to the headline inflation forecast. An upwards adjustment is made to the original bottom-up rents profile and the market services profile, as has been the case in previous forecast rounds, reflecting our internal judgement. These 'centralised' forecasts give us a starting point to run scenarios based around different outcomes at this component level.

A new way to calculate trimmed mean

Trimmed mean inflation is the main forecast variable for most of PWL's inflation models, but it is a challenge for the bottom-up model, particularly when running scenarios. The standard approach has been to run a regression with the growth rates of bottom-up components against trimmed mean inflation. In rough terms, the regression applies fixed weights to each bottom-up component regardless of how exceptional or typical

1 The motivation for adjusting larger components is that their growth rates might be a bit smoother (because they are the average of many items) and as a result, less noticeably distorted from these judgements.

inflation is for that component at present. This performs well over most of the historical data but can fail in some important ways. Rent inflation has a high weight in the regression because it's smooth and has usually remained within the trim, but in the current forecast, rent inflation is expected to be much stronger than other consumer items. The regression approach can't consider this and calculates a strong forecast for trimmed mean inflation. This flaw is also important for running scenarios where some components are shocked into being very strong or weak.

I have developed a new 'synthetic trim' to address this issue. This approach calculates an actual trimmed mean on simulated low-level expenditure class (EC) outcomes. For each bottom-up component, a set of EC outcomes are created from a normal distribution, where the average of the distribution is the current actual growth rate of the bottom-up component, and the standard deviation is set to a historical average. The number of EC outcomes created matches the number of EC's in the component. The weight of each EC is simplified to be the average weight of an EC within that component.[2] A trimmed mean for the quarter is then calculated on the entire set of 'synthesised' EC outcomes, across every component.

This approach is well suited to forecasting environments in which some components are very strong or weak, unlike the previous regression approach. The method also has some downsides:

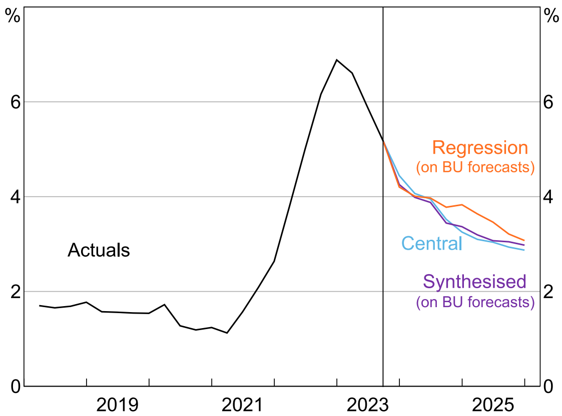
- It can make some large errors where items within a group diverge in an unusual way. For example, when childcare prices were reduced substantially via government subsidy in 2020, the synthetic trim only sees lower overall admin prices, which it assumes are distributed evenly across all admin items. This overestimates the impact on trimmed mean. This issue is not expected to be important when using model forecasts, because model forecasts don't usually embed these sorts of events. If it did prove important in future, then the method for the 'synthetic trim' could be expanded.
- It has a higher in-sample error and is more volatile than the regression approach. This is to be expected, as the synthetic trim approach isn't optimised to minimise error as in a regression.

When applied to the original bottom-up model forecasts, this approach produces a forecast below that of the regression approach over the second half of the forecast and fairly close to the central forecast. On the whole, because of the very strong rents forecast, this is probably a better signal of the bottom-up forecast at present (Graph 2).

Graph 2

Trimmed Mean Inflation Forecasts

Year-ended

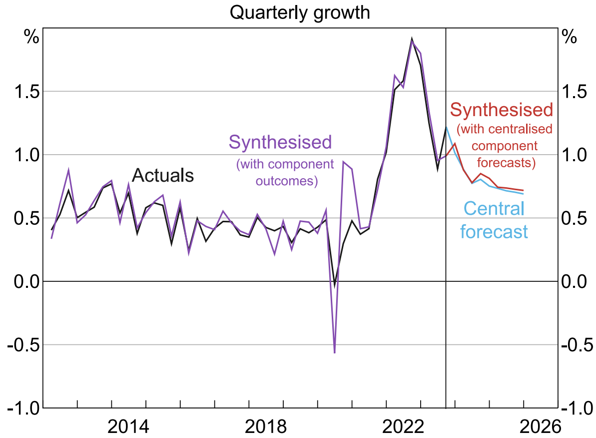


Sources: ABS; RBA.

Graph 3

Synthesised Trimmed Mean

Quarterly growth



Sources: ABS; RBA.

When this method is applied to the 'centralised' component forecasts (which as described above, are calibrated to add up to the headline forecast) the synthesised trim is quite similar to our actual trimmed mean forecast (Graph 3). This suggests the alignment between the forecasts for headline, trimmed mean and centralised components are fairly reasonable. At the margin, the synthetised trim is still a little bit stronger than the central trimmed mean forecast.

2 While this simplification creates a weighting for EC's which are more homogenous than the actual CPI there is still a large range of weights as the largest ECs tend to get their own model. For example, the synthetic ECs created for consumer durables have a weight of 0.5 per cent each, while the rent component maps to a single EC with a 5.9 per cent weight.

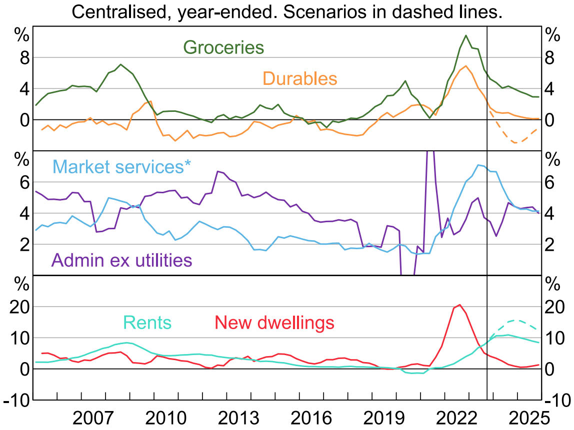
Scenarios

We can now consider two scenarios based on bottom-up outcomes, using these new tools to show plausible paths for headline and trimmed mean inflation. In the first scenario, the prices of some non-food retail goods face a substantial decline over the next two years (motivated by unwinding shipping costs and easing manufacturing constraints). In the second scenario, pressure on rent prices is around 50 per cent stronger than we anticipate (Graph 4). The differences in the calculated synthetic trim are used to get the impact of the scenario, but PWL's actual trimmed mean forecast is used as the starting point.

Graph 4

Inflation Forecasts By Component

Centralised, year-ended. Scenarios in dashed lines.

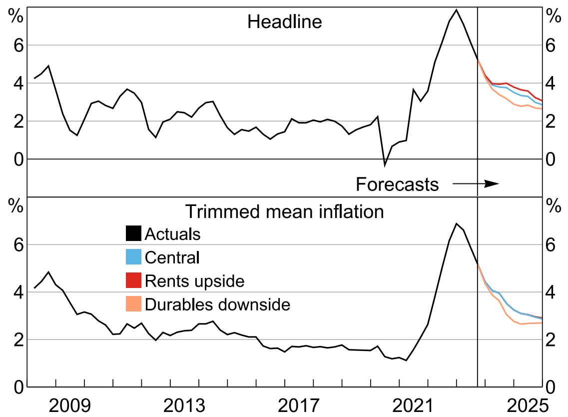


* Market services excludes domestic travel, accomodation and telecommunications.
Sources: ABS; RBA.

Graph 5

Inflation Forecast Scenarios

Year-ended



Sources: ABS; RBA.

Headline inflation is affected by both scenarios. However, the stronger path for rent inflation doesn't have a large impact on the trimmed mean inflation forecast (Graph 5; Table 1). This is because the rents component moves above the trim in the scenario, having already been partly trimmed in the recent June quarter CPI outcome when rents were running at a quarterly annualised pace of 10.2 per cent. The downside for consumer durables has a greater impact on trimmed mean than the rents scenario, because of the higher weight and number of items affected. While some durables ECs are trimmed due to the shock, the impact on trimmed mean inflation over the year to 2024 is still around 80 per cent of the headline CPI impact.[3]

Table 1: Central forecast and impact of scenarios

		Central forecast	Rents upside	Durables downside
		Year-ended	Year-ended ppt	Year-ended ppt
Headline CPI				
	Dec-23	4.4	+0.0	-0.1
	Dec-24	3.5	+0.3	-0.6
	Dec-25	2.9	+0.2	-0.2
Trimmed mean				
	Dec-23	4.4	0.0	-0.1
	Dec-24	3.3	0.0	-0.5
	Dec-25	2.9	0.0	-0.2

Conclusion

This new approach to scenarios is relatively simple to run and could be repeated to generate discussion in future forecast rounds. The centralised forecasts for inflation components have proved very helpful over recent forecast rounds and should be maintained, and the judgement and results should receive some interrogation from PWL management as part of the forecast process. However, we should probably avoid regularly publishing these forecasts at present: the forecasting focus of the inflation desk should remain primarily on headline and trimmed mean inflation. Applying judgement to the component forecasts such that they are robust and reliable for public dissemination is no small task (see DAT's GDP desk).

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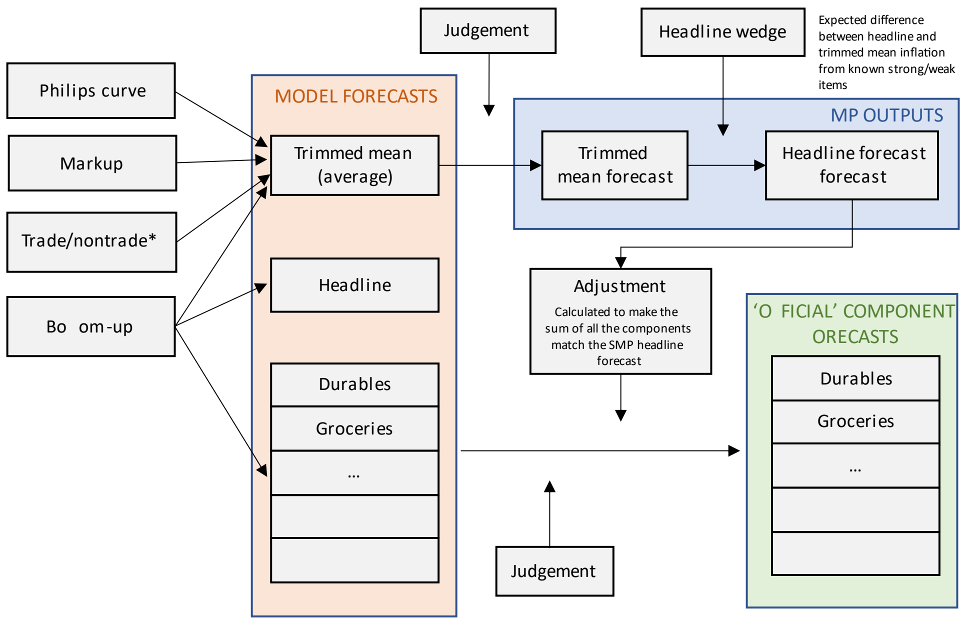
3 The trimming of some durables items is partly offset by the remaining items have a higher effective weight when calculating growth in trimmed mean compared to headline. Generally, it's possible for a shock to have a larger impact on trim than headline CPI. Consider a small shock to a few items, which are not trimmed. The impact on trimmed mean will be stronger than for headline, because the effective weight of those items is higher in the trimmed basket (which is 70% of the CPI) than headline.

Appendix A: Diagram showing how the 'centralised' component forecasts relate to the rest of the forecast



*The tradable model also produces a headline forecast and forecasts for tradable/nontradable components.

Appendix B: Background on bottom-up model components

The bottom-up inflation model is made up of 14 different models, as introduced in (2016) and improved since. Models for consumer durables and groceries take signal from unit labour costs, import prices and inflation expectations. They also have adjustments for apparent structural breaks in average inflation in these components; those adjustments have been remade recently as dummy variables for a period of elevated competition, having previously been state-space models with time varying intercepts. [4] New dwelling inflation and rents inflation are individually modelled, with new dwellings split into apartments and houses sub-models, while rent inflation has different models for the near term (1 year) and medium term. Market services is modelled in a Philips curve specification. Administered price inflation (excluding utilities) is modelled in nsa terms with a lag term of CPI outcomes, an unemployment gap and quarterly dummies for major policy changes past.

Appendix C: Synthesised Trim Method

1. For each bottom-up component, calculate the historical standard deviations of expenditure class growth rates within that component at each point in time, then average these into one number as below.

$$\frac{1}{T}\sum_{t=1}^{T}\left(sd\left(\sum\nolimits_{b=1}^{B} g_{b,t}\right)\right)$$

2. For each bottom-up growth rate, produce a simulated distribution of expenditure class outcomes using the number of ECs contained in that component. This distribution is calculated such that the average matches the growth rate of the overall component, and the standard deviation is equal to what was calculated for that component in step 1. The expenditure classes are assumed to be equally weighted for simplicity.[5]

3. Having produced simulated expenditure class outcomes for every bottom-up component, we can now run the normal trimmed mean procedure on this synthesized dataset.

4 This change was required because the time-varying intercept fully took on strength from recent outcomes and carried it perpetually through the forecast.

5 Using the actual weights of ECs would be much more complicated with regards to calculations. With equal weights, the simple mean of a normal distribution is the same as the weighted mean – this allows for a straightforward way of creating EC outcomes which align with an overall components growth rate.