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Measuring Core Inflation for Monetary Policy in Singapore

Scott Roger and Xiong Wei

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BY

Scott ROGER and XIONG Wei¹

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ABSTRACT: This paper examines alternative measures of core inflation for Singapore over the period 2004 to 2024. These include MAS Core Inflation, the CPI excluding fresh food and energy, a measure down-weighting volatile CPI components, and various trimmed means. Evaluation criteria include the volatility of the measures, and tests of their forward-looking information. The trimmed means and the volatility-adjusted series are found to be the least volatile, and better predictors of future inflation. The paper recommends adding a trimmed mean and the volatility-adjusted measure to a suite of core measures used by the MAS in its macroeconomic analysis.

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1. INTRODUCTION

Most central banks with the primary objective of maintaining low inflation construct, monitor, and publish measures of core or underlying inflation. Such measures generally aim to distinguish between price movements driven mainly by supply disturbances, and “core” price movements driven mainly by excess demand pressures in goods or labour markets.

The logic for focusing on core inflation is essentially two-fold. Most importantly, if monetary policy leans against core inflation movements, it will simultaneously lean against excess demand pressures, so that dampening core inflation should also help stabilise activity. Leaning against inflation driven by supply shocks would tend to accentuate the adverse impact of such shocks on activity. Second, demand-driven inflation is typically persistent, reflecting the nature of the underlying drivers, while supply-driven inflation is generally viewed as more transient. Given the slow impact of monetary policy on inflation, focusing on the more persistent element will be stabilising for inflation and activity. Additionally, supply shocks are often specific to certain sectors, leading some prices to rise or fall sharply, while most prices are little affected. Demand shocks tend to have a broader impact on prices, leading to a generalised pick up or slowdown in inflation. Monetary policy is primarily concerned with addressing the generalised inflation mainly associated with demand shocks.

Of course, these characterisations are somewhat simplistic. Supply shocks can sometimes be quite broadly based, or persistent. For example, technological advances in electronics have led to long-term declines in electronic goods prices as well as communications costs. And, during the COVID and post-COVID period, supply chain disruptions affected a wide range of goods prices. Likewise, demand shocks may also sometimes be relatively narrowly focused, or temporary. For example, consumer spending may surge temporarily in anticipation of a sales tax increase, and during the post-pandemic period there were substantial swings in spending between goods and services.

The experience with inflation over the 2021–2024 period, involving a combination of supply and demand shocks, highlights the importance of having robust measures of core inflation to support policy formulation and communication. The MAS Core Inflation measure, developed in the 1980s, was last reviewed in 2011. In this paper, we revisit the MAS Core Inflation and compare it with a variety of other measures used by major inflation-targeting

central banks. The aim is to identify which measure or measures are likely to best serve MAS in policy formulation and communication in coming years.

2. ALTERNATIVE APPROACHES

There are several different approaches to measuring core inflation. This paper focuses on those most commonly used internationally² (Table 1):

Table 1: Measures of Core Inflation

Inflation Measure	Type	Description
MAS Core Inflation	Exclusion-based	Excludes accommodation and private road transport prices
CPI ex Fresh Food and Energy (XFE)		Excludes fresh food and energy prices
CPI Volatility-Adjusted (VA)	Volatility-adjusted	Weights of components adjusted based on relative volatility (more volatile components are given smaller weight)
Weighted Median	Limited influence	Median price series by degree of price change
15% Trimmed Mean (T15)		Top 15% of extreme price changes are removed from each end of distribution
25% Trimmed Mean (T25)		Top 25% of extreme price changes are removed from each end of distribution

- **Exclusion-based measures.** These measures systematically exclude some specific components of the CPI that are regarded as being primarily driven by supply factors. This includes the MAS Core Inflation measure, which excludes accommodation and private transport, as both price series are largely driven by government administrative measures

² See Appendix 1 for a list of core inflation measures at use in selected central banks.

rather than by demand factors. We also construct an exclusion-based measure comparable to the original US core inflation measure, which excludes food and energy. For Singapore we exclude fresh food items together with private transport (mainly petrol) and utilities and fuel charges (mainly electricity).

- **Volatility-adjusted measures.**³ This kind of measure increases or decreases CPI expenditure weights in proportion to the relative volatility of CPI components over a particular period. The measure constructed for Singapore adjusts for the relative variance in 3-month, seasonally adjusted group level price changes.⁴ Items that were found to be particularly vulnerable, and down-weighted, include telecommunications equipment, private transport, other transport services, and utilities and fuels. Items that have low volatility and are up-weighted include an array of food components with a high service content (e.g. hawker food and restaurant meals), as well as personal services items (e.g. holidays and telecom services).⁵
- **Limited influence measures.**⁶ These include the median and trimmed-mean measures, and involve replacing extreme price changes, on both ends of the distribution of 3-month price changes, with the weighted average of the remaining prices, on a period-by-period basis. Unlike the exclusion-based or volatility-adjusted measures, the items excluded from the calculations are not predetermined, which makes the measures robust to a wide range of shocks. In this analysis, three measures are calculated: the weighted median; a 25% symmetrically trimmed mean; and a 15% symmetrically trimmed mean, based on 3-month seasonally-adjusted Group level price changes. Because the CPI involves a discrete rather than a continuous distribution, calculation of specific percentiles or trims is somewhat indeterminate. Some form of interpolation is needed.

3. DATA ISSUES

The data used in this analysis have three important characteristics:

³ Also known as Neo-Edgeworthian measures.

⁴ Variances are calculated over the period from April 2004 to July 2023.

⁵ The significantly down-weighted items account for 17% of the current CPI basket, and the most up-weighted items account for 21%.

⁶ Also known as Robust measures.

- **Aggregation.** Data used are at the Group level of aggregation, which consists of 42 categories of prices in Singapore's CPI basket.⁷ This level of aggregation was selected for two main reasons. First, it is the most detailed level of aggregation that is publicly available, so that core inflation measures derived from this can be externally verified. Second, the level of aggregation is detailed enough for analytical purposes, but not so detailed that it would complicate policy communication.
- **Frequency.** The analysis focuses on price changes over 3 months.⁸ Price changes over 12 months are relatively smooth, but are slow at catching turning points. Month to month price changes catch turning points quickly, but are noisy. Accordingly, the 3-month price changes strike a balance between immediacy and smoothness, and facilitates analysis and communication in conjunction with quarterly GDP data.
- **Seasonal adjustment.** All data used are seasonally adjusted by Department of Statistics (DOS).

Two statistical issues arise in the computation of core inflation measures based on price changes:

- **Interpolation between values.** The CPI, even at a detailed level, is a discrete rather than continuous distribution of prices. Consequently, there may not be a specific price change that corresponds exactly to the 50th percentile, for example. Similarly, in calculation of a 15 percent trimmed mean, there may not be price changes that correspond precisely to the 15th and 85th percentiles of the distribution. Some kind of approximation or interpolation is needed. A simple linear interpolation method is used in this paper and is described in Appendix 2.
- **Time-varying basket weights.** The CPI is calculated as a fixed weighted basket of price *levels*, indexed to some base period. When calculating trimmed means, however, it is important to take account of past movements in relative prices, not just the movement in the current period. This is done by using time-varying, history-dependent weights. The formula for calculating the time-varying weights is derived in Appendix 3.

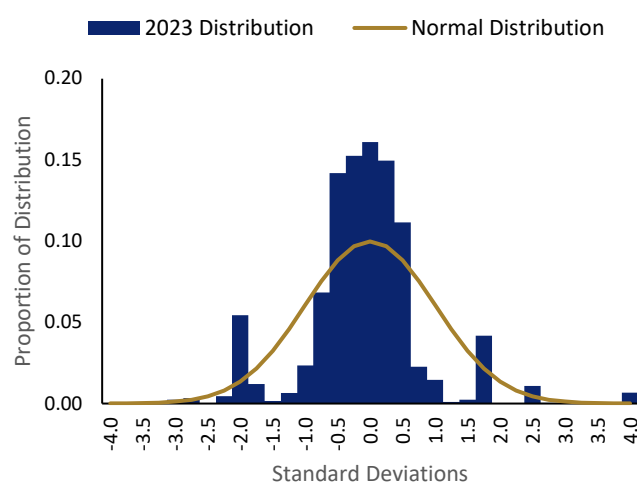
⁷ The Singapore CPI currently consists of 10 Divisions (e.g., Food), which are subdivided into 42 Groups (e.g., Bread & cereals); subdivided into 95 Classes (e.g., bread); subdivided into 975 items (e.g., Sliced white bread).

⁸ That is, the percentage change in each price from 3 months earlier. This provides a much timelier measure of inflation than the percentage change in the average price level in the latest 3 months compared with the average over the previous 3 months.

- **Adjusting basket weights for index base shifts.** The CPI database available from Singapore Department of Statistics (DOS) includes continuous time series for Group level prices in the 2019 CPI basket from 2004 to the present. These are indexed to 2019=100. The database also includes basket weights for the 2019 Group definitions at each of the basket revision dates. The weights need to be adjusted for the use of prices indexed to 2019, as explained in Appendix 4. The calculations in this paper use the DOS weights on the assumption that these adjustments were made.

The distribution of price changes at the Group level in each period is typically bell-shaped, with a central peak and is approximately symmetric,⁹ but with more frequent exceptionally large price increases or decreases than is characteristic of a Normal (Gaussian) distribution (Figure 1).¹⁰ As a result, the empirical distribution of price changes is found to be non-Normal in two-thirds of the sample period.¹¹ Internationally, price change distributions typically display high kurtosis, as well as significant right skewness (more frequent large price increases than decreases).¹²

Figure 1: Distribution of standardised Group level quarterly price changes, 2023Q1-Q4



Source: EPG calculations

⁹ The degree of asymmetry is summarised by the coefficient of *skewness*. As with a Normal distribution, the skewness of the empirical distribution of quarterly price changes is close to zero, indicating symmetry.

¹⁰ In statistical terminology, the distribution is significantly *kurtotic*, with a median coefficient of kurtosis of 5.8, compared with 3 for a Normal distribution.

¹¹ Based on the Jarque-Bera (1987) test for Normality, and Deb and Sefton (1996).

¹² The skewness and kurtosis are typically quite sensitive to the degree of aggregation. At high levels of price aggregation, the distribution of price changes tends to be nearly Normal, whereas for very disaggregated data, skewness and kurtosis tend to be high. The moderate skewness and kurtosis we find with Group level data reflect the intermediate level of aggregation.

High kurtosis in the distribution of price changes suggests that trimmed mean measures are likely to perform well as estimators of the underlying inflation rate. One way of thinking about the underlying inflation rate from a statistical perspective is that, in each period the measured prices in the CPI represent a sample of all the prices in the economy. The challenge is how to estimate the true or underlying inflation rate from the sampling of prices. If the distribution of price changes is approximately Normal, then the sample mean – the calculated CPI – is the most efficient estimator of the underlying inflation rate. However, if the distribution is typically kurtotic, then trimmed means and other robust estimators will be better estimators of the true underlying inflation rate.¹³

4. TESTS AND FINDINGS

For monetary policy purposes, core inflation measures have potentially key roles to play in policy formulation and communication:

- For **policy formulation**, the measures should be timely and provide reliable information for forward-looking policy making. The core inflation measures aim to filter out “noise” from transient, mainly supply-driven, price movements so that the “signal” part of inflation, reflecting a generalised and persistent element of inflation is clearer. However, there is a danger that the measures may filter out signal as well as noise. This is especially likely to happen when using quite aggregated data, because excluded components may be comprised of items that provide good “signal” as well as items that are “noisy”. For example, excluding all food items may exclude some fresh food items very susceptible to supply shocks but also restaurant meals that may provide an excellent barometer of generalised inflation pressures. To assess which core inflation measures have the highest “signal-to-noise” ratio and are most useful for policy formulation, econometric tests are used to check on which measures provide the most information on the future course of inflation.
- For **policy communication**, the measures should be readily understood, verifiable, and not significantly biased relative to the CPI or inflation target.¹⁴ The general public may not need to understand the details of calculation of the measure, but the central bank does need to be able to explain differences between the core and headline inflation rates. To be verifiable, the data used to construct the measures and the

¹³ Roger (2000)

¹⁴ Roger (1998).

methodology should be available to the public. The measures in this paper are all based on data available on the DOS website.

4.1. Bias and Volatility

To be helpful in making decisions on monetary policy, the measures of core inflation should not be highly volatile. Volatility obscures the trend of inflation, which will tend to delay policy adjustments until enough time has passed that the trend is obvious. Smoothing by looking at average inflation over several months, such as the year-on-year inflation rate brings out the trend, but with a long lag, again delaying timely policy adjustments. Consequently, an important criterion for assessing the usefulness of the core inflation measures is how volatile they are. A second consideration is whether the measures show a significant and systematic bias compared with the CPI itself.

Table 2 shows average rates of inflation and volatility indicators for the CPI and alternative core inflation measures over the period from 2004–2024, based on 3-month annualised inflation rates.¹⁵ To assess volatility, we focus on changes in the inflation rate. An erratic, saw-tooth pattern of inflation around the trend would be reflected in a high standard deviation of changes in the inflation rate, while a smoothly evolving inflation rate would be reflected in a low standard deviation. Table 2 shows four measures of volatility. The first two show the volatility of changes in annualised 3-month inflation from one month to the next, and from the end of one quarter to the next. The third and fourth look at the volatility of changes in year-on-year changes in inflation from month to month and from one quarter to the next.

¹⁵ Note that the quarterly data are calculated as the annualized 3-month price change from the end of one quarter to the end of the next, (i.e., $((P_t/P_{t-3})^4)$) rather than as changes in the average CPI for one quarter compared with the preceding quarter (i.e., $((P_t+P_{t-1}+P_{t-2})/(P_{t-3}+P_{t-4}+P_{t-5}))^4$).

Table 2: Average Inflation and Inflation Volatility 2004–2024Q3

Inflation Measure	Average 12-month inflation rate (%)	Inflation Volatility (Standard Deviations)			
		MOM change in 3-month annualised inflation rate (%)	QOQ change in 3-month annualised inflation rate (%)	MOM change in 12-month inflation rate (%)	QOQ change in 12-month inflation rate (%)
CPI-All Items (Headline)	2.2	1.7	2.7	0.5	0.9
MAS Core Inflation	1.9	1.1	1.8	0.3	0.7
CPI ex Fresh Food and Energy (XFE)	1.7	1.1	1.8	0.3	0.7
CPI Volatility-Adjusted (VA)	1.9	0.9	1.5	0.3	0.6
15% Trimmed mean (T15)	2.1	1.1	1.7	0.4	0.7
25% Trimmed mean (T25)	2.1	1.0	1.5	0.4	0.6
Weighted Median	2.0	1.2	1.4	0.6	0.6

Source: EPG estimates

The results show that:

- Most measures of core inflation, except CPI XFE, have tracked 0.1–0.3% point below the headline CPI rate, which averaged 2.2%. The trimmed mean measures tracked closer to the headline rate than other measures.
- 12-month inflation rates are much smoother than annualised quarterly rates. The volatility of both quarter-to-quarter and month-to-month changes in 12-month inflation rates is typically less than half as volatile as the changes in annualised 3-month inflation rates. This smoothness, however, comes at the cost of obscuring what is happening to inflation

currently, and is therefore more useful for policy accountability than for policy formulation.

- The 3-month annualised core inflation measures are substantially less volatile than the CPI headline rate, whether looking at month-to-month or quarter-to-quarter changes. With the monthly changes for example, the volatility of the various core measures, excepting XFE, are 30–40% less volatile than the CPI, and the reduction at the quarterly frequency is 40–50%.

4.2. Information Content of the Core Measures

Smoothness or lower volatility in the core measures does not necessarily mean that they are better as guides for monetary policy than the headline CPI. There is a risk that reduction in noise in the CPI might also lead to a reduction in the signal about future inflation. For this reason, the paper next considers the forward-looking information content of the various core measures. An important note in this context, however, is that the focus is mainly on the forward-looking information content over a fairly short horizon. At longer horizons, beyond about a year, forward-looking assessments of inflation need to be based on a comprehensive forecasting framework involving all the relevant drivers of inflation.¹⁶

Two sets of tests were performed to assess the information content of the core inflation series. The first is a Granger-causality test on whether current and past values of the core inflation measures are useful in predicting headline inflation. The second is a specification set out by Cogley (2002) to measure the extent to which core inflation series removes the transitory elements of inflation.

4.2.1. Granger-Causality Tests

The Granger-causality test (1969) assesses whether future values of a time series can be predicted using past values of another time series, in addition to its own past values. For example, if a particular core inflation measure “X” is found to Granger-cause the headline inflation rate, but not the other way around, it implies that past values of “X” are a better predictor of future headline inflation than the past values of headline inflation. In principle, causality can run both ways.¹⁷

¹⁶ See Richards (2024).

¹⁷ Granger “causality” does not necessarily imply true causality since both series might be driven by a common third process.

The two-way Granger-causality tests are run on each underlying inflation measure for lag lengths of 1 to 4 quarters, with inferences drawn based on a statistical significance of 5%.

The results show that the median and trimmed mean measures contain information content on and are useful in predicting headline inflation (Table 3). This suggests that these series tend to provide a less noisy signal as to the future path of inflation. The volatility-adjusted measure contains predictive information only at longer lags, while the MAS Core Inflation¹⁸ and CPI XFE measures contain little predictive information for headline inflation, which suggests that the information removed from these series may not be significantly improving their signal to noise ratios regarding future inflation. Although two-way causality is possible, tests of whether the headline CPI helps predict the core measures consistently showed no evidence of causality.

Table 3: Results from Granger-Causality Test

	Rejection of Null Hypothesis that Core Inflation Measure Does Not Granger-cause Headline Inflation			
	Lag Length = 1	Lag Length = 2	Lag Length = 3	Lag Length = 4
Weighted Median	Yes	Yes	Yes	Yes
15% Trimmed Mean	Yes	Yes	Yes	Yes
25% Trimmed Mean	Yes	Yes	Yes	Yes
MAS Core Inflation	No	No	No	No
CPI XFE	No	No	No	No
Volatility-Adjusted	No	No	No	Yes

Source: EPG estimates

¹⁸ The Granger-causality test was repeated in rolling 10-year regressions over the sample period and the results showed no evidence of structural breaks. While the focus of this note is on quarter-on-quarter results due to their relevance to policy, tests on month-on-month inflation data showed the presence of two-way causality between MAS Core Inflation and headline inflation at higher frequencies.

4.2.2. Cogley Test for Predictive Power

Another approach to evaluating the predictive power of core inflation measures on future headline inflation was proposed by Cogley (2002).¹⁹ It assumes that current deviation of core inflation from headline deviation should be inversely related to subsequent changes in headline inflation. This implies that if a core measure indeed captures underlying trend inflation and headline inflation is above (below) trend, the headline series should correct itself by falling (rising) over time. The test uses a regression of the following form:

$$\pi_{t+L}^H - \pi_t^H = \alpha + \beta(\pi_t^H - \pi_t^U) + \varepsilon_t$$

where π_t^H represents headline inflation, π_t^U represents the underlying core inflation series, and β measures the degree to which the transitory component is corrected over time. If this component is fully captured, the coefficient β should be close to -1 .

Results from the tests (Table 4), which report on a 4-quarter horizon, suggest that the trimmed mean measures neither overstate nor understate future headline inflation, as indicated by the magnitudes of the β coefficients being close to 1. All other types of core measures tend to understate future headline inflation. The R^2 values for the weighted median and 25% trimmed mean are the highest, with the CPI VA and 15% trimmed mean also performing moderately well.

Results at shorter (2-quarter) and longer (6-quarter) forecast horizons show similar comparative results between each measure (see Tables A5.1 and A5.2 in Appendix 5 for details). Moreover, the 2-quarter forecast results indicate that shocks to the inflation rate, as measured by the trimmed mean measures, very largely drop out of the CPI within a half year, while shocks as filtered by the other core measures appear to take up to 6 quarters to drop out of headline inflation.

¹⁹ Empirical methodology and estimates of the Cogley tests are available in Appendix 5.

Table 4: Results from Cogley Test for Predictive Power

Forecast Length = 4 Quarters	β	R ²
Weighted Median	-0.84 (0.23)*	0.14
15% Trimmed Mean	-1.03 (0.31)*	0.11
25% Trimmed Mean	-1.04 (0.27)*	0.15
MAS Core Inflation	-0.52 (0.19)*	0.08
CPI ex Fresh Food and Energy (XFE)	-0.57 (0.23)*	0.06
CPI Volatility-adjusted (VA)	-0.65 (0.20)*	0.11

Source: EPG estimates

Note: numbers in parentheses refer to the standard error of coefficient

* denotes statistical significance at the 5% level

A reversed specification of the test was conducted to see whether movements in headline inflation lead movements in the core measures.²⁰ If some component price series move more quickly than others in response to a generalised pickup or slowdown of inflation, excluding these could mean that the core inflation series would in turn be better measured by headline inflation. The test results show that in almost all cases, however, the deviations of current period core inflation from headline inflation have no statistically significant predictive power for future values of core inflation. This gives comfort that the core inflation series are not excluding components of CPI that help predict future inflation.

4.2.3. Core inflation in Phillips Curves

In addition to the preceding tests, the responsiveness of each of the core inflation measures was examined in a standard Phillips Curve specification including inflation expectations, changes in the exchange rate, and an estimate of the output gap or unemployment gap. In principle, core inflation measures that best filter out supply shocks should tend to exhibit statistically more significant coefficients on the demand shock variables, together with better forecast performance. However, the results were inconclusive in this regard. This could be caused by a number of factors, including shifts in the Phillips Curve relationship over time, deficiencies in the measurement of inflation

²⁰ Details of the specifications and estimation results can be found in Appendix 5.

expectations and excess demand pressures, or a sample period too dominated by the lack of variation in inflation between 2015 and 2021.

5. INFLATION DEVELOPMENTS SINCE 2020

At the outset of the Covid pandemic, inflation in Singapore was very low. Headline inflation as well as MAS core inflation were running slightly negative, while the median, trimmed mean, and variance-adjusted measures were running at rates of under 1%. In 2020Q3, however, quarterly headline and most core inflation rates began to pick up (Figure 2). Note that the YOY inflation rates did not begin to pick up until 2021Q1 (Figure 3). Over the next year, all the measures of inflation picked up to annualised rates of 2–3%, with the trimmed mean measures increasing faster and more steadily than the MAS core and volatility-adjusted measure.

The inflation surge began in late 2021, with the annualised headline inflation rate rising to 7%, and then to a peak of nearly 9% in early 2022 as the escalation of hostilities in Ukraine led to soaring energy and food prices, and then began to come down. Core inflation rates picked up in 2022Q1, reaching peak annualised rates of 6–7% in mid-2022, before decelerating. YOY inflation rates peaked in 2022Q3, with the headline rate reaching 7.5%, while core rates peaked at around 5–5.5%.

The deceleration of quarterly inflation since 2022Q3 has been fitful for most measures. Headline CPI, MAS core, and volatility-adjusted inflation have all seen a sawtooth pattern of rising and falling quarterly rates, obscuring the overall slowdown from around 4% to 2%. The trimmed mean and median measures showed a much clearer trend of slowing inflation, as did the YOY measures.

Figure 2: Headline and Core Inflation QOQ % at annualised rates, 2020–2024

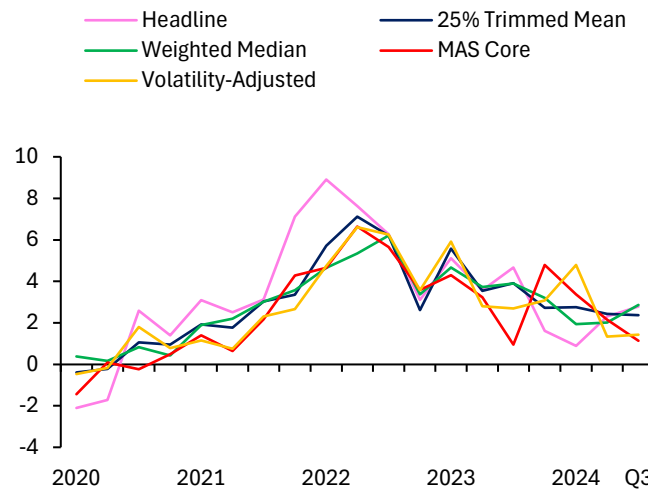
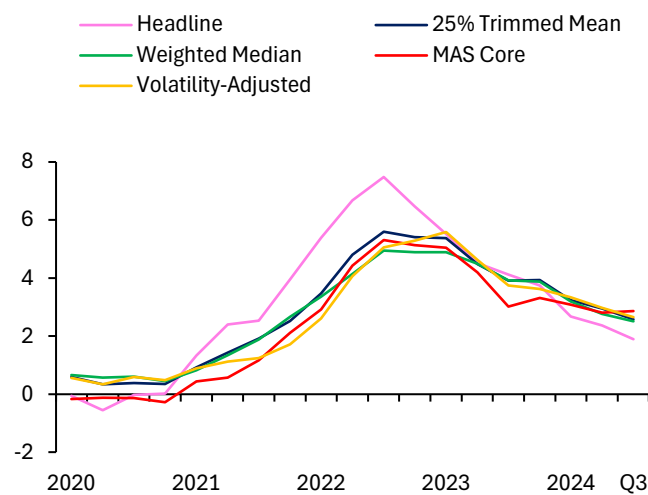


Figure 3: Headline and Core Inflation YOY %, 2020–2024



Source: EPG calculations

The experience over the past few years illustrates a few important characteristics of the various inflation measures:

- The quarterly measures are noisier than the annual inflation measures, but the turning points for the annual inflation rate are typically 2 quarters behind the quarterly measures;
- Turning points of rising or falling trend inflation are generally similar for the various measures of core inflation. Statistically, the trimmed means, median, and volatility-adjusted measures appear to provide leading information on the other measures, but the lead is not long;
- The key difference among the measures of core inflation appears to be the relative smoothness of the trimmed mean and median measures. This characteristic means that the evolving trend of inflation, including turning points, is generally clearer for these measures than for the others.

6. CONCLUDING COMMENTS

In this paper, we have constructed and examined the performance of several different measures of core inflation for Singapore over the past 20 years. Our findings are consistent with the results of similar investigations in other economies such as the US, Japan, Canada, Australia, Sweden and New Zealand.²¹ In these and numerous other countries, research has found that various measures of core inflation tend to be less volatile than the headline rate and contain leading information about future headline inflation.

In most cases, the traditional exclusion based measures, such as CPI excluding food and energy items tend to perform less well than measures such as trimmed means, or volatility-adjusted measures. In some countries, measures which adjust for administered prices, persistence-adjusted measures, or dynamic factor (smoothing) measures are also used.

The findings for Singapore strongly support the use of the 25% trimmed mean, median, and volatility-adjusted measures in policy analysis. The CPI excluding food and energy items, and the 15% trimmed mean appear to be less informative than the other measures.

As in other countries, it makes sense to compute and monitor several measures rather than focus narrowly on just one. None of the measures should be over-

²¹ See, e.g., Brischetto and Richards (2007), Johanssen et al (2013), Khan et al (2015), Ranchhod (2013), and Richards (2024).

emphasised, but if they are all pointing in the same direction, greater comfort can be taken that they are providing a correct signal. It would also provide an element of insurance against false signals coming from any individual indicator.

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7. APPENDICES

7.1. Appendix 1: Underlying Inflation Measures used at Selected Central Banks

With various types of underlying inflation measure having their own sets of strengths and weaknesses, central banks tend to make use of a combination of measures in their policy processes and communications. Table A1 provides a (non-exhaustive) list of the series that are monitored by some inflation targeting central banks²².

²² The Bank of England's Centre for Central Banking Studies identified 27 countries as having inflation targeting regimes in 2012. Since then, 6 other countries have adopted inflation targets. The countries are (in order of adoption): New Zealand, Canada, United Kingdom, Sweden, Australia, Israel, Czech Republic, Poland, Brazil, Chile, Colombia, South Africa, Thailand, Hungary, Mexico, Norway, Iceland, Peru, Philippines, Guatemala, Indonesia, Romania, Armenia, Turkey, Ghana, Georgia, Serbia, United States, Japan, Russian Federation, Kazakhstan, Ukraine, and India.

Table A1: Underlying Inflation Measures used at Selected Central Banks

Central Bank	Series Monitored
Reserve Bank of Australia	• Exclusion-based • Trimmed mean • Weighted median • Volatility-adjusted
Bank of Canada	• Exclusion-based • Trimmed mean • Median
Bank of England	• Exclusion-based • Trimmed mean
European Central Bank (ECB)	• Exclusion-based • Trimmed mean • Weighted median • Factor model: Persistent and Common Component of Inflation (PCCI) • Supercore (components are excluded based on their sensitivity to output gap)
Bank of Japan	• Exclusion-based • Trimmed mean • Weighted median
Reserve Bank of New Zealand	• Exclusion-based • Trimmed mean • Volatility-adjusted • Factor model
Swedish Riksbank	• Exclusion-based • Trimmed mean • Volatility-adjusted • Factor models
US Federal Reserve	• Exclusion-based • Trimmed mean • Weighted median • Factor models

7.2. Appendix 2: Interpolation in a Discrete Frequency Distribution

For a continuous frequency distribution, each value of x corresponds to a precise percentile of the cumulative distribution ($F(x)$) and vice versa. For discrete frequency distributions, however, an element of indeterminacy arises in matching of values of x to $F(x)$. This indeterminacy falls as the sample size increases. Since publicly available consumer price data are typically highly aggregated, the indeterminacy is substantial enough to matter. For example, if the level of data aggregation consists of around 40 price groups, then any given price will correspond to an average of around 2.5 percentage points of the distribution.

To provide a unique correspondence between values and percentiles of a discrete frequency distribution, some method of interpolation must be used to approximate a continuous distribution. In this appendix, a piece-wise linear interpolation is described. Although more complex interpolation methods are easy to imagine, the linear method is chosen because it is comparatively simple, not obviously biased, and was recommended by Fisher (1922).

To illustrate the problem, consider the following table in which price changes (x) have been arranged in ascending order:

Weight in CPI	Cumulative weight	Price change
W_1	W_1	X_1
...	...	...
W_a	A	X_a
W_b	B	X_b
W_c	C	X_c
W_d	D	X_d
...	...	...
W_n	C_n	X_n

Now suppose that we seek a value of x (e.g., the median) corresponding to a particular percentile of the cumulative frequency distribution between, say, B and C . One approach is to use the value of x corresponding to the closest higher percentile — in this case x_c . This is the approach used, for example, in

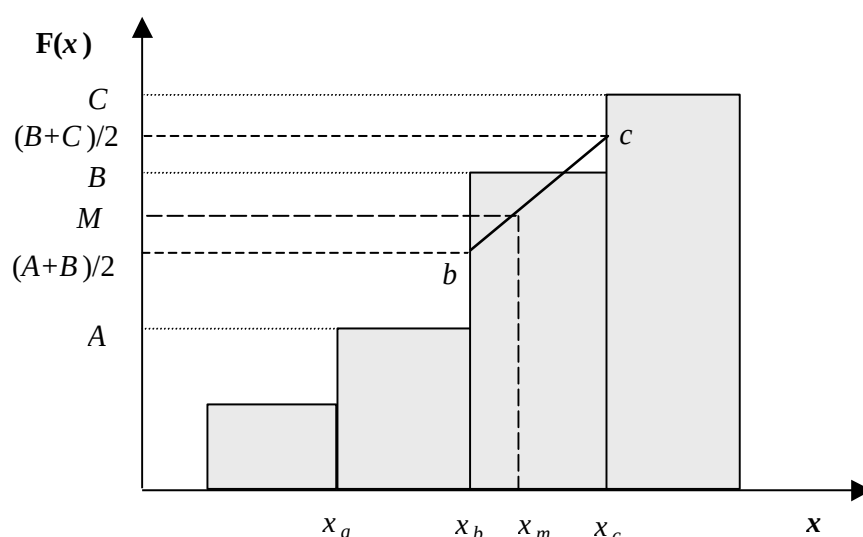
Roger (1995, 1997) and Kearns (1998). An alternative is to use a simple average of x_c and x_b (as in Microsoft Excel).

Both approaches will be fairly satisfactory if there are a large number of prices in the sample and if there are not very great differences in the weights attached to each price. For most available CPI data, however, this is not the case. Consequently, estimates based on these approaches may be quite incorrect as well as biased.

An alternative approach is to interpolate values of x between x_c and x_b . The method of linear interpolation employed in this paper is described below.

First, consider the percentile of the distribution corresponding to x_c . In the table and the figure below, x_c is shown as corresponding to point C of the cumulative frequency distribution. However, x_c is actually the average value for the percentiles between B and C . If the distribution of price changes in the B - C interval is approximately symmetric, then the value x_c will actually correspond to a percentile very close to $(B+C)/2$, the median of the range B - C interval. Similarly, x_b will correspond to percentile $(A+B)/2$, and so on.

Linear interpolation between values and percentiles of a discrete frequency distribution



Let us also assume that the value of x increases linearly from x_b to x_c over the range $(A+B)/2$ to $(B+C)/2$ and vice versa, as shown by the sloping line segment b - c in the figure. Now if we wish to estimate a value of x_m corresponding to a

particular percentile, M , of the distribution, where $[(A+B)/2] < M < [(B+C)/2]$, the estimate will simply be x_b plus $(M-(A+B)/2)$ divided by the slope of $b-c$. That is:

$$\begin{aligned}
 x_m &= x_b + [M - (A+B)/2] \div \left\{ \frac{[(B+C)/2 - (A+B)/2]}{(x_c - x_b)} \right\} \\
 &= x_b + (x_c - x_b) \bullet \left[\frac{2M - (A+B)}{(C-A)} \right] \\
 &= x_c - (x_c - x_b) \bullet \left[\frac{(B+C) - 2M}{(C-A)} \right]
 \end{aligned} \tag{1}$$

Alternatively, suppose that we wish to estimate the percentile, M , of the distribution corresponding to a particular value of x_m , where $x_b \leq x_m \leq x_c$. Interpolating linearly between percentile $(A+B)/2$, corresponding to x_b , and percentile $(B+C)/2$, corresponding to x_c , we obtain:

$$\begin{aligned}
 M &= \frac{(A+B)}{2} + (x_m - x_b) \left\{ \frac{[(B+C)/2 - (A+B)/2]}{(x_c - x_b)} \right\} \\
 &= \frac{1}{2} \left[(A+B) + \frac{(C-A)(x_m - x_b)}{(x_c - x_b)} \right]
 \end{aligned} \tag{2}$$

It may be noted that the interpolation given in equation (1) is very similar to, but not identical to, that given in Laflèche (1997, p.34). In terms of the notation used here, Laflèche's formula can be written as:

$$x_m = x_c - (x_c - x_b) \bullet \left[\frac{(C-M)}{(C-B)} \right] \tag{3}$$

The difference between equation (1) and equation (3) is simply that equation (3) implicitly assumes that the value x_b corresponds to percentile B rather than to $(A+B)/2$, and that x_c corresponds to percentile C rather than to $(B+C)/2$.

7.3. Appendix 3: Weighted Price Levels vs Weighted Price Changes

The CPI is defined as a weighted arithmetic average of price indices:

$$P_t = \sum_{i=1}^n w_i P_{it} \quad (1)$$

Where:

P_t is the CPI index in period t

P_{it} is the price index for component i of the CPI; $i = 1 \dots n$

w_i is the CPI weight of component i . Note that the weights are *time-invariant*.

Equation (1) can be divided through by the aggregate CPI in the previous period:

$$P_t/P_{t-1} = \sum_{i=1}^n w_i P_{it}/P_{t-1} = \sum_{i=1}^n w_i (P_{it}/P_{it-1}) \times (P_{it-1}/P_{t-1}) \quad (2)$$

Equation (2) can be re-written as:

$$1 + p_t = \sum_{i=1}^n w_i (1 + p_{it}) \times (P_{it-1}/P_{t-1}) = \sum_{i=1}^n w_{it} (1 + p_{it}) \quad (3)$$

Where:

p_t is the aggregate CPI inflation *rate*

p_{it} is the inflation rate for CPI component i

$w_{it} = w_i \times (P_{it-1}/P_{t-1})$ is a *time-varying* weight for the rate of inflation of CPI component i

Equation (3) shows that the aggregate CPI rate of inflation can be constructed as a time varying weighted average of CPI component price inflation. The weights essentially rebase the initial, base period weights according to movements in the relative price of each component. This highlights the Laspeyres nature of the CPI.

7.4. Appendix 4: CPI Rebasing Adjustments to Basket Weights

The CPI is constructed as a weighted average of prices, indexed to some base period j :

$$P_{jt} = \sum_{i=1}^n W_{ij} P_{ijt} \quad (1)$$

Where:

P_{jt} is the CPI aggregate

W_{ij} are the weights of the n items in the basket in the base period j

P_{ijt} are the price indexes for the n items in the basket in the base period j

When the CPI basket is periodically modified to take changes in consumption patterns into account, the basket weights are rebased to period k , and prices in the basket are indexed to the new base period.

The data available from DOS provide original base weights for each CPI basket period, but the prices are all indexed to the 2019 base period. In this case, if a weighted average of the price series is calculated, we will have:

$$P_{jkt} = \sum_{i=1}^n W_{ij} P_{ikt} \quad (2)$$

This mixes up the base periods, with the result that the calculated CPI using 2019 base prices will be incorrect, except during the period when $j=k$. To correct the problem, the 2019 base prices need to be rebased to the original base periods. This can be done by multiplying each price series by the relevant base period starting value (usually 100) and dividing by the price level in the base period using 2019 prices:

$$P_{jt} = \sum_{i=1}^n W_{ij} P_{ikt} \times \left(\frac{P_{ij}^*}{P_{ik}^*} \right) \quad (3)$$

Where:

P_{ij}^* is the price level for item i at the original prices in period j (usually 100)

P_{ik}^* is the price level for item i at the 2019 prices

What equation (3) shows is that the base 2019 price series can be rebased using the ratio $\left(\frac{P_{ij}^*}{P_{ik}^*}\right)$ to correct the error in equation (2). However, equation (3) also shows that, if what we want to do is to calculate the aggregate price level, we can leave the prices at their 2019 index values and, instead, adjust the period j base weights by multiplying them by $\left(\frac{P_{ij}^*}{P_{ik}^*}\right)$.

As a concrete example, consider the prices of the first 3 items in the CPI: (i) Bread & cereals; (ii) Meat; and (iii) fish & seafood, and focus on the beginning of 2014, with the new CPI basket, using 2014 as the base.²³ Note that an implication of this is that the use of the unadjusted weights will typically lead to understatement of the inflation rate, because items which rose in relative terms are given too little weight and items that declined in relative terms are given too much weight.

Item	P_{ij}^*	P_{ik}^*	$\frac{P_{ij}^*}{P_{ik}^*}$	$W_{ij} (\%)$	$W_{ij} \left(\frac{P_{ij}^*}{P_{ik}^*}\right)$
	$J=2014$	$K=2019$		$J=2014$	
Bread & cereal	100	94.1	1.062	1.41	1.50
Meat	100	96.7	1.034	1.20	1.24
Fish & seafood	100	88.6	1.129	1.18	1.33

²³ That is, the average levels of the prices for each item in 2014 were set at 100.

7.5. Appendix 5: Specifications of Cogley Tests

This section provides further details on the Cogley (1998) specification, which represents a simple approach to evaluate the predictive content of underlying inflation, using a regression of the following form:

$$\pi_{t+L}^H - \pi_t^H = \alpha + \beta(\pi_t^H - \pi_t^U) + \varepsilon_l$$

where π_t^H = headline inflation

π_t^U = underlying inflation

Ideally, the coefficient α should be close to 0 under the assumption that $(\pi_{t+L}^H - \pi_t^H)$ and $(\pi_t^H - \pi_t^U)$ are mean zero. A deviation from this could mean that either the headline inflation itself follows an increasing or decreasing trend over time, or that underlying inflation deviates from headline inflation over the long run.

Meanwhile, the coefficient of β should be close to -1 . This coefficient effectively measures how much of the deviation of underlying inflation from headline inflation $(\pi_t^H - \pi_t^U)$, or the transitory component of inflation, shows up in the future changes in headline inflation $(\pi_{t+L}^H - \pi_t^H)$. The farther this number deviates from unity, the more under- or over-stated the magnitude of the future changes in headline will be, suggesting that the information content of the underlying series is impaired.

We present results at one-year ($L = 4$) and two-year ($L = 8$) forecast lengths, which are generally relevant in the context of monetary policy. On the whole, the coefficient for β is negative and statistically different from zero, with the sole exception of CPI XFE at a one-year horizon. However, the degree of deviation from unity varies across measures (Table A5.1).

Table A5.1: Results from Cogley Test

Forecast Length = 2 Quarters	α	β	R^2
Weighted Median	0.04 (0.08)	-0.88 (0.19)*	0.21
15% Trimmed Mean	0.01 (0.08)	-1.17 (0.25)*	0.20
25% Trimmed Mean	0.03 (0.08)	-1.07 (0.22)*	0.23
MAS Core Inflation	0.04 (0.08)	-0.63 (0.15)*	0.17
CPI XFE	0.08 (0.08)	-0.66 (0.19)*	0.13
Volatility-weighted	0.05 (0.08)	-0.71 (0.16)*	0.19

Forecast Length = 4 Quarters	α	β	R^2
Weighted Median	0.06 (0.1)	-0.84 (0.23)*	0.14
15% Trimmed Mean	0.03 (0.1)	-1.03 (0.31)*	0.11
25% Trimmed Mean	0.05 (0.09)	-1.04 (0.27)*	0.15
MAS Core Inflation	0.06 (0.1)	-0.52 (0.19)*	0.08
CPI XFE	0.10 (0.1)	-0.57 (0.23)*	0.06
Volatility-weighted	0.08 (0.1)	-0.65 (0.20)*	0.11

Forecast Length = 6 Quarters	α	β	R^2
Weighted Median	0.09 (0.11)	-1.24 (0.26)*	0.23
15% Trimmed Mean	0.04 (0.11)	-1.41 (0.36)*	0.16
25% Trimmed Mean	0.08 (0.11)	-1.38 (0.31)*	0.20
MAS Core Inflation	0.09 (0.11)	-0.85 (0.22)*	0.16
CPI XFE	0.17 (0.12)	-1.07 (0.26)*	0.18
Volatility-weighted	0.11 (0.11)	-1.05 (0.23)*	0.21

Source: EPG estimates

Note: numbers in parentheses refer to the standard error of coefficient

* denotes statistical significance at the 5% level

The Cogley test can also be conducted in reverse, using the deviation of future from present core inflation as the dependent variable, with the following formal specification:

$$\pi_{t+L}^U - \pi_t^U = \alpha + \beta(\pi_t^H - \pi_t^U) + \varepsilon_t$$

The β coefficient in this case measures how the difference between underlying and total inflation can predict the future course of core inflation. If the excluded components in a core series are simply more flexible than others and respond more quickly to changes in aggregate demand, trend inflation would be better measured by headline inflation itself, and β would be statistically different from zero. The results show that this is not the case (Table A5.2), with low statistical significance for β and low explanatory power for the regressions (as measured by the R^2). This suggests that on the whole, the selected core inflation measures do not exclude components or information that are good predictors of headline inflation.

Table A5.2: Results from Reverse Cogley Test

Forecast Length = 2 Quarters	α	β	R^2
Weighted Median	0.01 (0.05)	0.10 (0.12)	0.00
15% Trimmed Mean	0.01 (0.06)	-0.04 (0.19)	-0.01
25% Trimmed Mean	0.01 (0.05)	-0.01 (0.15)	-0.01
MAS Core Inflation	-0.01 (0.06)	0.26 (0.12)*	0.04
CPI XFE	-0.03 (0.06)	0.37 (0.13)*	0.09
Volatility-weighted	0.00 (0.05)	0.08 (0.10)	-0.01

Forecast Length = 4 Quarters	α	β	R^2
Weighted Median	0.03 (0.07)	0.12 (0.17)	-0.01
15% Trimmed Mean	0.02 (0.08)	-0.17 (0.26)	-0.01
25% Trimmed Mean	0.03 (0.07)	-0.12 (0.20)	-0.01
MAS Core Inflation	0.02 (0.08)	0.00 (0.15)	-0.01
CPI XFE	0.01 (0.08)	0.20 (0.19)	0.00
Volatility-weighted	0.03 (0.07)	-0.01 (0.14)	-0.01

Forecast Length = 6 Quarters	α	β	R^2
Weighted Median	0.06 (0.08)	-0.21 (0.19)	0.00
15% Trimmed Mean	0.04 (0.1)	-0.4 (0.31)	0.01
25% Trimmed Mean	0.05 (0.09)	-0.35 (0.24)	0.01
MAS Core Inflation	0.02 (0.09)	0.01 (0.18)	-0.01
CPI XFE	0.04 (0.09)	0.02 (0.21)	-0.01
Volatility-weighted	0.05 (0.08)	-0.12 (0.16)	-0.01

Source: EPG estimates

Note: numbers in parentheses refer to the standard error of coefficient

* denotes statistical significance at the 5% level