Towards a Measure of Core Inflation using Singular Spectrum Analysis

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Abstract

This paper constructs a number of possible core measures of annual inflation using Singular Spectrum Analysis (SSA). Annual inflation is decomposed into its trend, oscillating and noise components in order to develop an understanding of the trend and cyclicality in South African headline inflation. Five cyclical components are identified with differing amplitude and frequency. The trend and cyclical components of inflation are found to be a good approximation of core inflation, the inertial part of inflation. These core measures are compared to other candidate core measures based on the properties of a good core inflation measure. Generally, the SSA measures outperform commonly use measures of core inflation.

JEL classification: C41, C14, E31, E37, N17

Keywords: Singular Spectrum Analysis, Core Inflation, Non-parametric estimation.

1 Introduction

Core inflation has become a topic of interest in South Africa (Blignaut *et al,* 2009; Rangasamy, 2009) as policymakers attempt to react to the underlying trend in inflation rather than the transitory noise. Clark (2001) argues that policymakers and analysts have reached consensus on the defining properties of a good measure of core inflation. First and foremost this measure should track the components of inflation that persist for several years; this point in exposited in Blinder (1997) and Bryan and Cecchetti (1994). Basic measures such as a 36-month moving average inflation rate or a Hodrick-Presscott (HP) filtered inflation rate have formed part of defining the underlying trend in this context with mixed success. Second, a core measure should provide as much information of this trend given each month's Consumer Price Inflation (CPI) data. An example of this type of core measure is the trimmed mean measure calculated in Blignaut *et al.* (2009) and the persistence and CPI weighted measure in Rangasamy (2009). Third, a core inflation measure should help predict future headline inflation. Fourth, core inflation should track headline inflation with no clear bias and be less volatile. Fifth, a core measure of inflation should be as simple as possible; if this measure is used for policy it should be understood readily by the public. Finally, Bryan and Cecchetti (1994) (as well as Wynne (1997, 1999)) argue that core inflation should exclude changes in the relative prices of goods and services. This final point is linked to the idea of core inflation as a monetary phenomenon such that an underlying trend of inflation should not take account of changes in the relative demand or supply of an item but rather a change in monetary policy.

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Another important dimension of core inflation as identified by Cecchetti (1997) is the reduction of noise[1]. Noise is inherent due to "seasonal patterns, broad-based resource shocks, exchange-rate changes, changes in indirect taxes, and asynchronous price adjustment". Through the application of Singular Spectrum Analysis (SSA), the high-frequency component of headline CPI is removed and therefore most of this noise.

With the introduction of inflation targeting in South Africa in 2000, the central bank initially targeted CPIX (CPI excluding mortgage costs) in metropolitan and other urban areas. This decision was made due to the desire to exclude the direct impact of a change in the repurchase rate on inflation (through mortgage costs) and to provide a readily understood measure for the public (van der Merwe, 2004). More recently, the target variable shifted to headline CPI as methodological changes in the construction of the CPI changed how housing costs were calculated. Despite the focus of monetary policy on headline inflation as a target variable, a comprehensive understanding of core inflation shouldn't be understated. As recently as the July 2011 Monetary Policy Committee meeting, the South African Reserve Bank took cognisance of the forecasts of core inflation and the possibility of second round effects on underlying inflation to help determine the stance of monetary policy (Marcus, 2011).

We deviate from the current South African literature by explicitly defining the different recurrent oscillations (both periodic and quasi-periodic) in inflation through SSA, providing possible core measures which take into account the duration of its cyclical components. Cycles of between 8 and 65 months are indentified, allowing the policymaker to determine what is appropriately defined as a core inflation measure. The cyclical components have varying amplitudes over the period studied and we find, similarly to .Gupta and Uwilingiye (2009), that inflation volatility has increased since the inflation targeting period (at least in the long-run cyclical components). The core measures identified using SSA are compared to other possible core inflation measures identified in the literature; such as a trimmed mean inflation rate and a persistence augmented core measure (calculated in Rangasamy (2009)), as well as to popular measures such as exclusion based measures (headline CPI excluding food)[2], a moving average core measure and a HP-filtered core measure.

This paper proceeds as follows: Section two introduces SSA as a means to decompose South Africa's annual inflation. Section three discusses the data. Section four summarises results as well as compares the core measures calculated using SSA with alternative measures of core inflation, such as trimmed-mean inflation measures, headline CPI excluding food, HP filtered inflation and moving averages. Section five discusses caveats and possible future research and section six concludes.

2 Methodology

SSA is a non-parametric method used to decompose a time series variable into its trend, oscillatory (whether periodic or quasi-periodic) and noise components in order to, among other things, reduce the noise in a series, identify seasonality, provide alternative forecasts (to model-based procedures) and to understand the underlying structure of a series (Golyandina *et al.*, 2001). Only recently has this technique been introduced to economic variables (see Hassani *et al.*, 2007). SSA involves four distinct steps, namely embedding, decomposition, grouping and reconstruction. SSA can be seen as an alternative to wavelet analysis.

2.1 Step 1: Embedding Step

Following Golyandia *et al.* (2001), assume a time series variable $F = (f_0, ..., f_{N-1})$ of length N. This can be decomposed into L,an integer representing the only parameter in the estimation process

[1] Cecchetti also discusses bias which is present due to "weighting schemes, sampling techniques, and quality adjustments employed in the calculation of price indexes".

[2] Exclusion-based measures are the common core inflation measures used in SA.

and called the "window length". The window length should be chosen taking into account the properties of the initial series as well as the purpose of the analysis. This forms an LxK matrix, where $K = N - L + 1$, trajectory matrix $X = [X_1, ..., X_K] = (X_{ij})_{i.j=1}^{L,K}$ of $L-$lagged vectors (X_i).

X has the following form:

$$X = \begin{pmatrix} f_0 & f_1 & f_2 & \cdots & f_{K-1} \\ f_1 & f_2 & f_3 & \cdots & f_K \\ f_2 & f_3 & f_4 & \cdots & f_{K+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{L-1} & f_L & f_{L+1} & \cdots & f_{N-1} \end{pmatrix}$$

X is a Hankel matrix since all elements along the anti-diagonals are constant and equal. The window length should be chosen such that $2 \leqslant L \leqslant \frac{N}{2}$. When the series contains some form of periodicity, the window length should also be a multiple of this value.

Step 2: Singular Value Decomposition (SVD) applied to

The trajectory matrix is post-multiplied by its transpose to provide a matrix for the Singular Value Decomposition (SVD) step, such that we compute a matrix $s = XX^{'}$. In this step we compute the eigenvalues and eigenvectors of matrix S such that $S = P \wedge P$. Therefore, $\wedge = diag(\lambda_1, \ldots, \lambda_L)$ is the diagonal matrix of eigenvalues of S ordered in descending magnitude and $\mathbf{P} = (P_1, \ldots, P_L)$ is an orthogonal matrix of eigenvectors of S. This step is analogous to principal components analysis.

Step 3: Grouping

In step three the components of the elementary matrices are grouped into sub-groups in order to define the trend, oscillatory and noise components and sum these matrices within groups. Selection is done based on the eigenvectors $\mathbf{P}$. Let $I_1, \ldots I_m$ be the index of groups such that:

$$X = \sum_{k=1}^{m} X_{I_1}, \text{ where } X_{I_1} = \sum_{i \epsilon I_1} X_i$$

Weak separability is required in order to group and diagonally average the sub-groups into the reconstructed series. Weak separability ensures that the groups are independent.

A number of factors determine the groupings of the elementary matrices. First, groups are determined by the size of the eigenvalues; i.e. those similarly sized would generally form a group. Second, generally the first principal component will form the trend component (Golyandina *et al.*, 2001). Third, phase plots of the relationship between the principal components would reveal patterns in the data and infer adequate groupings. Fourth, periodograms of the groups would verify the chosen groupings and reveal a unique periodicity. Finally, ensuring the weighted or w-correlations are zero between chosen groups will ensure approximate weak separability[3].

Step 4: Reconstruction through diagonal averaging

In the final step, an estimate of the original series is constructed using diagonal averaging over the matrix $\tilde{X} = \|\tilde{x}_{i,j}\| = \sum_{k=1}^{l} P_{i_l} P_{i_l}^{'} X$.

3 Data

We use headline CPI data provided by Statistics South Africa (SA) from 1946M01 to 2011M04, in annual changes[4], as plotted in Figure 1. An important break in the data needs to be taken into account. In 2008, Statistics SA reclassified the CPI basket in order to realign South Africa's inflation calculation with international best practice as well as introduce a number of other changes, including changing the calculation of household rent, reweighting, rebasing and greater regional

[3] For more details refer to Golyandina *et al* (2001).

[4] $\log(\frac{CPI_t}{CPI_{t-12}}) * 100$

integration among other things. The classification basket shifted to the Classification of Individual Consumption by Purpose (COICOP) from the previous International Trade Classification (ITC). The regional composition of headline CPI also shifted from historical metropolitan urban areas to primary and secondary urban areas. To ensure comparability, headline inflation is used in both periods, with the new headline inflation rate (post-2009) appended to the previous headline inflation rate.

4 Results

A window length of 120 is chosen to ensure that any periodicity in the data is identified based on the likelihood that any periodic components would be multiples of 12. This provides 120 variables of the decomposed series to create 120 principal components. Figure 2 shows the series representing the principle components (PC) of the main CPI series (only 12 are graphed for convenience). The first component explains 92.6 per cent of the variance in annual inflation, followed by 3.1 per cent and 0.9 per cent explained by the second and third components respectively. Thereafter the amount of variance explained by each component diminishes gradually.

The relationship between the principal components are then analysed to determine groupings based on cyclical behaviour. Most of the variation in annual headline inflation will be captured in the first few components. Each group of principle components will capture some key features of the original time series, with specific focus on trend and cyclicality. Once the groupings are sufficiently identified and analysed, groupings are combined in order to define alternative core inflation measures. These measures are then compared to the original annual inflation series to ensure that they are unbiased and robust as well as tested for their predictive content using a gap approach and in-sample performance.

The core measures proposed in this paper are compared to six other core measures namely; hp-filtered inflation with a conventional $\lambda = 14400$ (CoreCPI_HP), a 36-month moving average inflation rate (CoreCPI_MA36), headline CPI excluding food (CoreCPI_XF), the persistence and CPI weighted core measure calculated in Rangasamy (2009) (CoreCPI_PC) and two trimmed mean core measures as calculated by Blignaut *et al.* (2009) – a symmetric trim of 5 per cent on each tail (Symtrim(5,5)) and an asymmetric trim with 24 and 17 per cent respectively trimmed off the top and bottom tails of the distribution (Asymtrim(24,17)).

4.1 Components of Annual Inflation

In order to identify the logical groupings, if any, in annual inflation, patterns in the relationships of the principal components are identified and compared (Golyandina *et al.*, 2001). Figure 3 shows the first three vital relationships and identifies the grouping of principle components with the same cyclical period. Each one of these groups is now represented by a single series (additive); either conveying a trend component of the original series; as is the case with PCs one and two, or a specific cyclical element thereof; for example PCs three and four. A plot of the between-group weighted correlations reveals that the groupings are weakly separable. Using spectral analysis, the periodicity of each group is identified and plotted in periodograms given in Figure 4. A summary of the groups and their dominant periods is given in Table 1.

A brief description of these groups and their characteristics is in order. The first group consists of the first two principle components (Figure 5), which explain the largest part of the variance of the original series. It has no apparent cyclical component and the variance appears to remain fairly constant over the sample period. This is the group that tracks the general movements of the annual headline CPI.

Figure 6 shows the first cyclical component identified using SSA, consisting of the third and fourth PCs. The periodogram in Figure 4 suggests that this series follows a cyclical pattern that repeats every 65 months and this is supported through graphical inspection of Figure 6. This group represents the most important cyclical component identified both in terms of magnitude and duration, however only 1.7 per cent of the total variation in headline CPI is represented. The volatility is analysed through examining changes in the amplitude of the cycles (measured as distance from the origin), calculated as the average of the upward and downward phases of each cycle. The average amplitude over the entire cycle was 1.4 per cent. However, it is clear the volatility does not remain constant and increased after the year 2000 compared to its pre-2000 level. The amplitude of the last cycle was much larger than any of the amplitudes previously observed, the former being 2.51 per cent whereas none of the latter ever exceeded 1.6 per cent.

Principle components 8 to 13 are included in the group illustrated by Figure 7. To establish the dominant period of cyclicality, the peaks in the periodogram in Figure 4 are compared. Although not immediately obvious, the dominant period in this group is about 42 months, however the large number of PCs included in this group causes it to exemplify noticeable irregularity. The amplitude over the sample period averages just less than 1 per cent, with larger volatility during the 1940s and 1950s and again post-2000. Although there are signs of moderation in the last few cycles, those in 2003 and 2006 again average over 2 per cent.

Figure 8 plots the group consisting of PCs 6 and 7. This grouping observes a clear 24-month cycle over the sample period, but again differs in amplitude over this period. It is also interesting to note that the amplitude remained fairly constant in the years preceding 1994, after which it shows a sudden increase. Performing a t-test of equal means on the average values of the amplitudes for the two periods, we find a p-value smaller than 0.00001, rejecting the null hypothesis of equal means.

Two further groupings are provided for completeness, consisting of PCs 15 and 16 and 17 and 18. The periodograms show these groups have a frequency of 8 and 18 months respectively. They are included in the last core measure of inflation.

The first three cyclical components of inflation support the findings of Gupta and Uwilingiye (2009), that inflation volatility has increased in the post-inflation targeting period. However, the 42-month, biennial, 8- and 18-month cyclical groupings suggest that this volatility may be decreasing since 2008. The amplitude of the last two cycles of the 42-month group were half the size of the 2003 and 2006 cycles, while the other three cyclical amplitudes have declined in the latter part of the decade. Although higher inflation volatility is observed during the post-2000 period, the reason and evidence supporting this finding is uncertain. Both international and domestic evidence on the effects of inflation targeting on inflation variability is mixed and does not shed light on this phenomenon[5]. Gupta and Uwilingiye (2009) argue that inflation volatility in South Africa has been higher during the post-inflation targeting period and attribute this to the width of the inflation target band (i.e. 3 to 6 per cent). Kahn and de Jager (2011) argue that inflation volatility has declined during this period and attribute this to the policy environment. Du Plessis and Kotze (2010) find similarly that inflation volatility has declined during this period, but attribute this to the great moderation. However, more research is required to determine what is driving inflation volatility post-2000.

4.2 Core Inflation Measures

This paper proposes five possible core measures of inflation, each consecutively adding an extra group of cyclical components to trend inflation (see Table 2 for the composition of the candidate core measures). Core measures consisting of more principle components will track the annual inflation more closely and therefore the variance will tend towards that of headline inflation. This technique provides a number of benefits over existing core measures. First, it allows for the disaggregation of inflation into specific frequency periods, adding to or subtracting from the resolution of the core measure. Second, it allows a modeller or policymaker to decide how much of the CPI movements to be

[5] For example Mishkin and Schmidt-Hebbel (2007) found that inflation targeting has lowered inflation volatility while studies by Johnson (2002), Truman (2003) and Ball and Sheridan (2005) argue otherwise. Ball and Sheridan (2005) argue there is no casual link between inflation targeting and inflation volatility.

included in the core measure, both in terms of magnitude and periodicity. Third, since the approach is model free, no assumptions need be made on the structure or expected shape of the inflation process. Fourth, this approach can provide spectral forecasts of inflation as an alternative to other types of forecasts (e.g. ARIMA forecasts). Fifth, the SSA measure of core inflation does not exclude any component of inflation (i.e. food or energy) as these could have important information regarding underlying trend inflation. Sixth, we explicitly define the cyclical components of inflation. This should allow a more concrete analysis surrounding core inflation and inflation cyclicality. Finally, it allows policymakers to determine what cyclical aspects are driving inflation in each specific period. Figure 9 plots all five candidate core measures suggested by this paper. Each consecutive core measure adds further detail to the inflation series from trend to CoreCPI4.

4.3 Unbiasedness of Core Inflation

4.3.1 Means

In order for the proposed core measures to be unbiased predictors of headline inflation the means have to be equal. This is tested using t-tests of equal means, with null hypothesis $\mu_{cpi} = \mu_{core}$, making an assumption regarding the equality of variances. Table 4 shows the values of the calculated means of various core inflation measures, for two time periods – 1981 to 2007 (restricted sample) and 1946 to 2011. Over the longer sample, the largest mean value is 7.14 per cent for trend inflation, with all other measures tending lower - towards the mean of headline inflation of 7.08 per cent. Over 1981 to 2007, the overall level of means average about 2.5 percentage points above the entire sample period means[6]. In this case headline CPI has a mean of 9.58 per cent, with the largest core measure mean due to Asymtrim(24,17) of 10.21 per cent. However, the hypothesis of equal means is not rejected for all of the core measures, with p-values being of magnitude of 0.78 and larger in the large sample and 0.08 and above in the restricted sample. Only the Asymtrim(24,17) measure can be rejected at a 10 per cent level of significance.

A further test of unbiasedness is to check the mean errors of each core series, where mean error (ME) is defined as:

$$ME = \frac{1}{T}\sum\nolimits_{i=1}^{T}(\pi_t - \pi_t^{core}) \tag{1}$$

The ME should to be close to zero otherwise it could indicate the existence of either an upward (+) or downward (-) bias. Table 4 shows that there is no clear negative or positive bias present in any of the measures with the largest ME of -0.63 from Asymtrim(24,17) in the restricted sample. The largest ME from the SSA core measures over the entire sample exists for Trend inflation at -0.059 per cent. The mean percentage error is provided in the last column to gauge the deviation of the core measures from annual inflation. However, all core measures have ME close to zero and therefore no presence of an upward or downward bias is found.

4.3.2 Volatility

The literature defines a good core measure as one that removes the transitory noise in the headline inflation and defines the underlying trend in inflation. Therefore, such a core measure should be less volatile than headline inflation. This is gauged by comparing the standard deviation of headline inflation with that of the core measures and testing for significant differences using F-tests of equal variance. The null hypothesis is defined as:

$$H_0 : \sigma_{cpi} = \sigma_{core} \tag{2}$$

A comparison of the standard deviations in Table 4 reveals that the SSA core measures all have a lower observed volatility than headline inflation (in both the restricted and entire sample). As

[6] Rossouw and Padayachee (2011) provide a history of inflation and monetary policy since 1921.

expected, the core measures including more principle components have a variance closer to that of CPI. However, the F-test shows that only the variance of the CoreCPI1 and Trend are statistically significantly different from the actual CPI variance, with a p-value of 0.045 and 0.001 respectively during the longer period (this hypothesis is also rejected in the restricted sample). In respect to the other candidate core measures, CoreCPI_HP and CoreCPI_MA36 also display statistically lower variance in the restricted sample, while CoreCPI1 and CoreCPI_XF are rejected at a 10 per cent level of significance. For all of the other core measures, the argument of reduced volatility due to a removal of noise does not hold.

4.4 Predictive Content of Core Inflation Measures

To assess the predictive content and provide robust results for the candidate core measures calculated in this paper, two approaches are followed. Firstly, root mean squared errors (RMSE) are calculated and compared (in-sample performance). Secondly, the "gap approach" as described by Clark (2001) and implemented in the South African context in Ricci (2005) and Farrell and Munyama (2008) is applied to the core measures.

4.4.1 In-sample performance

One measure of the in-sample performance of the candidate core measures is provided by RMSE, calculated as:

$$RMSE = \sqrt{\frac{1}{T}\sum\nolimits_{i=1}^{T}(\pi_t - \pi_t^{core})} \tag{3}$$

This provides a gauge for the predictive power, or "goodness of fit". Differences in RMSE's can be tested for significance using the Diebold-Mariano (DM) test statistic (Diebold and Mariano, 1994). A good core measure will have both a small volatility and a small RMSE.

Table 5 provides a matrix of the DM statistic comparing every core measure with each of the others showing the RMSE values for the respective core inflation measures[7], along with the p-values obtained from performing the DM test, the being that the two models under consideration have the same predictive capabilities. This hypothesis is rejected across the board at the 99 per cent confidence level, with only two comparison pairs revealing an insignificant difference between predictive powers. These two pairs are CoreCPI2 vs. Asymtrim(24,17) and CoreCPI1 vs. CoreCPI_XF. For all of the other pairs it is safe to assume that a lower RMSE value indicates significantly better prediction potential. Therefore, CoreCPI3 and 4 perform best in terms of in-sample predictive power, with RMSE values of 0.63 and 0.54 respectively.

There exists a trade-off in the core measures of inflation between volatility and in-sample predictive content (measured by root mean squared errors (RMSE)). Therefore, selecting alternative core measures based on volatility should be balanced with the predictive capabilities of these measures. Figure 10 plots the values of the RMSE against the standard deviation for the candidate core measures suggested in this paper. This trade-off is immediately apparent; there is a clear inverse relationship between the standard deviation of the core measure and the RMSE among the SSA measures and CoreCPI_HP. In fact, looking at Figure 10 the relationship can be accurately approximated using a linear trend. It is interesting to note that CoreCPI_HP lies very close to the line. Thus, it would seem that the core measures proposed by this paper are as effective as the CoreCPI_HP when a low RMSE and volatility pair is the target. However, the SSA measures do not suffer from the end point problem of the HP filter, severely hampering the effectiveness of this measure. Using the RMSE-standard deviation trade off as a benchmark, it would also seem that the SSA measures outperform the trim mean measures as well as CoreCPI_XF and CoreCPI_PC, since it is possible to create a measure that has a similar RMSE value, but a lower standard deviation than these measures.

[7] CoreCPI_PC is excluded due to data mismatch.

4.4.2 Gap Approach

Following Clark (2001) a "gap approach" to the measurement of the predictive content of candidate core measures is implemented[8]. This method establishes whether changes in annual headline inflation over a certain horizon (usually short- and medium-term) moves towards the core measure. This approach is used to overcome the problem of non-stationarity in the data. This method entails regressing the following:

$$\pi_{t+h} - \pi_t = \alpha + \beta(\pi_t^{core} - \pi_t) + \epsilon_t \tag{4}$$

Where π_t is annual headline inflation and π_t^{core} is the core measure of inflation under observation and $\epsilon_t \sim i.i.d.(0, \sigma)$. That is, the difference, or gap between the core measure and headline CPI at some future time period, on the difference between the current headline inflation and a future point in time. If headline inflation tends to revert towards a candidate core measure β is expected to be positive and statistically significantly different from zero; this will also indicate predictive content. If β=1 then headline inflation fully reverts to the specific core measure, while 0< β <1 refers to partial reversion[9]. Another measure used to compare the explanatory power of a candidate core measure is R^2. Cogley (2002) notes that β=1 and α=0 for the candidate core inflation measure to be an unbiased predictor of headline inflation.

Table 6 presents the results of the "gap approach" for the candidate core measures over a horizon of 3, 6, 9, 12, 18 and 24 months. Shorter horizons are included to achieve a clearer picture of the behaviour of these measures in the short term. The results are estimated on monthly data from 1981 to 2007. Standard errors are adjusted for serial correlation.

CoreCPI3 and 4 most consistently do not reject the combined hypothesis of β=1 and α=0, with this hypothesis only rejected at a horizon of 24 months. Problematically, these two measures do not seem to have much explanatory power with small values at most horizons. CoreCPI_MA36, CoreCPI_XF, CoreCPI_PC and the two trimmed means measures are biased at all horizons and generally have the lowest values. CoreCPI_HP most consistently has the highest explanatory power through all time horizons and in two cases (t+6, t+9) is found to be an unbiased predictor of headline inflation. Trend inflation becomes an unbiased predictor of headline CPI inflation at longer horizons, from t+9. However, the performance of the candidate core measures based on the gap approach does not single out any clear winners. Based on relative performance, the gap approach tends to favour the SSA core measures defined in this paper, especially CoreCPI3 and 4.

On the aggregate, the analysis of competing core measures does not indicate any clear winners in terms of all the properties of a good core measure of inflation. Due to the trade-off between volatility and predictive content it is unlikely to find a single core measure which satisfies all criteria. Therefore only relative winners can be found. The t-tests revealed that all of the measures can be regarded as being unbiased and therefore no single measure is superior to any other based on this criterion. The SSA measures containing more principle components appear to have a mean closer to the true mean of the underlying CPI, but the differences between the mean values for the different measures aren't statistically significant. Investigation into the volatility of the measures over the two time periods show that only the trend measure and the Core_HP have significantly lower volatility when compared to the actual CPI figures, over both periods. Although visual inspection provides some indication that observed noise was removed, this is not reflected by a significant reduction in the volatility. The predictive abilities of the various measures were tested by using RMSE values, followed by the "gap approach" as in Clark (2001). Both of these tests reveal that CoreCPI3 and 4 perform comparatively better in terms of predictive content than the other candidate core measures.

[8]This approach is also followed by Cogley (2002), Macklem (2001), Catte and Sløk (2005), Lafleche and Armour (2006).

[9]However this assumption is based on the effect that temporary shocks have on both core and headline inflation. For details see Catte and Slok (2005).

5 Caveats and Future Work

This approach has a number of caveats, mostly related to the choice of the window length and the groupings of the PCs. Since the choice of window length is effectively arbitrary, varying this parameter could significantly change the results of the paper. For example, if a short window length is chosen it may result in the combination of separately interpretable components. Alternatively if a large window length is chosen, this could allow for a more detailed decomposition. The grouping of the components is also potentially problematic even though it is based on eigenvalues and phase plots. In this paper, the choice of groupings balances the desire to explain most of the variation in inflation with the need to ensure weakly separable groups and parsimony. This method is also data-intensive, requiring long time-series in order to identify properly the cyclical components. Finally, since this approach is a-theoretical, assigning economic meaning to the cyclical components of inflation may be problematic.

Future work could include using other possible core measures to test whether the SSA measures suggested in this paper still perform adequately. These could include Cogley's (2002) exponential smoothing mean inflation measure, alternative trimmed mean measures as well as other exclusion-based measures such as headline CPI excluding food and fuel and the core measure suggested by Statistics South Africa. Further out-of-sample predictive ability should also be included to provide additional evidence of the comparative performance of core measures. Specific to this approach, the grouping of the different oscillatory components of inflation as well as the window length could be varied to test the robustness of the results presented in this paper. Other future work could focus on the economic significance of the cyclical components to determine whether they follow the business cycle as well as determine the reason for greater inflation volatility post-2000.

6 Conclusion

The paper reveals that no single candidate core measure outperforms all others based on all the properties of a good core measure. Only relative winners can be identified. The SSA core measures are shown to be unbiased and able to significantly reduce the noise component of inflation. The SSA core measures also possess sensible predictability characteristics, especially the measures consisting of more principle components. Moreover, the SSA method reveals clear cyclical patterns in headline CPI in South Africa and enables the identification of that part of inflation which persists for several years; this is a key definition of core inflation. Five important cyclical components are identified in this paper, elucidating the properties of South African inflation and providing more depth to the understanding of its cyclical pattern. Using SSA to identify core inflation holds potential as a useful instrument in the statistical arsenal of central bankers.

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Figures and Tables

Table 1 Grouped Principle Components and Periodicity

Principle Components	*Periodicity (months)*
1,2	Trend
3,4	65
6,7	24
8,9,10,11,12,13	42
15,16	8
17,18	18

Table 2 Structure of Core Measures

Measure	*Principle Components*	*Cycles Included*	*Variance explained*
TrendCPI	1,2	Trend	95.8%
CoreCPI1	1,2,3,4	Trend, 65m	97.4%
CoreCPI2	1,2,3,4,6,7	Trend, 65m, 24m	98.0%
CoreCPI3	1,2,3,4,6-13	Trend, 65m, 24m,42m	99.0%
CoreCPI4	1,2,3,4,6-13,15-18	Trend, 65m, 24m, 42m, 18m, 8m	99.1%

Table 3 Standard deviation (SD) and root mean squared error (RMSE) values for the various measures (Restricted Sample)

Core Measure	*SD*	*RMSE*
Trend	3.67	2.037
CoreCPI1	3.98	1.522
CoreCPI2	4.06	1.157
CoreCPI3	4.23	0.630
CoreCPI4	4.24	0.536
CoreCPI_HP	3.83	1.661
CoreCPI_MA36	3.77	2.434
CoreCPI_PC	4.79	0.739
Symtrim(5,5)	4.79	0.770
Asymtrim(24,17)	4.69	1.182
CoreCPI_XF[1]	4.81	1.352

[1]Quarterly Data

Table 4 Mean and Standard Deviations

1946m01-2011m04	*Mean*	*t-test (P-value)*	*Standard Deviation*	*F-test (P-value)*	*Mean Error (ME)*	*MPE[2]*
Headline CPI	**7.08**		**4.52**			
Trend	7.14	0.784771	4.01	**0.000888**	-0.05898	-34.54%
CoreCPI1	7.11	0.887984	4.21	**0.044986**	-0.03108	-25.36%
CoreCPI2	7.11	0.899575	4.26	0.092605	-0.02799	-19.64%
CoreCPI3	7.09	0.962506	4.38	0.365494	-0.01057	-8.36%
CoreCPI4	7.09	0.958088	4.39	0.396055	-0.01182	-7.42%
CoreCPI_HP	7.08	1	4.18	**0.027233**	-5.95E-13	0%
CoreCPI_MA36	-	-	-	-	-	-
CoreCPI_XF	-	-	-	-	-	-
Symtrim(5,5)	-	-	-	-	-	-
Asymtrim(24,17)	-	-	-	-	-	-
CoreCPI_PC[1]	-	-	-	-	-	-
1981m01 - 2007m12	Mean	t-test (P-value)	Standard Deviation	F-test (P-value)	Mean Error (ME)	MPE[2]
Headline CPI	**9.58**		**4.37**			
Trend	9.65	0.821805	3.67	**0.001668**	-0.0714	-41.00%
CoreCPI1	9.59	0.957711	3.98	0.09077	-0.01741	-29.00%
CoreCPI2	9.59	0.974778	4.06	0.192753	-0.01049	-18.35%
CoreCPI3	9.58	0.998369	4.23	0.572339	0.00069	-3.90%
CoreCPI4	9.58	0.999272	4.24	0.593436	0.00031	-3.48%
CoreCPI_HP	9.61	0.913881	3.83	**0.017291**	-0.03491	-30.51%
CoreCPI_MA36	9.94	0.260615	3.84	**0.019572**	-0.3637	-53.12%
CoreCPI_XF	9.76	0.613453	4.81	0.08591	-0.18242	3.60%
Symtrim(5,5)	9.84	0.470605	4.78	0.104139	-0.25984	0.235%
Asymtrim(24,17)	10.21	0.077874	4.69	0.200735	-0.62903	-15.13%
CoreCPI_PC[1]	10.12	0.283656	4.79	0.319979	0.038398	-4.15%

[1]Quarterly data. Estimation sample 1981Q1 to 2007Q4.

[2]Mean Percentage Error.

Table 5 Comparison of RMSE values using Diebold-Mariano test

P-values:		Trend	CoreCPI1	CoreCPI2	CoreCPI3	CoreCPI4	CoreCPI_HP	CoreCPI_MA36	CoreCPI_XF	Symtrim(5,5)	Asymtrim(24,17)
	RMSE	2.037	1.522	1.157	0.630	0.536	1.661	2.433	1.352	0.770	1.182
Trend	2.037		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CoreCPI1	1.522	0.00		0.00	0.00	0.00	0.00	0.00	**0.06**	0.00	0.00
CoreCPI2	1.157	0.00	0.00		0.00	0.00	0.00	0.00	0.01	0.00	**0.64**
CoreCPI3	0.630	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00
CoreCPI4	0.536	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
CoreCPI_HP	1.661	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
CoreCPI_MA36	2.433	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
CoreCPI_XF	1.352	0.00	**0.06**	0.01	0.00	0.00	0.00	0.00		0.00	0.01
Symtrim(5,5)	0.770	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Asymtrim(24,17)	1.182	0.00	0.00	**0.64**	0.00	0.00	0.00	0.00	0.01	0.00	

Table 6 Gap Equation Regression Results

t+3			P-values		R²	t+6			P-values		R²
	α	β	Ho: β=1	β=1 & α=0			α	β	Ho: β=1	β=1 & α=0	
Trend	-0.065921	**0.229872**	0.0000	0.0000	0.11	Trend	-0.112058	**0.535703**	0.0000	0.0000	0.24
	(0.1406)	(0.05942)					(0.23536)	(0.09859)			
CoreCPI1	-0.056205	**0.384593**	0.0000	0.0000	0.17	CoreCPI1	-0.088850	**0.863742**	0.2819	0.5206	0.35
	(0.13723)	(0.07402)					(0.21692)	(0.1264)			
CoreCPI2	-0.054809	**0.505519**	0.0000	0.0000	0.17	CoreCPI2	-0.083511	**0.925111**	0.6480	0.7855	0.24
	(0.14048)	(0.08413)					(0.23595)	(0.16386)			
CoreCPI3	-0.048718	**1.143971**	0.2546	0.5102	0.26	CoreCPI3	-0.072972	**1.214431**	0.3259	0.6095	0.12
	(0.14069)	(0.12616)					(0.25371)	(0.21793)			
CoreCPI4	-0.049119	**1.265762**	0.0638	0.1765	0.23	CoreCPI4	-0.073423	**1.259600**	0.2729	0.5313	0.09
	(0.14161)	(0.1429)					(0.25615)	(0.23639)			
CoreCPI_HP	-0.061623	**0.347028**	0.0000	0.0000	0.17	CoreCPI_HP	-0.101288	**0.787118**	0.0517	0.0977	0.35
	(0.13708)	(0.06971)					(0.21719)	(0.10899)			
CoreCPI_MA36	-0.067753	0.050161	0.0000	0.0000	0.01	CoreCPI_MA36	-0.137425	0.174908	0.0000	0.0000	0.04
	(0.14671)	(0.04957)					(0.2715)	(0.09062)			
CoreCPI_XF	-0.0527	0.017481	0.0000	0.0000	0.00	CoreCPI_XF	-0.07904	0.028663	0.0000	0.0000	0.00
	(0.14815)	(0.0937)					(0.27395)	(0.16769)			
SymTrim(5,5)	-0.055753	0.024029	0.0000	0.0000	0.00	SymTrim(5,5)	-0.041744	-0.123417	0.0001	0.0001	0.00
	(0.15193)	(0.16531)					(0.27205)	(0.27379)			
AsymTrim(24,17)	-0.065407	0.025273	0.0000	0.0000	0.00	AsymTrim(24,17)	-0.026728	-0.074851	0.0000	0.0000	0.00
	(0.14984)	(0.1041)					(0.26094)	(0.19553)			
CoreCPI_PC[1]	-0.074702	0.874548	0.8672	0.9651	0.05	CoreCPI_PC[1]	-0.063210	0.612391	0.4158	0.6843	0.04
	(0.44903)	(0.74822)					(0.31829)	(0.47445)			
t+9			P-values		R²	t+12			P-values		R²
	α	β	Ho: β=1	β=1 & α=0			α	β	Ho: β=1	β=1 & α=0	
Trend	-0.155976	**0.868638**	0.2999	0.3550	0.38	Trend	-0.207640	**1.190396**	0.1475	0.3307	0.52
	(0.28544)	(0.12653)					(0.30098)	(0.13113)			
CoreCPI1	-0.117323	**1.341884**	0.0469	0.1191	0.51	CoreCPI1	-0.152900	**1.737367**	0.0002	0.0006	0.62
	(0.24982)	(0.17139)					(0.26877)	(0.1931)			
CoreCPI2	-0.107913	**1.330823**	0.1985	0.4356	0.29	CoreCPI2	-0.142153	**1.860044**	0.0089	0.0293	0.41
	(0.29852)	(0.25673)					(0.32796)	(0.32679)			
CoreCPI3	-0.093218	**1.073491**	0.7865	0.9400	0.06	CoreCPI3	-0.121485	**1.687592**	0.0425	0.1253	0.10
	(0.34704)	(0.27115)					(0.40488)	(0.33753)			
CoreCPI4	-0.093602	**1.159763**	0.5866	0.8322	0.05	CoreCPI4	-0.122065	**1.899546**	0.0155	0.0532	0.09
	(0.34882)	(0.29351)					(0.40519)	(0.3697)			
CoreCPI_HP	-0.137438	**1.245550**	0.0682	0.1778	0.52	CoreCPI_HP	-0.180444	**1.655614**	0.0000	0.0000	0.67
	(0.2457)	(0.1342)					(0.24753)	(0.13154)			
CoreCPI_MA36	-0.220637	**0.348304**	0.0000	0.0000	0.09	CoreCPI_MA36	-0.321748	**0.547425**	0.0062	0.0003	0.16
	(0.36689)	(0.13358)					(0.4255)	(0.16423)			
CoreCPI_XF	-0.11018	0.088913	0.0000	0.0000	0.00	CoreCPI_XF	-0.16204	0.215942	0.0018	0.0014	0.01
	(0.37051)	(0.21982)					(0.4303)	(0.24963)			
SymTrim(5,5)	0.010721	-0.402872	0.0001	0.0005	0.01	SymTrim(5,5)	0.000623	-0.474432	0.0020	0.0071	0.01
	(0.3619)	(0.36507)					(0.415)	(0.47287)			
AsymTrim(24,17)	0.035313	-0.205513	0.0000	0.0001	0.01	AsymTrim(24,17)	0.002387	-0.198781	0.0014	0.0046	0.00
	(0.34917)	(0.28675)					(0.40024)	(0.37313)			
CoreCPI_PC[1]	-0.074702	0.874548	0.8672	0.9651	0.05	CoreCPI_PC[1]	-0.095559	1.131828	0.8850	0.9803	0.06
	(0.44903)	(0.74822)					0.553008	0.909615			
t+18			P-values		R²	t+24			P-values		R²
	α	β	Ho: β=1	β=1 & α=0			α	β	Ho: β=1	β=1 & α=0	
Trend	-0.331504	**1.244866**	0.0642	0.1346	0.52	Trend	-0.462541	**1.247035**	0.0506	0.0458	0.50
	(0.31263)	(0.13184)					(0.32739)	(0.12587)			
CoreCPI1	-0.266028	**1.344081**	0.1263	0.2847	0.34	CoreCPI1	-0.388868	**0.882171**	0.6441	0.5554	0.14
	(0.37081)	(0.22448)					(0.44152)	(0.25484)			
CoreCPI2	-0.261220	**1.773446**	0.0358	0.1096	0.34	CoreCPI2	-0.388376	**1.417993**	0.2659	0.4539	0.21
	(0.36709)	(0.36693)					(0.42417)	(0.37502)			
CoreCPI3	-0.241670	**1.383507**	0.2866	0.4975	0.06	CoreCPI3	-0.372209	**1.881136**	0.0161	0.0302	0.11
	(0.44117)	(0.35931)					(0.44539)	(0.3643)			
CoreCPI4	-0.242064	**1.822272**	0.0417	0.1159	0.08	CoreCPI4	-0.372818	**2.240770**	0.0038	0.0099	0.11
	(0.43705)	(0.4021)					(0.44285)	(0.42594)			
CoreCPI_HP	-0.296005	**1.529159**	0.0005	0.0015	0.52	CoreCPI_HP	-0.419826	**1.326877**	0.0493	0.0587	0.37
	(0.30709)	(0.15117)					(0.36755)	(0.16566)			
CoreCPI_MA36	-0.458824	**0.594444**	0.0274	0.0012	0.17	CoreCPI_MA36	-0.598113	**0.617560**	0.0190	0.0015	0.18
	(0.45613)	(0.18305)					(0.45736)	(0.16223)			
CoreCPI_XF	-0.32759	**0.465782**	0.0426	0.0442	0.03	CoreCPI_XF	-0.43584	0.341683	0.0139	0.0084	0.02
	(0.45798)	(0.26248)					(0.48257)	(0.2661)			
SymTrim(5,5)	-0.071848	-0.657256	0.0044	0.0144	0.02	SymTrim(5,5)	-0.171619	-0.776991	0.0055	0.0115	0.02
	(0.44351)	(0.57756)					(0.47849)	(0.63522)			
AsymTrim(24,17)	-0.089620	-0.243243	0.0026	0.0071	0.00	AsymTrim(24,17)	-0.214009	-0.253567	0.0059	0.0042	0.00
	(0.43236)	(0.40951)					(0.52457)	(0.45209)			
CoreCPI_PC[1]	-0.198061	0.366916	0.4979	0.6970	0.01	CoreCPI_PC[1]	-0.322145	0.081523	0.3431	0.5365	0.00
	(0.67352)	(0.93076)					(0.75255)	(0.96449)			

[1] Quarterly data. Estimation sample 1981Q1 to 2007Q4 .

* **Bold** coefficients are significant at 1 per cent, heteroskedasticity and autocorrelation consistent (HAC) standard errors reported in ().

Figure 1 Annual Consumer Inflation (1946-2011)

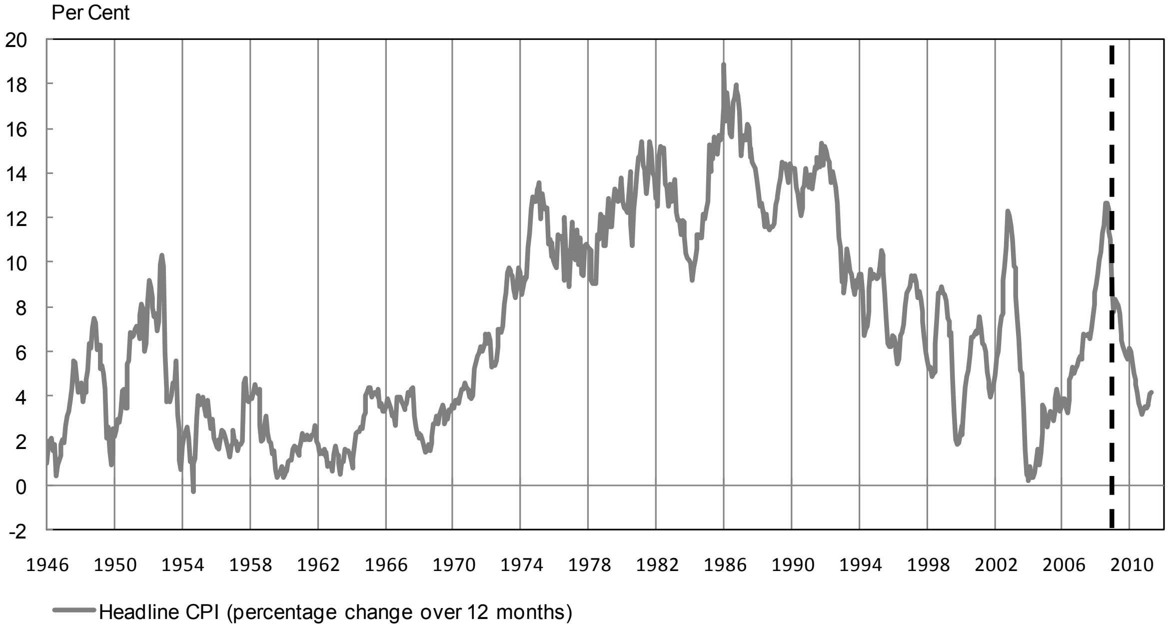

Figure 2 Principle Components of Annual Consumer Inflation

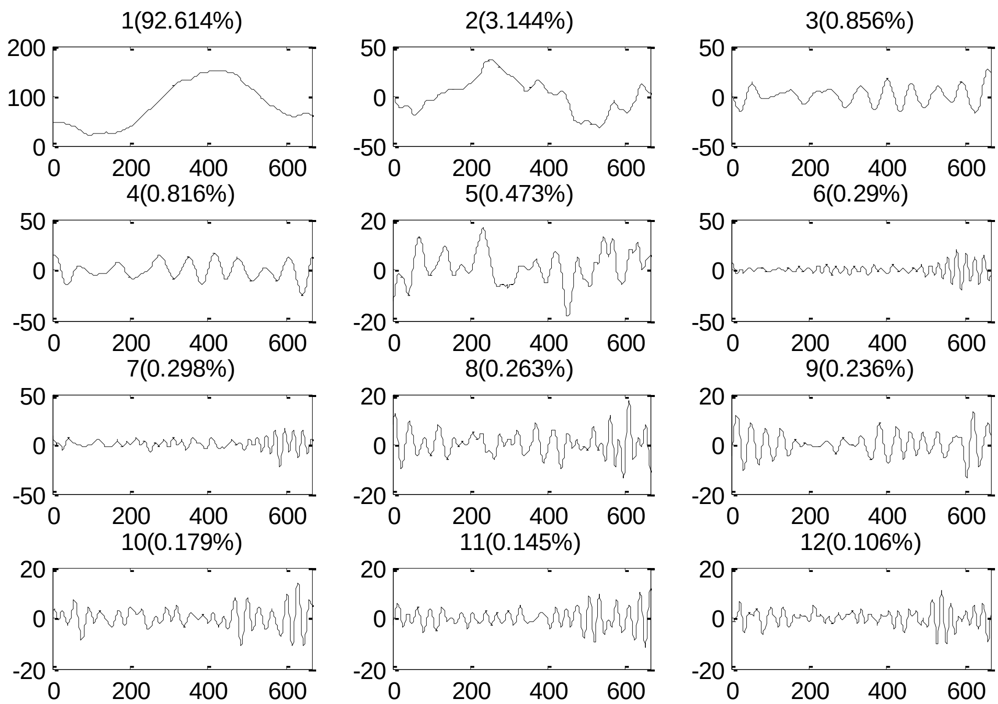

Figure 3 Phase Plots

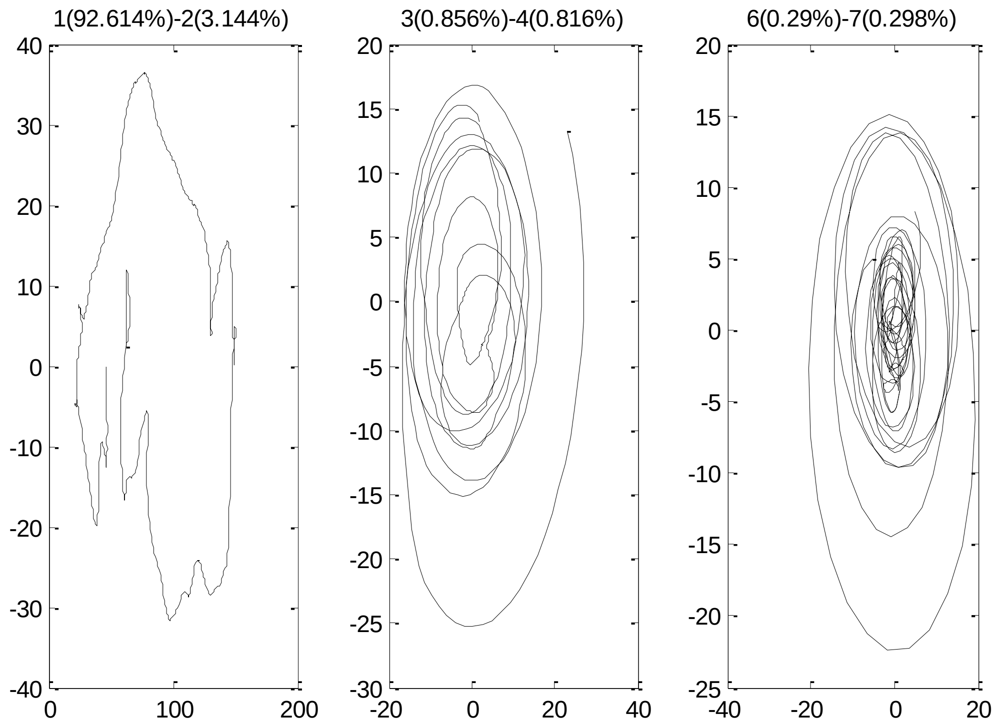

Figure 4 Periodograms of Cyclical Components

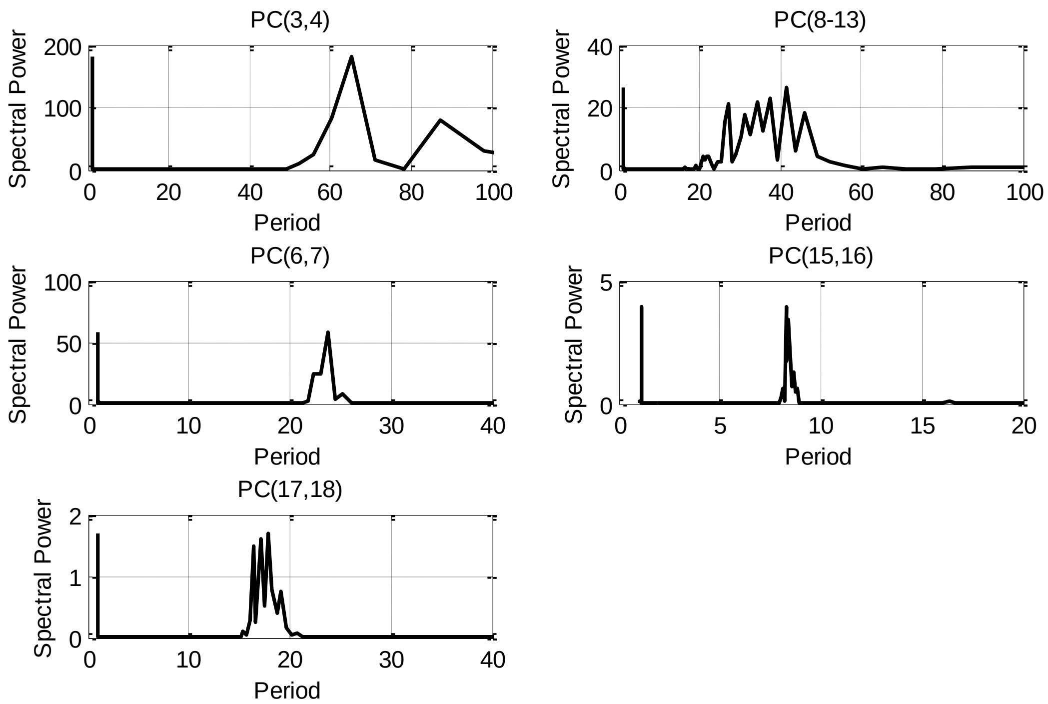

Figure 5 Trend in Annual Consumer Inflation

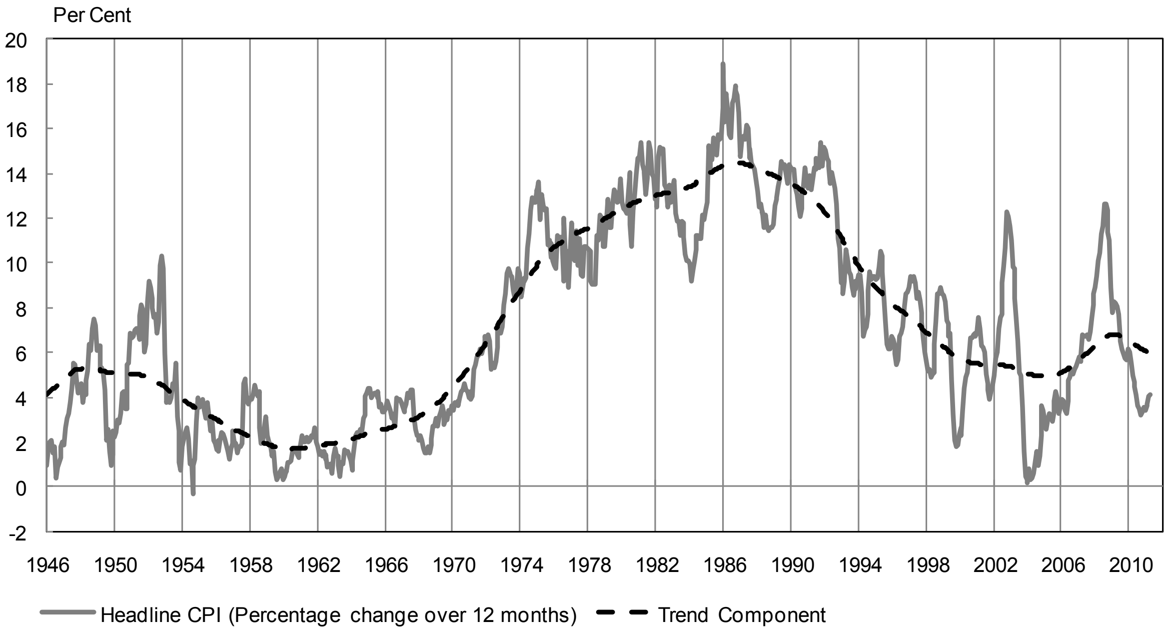

Figure 6 Long-run Cyclical Oscillation in Annual Consumer Inflation

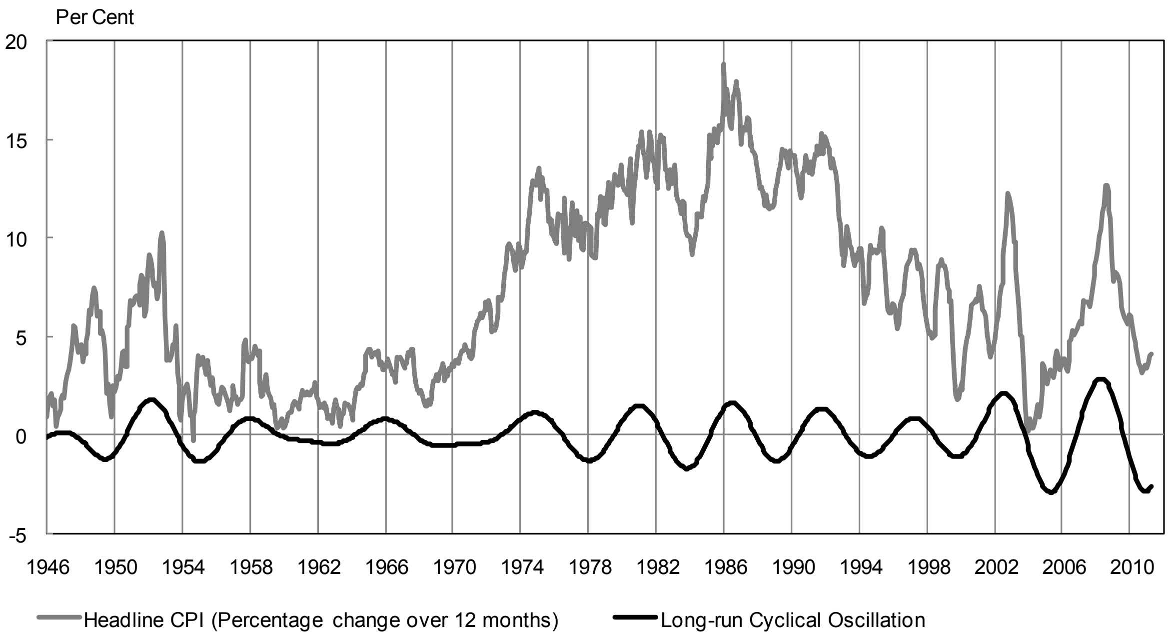

Figure 7 42-Month Oscillation in Annual Consumer Inflation

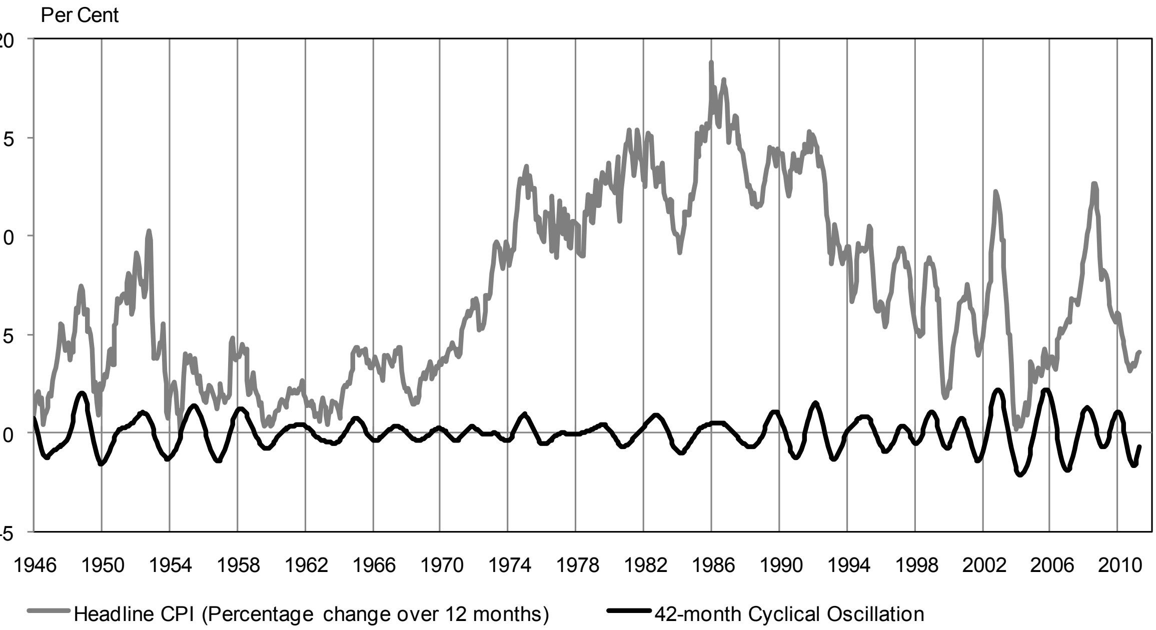

Figure 8 Biennial Cyclical Oscillation in Annual Consumer Inflation

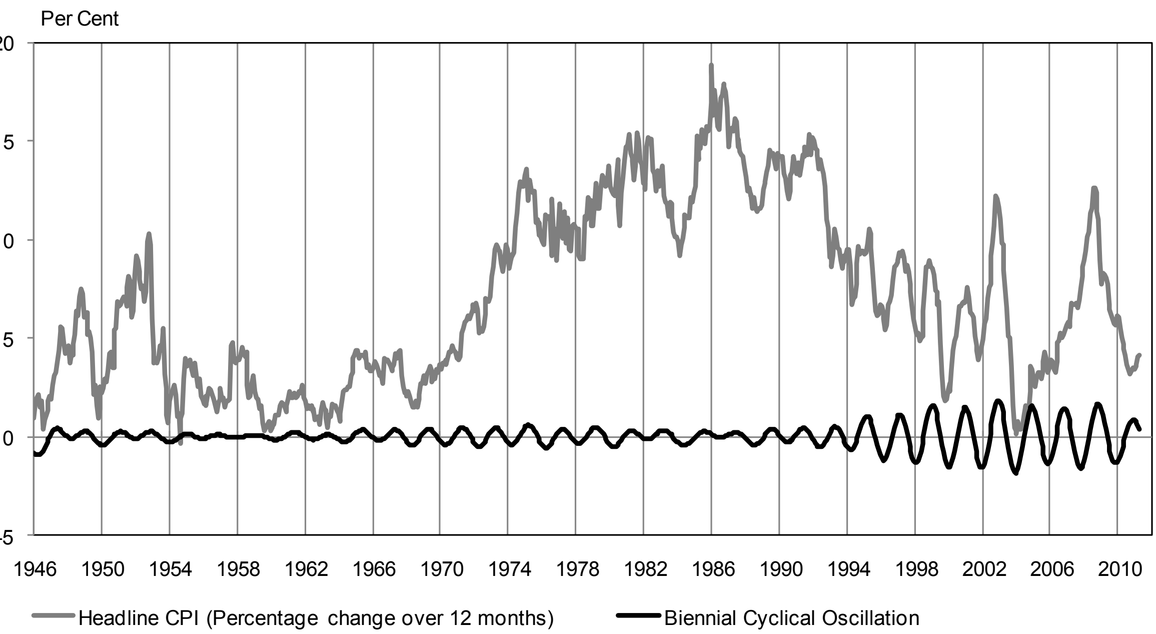

Figure 9 Core Inflation Measures

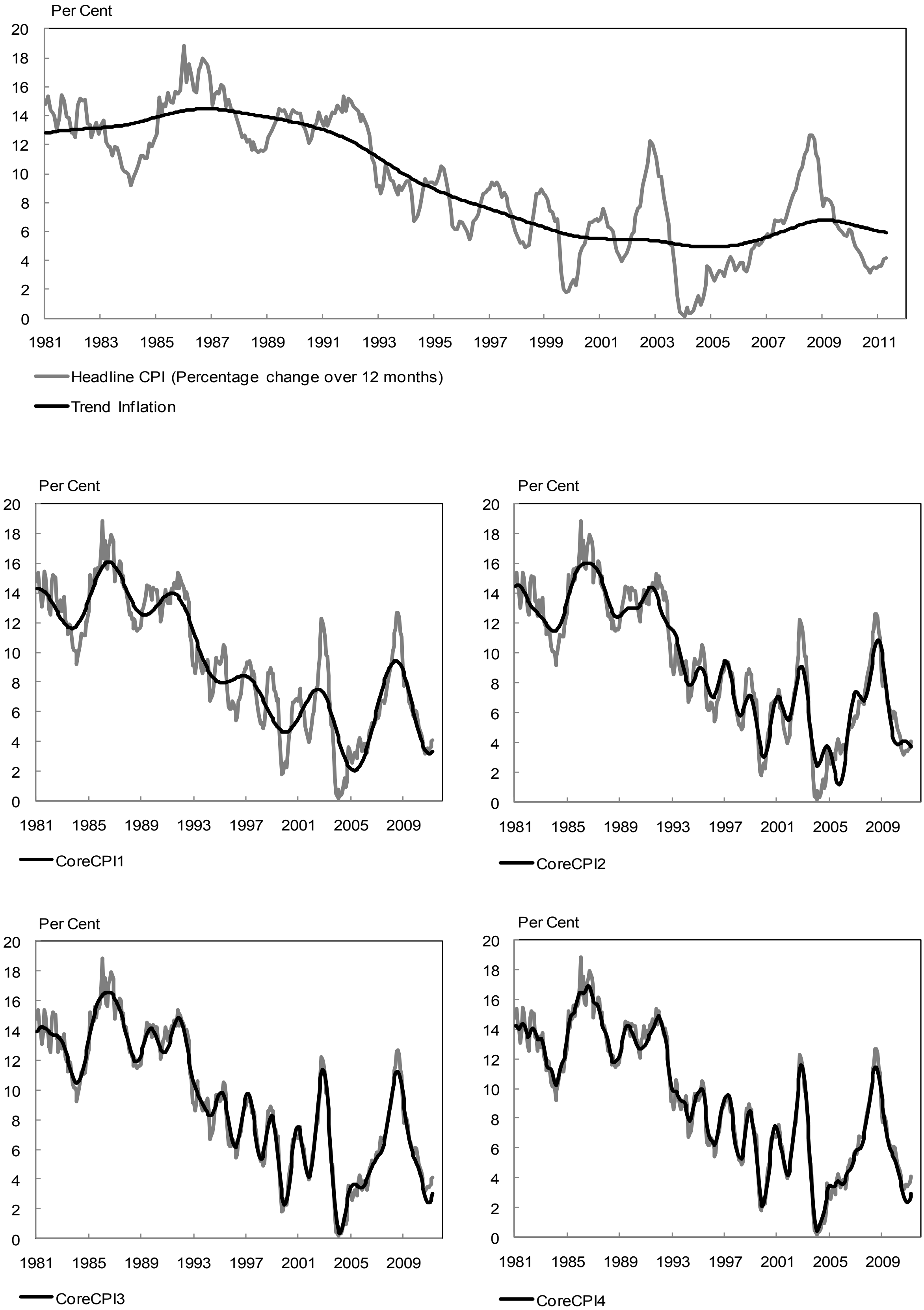

Figure 10 Core Inflation Measures Comparison (Restricted Sample)