

SELF-SIMILAR BEHAVIOR OF CPI HEADLINE INFLATION AND THE ROLE OF HURST EXPONENT IN DETERMINING CPI CORE INFLATION

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ABSTRACT. This paper aims to study the self-similarity behavior of inflation using the Hurst index. Previous studies reported the presence of long-range dependence (LRD) behavior in the inflation of some countries. Inspired by these facts, we examined the monthly consumer price index (CPI) headline inflation of India to check the self-similarity or LRD behavior. The current study to compute the Hurst index is based on different approaches methods like the R/S method, Variance-time method, Higuchi's method and Average periodogram method. This Hurst parameter estimate gives an idea about the strength of the self-similar nature in CPI headline inflation of India. A necessary condition for the core inflation indicator is stated in terms of the Hurst index value. The Hurst index value of conventional exclusion based measures of CPI headline inflation are compared for the possibility of being a core inflation indicator. The present study plays a prominent role in the determination of core inflation in the Indian context.

1. INTRODUCTION

Core inflation has a major role in monetary policy decisions. Core inflation is determined by removing the temporary price changes and retaining permanent (core) price changes of the commodity basket of the headline inflation. Forecasting inflation is of key interest to policymakers. Different methodologies

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are constructed for measuring core inflation like exclusion based method, symmetric trim method, asymmetric trim method, weighted median method, and moving average method. The inflation, a time series was estimated by applying the ARIMA model (Iqbal et al., 2016; Habibah et al., 2017). Long memory properties of inflation are studied at the global level and ARFIMA models are suggested (Hassler & Wolters, 1995; Baillie & Morano, 2012). The present paper is aimed at studying the self-similar behavior of CPI headline inflation by using several estimates of the Hurst exponent. Then core inflation indicators for CPI inflation are selected based on the exclusion rule and compared their Hurst exponents along with other properties of core inflation. The paper states a necessary condition for core inflation measures in terms of Hurst exponent.

The concept of core inflation is first defined by Eckstein in 1981 as *“the trend increase in the cost of factors of production that originates in the long-term expectations of inflation in the minds of households and businesses.”* With the experience gained from high inflation of the 1970s, several economists like (Bryan & Cecchetti, 1994) and (Blender, 1997) proposed core inflation for decisions regarding monetary policies as it tracks the main trend of inflation for long term forecasting.

At the global level, economists like (Bryan & Cecchetti, 1994) (Blender, 1997) (Clark, 2001) (Robalo Marques et al., 2003) (Rich and Steindel, 2005) (Mishkin, 2007) and (Gamber et al., 2015) contributed majorly for theoretical and empirical developments for core inflation. In the early stage of understanding core inflation, economists used exclusion based core measures and later on statistical-based core measures were developed. Exclusion based core measures are constructed by removing highly volatile components of the commodity baskets used to determine headline inflation. Economists, however question about the information contained in removed volatile components, and thus many economists started using statistical-based core indicators like symmetric and asymmetric trimming based method, moving average method, weighted median method, ARIMA method, VAR method, and HP filter method.

Bryan and Cecchetti (1994) sought attention to the weighted median approach which is a statistical-based measure of core inflation, while Clark (2001) chose trimmed mean for estimating core inflation. They explained the importance of these methods in dealing with temporary supply shocks. Quah and Vahey

(1995) opted for the VAR method to identify the important components of inflation that doesn't have much impact on headline inflation. Gamber et al. (2015) implemented a bivariate VAR model to identify the complicated relation between core and headline inflation. Hassler et al. (1995) identified long memory property in inflation rates. Iqbal et al. (2016) and Habibah et al. (2017) used ARIMA models for forecasting inflation. Baillie et al. (2012) stated modified ARFIMA models for inflation modeling.

In India economists like (Samanta, 1999) (Mohanty et al., 2000) (Durai & Ramachandran, 2007) (Kar, 2009) (Raj & Mishra, 2011) (Bicchhal et al., 2013) and (Sharma & Bicchhal, 2015) have a major contribution in the area of core inflation. Samanta (1999) determined exclusion based core measures for India. Mohanty et al (2000) determined exclusion based and trimmed mean based core inflation measures considering the WPI data (April 1983 - March 1999) and concluded 20% trimmed mean as the best core measure. Durai and Ramachandran (2007) compared core inflations computed using a multivariate model, trimmed mean method, and exclusion based method during April 1994-March 2005. The study stated the importance of core inflation based on trend model in forecasting inflation whereas the exclusion methods are confusing in nature.

Kar (2009) considered WPI data from Feb 1989 to Dec 2005 and constructed core inflation measures using an exponential smoothing method and compared it with other statistical methods. The study stated that exponential smoothing and weighted percentile-based models outperformed others in inflation identification. Raj and Misra (2011) from RBI examined various exclusion based indicators for WPI data considering the period: April 2005 to July 2011 and stated that only non-food manufacturing exclusion indicator satisfies the important properties required for core measure. Sharma and Bicchhal (2015) opted asymmetric trimmed mean method to compute core inflation measure for WPI data (April 1994 - April 2009) and stated that 29.5% left side trimming and 20.5% right side trimming resulted in the optimal estimator of core inflation measure. Krishna et al. (2020) constructed new exclusion based core indicator for CPI inflation that perform better than conventional exclusion measures by excluding sub-group level components of CPI basket.

In this study, we concentrate on characteristics of the headline and core inflation rather than the methods to determine the core inflation. Marques et al (2003) set three conditions for the core inflation indicators. Besides that, we try

to identify whether the headline inflation series belong to SRD or LRD. We categorize the inflation series by computing the Hurst exponent. Then we state a necessary condition for core inflation measure based on Hurst exponent. Lastly, we compare the conventional exclusion based measures of CPI inflation using the condition for the possibility of being a core inflation measure. The remaining work of the paper have been structured as follows: Section 2 presents about headline inflation, self-similarity and methods to determine it. Section 3 provides the description of the data and tools used for analysis. Section 4 presents the computation of Hurst exponent using various methods and derives a criteria for core inflation indicator based on Hurst exponent. Finally, Section 5 presents the conclusions of the study.

2. THEORY AND METHODS

This section is split into three sub-sections. Section 2.1 explains about the CPI data and the computation of CPI headline inflation. Section 2.2 presents the definition of the self-similarity and then method to classify a series as either short-range dependent or long-range dependent. Section 2.3 summarize some methods to determine the Hurst index of a series.

2.1. Headline Inflation. The CPI cross-sectional price distribution consists of a monthly price index of 23 individual commodities over the period of time. For each commodity of the CPI data, inflation is determined as the rate of change of its price index. To minimize the seasonal effect on inflation, we determine year-on-year inflation rates.

For an individual commodity (c) in the CPI basket, P_{ct} represent the price index of period (t) and w_{c_b} is the base year weight such that $\sum_{p=1}^{23} w_{c_b} = 1$. Then price level in period (t), P_t is defined as

$$P_t = \sum_{p=1}^{23} P_{ct} w_{c_b}.$$

The Y-o-Y rate of inflation for each commodity (c) for the period (t) is determined as

$$\pi_{c,t} = \left(\frac{P_{c,t} - P_{c,t-12}}{P_{c,t-12}} \right).$$

Similarly, Y-o-Y rate of inflation for all commodities in the CPI basket for the period (t) is given as

$$\pi_t = \left(\frac{P_t - P_{t-12}}{P_{t-12}} \right).$$

Thus the headline inflation rate is given as

$$(2.1) \quad \pi_t = \sum_{p=1}^{23} \pi_{c,t} w_{c,t},$$

where, $w_{c,t} = w_{c_b} \left(\frac{P_{c,t-12}}{P_{t-12}} \right)$ can be treated as the time-varying weight of the commodity (c) for the period or month (t) . Thus the headline inflation for period (t) , π_t is the weighted average of the Y-o-Y rate of inflation of all 23 commodities.

2.2. Self-Similarity and Hurst Index. The pioneer of the Self Similar process, Mandelbrot defined it as a stochastic process whose behavior is the same at different scales on a dimension (time or space). Let $X = \{X_t : t = 1, 2, \dots\}$ be the second-order stochastic process with mean μ (*constant* $\forall t$), variance σ^2 (*constant* $\forall t$) and ACF $\gamma(s)$ with lag s , i.e.,

$$\gamma(s) = \frac{\text{Cov}(X_t, X_{t+s})}{\text{Var}(X_t)}, s \geq 0.$$

Then the aggregating process, $X_t^{(p)}$ is computed using the initial process X_t as

$$X_t^{(p)} = \frac{1}{p} \sum_{i=1}^p X_{(t-1)p+i}, t = 1, 2, \dots,$$

where p is an integer (≥ 1) representing the size of blocks for the averaging process. The ACF of $X_t^{(p)}$ can be given as $\gamma^{(p)}(s)$ as it is also a second order stationary process.

Definition 2.1. The stochastic process ‘ X ’ is defined to be exactly second-order self-similar with variance σ^2 and Hurst exponent H if

$$(2.2) \quad \gamma(s) = \frac{\sigma^2}{2} [(s+1)^{2H} - 2s^H + (s-1)^{2H}], \quad \forall s \geq 1.$$

Definition 2.2. The stochastic process ‘ X ’ is defined to be asymptotically second-order self-similar with variance σ^2 and Hurst exponent H if

$$\sum_{m \rightarrow \infty} \gamma^{(p)}(s) = \frac{\sigma^2}{2} [(s+1)^{2H} - 2s^H + (s-1)^{2H}], \quad \forall s \geq 1.$$

Definition 2.3. *In the variance-time analysis, the process ‘X’ is defined to be exactly second-order self-similar with variance σ^2 and Hurst exponent $H = 1 - \frac{\beta}{2}$ if*

$$\text{Var}(X^{(p)}) = \sigma^2 p^{-\beta}, \quad \forall p \geq 1.$$

For $H \neq 0.5$, we can observe from (2.2) that

$$\gamma(s) = H(2H - 1)p^{2H-2} a s \rightarrow \infty.$$

Thus,

$$\sum_p \gamma(p) \sim c \sum_p s^{-\beta}, c = H(2H - 1).$$

The series $c \sum_p s^{-\beta}$ is divergent if $0.5 < H < 1$ or $0 < \beta < 1$ otherwise they are convergent, being a series of positive terms. The other series $\sum_p \gamma(p)$ can be interpreted accordingly. Thus, for $0.5 < H < 1$, the ACF decays hyperbolically and the stochastic process ‘X’ is classified as LRD (long-range dependent) and for $0 < H < 0.5$, $\sum_p \gamma(p)$ is finite and the stochastic process X is classified as SRD (short-range dependent).

2.3. Different Measures of Hurst Index. The Hurst exponent or index enables us to determine the strength of self-similar behavior in a time series. H.E. Hurst, hydrologist investigated the water storage problems and level patters regarding the Nile River for several years, and thus the index H had emerged. Even though Hurst exponent is mathematically well defined, it’s very difficult to determine for a given time series. To compute Hurst exponent for a small size time series, the observations must be taken at high lags. The range of the index H is $0.5 < H < 1$. Many methods are developed in the literature for determining H index for a time series. Here, we discussed the four widely used methods: R/S method, Variance-time method, Higuchi’s method, and Average periodogram method. Finally, we determined the Hurst index H for the CPI inflation time series using the above methods and compared them.

2.3.1. Rescaled adjusted range statistics (R/S method). For a self-similar process, the statistical characteristics are invariant with the partition of data. This idea is the sole of this method, where we determine the Hurst exponent by computing the rescaled range over sub parts of the main data (Mitko Gospodinov and Evgeniya Gospodina, 2005). Initially, the rescaled range is computed for

the main time series data ($RS_{ave_0} = RS_0$). Then the time series data is partitioned into two equal parts and rescaled range is computed giving rise to RS_0 and RS_1 . The partitioning of a section continues as in Figure 1 unless its sub sections have less than 8 data values. For each level, the rescaled range values are averaged and Hurst exponent is estimated. The adjusted partial sums for the data $X_1, X_2, \dots, X_n$ is defined as:

$$W_j = (X_1 + X_2 + \dots + X_n) - j\bar{X}(n), j = 1, 2, 3, \dots, n,$$

where $\bar{X}(n)$ is the sample mean. The range $R(n)$ and standard deviation $S(n)$ are defined by

$$R(n) = \max(0, W_1, W_2, \dots, W_n) - \min(0, W_1, W_2, \dots, W_n),$$

$$S(n) = \sqrt{E(X - \mu)^2}.$$

The rescaled adjusted range is defined by

$$(2.3) \quad \left(\frac{R}{S}\right)_{statistics} = \frac{R(n)}{S(n)}.$$

According to the power-law relation of $R(n)/S(n)$, we have

$$E \left[\frac{R(n)}{S(n)} \right] \rightarrow cn^H, \text{ as } n \rightarrow \infty,$$

where c is a positive finite constant and H is Hurst exponent. The robustness of this method is discussed in (Mandelbrot-Wallis, 1969).

RS ₀								Rsave ₀
RS ₀				RS ₁				Rsave ₁
RS ₀		RS ₁		RS ₃		RS ₄		Rsave ₂
RS ₀	RS ₁	RS ₂	RS ₃	RS ₄	RS ₅	RS ₆	RS ₇	Rsave ₃

FIGURE 1. Estimating Hurst parameter by R/S method

2.3.2. Variance-time method. This method is developed based on gradually decaying variance features of the self-similar process and its aggregated process. The p -aggregate process of $(X_1, X_2, \dots)$ is given by $X^{(p)} = (X_1^{(p)}, X_2^{(p)}, \dots)$ where

$$X_j^{(p)} = \frac{1}{p} \sum_{t=(j-1)p+1}^p X_t, j = 1, 2, \dots, \frac{N}{p}, j \in Z^+.$$

The variance of the aggregate process (X^p) is defined as:

$$(2.4) \quad \text{Var}(X^{(p)}) = \frac{1}{N/p} \sum_{i=1}^p (X_i^{(p)} - \bar{X}^{(p)})^2.$$

For large values of p , $\text{Var}(X^{(p)})$ decrease linearly. Thus we get

$$\text{Var}(X^{(p)}) = \text{Var}(X)p^{-\beta}.$$

The value of β can be found by estimating a regression line to the plot of $\log(\text{Var}(X^{(p)}))$ against $\log(p)$. This plot is defined as a variance-time plot. Small values of p should be ignored for regression fitting to increase accuracy. Finally, Hurst exponent can be computed using the relation $H = 1 - \frac{\beta}{2}$.

2.3.3. Higuchi's method. A technique suggested by T. Higuchi (1988) uses

$$(2.5) \quad L(p) = \frac{n-1}{p^3} \sum_{i=1}^p \left[\frac{n-1}{p} \right]^{-1} \sum_{k=1}^{\lfloor (n-1)/p \rfloor} \left| \sum_{j=i+(k-1)p+1}^{i+kp} X(p) \right|.$$

Here p represents block size, n represents the size of time series and $\lfloor \cdot \rfloor$ stand for the greatest integer function. For a time series with self-similarity or LRD, we have $E(L(p)) \sim cp^{(H-2)}$. Being computationally rigorous, the results of this method are more accurate especially in case of smaller time series like CPI headline inflation we considered. The more details of this method are discussed in (Taqqu et al. 1995)

2.3.4. Averaged periodogram method. In this method, the spectral representation is used for a stationary process. The averaged periodogram of the process $\{X_i, i = 1, 2, 3, \dots\}$ with Fourier frequency λ is given by

$$(2.6) \quad \bar{F}(\lambda) = \int_0^\lambda \bar{I}(\theta) d\theta, \quad 0 < \lambda \leq \pi,$$

where

$$(2.7) \quad \bar{I}(\lambda) = |\bar{w}(\lambda)|^2, \quad \bar{w}(\lambda) = \frac{1}{\sqrt{2\pi n}} \sum_{t=1}^n (x_t - \mu) e^{it\lambda}.$$

In this method, $\bar{F}(\lambda)$ is estimated using the Robinson integration technique (Robinson, 1994; Lobato and Robinson, 1996). The first step to determine Hurst exponent is to calculate periodogram and use the relation $\bar{I}(\lambda) \propto |\lambda|^{(1-2H)}$. By plotting periodogram against frequency on a log scale and fitting regression, one can obtain the slope $1-2H$.

3. DATA AND TOOLS

The empirical investigation has been conducted using data of monthly Combined CPI time series considering the period: Jan 2012-April 2019 (base year: 2011–2012). The secondary data is obtained from the Database of Reserve bank of India (RBI). The CPI headline Y-o-Y inflation is computed and checked for the self-similarity behavior by computing Hurst exponent. R programming and MS Excel tools are used for performing the analysis. The ‘fractal’ package in R programming is used for computing the Hurst exponent by various methods.

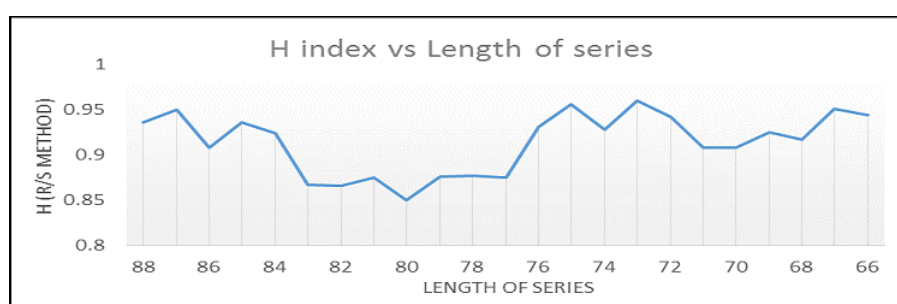


FIGURE 2. Plot of H index(R/S method) vs Length of series

4. RESULTS AND DISCUSSION

In this section, we first determined the CPI headline inflation mentioned in section 2.1 and using the (2.1). Now, we compute the Hurst index value of CPI headline inflation using the methods discussed. Applying the R/S approach, Hurst parameter value of the CPI inflation series is computed using the rescaled range over sub-parts of the data which is defined in (2.3) and finally using the relation $E[\frac{R(n)}{S(n)}] \rightarrow cn^H$, as $n \rightarrow \infty$. The Hurst index value obtained by this method is 0.9354. To further confirm the self-similarity behavior of the CPI inflation series, in Figure 2 we drew the plot for H value against the length of series considered. The range of H values in the plot concludes the self-similarity behavior of the CPI inflation series.

In Variance-Time method, the value of H can be found by estimating a regression equation to the plot of $\log(\text{Var}(X^p))$ against $\log(p)$ and using the relations $\text{Var}(X^p) = \text{Var}(X)p^{-\beta}$ and $H = 1 - \frac{\beta}{2}$ where $\text{Var}(X^p)$ is defined in (2.4).

The computed values of Variance-time are presented in Table 1 and from Figure 3(a) of Variance-time plot, the Hurst index value is obtained as 0.9578. In Figure 3(b), we present the H index values computed using the Variance-Time technique against the length of the series. The range of the plot concludes the presence of self-similar behavior in the CPI inflation series.

TABLE 1. Variance-Time values

p	$Var(X^p)$	$\log(p)$	$\log(Var(X^p))$
2	7.0819	0.3010	0.8502
4	6.8767	0.6021	0.8374
8	6.6454	0.9031	0.8226
16	5.5625	1.2041	0.7453
32	5.0262	1.5052	0.7012

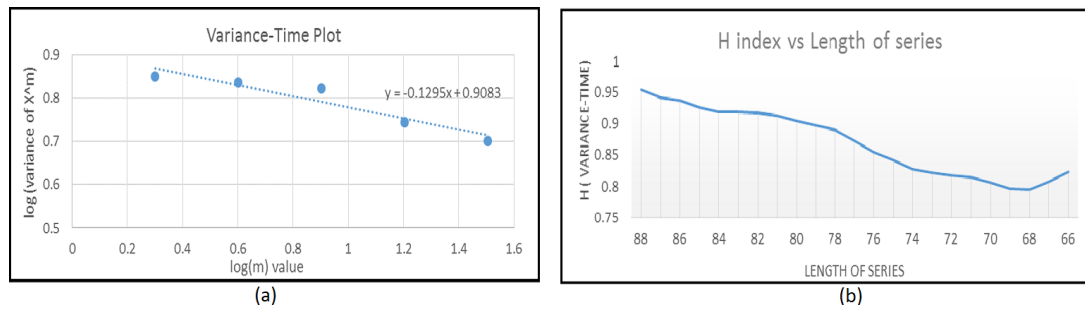


FIGURE 3. Variance-Time plot for calculating H value(Left) and plot of H index (Variance-Time method) vs Length of series(Right)

In the Higuchi method, we compute $L(p)$ which is defined in (2.5), and use the relation $E(L(p)) \sim cp^{(H-2)}$ to obtain the Hurst index value. The initial computed values of Higuchi-time are presented in Table 2 and then $\log(L(p))$ is plotted against $\log(p)$ in Figure 4(a) Higuchi-time plot. Thus, from the graph, the Hurst index value is obtained as 0.9857. In Figure 4(b), we present the H index values computed using the Higuchi method vs the length of the series. The range of the plot concludes the existence of self-similar behavior in the CPI inflation series.

In the averaged periodogram method, spectral representation defined in (2.6) and (2.7) are used in estimating the Hurst index value. Using the relation

TABLE 2. Higuchi-Time values

p	$L(p)$	$\log(p)$	$\log(L(p))$
2	261.45	0.301	2.4174
4	131.08	0.6021	2.1175
8	65.628	0.9031	1.8171
16	32.441	1.2041	1.5111
32	15.627	1.5052	1.1939

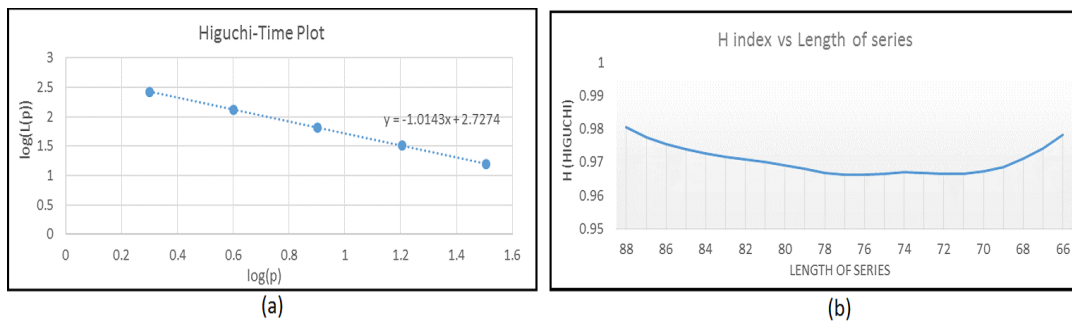


FIGURE 4. Higuchi-Time plot for calculating H value(Left) and plot of H index (Higuchi method) vs Length of series(Right)

$\bar{I}(\lambda) \propto |\lambda|^{(1-2H)}$ Hurst index value of CPI headline inflation is obtained as 0.9844. In Figure 5, we present the H index values computed using the Robinson Periodogram method vs the length of the series. The plot range suggests that the CPI inflation series has self-similarity nature.

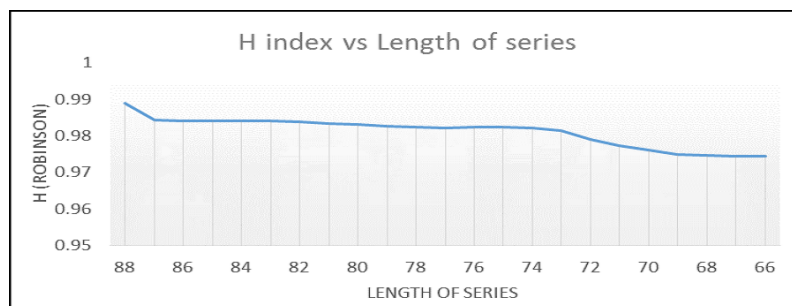


FIGURE 5. Plot of H index(R/S method) vs Length of series

All the four widely used methods: R/S method, Variance-time method, Higuchi's method, and Average periodogram method result in Hurst index value which

lies in (0.5, 1). All the Hurst index estimates are near to each other and greater than 0.9. This states that the CPI headline inflation time series satisfies the self-similarity or LRD property.

The intensity of LRD of a series is measured by the Hurst index value i.e., the larger the Hurst index value the larger the LRD nature. The range of Hurst index value for long-range dependence series lies in (0.5, 1). The above results state that the CPI headline inflation series has LRD property. We also know that the CPI core inflation indicator is identified by eliminating the transient price changes from the headline inflation, specifying that the Hurst index value of the core inflation indicator should be at least that of headline inflation.

Exclusion based indicators are determined by eliminating certain volatile commodities from the headline inflation. The conventional exclusion based indicators widely used in India for CPI inflation are excluding food commodities, excluding energy commodities and excluding food and energy commodities. CPI excluding food eliminates all the commodities under the food group which weighs 45.85% of the total CPI basket. CPI excluding energy eliminates the energy group commodities which weighs only 6.84% of the total CPI basket. Whereas CPI excluding food and energy eliminates both food and energy group commodities whose combined weight is 52.7% of the total CPI basket. Table 3 presents the other descriptive statistics of CPI exclusion based indicators. While the mean of CPI excluding energy is very close to the CPI headline inflation, the standard deviation and coefficient of variation of CPI excluding food and energy are less compared to other indicators. Figure 6 presents the time-series graph of CPI exclusion based indicators and CPI headline inflation. One can see that there is no much difference between the graphs of CPI headline inflation and CPI excluding energy, which question the core inflation behavior of the later.

Generally, the core inflation measure is expected to have the same mean as of the headline inflation. This property is usually known as unbiasedness and tested using the t-test. Table 4 presents the p-value results of the t-test and from which we can say that all the conventional CPI exclusion indicators obey the unbiasedness property of core inflation measure. Further, it is expected that errors should be stationary. So, the differenced series formed by CPI headline inflation and CPI exclusion indicators are examined for stationarity performing PP and ADF tests. The results of both the tests convey that only CPI excluding energy satisfies the stationarity criteria. So, CPI excluding food and CPI excluding

TABLE 3. Descriptive statistics of exclusion based indicators

S.No	Inflation (CPI)	Mean	Standard Deviation	Coefficient of Variation	Weight
1	Headline	5.994	2.701	0.451	100
2	Excluding food	6.071	1.821	0.299	54.14
3	Excluding energy	5.983	2.781	0.465	93.16
4	Excluding food and energy	6.058	1.767	0.292	47.30

TABLE 4. Characteristics of exclusion based indicators

S.No	Core Inflation Indicator (CPI)	Unbiasedness	Stationarity		LRD
		T-Test (P-value)	PP Test (P-value)	ADP Test (P-value)	Hurst Index
1	Excluding food	0.821	0.061	0.133	0.982
2	Excluding energy	0.984	0.043*	0.021*	0.946
3	Excluding food and energy	0.851	0.078	0.154	0.989

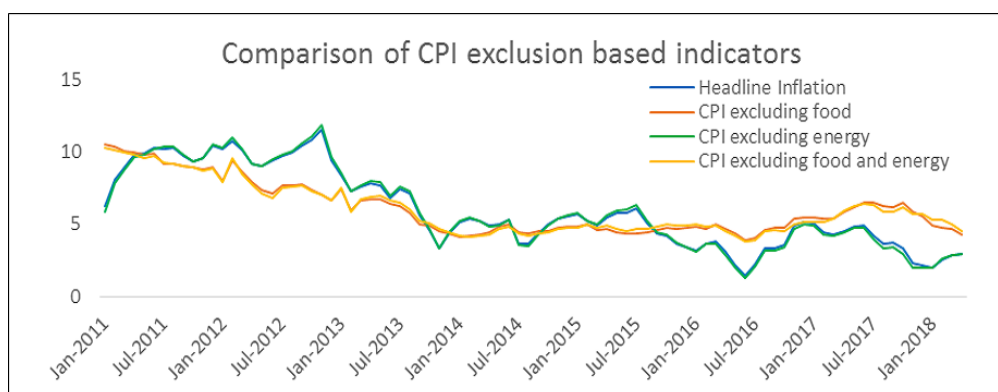


FIGURE 6. Time series plot to compare CPI exclusion based indicators

food and energy cannot be core inflation measures. As we stated that CPI headline inflation has LRD property, we expect the same from the CPI core measure. Also, the Hurst index value of CPI core measure is expected to be at least that of CPI headline inflation. Next, we computed the Hurst index value using the

Variance-Time method for the three CPI exclusion indicators. The CPI excluding energy has the Hurst index value of 0.946 which is lesser than the Hurst index value of CPI headline inflation which is 0.958 and thus it cannot be CPI core inflation measure. Even though the other two indicators satisfy the Hurst index criteria, they already failed in Stationarity criteria. Apart from these, core measures are also expected to satisfy attractor and exogenous property. Thus LRD or self-similar property of CPI headline inflation has simplified the screening for the core measures. All three conventional CPI exclusion based indicators cannot be treated as CPI core measures and a need to develop new CPI exclusion indicators is identified.

5. CONCLUSIONS

In this paper, CPI headline inflation is studied for self-similarity behavior by computing the Hurst index. Various methods of estimating the Hurst parameter have been discussed and applied to CPI headline inflation. The Hurst parameter estimates from various methods confirm the existence of self-similar or LRD nature in CPI headline inflation. This kind of analysis is very useful to CPI headline inflation especially for computing the CPI core inflation. Especially, the Hurst index criteria help in identifying the potential core inflation measure from a pool of indicators. The analysis also suggests to perform ARFIMA modeling in the computation of CPI core inflation.

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