South African Reserve Bank Special Occasional Bulletin of Economic Notes

Special OBEN/24/02

South African Reserve Bank Economic Notes are typically short economic analyses initially written for internal discussion and to stimulate debate. They are written by staff members of the South African Reserve Bank or visiting fellows and are released publicly on an occasional basis.

SOUTH AFRICAN RESERVE BANK

Authorised for publication by:

Chris Loewald

August 2024

SARB Special Occasional Bulletin of Economic Notes August 2024

Table of Contents

1. Likely near-term macroeconomic impact of the implementation of the two-pot retirement saving system
Nkhetheni Nesengani, Riaan Ehlers, Mish Choonoo, Annelie Van Niekerk and Theo Janse van Rensburg

2. PCCI of SA's CPI: Estimating the persistent and common component of inflation for South Africa
Ayrton Amaral, Marique Kruger, Dineo Lekgeu and Witness Simbanegavi

3. A supercore inflation measure for South Africa
Samantha de Kock, MG Ferreira, Mpho Rapapali, Witness Simbanegavi and Mokgabiso Tshenkeng

Information on South African Reserve Bank Special Economic Notes can be found at
http://www.resbank.co.za /Research/Special Occasional Bulletin of Special Economic Notes/Pages/EconomicNotes-Home.aspx

Enquiries
Head: Research Department
South African Reserve Bank
P O Box 427
Pretoria 0001

Tel. no.: +27 12 313-3911
0861 12 SARB (0861 12 7272)

Special OBEN 2402* – June 2024

PCCI of SA's CPI: Estimating the persistent and common component of inflation for South Africa

Ayrton Amaral, Marique Kruger, Dineo Lekgeu and Witness Simbanegavi

Abstract

This Note presents a new, additional measure of underlying inflation for South Africa, termed the persistent and common component of inflation (PCCI). The PCCI indicates that inflation pressures in the domestic economy are elevated, with outcomes remaining closer to the upper limit of the target band over the past year. The information content of the PCCI is similar to that of the other measures of underlying inflation, such as core and trimmed mean inflation. In particular, all three measures presently indicate that the persistence of headline inflation above the 4.5% midpoint partly reflects elevated underlying inflation. Reliability assessments show that the PCCI has high predictive power on headline inflation, is stable and is less volatile than headline inflation. Future work will consider estimating the PCCI with other methods as part of further testing the measure's validity (i.e. whether it measures underlying inflation accurately) and reliability (i.e. if it does so consistently).

1. Introduction

A central challenge for inflation-targeting central banks is to decode from monthly inflation data the component of inflation that is durable (persistent) and the component that is transitory. It is the durable component that provides the signal of where inflation is headed and thus matters for monetary policy. The fleeting component washes off in a shorter time horizon than it would normally take for policy to transmit.[1] Techniques/approaches have been devised in the literature for extracting the signal from noisy high-frequency inflation data, and these have generated various indicators of underlying inflation pressures.[2]

The SARB tracks two 'official' measures published by Statistics South Africa (Stats SA), namely, core inflation and trimmed mean inflation, to gauge underlying inflation pressures and, thus, the likely trajectory for headline inflation. Core inflation, measured as headline inflation excluding food and non-alcoholic beverages (NAB), fuel and electricity, is the most widely used

---

1 Blinder, (1997).

2 Popular measures of underlying inflation include core inflation, trimmed mean inflation and weighted median inflation.

indicator, with applications in the SARB's Quarterly Projection Model (QPM). The trimmed mean inflation is also an exclusion-based measure, but it determines which components to exclude in a more systematic way. It drops different items each month by assigning a weight of zero to those components with the highest and lowest changes on a month-on-month basis ("trimming" 5% on either side).

While these exclusion-based measures are intuitive and easier to communicate, they have two major weaknesses. First, such measures could still carry substantial 'noise' as they may retain elements of transitory shocks in the included components.[3] Second, by throwing away certain data, potentially durable information in monthly data relevant for policy may be lost. This is especially likely in the context of persistent shocks to the excluded components that contribute to second-round effects in included components, as we have seen over the past four years.[4]

In this Note, we estimate a new measure of underlying inflation, hereafter referred to as the Persistent and Common Component of Inflation (PCCI), for South Africa, using factor modelling. The PCCI is a non-exclusion-based measure and thus does not suffer from the drawbacks highlighted above. The addition of this measure enriches the set of indicators to be considered by the SARB when assessing inflationary pressures in the domestic economy.

2. A factor model for underlying inflation

Factor modelling is a statistical technique that works off the premise that common dynamics of a large number of time series can be explained by a few unobserved factors.[5] While applying factor modelling to macroeconomic data is not new, the ever-increasing production of new data series published at a high frequency has made these models a popular data dimensionality reduction technique. Factor models have seen considerable uptake as a tool for analysing the vast information contained in consumer price subindices, especially since the method underpinning these models is data-driven (i.e. no structural economic assumptions are needed). Applications have included the derivation of underlying inflation measures such as the PCCI.

In factor modelling, inflation for a particular subseries i of the CPI can be thought of as being driven by two sources of variation: a persistent trend element that shares a common source of variation across the series in the system and a series-specific idiosyncratic disturbance denoted $\varepsilon_{i,t}$. The common variation can be thought of as encapsulating underlying price pressures stemming from drivers such as the output gap and second-round effects originating from supply shocks.[6, 7] In effect:

3 For example, transport services inflation (included in core inflation) can see significant volatility stemming from fuel price shocks.

4 As Rangasamy (2011) shows, for example, food inflation in South Africa can be persistent and result in second-round price effects and he argues that, by excluding such a component from measures of core inflation, one could run the risk of failing to accurately capture underlying price pressures in the economy.

5 See Stock and Watson, (2016).

6 Since this modelling framework imposes no structural economic assumptions, it is not possible to pinpoint exact sources of underlying inflation pressures such as demand pressures or second-round effects. They are, however, implied given the described decomposition.

7 Non-exclusion-based measures derived from factor models have their own drawbacks. For one, their computation is more complicated and opaque than with exclusion-based measures. For example, and as

$$\pi_{i,t} = \Lambda_i F_t + \varepsilon_{i,t} \tag{1}$$

where F_t is the common factor driving inflation. Each subindex, i, is related to this common factor via a so-called factor loading, Λ_i. The term $\Lambda_i F_t$ therefore gives the persistent component of inflation of the i^{th} subindex.

From a monetary policy perspective, this decomposition is helpful since it breaks down inflation into a part over which policy can exert influence (i.e. the persistent or long-lasting component) and a part that policy should "look through" (i.e. the idiosyncratic component).

Factor models can be estimated parametrically by specifying a model for the factors or non-parametrically.[8] The non-parametric approach has the advantage that estimation tends to be computationally less taxing to implement when both the number of observations, N, and the time periods, T, are large, as is often the case with consumer price subindices. Examples of non-parametric studies of underlying inflation include Cristadoro et al. (2005) for the Euro Area, Giannone and Matheson (2006) for New Zealand, Khan et al. (2013) for Canada and Abenoja et al. (2017) for the Philippines. The present study follows this literature.

Along with Khan et al. (2013) and Abenoja et al. (2017), we consider a (static) factor model of the form:

$$\boldsymbol{\pi_t} = \boldsymbol{\Lambda}\mathbf{F_t} + \boldsymbol{\varepsilon_t} \tag{2}$$

where $\boldsymbol{\pi_t}$ is a matrix of the inflation rates of the various series in the system, $\boldsymbol{\Lambda}$ is the matrix of factor loadings that relate the unobservable factors $\mathbf{F_t}$ with the different series in $\boldsymbol{\pi_t}$.[9] The matrix $\boldsymbol{\pi_t}$ has dimension $N \times T$, $\boldsymbol{\Lambda}$ is an $N \times r$ matrix (where r is the number of unobserved factors; the exact number to include is an empirical question which we address in Section 3), $\mathbf{F_t}$ is an $r \times T$ matrix and $\boldsymbol{\varepsilon_t}$ is of dimension $N \times T$.

Finally, each series' persistent component is then given by:

$$\widetilde{\boldsymbol{\pi}}_{\boldsymbol{t}} = \boldsymbol{\Lambda}\mathbf{F_t} \tag{3}$$

3. Data and estimation

We estimate the PCCI for South Africa using consumer price subindices based on a COICOP four-digit level of aggregation, which equates to a total of 83 unique time series.[10] We calculate

---

we outline in Sections 2 and 3, the estimated factors of the PCCI are not necessarily observable, possibly making its interpretation and communication to the public more complex.

8 See Stock and Watson (2016) and Doz and Fuleky (2019) for a more detailed exposition of factor models and the different estimation techniques.

9 The model in the dynamic form can be written as:

$$\boldsymbol{\pi_t} = \boldsymbol{\Lambda}(\mathrm{L})\boldsymbol{f_t} + \boldsymbol{\varepsilon_t}$$

where the other components are defined as above and $(\mathrm{L})\boldsymbol{f_t}$ represents the common factor matrix and its lags.

10 The four-digit COICOP is the most disaggregated level of CPI subindices stored consistently on the SARB's internal databases; a detailed list of the various series is given in Table A1.

the inflation rates of these 83 series as the year-on-year percentage changes. Four of these series were, however, dropped from the analysis because they either have too few data points since they only begin after 2012 (musical instruments, services for the maintenance and repair of dwelling and package holidays) or because there is insufficient variation in the series (games of chance).[11] The remaining 79 series were then reweighted.

The model in (2) is estimated non-parametrically with the aid of principal component analysis (PCA) to obtain estimates for the underlying factors as outlined in the methodology proposed by Stock and Watson (2002a; 2002b).

PCA is, however, sensitive to the scale of the time series; thus, it is common in the literature to standardise the series contained in $\boldsymbol{\pi_t}$ prior to performing the PCA.[12] There are various standardisation techniques in the literature. Here, we follow Leung et al. (2009) and Abenoja et al. (2017) and define the transformed variable as:

$$x_{i,t} = \frac{\pi_{i,t} - \bar{\pi}_i}{\sigma_{\Delta_i}} \quad (4)$$

where $\pi_{i,t}$ is the year-on-year inflation rate of the i^{th} subindex of CPI, $\bar{\pi}_i$ is the corresponding series' sample mean and σ_{Δ_i} is the standard error of the first difference of the series and $x_{i,t}$ is the standardised i^{th} series. The specification in (4) is deemed more appropriate when the time series data are non-stationary.[13] Let $\boldsymbol{X_t}$ be a matrix of all the standardised $x_{i,t}$ series.

We can derive an estimate for the loadings matrix in (2), $\widehat{\boldsymbol{\Lambda}}$, with PCA to obtain the loadings that correspond to the r^{th} principal component of the correlation matrix of $\boldsymbol{X_t}$ (recall that r is the number of factors to be included in the model). While statistical methods, such as information criteria, provide a systematic way of determining r,[14] in the PCCI literature, the focus is generally on obtaining a single underlying factor that drives variation across multiple inflation time series. Accordingly, r is typically set equal to one, implying that $\widehat{\boldsymbol{\Lambda}}$ is the vector of factor loadings corresponding to the first principal component from the PCA. $\widehat{\mathbf{F}}_{\mathbf{t}}$ is then given by:

$$\widehat{\mathbf{F}}_{\mathbf{t}} = \frac{\widehat{\boldsymbol{\Lambda}}' \boldsymbol{X_t}}{N} \quad (5)$$

Evaluating $\widehat{\boldsymbol{\Lambda}}\widehat{\mathbf{F}}_{\mathbf{t}}$ gives the standardised common component of each series, which needs to be rescaled to be comparable with the respective series' inflation rate.[15] Multiplying each rescaled series by its weight in CPI and taking the sum yields the overall PCCI measure. The results are presented in Figure 1. While headline inflation and the PCCI generally correlate well, there

---

11 The dropped series comprise of 2.36% of the total weight in CPI.

12 See, for instance, Khan et al. (2013) and Abenoja et al. (2017).

13 See Marques, Neves and da Silva (2001) for details.

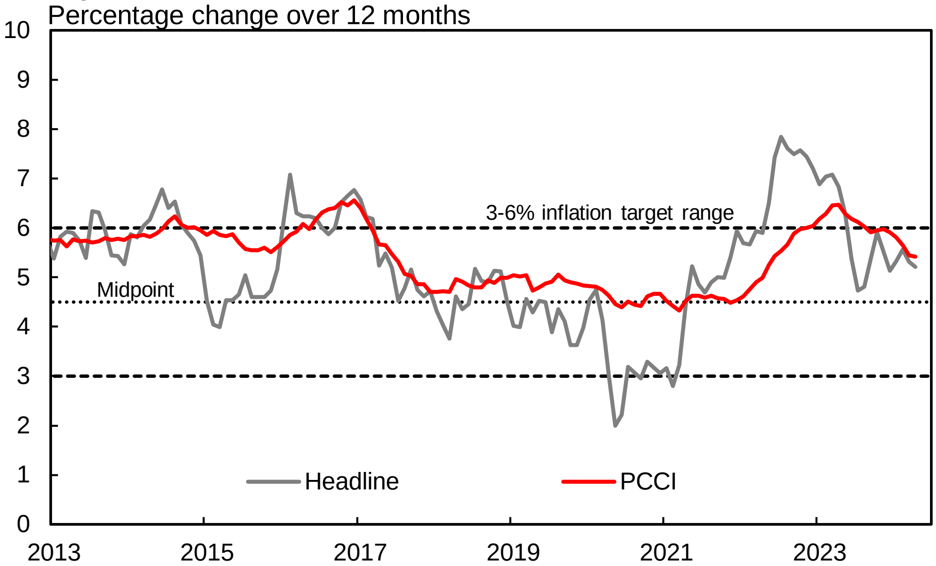
14 See Bai and Ng, (2002).

15 The series can be rescaled by multiplying the standardised PCCI by the standard deviation of the first difference of headline inflation and then adding back the mean (See for example Khan et al. (2013) and Abenoja et al. (2017)) or by regressing the original ith series on its standardised common component and a constant (see for example Marques, Neves and da Silva (2001)). We use the latter.

also are periods of sharp divergence. These periods of marked divergence largely reflect supply-side shocks, such as sharp swings in fuel or food price inflation.[16]

Figure 1: PCCI and other inflation measures

Percentage change over 12 months



Sources: Stats SA and SARB

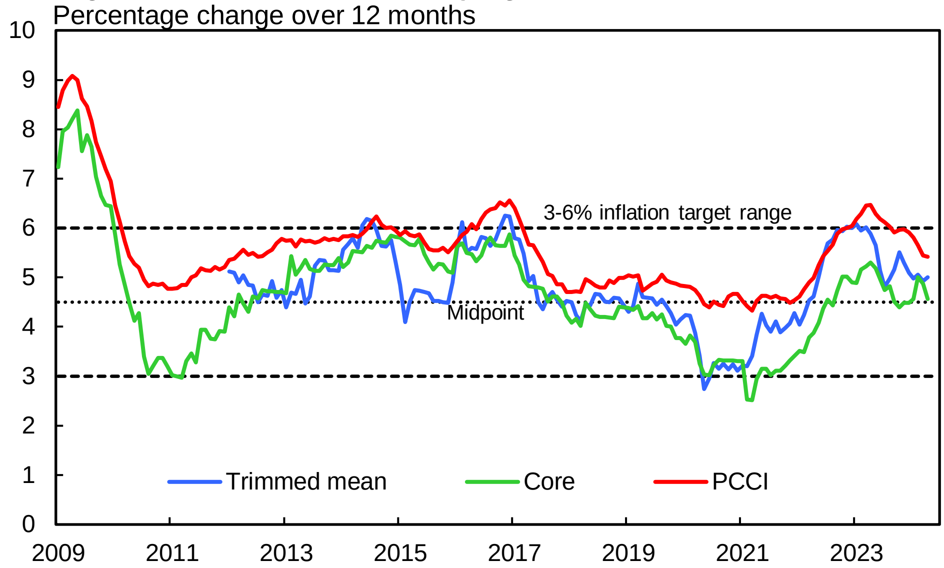
Figure 2 shows the extracted PCCI along with the exclusion-based measures of underlying inflation, namely core and the trimmed mean inflation. Visually, the PCCI is the smoothest of the measures. The lower volatility of the PCCI accords with expectations and intuition, given that it is constructed by isolating common, underlying drivers of inflation, which tend to be stable and slow-evolving since the PCCI excludes transitory/sectoral shocks. Another feature immediately obvious from Figure 2 is the PCCI's ability to smooth over periods of considerable shocks, such as during lockdowns in 2020-2021 and the subsequent post-COVID supply chain disruptions and the Russia-Ukraine war.[17] The PCCI correlates strongly with both core and the trimmed mean inflation, which suggests these measures capture a significant part of *true* underlying inflation.[18]

16 For example, the sharp drops in headline inflation around 2015 and then at the onset of the COVID-19 pandemic in 2020 resulted predominantly from fuel deflation (annual fuel inflation in 2015 and 2020 was -10.7% and -6.9% respectively). The model identified these events as idiosyncratic fuel inflation shocks, allowing the PCCI to smooth over these periods. Likewise, during the food- and fuel-driven surge in inflation in 2021 and 2022, the model also smoothed this shock, resulting in the PCCI measure coming out lower than the headline outcome.

17 PCCI moved by 1.8 percentage points from trough to peak while core inflation rose by 2.7 percentage points and trimmed mean by 3.3 percentage points.

18 The correlation coefficients between the PCCI and trimmed mean and core inflation are 0.86 and 0.89 respectively.

Figure 2: Measures of underlying inflation

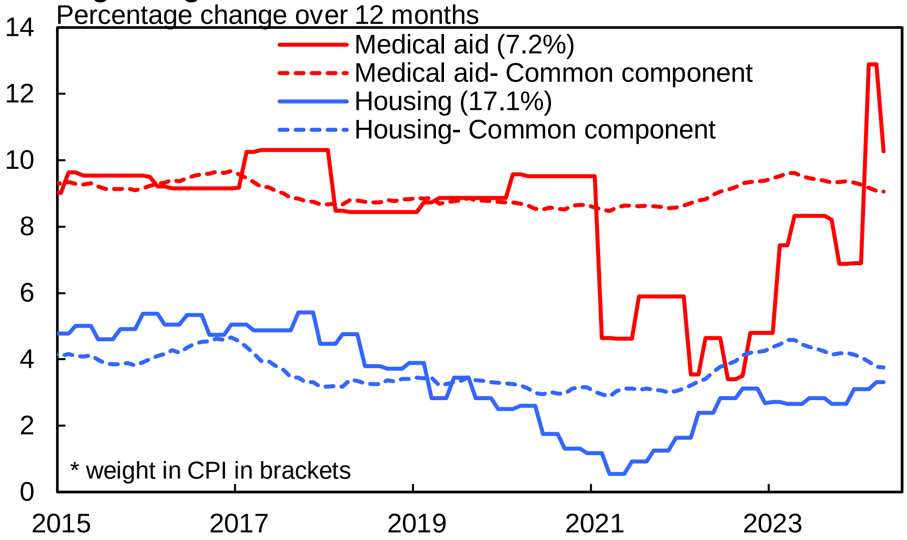


Sources: Stats SA and SARB

Figure 2 also shows a sustained divergence between the PCCI and core inflation since the COVID-19 pandemic in 2020. In addition, the PCCI measure indicates that underlying inflationary pressures are stronger than suggested by core inflation. These observations are related in that the main reason for both stems from the sizeable downside idiosyncratic shocks among large-weight components of the core CPI basket. In particular, actual inflation outcomes for medical insurance inflation and housing have been below their long-term trends since around 2020-2021 (Figure 3). This has slowed the rise in core inflation over this period. However, as inflation for these items returns to levels more aligned with long-term averages, core inflation will shift closer to the PCCI, as we have observed in recent months.[19]

[19] More generally, PCCI has tended to be consistently above core inflation, to varying degrees, over the sample period in question. One of the primary reasons for this gap is the inclusion of traditionally 'non-core' elements, specifically food and non-alcoholic beverages (FNAB), in the PCCI's construction. FNAB inflation is higher, on average, than core inflation (6.6% vs 4.7%; from Jan 2009 to Jan 2024). Our model identifies a non-negligible persistent/common component among the series that together constitute the FNAB basket and that ultimately contributes to the aforementioned gap. The presence of a persistent component for FNAB is in line with findings by Rangasamy (2011) which suggests that food inflation may be an important contributor to underlying inflation dynamics in South Africa.

Figure 3: Inflation and common components for selected large-weight items*



Sources: Stats SA and SARB

4. Is the PCCI a valid and reliable measure of underlying inflation?

To be useful and informative for monetary policy, a measure of underlying inflation must have predictive power for headline inflation, be stable with respect to historical revisions as new inflation data is introduced to the model and be less volatile than headline inflation.[20] In this section, we evaluate the PCCI against these criteria.

We first evaluate the predictive ability of the PCCI. To evaluate this, we follow Giannone and Matheson (2006) and run a regression of the form:

$$\pi_{t+4} - \pi_t = \alpha + \beta(\pi_t^u - \pi_t) + \varepsilon_{t+4} \quad (6)$$

where π_t^u denotes a measure of underlying inflation such as the PCCI (we carry out similar regressions using trimmed mean and core inflation for comparative purposes).

Table 1 includes descriptive statistics and estimates from a regression testing the predictive power of the various underlying measures.[21] By these metrics, the PCCI is a valid and reliable indicator of inflationary pressure and has predictive power regarding the future direction of headline inflation.

---

20 See, for example, Khan et al. (2013), Einarsson, (2014) and Abenoja et al. (2017).

21 The regression is to test whether the current gap between underlying inflation measure and headline inflation predicts future changes in headline inflation. Predictive power is indicated by $\beta > 0$ and α should also be equal to 0. R^2 shows the goodness of fit and thus gives an indication of the predictive power of the variable in question (see Giannone and Matheson (2006)).

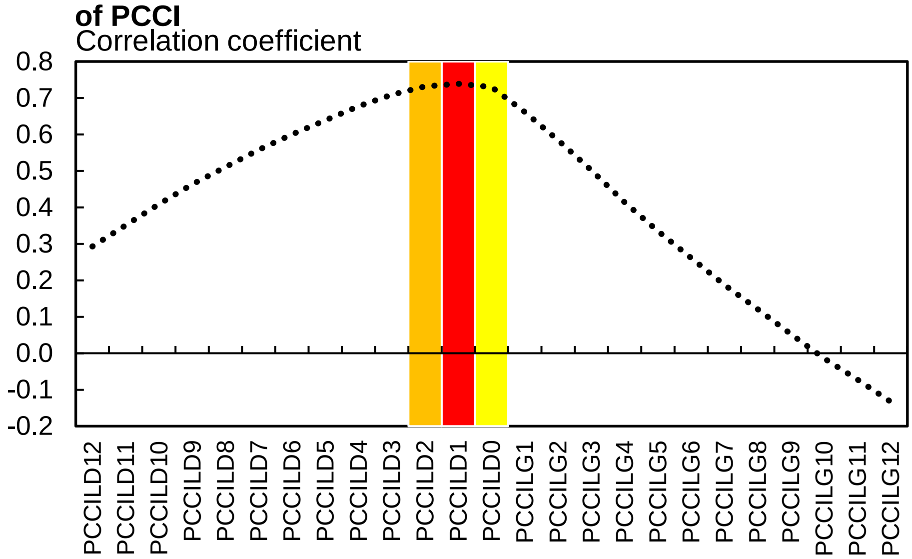
Table 1: Descriptive statistics and predictive ability of underlying inflation measures

	Mean	Standard deviation	Correlation	$\pi_{t+4} - \pi_t = \alpha + \beta(\pi_t^{core} - \pi_t) + \varepsilon_{t+4}$		
				α	β	R^2
Headline CPI	5.68	1.96				
Core inflation	4.67	1.12	0.68	-0.015	0.083	0.36
Trimmed mean	4.81	0.79	0.88	0.09	0.263	0.41
PCCI	5.57	0.93	0.73	-0.013	0.216	0.38

When comparing the three measures of underlying inflation, the trimmed mean performs the best, followed by the PCCI.[22] Figures A1 to A3 in the appendix show in-sample forecasts of headline inflation with the various measures as the primary explanatory variable and show similar conclusions regarding each measure's predictive ability as the analysis in Table 1.

We also analyse correlations of headline inflation to leads and lags of the PCCI, and the results suggest that the latter contains information that could help in identifying turning points in headline inflation (Figure 4).[23]

Figure 4: Correlation of headline inflation to leads and lags of PCCI



Source: Own calculations

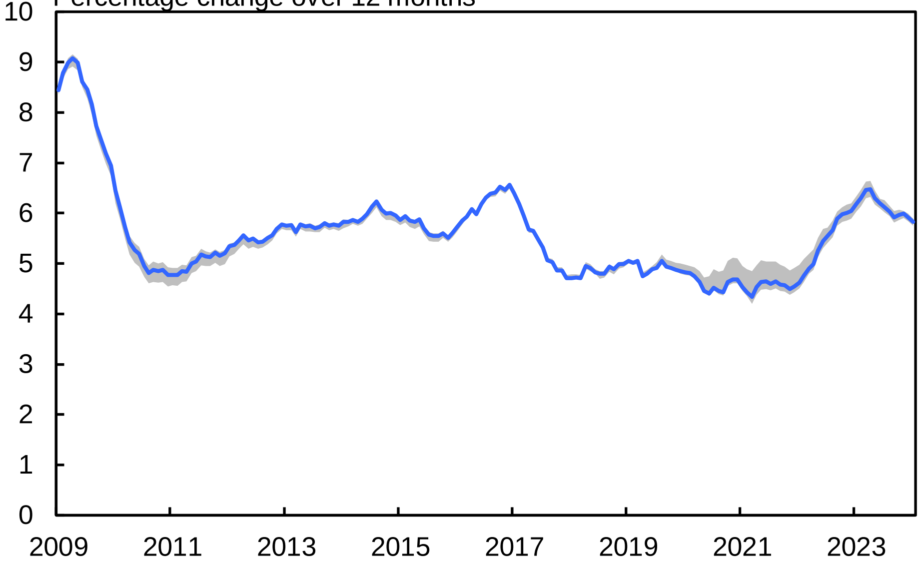
22 The superior performance of trimmed mean is unsurprising given that it tracks 90% of the CPI basket and that it incorporates some transitory shocks (except for the excluded 10%).

23 See Ehrmann et al. (2018) as well as Bańbura and Bobeica, (2020).

The stability of the PCCI is assessed through the evaluation of the sensitivity of the PCCI to historical revisions each time new inflation data is added to the model.[24] Large and significant revisions to the PCCI would cast doubt as to the measure's real-time accuracy and, thus, usefulness for policy purposes. To test the sensitivity of the PCCI to data revisions, we run the PCA over ten years. We then expand the PCA window by one month at a time and get a new PCCI series each time. We iterate this process until the whole sample is covered in the PCA. Figure 5 shows that, except for the COVID period, the PCCI measure is remarkably stable.[25]

Figure 5: PCCI revisions

Percentage change over 12 months



Source: Stats SA and own calculations

One of the essential characteristics of underlying inflation measures is that, by construction, they should reduce or eliminate volatility arising from transitory or sectoral disturbances (i.e. extract the signal from noise in inflation data). Accordingly, at the very minimum, it should be smoother than the headline inflation measure. Figure 6 (see also Table 1) shows that the various measures of underlying inflation exhibit lower volatility compared to headline, with the PCCI performing relatively well in this regard.[26] Also worth highlighting in Table 1 is that the PCCI seems to provide the most accurate estimate for the mean of actual inflation.[27]

---

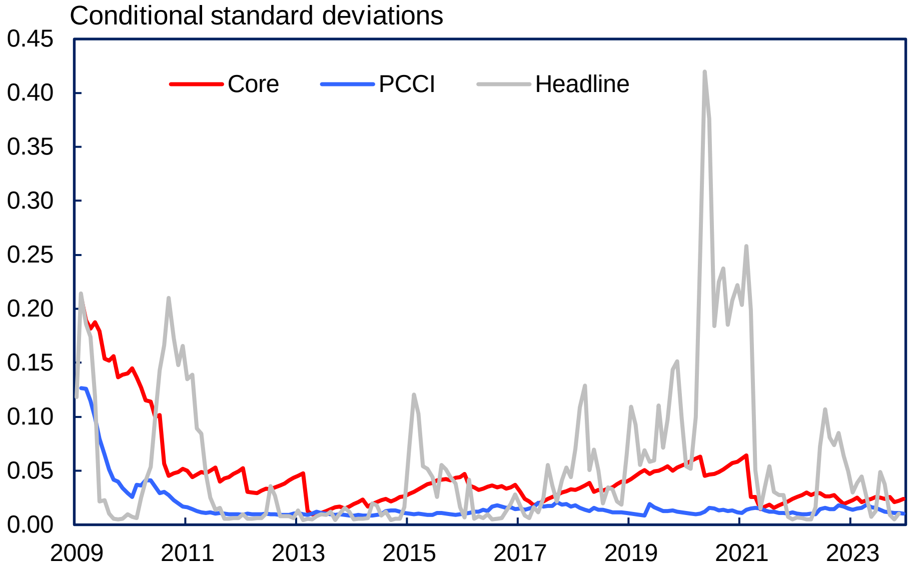
24 CPI data itself is not subject to historical revisions, however, since the PCCI is estimated each time new CPI data is released, PCCI estimates may be subject to historical revisions.

25 For our full sample, revisions averaged around 0.06pp in absolute terms. During 2020/2021, as the real-time sensitivity to new data picked up, this value increased, averaging 0.12pp in absolute terms. Since 2022, the number has fallen again, averaging 0.07pp.

26 In Figure 6, volatility is determined using the generalized autoregressive conditional heteroscedasticity methodology.

27 As highlighted by du Plessis, du Rand and Kotzé (2015), such in-sample statistics serve as additional ways of evaluating the usefulness of core inflation measures more generally.

Figure 6: Volatility of Core, Headline and PCCI



Source: Stats SA and own calculations

In all, the above analyses confirm that the PCCI is a reliable and informative alternative measure of underlying inflation. This provides confidence for its use as an alternative measure of underlying inflationary pressures in the domestic economy.

5. Conclusion

In this research, we estimated the PCCI for South Africa. It serves as an additional gauge of underlying inflation that complements existing measures by seeking to counter shortcomings of core and trimmed mean inflation. This new measure shows more elevated underlying inflationary pressures than suggested by core inflation, but direction of travel is similar. PCCI as well as core inflation and trimmed mean inflation all point to elevated underlying inflation, with outcomes above the target midpoint over the past year.

A battery of tests indicates that this measure is a reliable and informative measure of underlying inflation and is thus potentially useful for monetary policy. Future research on the PCCI will consider different estimation strategies and alternative model specifications.

References

Abenoja, Z. R., Basillio, J. R., Ramos, C. F., & Allon, J. C. (2017). An Alternative Core Inflation Measure for the Philippines using Principal Components Analysis. *Bangko Sentral ng Pilipinas Review*.

Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica, 70*(1), 191-221.

Bańbura, M., & Bobeica, E. (2020). PCCI - a data-rich measure of underlying inflatoin for the euro area. *ECB Statistics Paper Series, 38*(2020).

Blinder, A. S. (1997, May). Measuring short-run inflation for central bankers - commentary. *Review, Federal Reserve Bank of St. Louis.*, pp. 157-160.

Cristadoro, R., Forni, M., Reichlin, L., & Veronese, G. (2005). A Core Inflation Indicator for the Euro Area. *Journal of Money, Credit and Banking, 37*(3), 539-560.

Doz, C., & Fuleky, P. (2019). Dynamic Factor Models. *Paris School of Economics Working Papers, 2019-45*.

du Plessis, S., du Rand, G., & Kotzé, K. (2015). Measuring Core Inflation in South Africa. *South African Journal of Economics, 83*(4), 527-548.

Ehrmann, M., Ferrucci, G., Lenza, M., & O'Brien, D. (2018). Measures of underlying inflation for the euro area. *ECB Economic Bulletin*(4).

Einarsson, B. G. (2014). A Dynamic Factor Model for Icelandic Core Inflation. *Central Bank of Iceland Working Paper, No. 67*.

Giannone, D., & Matheson, T. D. (2006). A New Core Inflation Indicator for New Zealand. *Reserve Bank of New Zealand Discussion Paper Series, DP2006/10*.

Khan, M., Morel, L., & Sabourin, P. (2013). The Common Component of CPI: An Alternative Measure of Underlying Inflation for Canada. *Bank of Canada Working Paper, 2013-35*.

Kirker, M. (2010). What Drives Core Inflation? A Dynamic Factor Model Analysis of Tradable and Nontradable Prices. *Reserve Bank of New Zealand Discussion Paper Series, DP2010/13*.

Leung, F., Chow, K., & Chan, S. (2009). Measures of Trend Inflation in Hong Kong. *Hong Kong Monetary Authority Working Paper*(07/2009).

Marques, C. R., Neves, P. D., & da Silva, A. G. (2001). Using the First Principal Component as a Core Inflation Indicator. *Bank of Portugal Economic Bulletin*.

Palazzi, A. L., & Simbanegavi, W. (2023). Mind Second-round Effects! The Effects of Food and Energy Inflation on Core Inflation in South Africa. *South African Reserve Bank Occasional Bulletin of Economic Notes, OBEN 2301*.

Rangasamy, L. (2011). Food Inflation in South Africa: Some Implications for Economic Policy. *South African Journal of Economics, 79*(2), 184-201.

Stock, J. H., & Watson, M. W. (2002a). Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business & Economic Statistics, 20*(2), 147-162.

Stock, J. H., & Watson, M. W. (2002b). Forecasting Using Principal Components From a Large Number of Predictors. *Journal of the American Statistical Association, 97*(460), 1167-1179.

Stock, J. H., & Watson, M. W. (2016). Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. In J. B. Taylor, & H. Uhlig (Eds.), *Handbook of Macroeconomics* (Vol. 2A, pp. 415-525). Elsevier.

Appendix

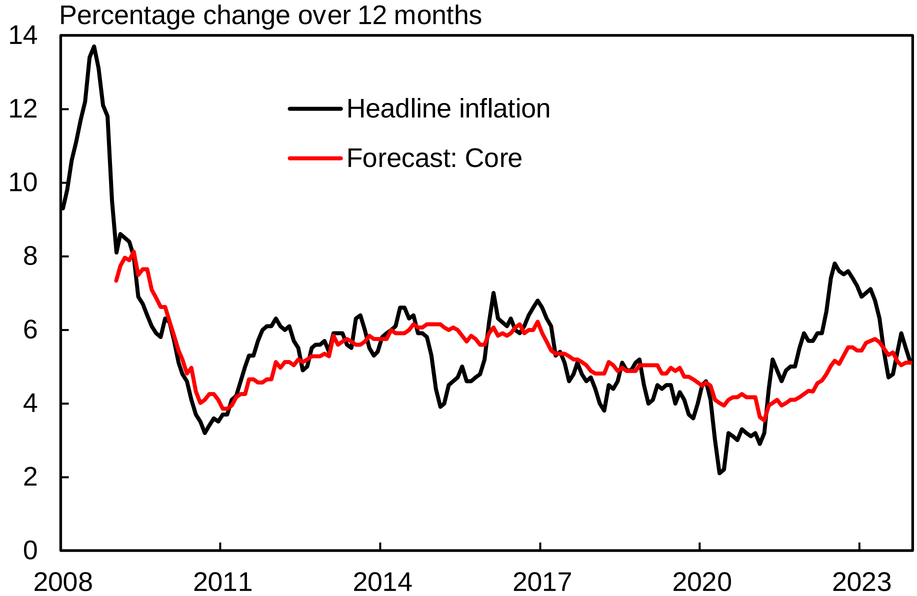
Table A1: Relationship between PCCI and individual components of CPI

CPI Components	Weight	Correlation
Goods: Hot beverages	0.67	0.873
Goods: Personal care	1.38	0.868
Goods: Large appliances	0.36	0.844
Services: Restaurants	2.30	0.838
Goods: Other foods	1.16	0.823
Goods: Games, toys and hobbies	0.08	0.794
Goods: Fish	0.40	0.729
Goods: Spirits and liqueurs	0.94	0.714
Goods: Pharmaceutical products	0.57	0.705
Goods: Tools and equipment for house and garden	0.02	0.694
Goods: Clothing	2.64	0.691
Services: Health Medical services	0.97	0.684
Goods: Small appliances	0.08	0.678
Services: Accommodation services	1.14	0.676
Services: Financial services N.E.C	1.63	0.662
Goods: Milk, cheese and eggs	2.53	0.658
Goods: Footwear	1.01	0.653
Goods: Small tools & equipment	0.07	0.622
Goods: Garden products	0.08	0.616
Services: Actual rentals for housing: Houses	2.16	0.607
Goods: Maintenance and repair	0.51	0.581
Services: Owners' equivalent rent: Houses	11.43	0.577
Goods: Vegetables	1.27	0.570
Goods: spare parts and accessories	0.43	0.566
Goods: Cigarettes	1.85	0.559
Goods: Personal effects: Travel goods and other carriers	0.17	0.559
Goods: Cleaning & maintenance products	0.35	0.553
Services: Other services	1.39	0.549
Goods: Photographic and cinematographic equipment	0.28	0.530
Goods: Glassware, tableware and household utensils	0.13	0.529
Goods: Sugar, sweets and desserts	0.58	0.522
Goods: Stationery and drawing materials	0.13	0.521
Goods: Electricity	3.63	0.519
Goods: Personal effects: Other	0.05	0.513
Goods: Newspapers and periodicals	0.33	0.510
Services: Owners' equivalent rent: Townhouses	1.31	0.510
Goods: Cold beverages	1.17	0.505
Goods: Information processing equipment	0.32	0.502
Goods: Equipment for recording & reproduction of sound & pictures	0.22	0.497
Other recreational items: Pet products	0.27	0.491
Services: Insurance connected with the dwelling	1.25	0.480
Goods: Outdoor recreation items	0.23	0.473
Goods: Bread and cereals	3.16	0.466
Services: Domestic services	2.63	0.464
Goods: Jewellery, clocks and watches	0.12	0.453
Services: Actual rentals for housing: Townhouses	0.55	0.450
Goods: Fruit	0.33	0.431
Services: Pre-primary and primary education	0.88	0.430
Services: Personal care services: All	0.48	0.430
Goods: Household textiles	0.45	0.421
Services: Secondary education	0.89	0.421
Services: Owners' equivalent rent: Flats	0.55	0.400
Services: TV licence & subscription	1.12	0.394
Services: Postal services	0.12	0.379
Services: Actual rentals for housing: Flats	1.09	0.373
Goods: Other tobacco	0.12	0.365

Services: Public transport: Air	0.40	0.317
Goods: Recording media for pictures and sound	0.03	0.263
Services: Telephone services	2.31	0.255
Goods: Beer	2.21	0.236
Services: Insurance connected with health	7.21	0.234
Goods: Furniture & furnishings	0.37	0.216
Goods: Purchase of vehicles	5.91	0.205
Goods: Telephone equipment	0.19	0.195
Services: Public transport: Road	2.14	0.164
Services: Insurance connected with transport	0.74	0.162
Services: Cinemas, theatres & concerts	0.20	0.144
Services: Tertiary education	1.15	0.104
Goods: Books	0.15	0.071
Goods: Meat	5.42	0.064
Goods: Photographic and cinematographic equipment	0.03	0.057
Services: Assessment rates	2.33	0.018
Goods: Wine	1.14	-0.021
Goods: Liquid fuels	0.07	-0.076
Services: Public transport: Railway	0.19	-0.126
Goods: Oils and fat	0.45	-0.175
Services: Other	1.09	-0.180
Services: Water supply	1.33	-0.356
Goods: Fuel	4.82	-0.415

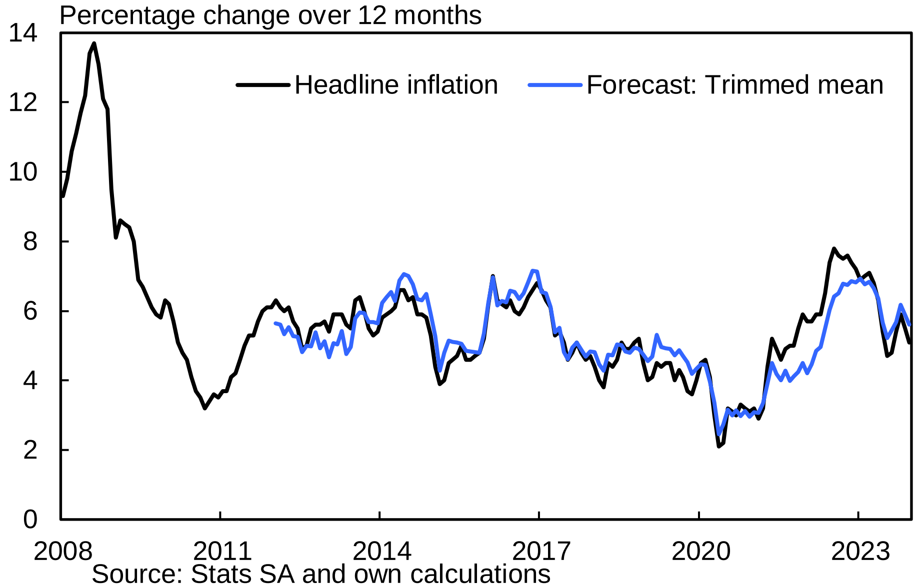
Figure A1: In-sample forecasts with Core inflation

Percentage change over 12 months



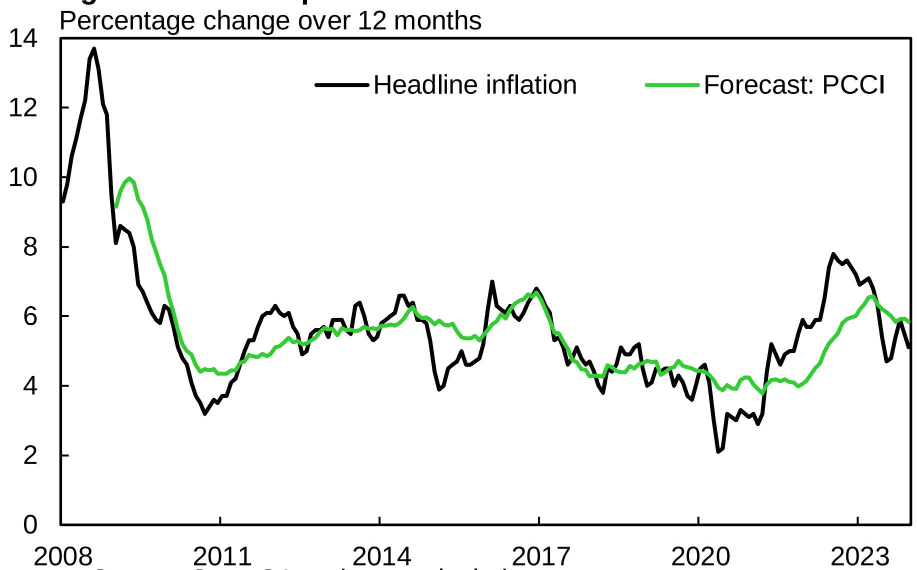
Source: Stats SA and own calculations

Figure A2: In-sample forecasts with trimmed mean



Source: Stats SA and own calculations

Figure A3: In-sample forecasts with PCCI



Source: Stats SA and own calculations