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Abstract

Zambia has grappled with high inflation since August 2015, posing challenges to maintaining it within the 6-8 percent target band. This study, using data spanning from January 2010 to September 2023, adopts a novel approach by focusing on the new consumer price index inflation series based on the geometric mean first recorded in January 2010. It employs innovative methods like power spectral density for fractal signal classification as a complement to the Hurst parameter estimation of its long memory, providing a unique perspective on inflation dynamics by also utilising information on structural breaks in each series: food, non-food, and overall inflation. This is in addition to estimating steady-state inflation values and speed of adjustment based on the Beta convergence method of the Solow growth model. The results reveal that before structural breaks in early 2013, all the inflation series exhibited anti-persistent fractional Brownian motion (fBm) process, indicating a mean-reverting pattern. Following structural breaks until November 2021, persistent processes were observed, implying trend reinforcing. Recent data suggest a likely gradual decline in inflation once it starts falling based on the estimated underlying process of the anti-persistent fBm type. It is important to note that the estimated steady-state values for overall and food inflation series, based on the recent data segment, exceed the target band of 6-8 percent at 9.3 and 11.8 percent, respectively. In contrast, non-food inflation lies within the target range, but in the epsilon neighbourhood of the upper bound at 7.8 percent. These results justify an aggressive monetary policy action to bring overall inflation within the 6-8 percent target band.

Key words: Fractional Brownian motion; anti-persistent; fractal signal classification; Hurst; steady state; and speed of adjustment.

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Table of Contents

1. Introduction

High inflation undermines purchasing power, erodes savings, and dampens economic growth by reducing investments and private consumption. Since August 2015, endeavors by the authorities to confine headline inflation within the policy target range of 6-8 percent—adopted in 2018—have yielded limited success as depicted in the appendix. This outcome is despite several studies aiming to uncover the determinants behind inflation in Zambia (see for example Chipili, 2021; Bulawayo, Chibwe and Seshamani, 2018; and Roger, Smith and Morrissey, 2017). Phiri (2022) introduces a fresh perspective by delving into the potential influence of Governors (leadership) tenure at the Bank of Zambia on inflation outcomes.

Inflation outcomes are influenced by a range of factors that can even be hard to pin down (Durevall et al, 2013). These factors can have varying degrees of impact with some exerting a lasting effect on inflation, and others temporary. Central banks prioritise addressing persistent factors as accommodating transient influences through monetary policy actions can be costly—as monetary policy actions are not a cheap undertaking.

Meanwhile, when inflation is taken as a sequence of real numbers indexed by time can be distinguished into two broad components: signal and noise. The signal component, although unobservable, represents the underlying process driving inflationary trends. On the other hand, the observable noise component represents fluctuations or deviations from the underlying signal. These fluctuations might arise from transitory influences. Monetary policy should not react to noise as this would be akin to responding to influences arising from transitory effects of shocks.

The underlying process of a time series can exhibit different characteristics ranging from anti-persistent to persistent. Anti-persistent processes, such as fractional Gaussian noise (fGn) and anti-persistent fractional Brownian motion (fBm), involve mean reversion. Persistent fBm processes, however, reinforce their trend over subsequent periods and exhibit long memory, indicating correlations between distant observations. Brownian motion falls between these two processes and is akin to a random walk. The fBm is a non-stationary process, but with stationary increments while the fGn series are the successive differences between elements of a fBm series. The fGn process is, nonetheless, stationary with constant mean and variance.

Long memory—sometimes referred to as long range dependence—is, to put it in a more practical way, a characterisation where the process at a given point in time is not only influenced by state conditions obtaining at that moment but also on events past (Baudoin, 2010). Long memory is synonymous with fractional integration (Baillie, 1996). The memory phenomenon is prevalent in economic variables. This includes Zambia's inflation as established by Musongole (2008) using the Hurst parameter estimation based on time series data covering the period January 1986 - December 2007. The Hurst coefficient was used as a measure of long memory/long range dependence for three measures of the consumer price index (CPI) inflation: food, non-food and overall inflation series.

The challenge with persistent inflation in Zambia despite extensive studies focusing on its determinants may stem from its order of integration being fractional in nature.

Previous analysis considered integer-order integration neglecting the possibility of fractional-order integration (indicating possibility of long memory). Currently, there may be no information regarding fractional-order integration in the inflation series under the geometric mean for computing the CPI. The geometric mean method for computing elementary aggregate indices of the CPI was adopted in 2009 with the month of January being the base period. The first annual inflation digit in the series under the geometric mean was recorded in January 2010. Musongole (2008)'s study used the inflation data from the previous arithmetic mean approach.

To comprehensively address the complexities of Zambia's seemingly persistent inflation, it is imperative to explore the potential fractional nature of its underlying process and consequently investigate, if any, the presence of long-range dependence in the geometric mean based inflation series given the intractable nature observed so far. This should also explore the signal classification of the inflation series as it relates to long memory processes, which is lacking in Musongole (2008). Further, this includes investigating the presence of structural breaks as this may have implications on long memory in the time series data.

At this point, let me give away the main conclusion of this paper: when considering the entire sample, inclusive of structural breaks. The three measures of inflation are estimated to have an underlying process that is akin to persistence. However, once structural breaks are taken into account, the underlying process becomes dynamic. It exhibits anti-persistence before and after the structural breaks, yet within the sub-sample with identified structural breaks (inclusive of the actual break points), the process is persistent. Furthermore, the estimated steady state values for food and overall inflation, based on the sub-sample following the last detected structural break in the respective datasets, fall outside the 6-8 percent inflation policy bounds. Additionally, these series show low speed of adjustment of less than 30 percent similar to Chipili (2021).

It is imperative to emphasise that this study makes a noteworthy contribution by being the first to investigate the behavior of the underlying process of the geometric mean CPI inflation for Zambia using the Hurst exponent. Additionally, it pioneers the incorporation of fractal signal classification into the analysis of inflation thereby preventing spurious interpretations of the Hurst coefficient. Furthermore, it is the first to infuse together information about the Hurst coefficient and fractal signal classification to simulate a sample path of the underlying process for inflation on a sub-Saharan Africa country to the best of my knowledge.

The rest of the paper is structured as follows: Section 2 presents a summary from the survey of related literature essential in guiding this study. Section 3 describes the empirical strategy adopted in this paper, partly influenced by data description contained within this section and the literature. Section 4 contains information on findings that includes a discussion on their implications. The conclusion is presented in section 5.

2. Review of Related Literature

Studies investigating the underlying behaviour of inflation, particularly its long-range dependence or long memory, through Hurst parameter estimation, is seemingly not common. However, fractal analysis, specifically estimating long-range dependency using the Hurst statistic, is extensively applied on other economic and financial variables (see for example, Nguyen et al., 2019; Auer, 2018; Dima and Dima, 2017; Martinez et al., 2016; Gyamfi et al., 2016; Chimanga and Mlambo, 2014; Sensoy and Tabak, 2016; Sensoy and Tabak, 2015; Sensoy, 2013; Auer, 2016a; and Auer, 2016b). Beran (1992) has emphasised that overlooking this aspect in statistical inference can result in invalid conclusions.

Nevertheless, in a notable exception, Musongole (2008) utilised fractal analysis to estimate long memory in Zambia's annual overall, food, and non-food inflation based on the Hurst parameter using rescaled range (R\S) analysis. This is for the period covering January 1986 to December 2007. The findings revealed that all the three inflation series exhibited a Hurst coefficient above 0.62, indicating persistence, and, therefore, a long-memory inclined underlying process. Essentially, this result suggests that all the three measures of inflation in Zambia are trend reinforcing. Consequently, to control inflation effectively, monetary policy in Zambia should typically be kept extremely tight to prevent runaway inflation given many shocks that have affected inflation. However, in view of the study having not considered the possibility of structural breaks in the series as well as fractal signal classification, one may have to interpretate the results with some caution.

Structural breaks in data refer to changes at specific dates in the trend and parameters—mean and variance that governs the evolution of data—with such parameters typically assumed to be stationary over time (Hansen, 2001). Hansen argues that ignoring structural breaks can result in misleading empirical-based policy advice as they have the potential to distort statistical inferences. This is because the effect of structural breaks in the data can be mistaken for long memory since the two tend to have similar characteristics such as slowly decaying autocorrelation functions (Wenger, Leschinski and Sibbertsen, 2018). Further, the influence of structural breaks on the memory process in time series data relates to Ngene, Tah and Darrat (2017) observation that the long memory identified in the data might be an outcome of short memory encountering structural breaks.

The significance of fractal signal classification alluded to lies in its pivotal role in interpreting the estimated Hurst parameter to avoid spurious conclusions. Serinaldi (2010), Delignieres *et al.* (2006), Eke *et al.* (2002), and Cannon *et al.* (1997) have established that a unique Hurst coefficient value can characterise both fractional Brownian motion (fBm) and corresponding fractional Gaussian noise (fGn) type of time series data (signal). In light of this dichotomy, Serinaldi (2010), among others, advise on interpreting the estimated Hurst coefficient with careful consideration of the specific type of signal under examination (fGn or fBm) to avoid any ambiguities. This means that, although fGn and fBm signals can yield the same Hurst parameter value, the interpretation must be guided by the inherent nature of the signal being analysed.

Garcin (2018) examined time series data suggesting that the series exhibits mean reversion dominance at higher scales while persistence prevails at lower scales. This complexity in fractional Brownian motion (fBm) processes, as indicated by the Hurst parameter, prompts caution in interpretation. To address potential ambiguities, Garcin (2018) recommends applying the inverse Lamperti transform to the fBm. This transformation yields a delampertised fractional Brownian motion that incorporates both persistence and mean reversion, proving valuable for analysing economic and financial time series data.

However, in this study, our approach differs from Garcin (2018). Instead, we align somewhat with the methodologies proposed by Serinaldi (2010), Delignieres *et al.* (2006), Eke *et al.* (2002), and Cannon *et al.* (1997). This involves complimenting the Hurst coefficient results with the fractal signal classification estimated results for the sake of simplicity while maintaining robustness in the interpretation of the estimated Hurst parameter.

For this reason, the present study builds upon Musongole (2008)'s long memory estimation of Zambia's inflation by incorporating fractal signal classification into the analysis. This is lacking in Musongole (2008). The approach of incorporating fractal signal classification is essential to prevent any erroneous interpretation of the estimated Hurst coefficient.

Similar to Musongole (2008), Krishna and Reddy (2020) utilised the Hurst parameter to establish long range dependence of India's CPI headline inflation. This was in addition to estimating the Hurst parameter for the different measures of India's core inflation. Utilising multiple methods (R/S, Variance-time, Higuchi's and Average periodogram), the findings indicated that India's CPI headline inflation exhibits a persistent process with $H > 0.9$ across each method, mirroring the case established for Zambia by Musongole. Even one of the core inflation measures that met the stationarity condition also yielded a Hurst coefficient exceeding 0.9, suggesting the presence of long memory in the series. The paper concludes by asserting that none of the three conventional CPI exclusion-based indicators monitored by the Reserve Bank of India can be considered as CPI core measures, emphasising the need to develop new CPI exclusion indicators.

Related to the argument made regarding Musongole's interpretation of the Hurst results, the conclusion drawn by Krishna and Reddy concerning the core inflation measure—that passed the stationarity test but was identified as persistent based on the estimated Hurst parameter value—should be approached with caution. This caution stems from the absence of establishing the presence of structural breaks and the inability to ascertain the fractal signal classification of each series. The implications of ignoring the two in the interpretation of the Hurst parameter is more likely to lead to supurious conclusions as argued earlier. The present study seeks to avoid this potential problem by undertaking additional empirical works involving determination of structural breaks and fractal signal classification.

Elsewhere in sub-Saharan Africa, specifically for 12 Communauté Financière Africaine (CFA) member states (the Franc zone), the long-range dependence in inflation has been investigated but using fractional integration method by Coleman (2010). Like Musongole (2008), Coleman looks at disaggregated inflation—food and non-food—but takes into account information on structural breaks in the estimation for the data set based on month-on-month (mom) change covering the period November 1989 to September 2002. The results indicate anti-persistence in both inflation series, which may imply mean reversion to some extent. This result is not surprising in my view. Intuitively, mom inflation data should be stationary under some compact form (bounds) and therefore mean reverting because a bounded sequence converges to some limit. The only exception in my view would be in the era where monetary policy is non-functional and or annual inflation is in a hyper sense. Nonetheless, by taking care of structural breaks, mean reversion may be a plausible outcome as established by the study.

Additionally, Tule et al (2020) used fractional integration to assess the persistence of Nigeria's three measures of inflation: core, food and headline. Unlike Musongole (2008), but consistent with Coleman (2010), all the three series of inflation were found to be anti-persistent. This aligns with the idea above that in the presence of some measure of monetary policy interventions, inflation should ideally display some level of anti-persistence. The key consideration, however, lies in the speed at which inflation adjusts to the desired target.

To avoid suffering the problem of misinterpretation of the results on long memory, this study is motivated by the approach adopted by Tule et al (2020) and Coleman (2010) of undertaking structural breaks on the inflation series. This will help avoid the Ngene et al (2017) problem: the long memory detected in the data may be an artifact of short memory encountering structural breaks.

Unlike the mono-fractal approach utilised by Musongole (2008) and Krishna and Reddy (2020), long range dependence is also measured in the context of multifractality through the generalised Hurst exponent. This has seen its applications to inflation among other economic and non-economic time series data. The multifractal approach identifies the deviations in fractal structure within time periods with large and small fluctuations (Ihlen, 2012). Fernandes et al (2020) investigated the presence of multifractality in the various types of inflation monitored by Brazil, and similarly, Álvarez (2022) also investigated price behaviour in Uruguay from the perspective of multifractality. This study does not, however, pursue that form of inquiry on Zambia's inflation but instead is motivated to use the mono-fractal approach as for example done by Musongole but by also considering structural breaks and fractal signal classification. This is for easy understanding and interpretation.

The Hurst coefficient is a popular measure for long memory. An alternative measure is the fractional integration (d) discussed extensively by Baillie (1996) in the context of its implications in econometric modelling, and utilised by Tule et al (2020) and Coleman (2010) as indicated earlier. It is related to the Hurst parameter (H) as $d = H - 0.5$.

Several methods for estimating the Hurst parameter have been developed (Cajueiro et al, 2009). Nonetheless, evaluations have found the detrended fluctuation analysis (DFA), wavelets methods and the R\S methods to be unbiased as they yield consistent results regardless of data length (Rea *et al.*, 2013; Kirichenko, Radivilova and Deineko, 2011; Chamoli, Ram Bansal and Dimri, 2007). The DFA has also been found to be fairly consistent with both stationary and non-stationary time series data (Kirichenko et al, 2011).

There may be a possibility that the estimated Hurst coefficient for Zambia's inflation series can be anti-persistent—when structural breaks and fractal signal classification are considered—and therefore likely to be mean reverting. This may require further analysis related to establishing the long run steady state value and speed of adjustment to the long run to help with policy orientation. It is argued in the literature that there is a relationship between mean reversion and some degree of persistence when considered from the perspective of speed of adjustment to the long run mean in a univariate set up (Marques, 2005; Dias and Marques 2010). As argued by Dias and Marques (2010), the degree of persistence of shocks on inflation can have a bearing on policy response, an assertion echoed by Tule et al. (2020).

The level of the steady state value of inflation and speed of adjustment to the steady state can be useful metrics to guide monetary policy response to inflation developments. In this regard, one possible framework to use in estimating the two metrics for Zambia's inflation is the Beta convergence technique of the Solow model of the neo-classical growth theory credited to Solow (1956). Hlivnjak (2009) and Mbao (2021b) have used a modified version of the Beta convergence framework on non-GDP economic data to determine long run means and speeds of adjustment for the variables considered. This means that the framework has the potential to determine the steady state value of inflation and speed of adjustments for policy guidance, a feature that is also missing in Musongole (2008). This was not undertaken by Musongole most likely because the results found indicated the three series to be persistent processes.

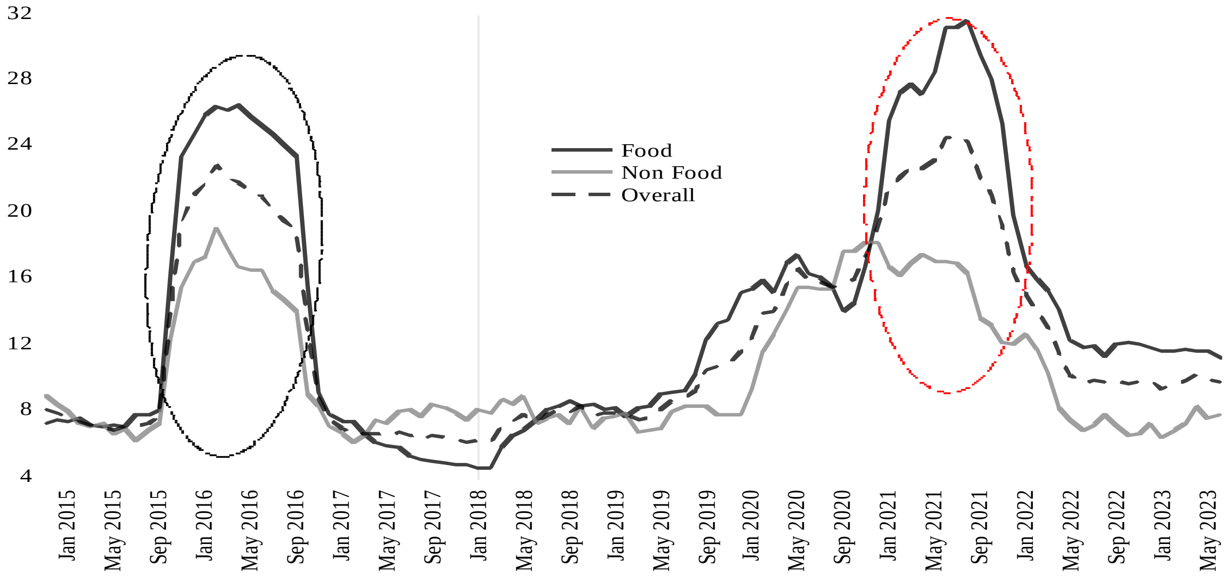
3. Empirical Strategy

The empirical strategy adopted in this paper is one that partly is data driven for the reason being that there is no theoretical argument on the long-range dependence in inflation. In this regard, some detailed data description is undertaken to guide the empirical work. It involves establishing the autocorrelation behaviour of each of the three inflation series. This is followed by testing for structural breaks given that in the literature, long-range dependence may be due to structural breaks in the time series data.

3.1. Trend Behavior and Stylised Facts about Inflation in Zambia

After rebasing the consumer price index in 2009, with the adoption of the geometric mean approach, which replaced the arithmetic mean approach used for many years, two instances of inflation overrun have been observed. These episodes occurred in the vicinity of 2016 and 2021 (Chart 1).

Chart 1: Inflation Trends, January 2010-June 2023



In 2016, the overshooting in inflation was largely due to the lag effects of sharp exchange rate depreciation that characterised commodity exporting emerging and frontier market economies (EFMEs) beginning in September 2015. Inflation in Zambia is susceptible to exchange rate movements (see for example Zgambo, 2015; Roger et al., 2017; Mbao, 2021a; Chipili, 2021; and Chisha et al., 2023).

The driving force behind the sharp exchange rate depreciation of 2015 was the monetary policy normalisation initiated by the US Federal Reserve Bank (the Fed) (Dahlhaus and Vasishtha, 2014, Anaya et al., 2017, and Acharya and Krishnamurthy, 2018) in addition to domestic factors highlighted in Bank of Zambia (2015). This came to the fore as the Fed concluded its asset purchase program and shifted away from its near-zero interest rate policy. These measures, collectively referred to as unconventional monetary policy (UMP) in literature, were initially implemented to counteract the adverse impacts of the global financial crisis of 2008-2009 on the US economy.

However, as the UMP was unwound, a decline in commodity prices, notably copper which is Zambia's major foreign exchange earner, ensued. Additionally, there was an accompanied substantial outflow of foreign portfolio funds from economies within EFMEs (Dahlhaus and Vasishtha, 2014; Anaya et al., 2017). These combined effects of monetary policy normalisation resulted in a significant depreciation of the Kwacha/US dollar exchange rate. This, in turn, triggered an adverse pass-through to inflation, attributed to a level shift in September 2015 in the Consumer Price Indices (CPIs) of the three types of inflation monitored in Zambia.

During the same year, Zambia experienced one of the worst rain droughts. The Zambian currency tends to depreciate during these drought periods. This can be attributed to the heightened demand for foreign exchange within Zambia, which tends to surge during episodes of drought (Mbao, 2021a). As a result, this increased demand contributes to the depreciation of the Kwacha, as outlined in a study by Mbao (2021a).

In 2021, the occurrence of inflation overshooting can be attributed, much like in 2016, to a significant exchange rate depreciation observed in 2020. This depreciation led to a notable level shift in all three monitored CPIs within the same year. The resultant level shift across the three CPIs during 2020 consequently resulted into a peak in inflation at some point in 2021. The depreciation of the Kwacha against the US dollar was influenced by several factors, with adverse sentiments taking center stage (Bank of Zambia, 2021). Notably, these negative sentiments were associated with economic fallout from COVID-19 pandemic's outbreak in addition to Zambia's credit rating downgrade in the first quarter of 2020. In the latter half of 2020, concerns surrounding the Government of Zambia's default on foreign debt also contributed to the prevailing unfavourable sentiments.

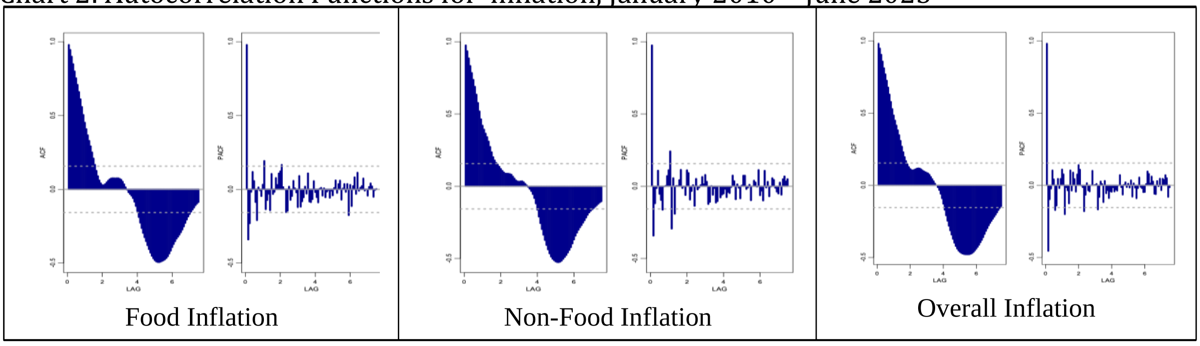
In the two instances of overshooting inflation episodes, the increase in non-food inflation was notably more modest compared to its food counterpart. Recent research on inflation in Zambia reveals a distinct tendency for exchange rate pass-through to exert a more pronounced impact on food inflation than on non-food inflation as highlighted by Chisha et al. (2023), Chipili (2021), Roger et al. (2017), and Zgambo (2015).

Generally, food inflation exhibited a consistent upward trend from May 2011 to January 2013. The relatively lower levels observed in 2010 can be attributed to an ample food supply resulting from a bountiful harvest of maize and other cereals during the 2009/2010 farming season. Notably, the country achieved an unprecedented maize output of 2.8 million metric tons during this period (Bank of Zambia, 2011). The decline in food inflation recorded in 2017 was also due to favourable supply of maize and cereals as the agricultural sector recovered from the drought experienced in the previous season.

3.1.1. Autocorrelation Functions and Partial Autocorrelation Functions

The autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) for the three inflation series in Zambia exhibit a gradual decay (Chart 2). This initial observation provides prima facie evidence of the presence of long-range dependence in each series, indicative of a potential fBm nature. This inference is drawn from the extended periods of positive ACFs followed by negative counterparts, suggesting some persistence, especially considering the slow decline in ACFs. This memory behaviour exhibited in the three datasets could arise from complex behavioral patterns displayed by economic agents or potentially stem from structural shifts within each individual series owing to shocks. Additionally, this could be the result of base effects arising from some wild swings in the CPI itself.

Chart 2: Autocorrelation Functions for inflation, January 2010 – June 2023



Analysing the ACF and PACF visualisations, it also appears the three measures of inflation broadly have similar underlying structure. However, overall inflation seems to mirror somewhat that of food inflation, showcasing some analogous correlation patterns. In view of this, it becomes imperative to investigate whether the three series share comparable structural breakpoints as the issue of long memory in time series data owing to presence of the structural breaks also aligns with findings in the existing literature.

3.1.2. Structural Breaks

Structural breaks, as stated before, can lead to misleading empirical based policy advice if ignored. The analysis of structural breaks in the inflation series in this study utilises the R package "*Strucchange*" based on Zeileis et al. (2002) routine that combines features from the generalised fluctuation framework and F-statistics for multiple structural breaks detection.

Indeed, *Strucchange* reveals the existence of such multiple structural breaks within the three inflation series (Tables 1a-Ic). Notably, all the three series exhibit substantial structural breaks, with observation breakpoints displaying confidence levels of up to 97.5%, occurring in the years 2013, 2016, and 2018. Intriguingly, an additional break emerges within the food and overall inflation series, resulting in a total of four structural breaks, as opposed to the three identified in the non-food inflation series.

Table 1a: Food Inflation Estimated Structural Breaks, January 2010–June 2023

Description	2.50%			Observation Breakpoints 97.5%		
	Year	Month	Observation	Year	Month	Observation
1	2012	Nov	35	2013	Mar	39
				2013	Apr	40
2	2015	Nov	71	2016	Jan	73
				2016	Apr	76
3	2017	Dec	96	2018	Jan	97
				2018	Feb	98
4	2020	Sep	129	2020	Oct	130
				2021	Oct	142

Source: Author, Studio R strucchange Package output.

Table 1b: Non-Food Inflation Estimated Structural Breaks, January 2010–June 2023

Description	2.50%			Observation Breakpoints 97.5%		
	Year	Month	Observation	Year	Month	Observation
1	2013	Mar	39	2013	May	41
				2013	Jun	42
2	2015	May	65	2016	Mar	75
				2016	Aug	80
3	2018	Feb	98	2018	Mar	99
				2018	May	101

Source: Author, Studio R strucchange Package output.

Table 1c: Overall Inflation Estimated Structural Breaks, January 2010–June 2023

Description	2.50%			Observation Breakpoints 97.5%		
	Year	Month	Observation	Year	Month	Observation
1	2013	Jan	37	2013	Apr	40
				2013	May	41
2	2015	Sep	69	2016	Jan	73
				2016	Apr	76
3	2018	Jan	97	2018	Feb	98
				2018	Mar	99
4	2021	Jan	133	2021	Feb	134
				2021	Nov	143

Source: Author, Studio R strucchange Package output.

The breakpoints under the 97.5% confidence for the year 2013 for all the three series falls within the months encompassing March to June. During this time frame, the Government made the decision to eliminate subsidies on maize and fuel. This action might have been the one that adversely affected the inflationary process at the time.

The structural breaks under the 97.5% confidence in 2016 are around January - April for all the three series. There is an additional break recorded in August for the non-food inflation. Around the January-April period, all the three types of inflation started declining as tight monetary policy and the appreciation of the Kwacha against the US dollar fed favourably into the inflationary process. The 2018 structural breaks captured in the period January - May for all the three types of inflation is associated with a rise in each series. Exchange rate depreciation, and a rise in grain prices in case of food and overall inflation, largely explain the increase.

The 2020 structural break in food inflation stemmed from a sharp increase in the inflation series and largely occurred due to the depreciation of the Kwacha, leading to increased prices for imported foods and locally produced stock feed. One of the essential components of local stock feed production, soya beans to be specific, is priced in US dollars. As mentioned earlier, the exchange rate pass-through to inflation in Zambia is significant, underscoring the impact of exchange volatility on the country's key macroeconomic variables.

Similar to the factor responsible for the 2020 structural break in the food series, the 2021 structural break in the overall inflation series was due to the depreciation of the exchange rate combined with food supply constraints that caused a sharp increase in overall inflation at the beginning of the year. However, the appreciation of the exchange rate later in the year led to both food and overall inflation declining. This phenomenon led to the observed structural change in the food and overall inflation around October-November of 2021.

3.2. Methodology

3.2.1. Fractal Signal Classification Estimation: Power Spectral density (PSD) Approach

Considering the presence of long memory patterns in all the three series due to their slow decay in the ACFs and also the occurrence of structural breaks, it becomes inevitable to determine fractal signal classification of each series. This can be meaningful in the interpretation of the measure of long memory, specifically the Hurst coefficient, which can yield the same result for the data that is either of fGn or fBm type of the underlying process. The proposed approach involves evaluating data for the fractal signal classification at various stages: before the initial structural break, during the intervals between structural breaks, and after the last structural break—if there is adequate data for this segment.

To compute the PSD ($1/f^{\beta}$), a technique called low*PSD* was used as it is ideal for both fBm and fGn type of signals compared to alternative methods (Torre et al, 2007; Delignieres *et al.* 2006: and Eke et al, 2000).

The procedure involves the following steps for a given series (signal) $x[n]$:

a) Compute the mean

$$\bar{x} = n^{-1} \sum_{1}^{n} x[n] \tag{1}$$

b) Subtract the mean of the series from each value to generate a new series $z[n]$.

$$z[n] = x[n] - \bar{x} \tag{2}$$

c) Using OLS on the data in (b), (i.e. $z[n]$), which is taken as having a power law relationship ($1/f^{\beta}$), the power law parameter α is estimated by excluding 7/8 of high-frequency power estimates as it improves the estimates (Eke *et al.*, 2000).

The estimated PSD coefficient ($\beta \in (-1,3)$) can be interpreted as follows:

i) $-1 < \beta < 0$ means the process is a fGn and is a mean reversion process;

ii) $0 < \beta < 2$ refers to an anti-persistent fBm process and this kind is also characterised by mean reversion behaviour;
iii) $\beta = 2$ implies a Brownian motion, akin to a random walk process; and
iv) $2 < \beta < 3$ indicates the process being a persistent fBm.

Data for the sub-samples was distinguished by the respective series identified structural breaks, with one set involving data prior to the identified structural break associated with each country's inflation series. Another set consists of data between the first and last identified structural break, including observations on actual breakpoints. The last set from November 2020 is sufficient to undertake empirical work. It only excludes the October 2020 structural break for the food and overall inflation series. The estimation is based on the algorithm and codes by Stadnitski (2012) implemented in R with a *PSD* package.

3.2.2. Long Range Dependence (Long Memory) Estimation: The Hurst Exponent

To assess long-range dependence in the inflation series using the Hurst coefficient, we employ a fractal analysis method known as detrended fluctuation analysis (DFA). While DFA was initially developed for non-stationary data, it has been demonstrated to be equally applicable to stationary data as in Løvsletten (2017). Furthermore, Kirichenko et al. (2011) have shown that DFA exhibits minimal bias when applied to stationary data, a perspective that finds support in Fernandez (2011). A detailed description of the procedure is available in Løvsletten (2017), Lahmiri (2015), Heneghan and McDarby (2000) and Peng *et al.* (1994).

The DFA, credited with Peng et al. (1994), vary as a power law of the form:

$$F(M, n) \propto M^{H} \tag{3}$$

where H is the Hurst exponent that can be estimated by OLS regression of $log(F(M, n))$ on $log(n)$.
The following steps involves the estimation procedure:

(i) For a given signal (data), $x[n]$, compute the mean:

$$\bar{x} = n^{-1} \sum_{1}^{n} x[n] \tag{4}$$

(ii) Subtract $\bar{x}$ from the series $x[n]$ and add all the mean adjusted sequence to form a new series $y[n]$:

$$y[n] = \sum_{1}^{n}(x[n] - \bar{x}\,) \tag{5}$$

(iii) Divide $y[n]$ into M non-overlapping windows such that each window has K samples in such a way that $M = \frac{n}{K}$ to obtain a new series $y_m[n]$:

$$y_m[n] = y[mK + n], \qquad 0 \le m \le M - 1, \qquad 0 \le n \le K - 1 \tag{6}$$

(iv) In each window, a polynomial of a given degree is fitted to the data to get a local trend $y_{m,t}[n]$:

(v) Subtract the local trend, $y_{m,t}[n]$, from the data, $y_m[n]$, in each window to get a detrended sequence (i.e. series of residuals) $y_{m,d}[n]$:

$$y_{m,d}[n] = y_m[n] - y_{m,t}[n] \tag{7}$$

(vi) From the residuals obtained in the previous step, compute the standard deviation for each window and obtain the average of the derived standard deviations denoted as $F(M,n)$:

$$F(M,n) = \sqrt{M^{-1}\sum_1^M \left(y_{m,d}[n]\right)^2} \tag{8}$$

An OLS regression of $log(F(M,n))$ on $log(n)$ is then estimated to obtain H such that $0 < H < 1$ and means as follows:

a. $0 < H < 0.5$ means an anti-persistence process. An anti-persistence process reverses itself more frequently than a random process. It is a mean reverting process;
b. $\mathrm{H} = 0.5$ implies an independent process akin to a random walk process; and
c. $0.5 < \mathrm{H} < 1$ refers to a persistent process characterised by long memory also called long-range dependence.

In an anti-persistent process, extended periods of increase (decline) are followed by successive periods of decline (increase) while a persistent process is trend reinforcing. In this study, the DFA is implemented in Studio R, version 3.4.1, using a package called *fractal*, a time series modelling and analysis package version 2.0-4.

3.2.3. Mean Reversion Estimation: The Beta (β) Convergence Procedure

The possibility of the series assuming the anti-persistent fBm, an estimation of the long run steady state value and the speed of adjustment of the inflation series, respectively, can based on equations 9 and 10 similar to Hlivnjak (2009) and Mbao (2021b):

$$\Delta x_t = \alpha + \beta(x_{t-1}) + \theta_t \tag{9}$$

where,

Δ = first difference of the variable of interest;
α = constant term representing autonomous growth in the variable of interest;
β = speed of convergence/adjustment to long run mean; and
θ_t = the error term such that $\theta_t \sim N(0,\sigma^2)$.

Equation (9) can alternatively be expressed as:

$$x_t - x_{t-1} = \alpha + \beta(x_{t-1}) + \theta_t$$
$$x_t = \alpha + x_{t-1} + \beta(x_{t-1}) + \theta_t$$

$$x_t = \alpha + (1+\beta)x_{t-1} + \theta_t.$$

Either way, equation (9) can be conditioned on $-1 \leq \beta \leq 0$, and the two equations are based on the Beta convergence technique of the Solow model of the neo-classical growth theory of Solow (1956). Further, the speed of adjustment (β) is supposed to be negative if convergence to the long run average occurs, which means an anti-persistence type of underlying process of the inflation series. The closer the absolute value to one (1) (i.e. 100%), the greater the speed of adjustment. In this study, the null hypothesis tested is that the underlying process of inflation is of persistence nature (i.e. $\beta \geq 0$.) against the alternative of anti-persistence ($-1 \leq \beta < 0$).

To estimate the long run steady state values for the samples, equation (10) is employed.

$$Long\ run\ steady\ state = -\frac{\alpha}{\beta} \tag{10}$$

where, α and β are as defined earlier.

The Beta convergence estimate is achieved using the ordinary least square estimation (OLS) procedure. The OLS is preferred because it is ideal for stationary data. The OLS estimations are fitted according to equation (9). This procedure is in the spirit of Monfort (2008) and Hlivnjak (2009).

4. Results and Discussion

4.1. Fractal Signal Classification: The PSD Estimate

Utilising the power spectral density (PSD) methodology, an analysis of the complete dataset from January 2010 to June 2023 presented in Tables 2a-2c reveals distinct findings. Specifically, the fractal signal classification for food and overall inflation suggests characteristics akin to Brownian motion processes given their estimated parameter values of approximately 2.0—and, therefore, likely to be unpredictable—whereas non-food inflation exhibits attributes of anti-persistent fBm—thus expected to be predictable. However, a closer examination of the individual series, segmented based on structural breaks, more nuanced perspective emerges. Before their respective initial structural breaks, all the three series display characteristics indicative of anti-persistent fBm processes and thus under the influence of some memory function of fractional order of integration. This suggests that both food and non-food inflation shared a common underlying process with overall inflation during that period. All the three series had a mean-reversion kind of process before March 2013.

Nonetheless, upon analysing the data within the intervals encompassing structural breaks, including the actual break points, a notable shift becomes evident: all the three-inflation series transition into a persistent fBm process. These findings suggest that when structural breaks are comprehensively considered, excluding periods beyond the influence of all identified structural breaks, it becomes apparent that the underlying process of overall inflation may indeed have been influenced by that of food inflation given the almost identical sample size with overall inflation and relatively larger PSD coefficient of food inflation compared to that of non-food inflation.

For the relatively recent dataset spanning from November 2020 to June 2023—that is with enough observations for estimation—the fractal signal classification reveals distinct patterns too. Specifically, during this period, food inflation exhibits characteristics of a persistent fBm process, whereas both non-food inflation and overall inflation are indicative of non-persistent fBm processes and thus a mean reversion type of process. This suggests an interesting effect: the recent underlying behaviour of overall inflation may be primarily influenced by the underlying process of non-food inflation as both are mean reverting.

Nevertheless, it is essential to interpret the results regarding food inflation with a degree of caution. The presence of a structural break in the series around October 2021 could potentially account for the persistent fBm process identified by PSD. This structural break might have introduced some significant shift in the underlying process affecting food inflation, potentially influencing the observed patterns.

Table 2a: Fractal Signal Classification for Overall Inflation

Description	Beta	Signal Classification
Overall sample (Jan 2010 - June 2023, 162*)	1.9613050	Brownian motion
Sample before structural break (Upto Mar 2013, 39)	0.2242351	Anti-Persistent fBm
Sample between structural breaks (Apr 2013 - Nov 2021, 104)	2.6516100	Persistent fBm
After Oct 2020 (ignoring 2021structural break, Nov 2020 - Jun 2023)	0.2383133	Anti-Persistent fBm

* Last set of digits indicate number of observations.
Source: Author's, Output from R Package-*PSD*.

Table 2b: Fractal Signal Classification for Food Inflation

Description	Beta	Signal Classification
Overall sample (Jan 2010 - June 2023, 162)	2.0225400	Brownian motion
Sample before structural break (Upto Feb 2013, 38)	1.5904720	Anti-Persistent fBm
Sample between structural breaks (Mar 2013 - Oct 2021, 104)	2.2238260	Persistent fBm
Sample after Oct 2020 structural break (Nov 2020 - Jun 2023, 32)	2.3318300	Persistent fBm

Source: Author's, Output from R Package-*PSD*.

Table 2c: Fractal Signal Classification for Non-Food Inflation

Description	Beta	Signal Classification
Overall sample (Jan 2010 - June 2023, 162)	1.8126820	Anti-Persistent fBm
Sample before structural break (up to Mar 2013, 39)	1.0214770	Anti-Persistent fBm
Sample between structural breaks (Apr 2013 - May 2018, 62)	2.1158290	Persistent fBm
Sample after structural breaks (Jun 2018 - Jun 2023, 100)	2.0571480	Brownian motion
Sample period same as last one in food series (Nov 2020 - Jun 2023, 32)	0.6570138	Anti-Persistent fBm

Source: Author's, Output from R Package-*PSD*.

4.2. Long Range Dependence (Long Memory): The Hurst Parameter

The estimated Hurst coefficients for each of the three series in the full sample (Table 3), similar to Musongole (2008), suggest a degree of persistence within the inflation series (Hurst parameters of greater than 0.5). This persistence might be attributed to the potential role of structural breaks, which could be erroneously interpreted as long-range dependence given the similar characteristics exhibited by both phenomena (Wenger et al., 2018).

Table 3: Long Range Dependence – The Hurst Parameter – Estimation Results

Description	Overall Sample	Before Structural Break	Between Structural Breaks	After Structural Breaks	Fairly Recent Data (Nov 2020 - Jun 2023)
Overall	0.5673379 *Brownian motion** (162)	0.401097 *Anti-Persistent fBm* (39)	0.5200513 *Persistent fBm* (104)		0.2930548 *Anti-Persistent fBm* (32)
Food	0.5775744 *Brownian motion* (162)	0.3527072 *Anti-Persistent fBm* (38)	0.5578861 *Persistent fBm* (104)		0.2519828 *Persistent fBm* (32)
Non-Food	0.5221442 *Anti-Persistent fBm* (162)	0.4278433 *Anti-Persistent fBm* (39)	0.5125543 *Persistent fBm* (62)	*Persistent fBm* (100)	0.3569285 *Anti-Persistent fBm* (32)

H=0.5, random walk process; 0<H<0.5, anti-persistent process; and 0.5<H<1, persistent process

* Words in italic are respective fractal signal classifications obtained from Table 2; figures in brackets are number of observations (sample size)

Source: Author's, Output from R Package-DFA, Studio R version 3.4.1.

It is worth noting that indeed the presence of structural breaks can significantly impact the underlying process of the time series, and this impact may vary throughout the data series. For example, all the three inflation series for the period before respective first structural breaks are estimated to be anti-persistent in view of respective H parameters being less than 0.5. However, they are persistent processes during periods between structural breaks given the estimated H coefficients of greater than 0.5. For the recent data set (November 2020 – June 2023), where no structural break is detected, all the three series exhibit anti-persistent behaviour. In this regard, the underlying process of inflation in Zambia has not been static.

Since all the estimated Hurst parameters are not equal to 0.5, the underlying process of the overall, food, and non-food inflation series in Zambia is governed by some memory function and, therefore, could be of fractional order of integration. This validates the results in respect of fractal signal classification. Combining information from the signal classification (β) and the Hurst parameter estimations above, the visualisation of the dynamic underlying process of inflation is obtained using Matlab codes based on the *wfbm* function that generates a fBm processes. The function is used to obtain each sample path based on the H parameter estimates.

Certainly, the visualisation demonstrates that before the initial set of identified structural breaks, the food, non-food, and overall inflation's underlying process exhibit anti-persistence with some degree of stationarity if the compact form [-4, 6] is considered (Chart 3a). To the contrary, visualisations for the period within structural breaks appears relatively different being a persistent process (Chart 3b). In the case of the recent dataset, spanning from November 2020 onwards, the visualisation (Chart 3c) also unveils anti-persistence in the inflation underlying process for some compact form [-3, 6]. This compact range is relatively tighter than the one observed before the structural breaks of 2013 (Chart 3a). It may then imply that the potential for mean reversion in the inflation process is stronger than in the pre-2013 era for each series. This offers some optimism that inflation in Zambia, which reached double digits in August 2023, may gradually decrease.

Chart 3a: Underlying Process of Inflation Series Before Structural Breaks

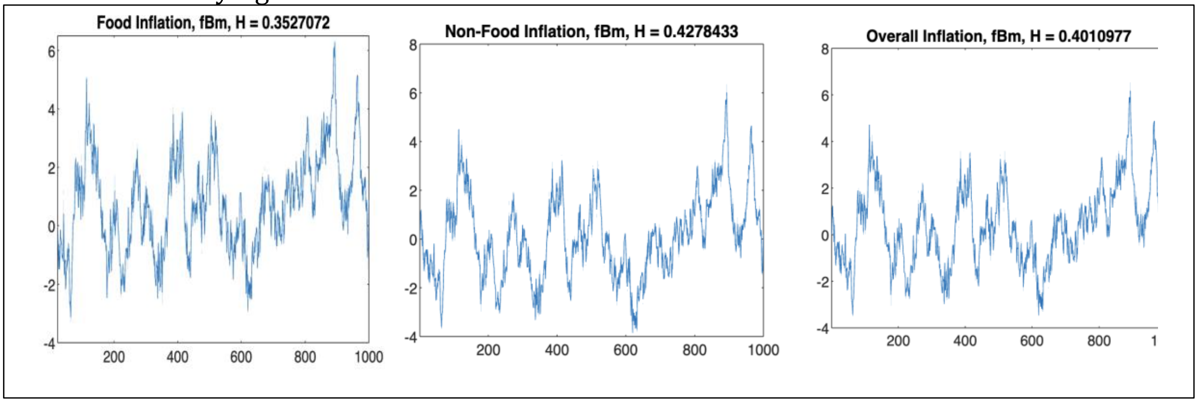


Chart 3b: Underlying Process of Inflation Series for the period In-between Structural Breaks

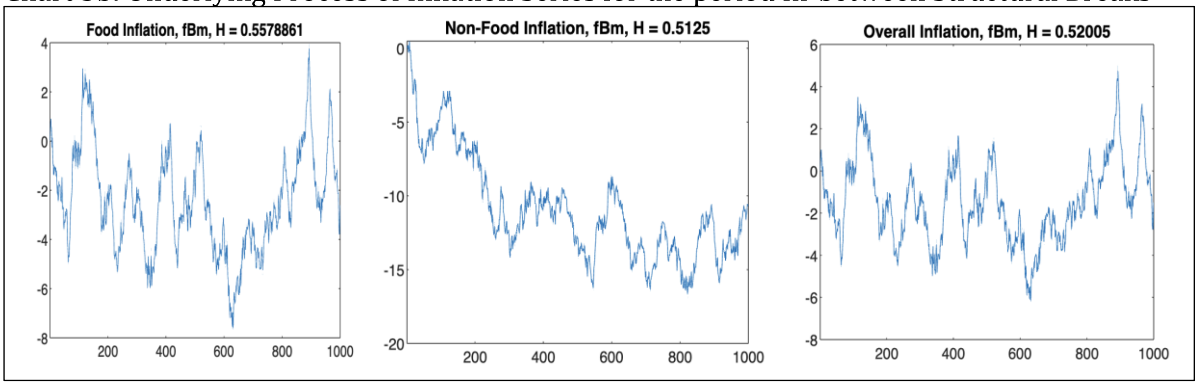
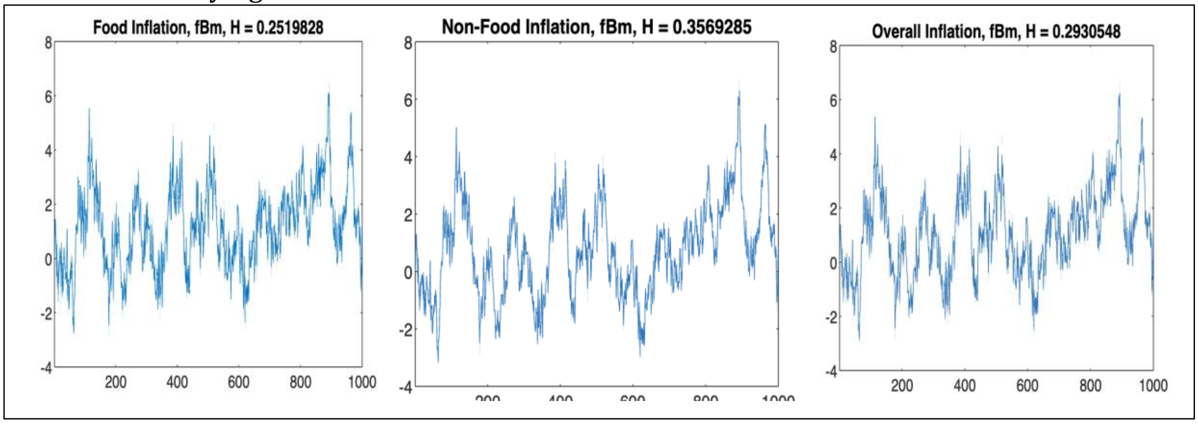


Chart 3c: Underlying Process of Inflation Series Since November 2020



It's important to note that the optimism of inflation gradually coming down is grounded in the findings that overall and non-food inflation exhibit anti-persistent fractional Brownian motion (fBm) processes. In such processes, as stated earlier, extended periods of increase are typically followed by similarly extended periods of decline and vice versa. However, data permitting, it remains critical to understand the duration required for each series to revert to its respective long-run average and what the average value is.

This understanding is crucial for informing policy decisions. For example, a low speed of adjustment may require more policy effort. Similarly, if the long run average (steady state value) is way above the upper bound of the inflation policy range, more effort will be required to bring down the steady state value of inflation within the inflation policy bounds or target.

Overall, the observed anti-persistence in the dataset excluding structural breaks aligns with the results reported by Tule et al. (2020) on Nigeria and Coleman (2010) for the Franc zone. This pattern more likely indicates the effects of monetary policy on inflation within each jurisdiction but masked by the consequences of structural breaks in the data. Nevertheless, the ultimate efficacy of monetary policy in each region hinges on the speed at which inflation can adjust to the intended steady state level. Failure to achieve that may imply time inconsistent monetary policy actions.

4.3 What then is the Inflation Steady State Value and its Speed of Adjustment?

Based on the recent data (November 2011 – September 2023) fitted to equation 9 and estimated using EViews 12 under the OLS estimation procedure with the outcomes utilised to fit equation 10, the resulting steady state inflation of 9.3 percent (Table 4) is outside the policy bound of 6-8 percent. This is largely due to the food inflation whose steady state value is estimated to be 11.8 percent. Food inflation accounts for about 55 percent in the overall inflation.

Table 4: Results of Beta (β)Estimations of Inflation's Steady State Values and Speed of Adjustment

Description	Variable coefficients	Std. Error	t-Statistics	Probability Values.	Long Run Steady State Value (percent)	Speed of Convergence to the steady state value (percent)
Overall Inflation	α= 2.002303	0.353321	5.667091	0.00000	9.3	21.5
	β= −0.215197	0.028476	-7.557229	0.00000		
Food Inflation	α= 3.27312	0.527595	6.20385	0.00000	11.8	27.6
	β= −0.276357	0.035566	-7.770233	0.00000		
Non-Food Inflation	a= 1.319544	0.695642	1.896872	0.07170	7.8	16.9
	b= -0.168767	0.078318	-2.154899	0.04290		

Source: Author's computations based on EViews 12 estimation outputs

While the steady state value for non-food inflation, at 7.8 percent, falls within the inflation bound, it is worth noting that this value is lying in the epsilon neighborhood of the upper bound. This small proximity to the upper bound warrants careful consideration, indicating a delicate balance within the policy framework.

The speed of adjustment to their respective steady state inflation levels is estimated to be less than 30 percent for all the three inflation series. Specifically, this rate varies from 16.9 percent for non-food inflation to 27.6 percent for food inflation. It is noteworthy that these levels of speed of adjustment are relatively low and align with the patterns observed in fractional Brownian motion (fBm) processes, indicating a gradual adjustment behavior in the inflation dynamics.

It is important to highlight that the relatively higher speed of adjustment observed for food inflation, categorised as a persistent fBm under the PSD-based signal classification, raises questions about the nature of this process. This is further evidence that this process might actually be an anti-persistent fBm as earlier argued, contrary to the initial classification. In this regard, the notion that structural breaks within the data can potentially lead to misleading conclusions about the persistence of a specific series is non-trivial.

Given the sluggish adjustment rates to respective steady states, a more significant policy intervention is necessary to effectively steer the inflation rate back within the desired target band. A significant policy shock has the potential to accelerate the adjustment speed of the inflation series to their respective steady state values in addition to reducing such steady state values. This rapid adjustment is crucial for bringing the overall inflation back within the desired target band swiftly and effectively.

However, in the case of non-food inflation, it's imperative for a monetary policy shock to aim at pushing it below the lower bound of the 6-8 percent target band. This signifies the need for non-food inflation to decrease and stabilise below 6 percent. In terms of context, during the period January 2017 - January2018 when overall inflation was within the policy bounds, non-food inflation was around the upper policy bound of 8 percent (appendix). This historical reference underscores the need to lower non-food inflation below the lower bound to help overall inflation be in the 6-8 percent target band.

While I acknowledge that food inflation is susceptible to both supply and demand shocks, it is important to note that the component associated with demand shocks can be mitigated through monetary policy measures. In this context, a substantial monetary shock should not be underestimated in its ability to significantly reduce food inflation from its presently estimated high steady state value of 11.8 percent to a more moderate level.

To provide context, during the period May 2017- March 2018, when overall inflation was within the policy bounds as illustrated in the appendix, food inflation remained below 6 percent largely due to a favorable supply shock, notably enhanced food production. However, if monetary policy can effectively address food inflation stemming from demand shocks and maintain it around 8 percent, this would significantly contribute to aligning overall inflation within the desired policy range of 6-8 percent. This emphasises the pivotal role of monetary policy in not only stabilising food inflation but also in achieving the broader objective of maintaining overall inflation within the specified policy boundaries.

Considering the well-documented high exchange rate pass-through to food inflation in Zambia as highlighted in existing literature for instance by, Chisha et al. (2023), Chipili (2021), Roger et al. (2017), and Zgambo (2015), a substantial monetary policy intervention holds the potential to stabilise the exchange rate. This stabilisation may likely have a favourable impact on food inflationary dynamics and by extension on overall inflation.

Another implication of these results relates to the forecasting of inflation. Considering the dynamics in the underlying inflation processes observed since January 2010, marked by both anti-persistent and persistent behaviors and characterised as memory processes, forecasting models for inflation may have to adopt a sophisticated approach. Developing regime-switching models, alongside those grounded in fractional integration, could be essential in capturing the complexity and variability inherent in the inflation patterns revealed by this study.

Since this study has identified three distinctive regimes or states in the geometric mean CPI based inflation data, which include the anti-persistence (before the 2013 structural breaks), persistence (in between structural breaks), and the anti-persistence (after structural breaks or recent data series), state or regime switching models may be needed to complement the existing ones used in forecasting inflation. In a regime switching process, the underlying unobservable state conditions tend to influence the way some or all parameters in a time series framework may change over time. This phenomenon may be non-trivial when it comes to a model's best fit of future data (forecasts).

The identification of structural breaks in the series also underscores the importance of incorporating regime-switching models for inflation analysis and forecasting. Notably, Ikwor and Nkama (2018), having identified structural breaks in Nigeria's macroeconomic and financial data (that includes interest rates, exchange rates, and inflation), advise researchers using Nigerian data to consider employing regime-switching models to prevent potentially misleading results. This highlights the necessity of not ignoring structural breaks in economic and financial data, emphasising the adoption of suitable models for generating policy relevant information to prevent policy regrets.

The results that the three inflation series are fBm processes with the Hurst parameter not equal to 0.5 means that inflation in Zambia is governed by some memory process. Memory processes are not integrated of the integer order (a widespread assumption in economics about the order of integration of economic variables), but rather have a fractional order of integration. Structural models, like the ones currently in service at the Bank of Zambia and many other central banks, are based on integer order of integration. Since structural models are difference or differential equations, the challenge is that derivatives of integer order are determined by properties of differential functions only in the infinitesimal neighborhood. Therefore, they may not capture the full extent of persistence in the variable(s) despite number of lags used. It is therefore imperative to consider adding to the existing suite of inflation forecasting models the models based on fractional integration as well as those based on frequency domain to improve forecasting capability.

5.0 Conclusion

Zambia has been grappling with persistent higher inflation since August 2015, and attempts to keep it within the 6-8 percent target band have proven challenging. Despite numerous empirical investigations into its causes, finding a solution remains elusive. Addressing this issue might necessitate a deeper understanding of the fundamental underlying inflationary processes and their individual speeds of adjustment in a single framework as opposed to a system approach. The previous study on the underlying process of inflation in Zambia focused on a series based on the arithmetic mean while this study focuses on the geometric mean-based series.

This study focused on the new series implemented in January 2010 encompassing all the three measures of inflation. Through power spectral density analysis for signal classification of the inflation series, the first time this is applied to inflation series in Zambia, and fractal analysis of the Hurst exponent along with the utilisation of information on structural breaks in each series, the empirical findings reveal that all the three series exhibit anti-persistent fBm processes before their respective structural breaks, which occurred in early 2013. This indicates a mean-reverting process where prolonged periods of increase or decline are followed by extended periods of decline or increase. However, following the structural breaks, all the series display persistent fBm processes. For food and overall inflation, the persistent period spans from March and April 2013, respectively, up to October and November 2021 in that order. In the case of non-food inflation, the persistent period ranges from May 2013 to May 2018. Nonetheless, in the period after structural breaks, the three inflation series assume an anti-persistent fBm process and therefore mean reverting processes, but with low speeds of adjustment to their respective steady state values. The results are based on the recent data set covering November 2021-June 2023.

The identified anti-persistent or mean-reverting behavior observed during periods excluding structural breaks aligns with findings from other regions, notably, Nigeria and the Franc zone, as reported by Tule et al (2020) and Coleman (2010), respectively. This may mean that in these jurisdictions, certain monetary policy measures have been implemented to ensure inflation with a persistent underlying process is less likely.

The results for the recent data set showing that the three measures of inflation largely have an anti-persistent underlying process implies that inflation is more likely to decline but at a sluggish speed given the estimated relatively low speed of adjustment. Aggressive tightening of monetary policy may accelerate the pace of decline and thus the period it will take to bring inflation in the target band of 6-8 percent.

The study identifies distinctive regimes in inflation data's underlying process, suggesting the need for regime-switching models for forecasting inflation. The presence of structural breaks in the inflation series underline the importance of incorporating such models, as ignoring them may lead to poor forecasts. The study has also revealed that inflation in Zambia follows a memory process, emphasising the necessity of fractional integration models for accurate forecasting, considering the limitations of current structural models.

Considering the undertaken research, this study makes a noteworthy contribution as the first to examine the dynamics of the underlying process of geometric mean CPI inflation in Zambia using the Hurst exponent. Furthermore, it pioneers the integration of fractal signal classification into the analysis of inflation, thereby averting misleading interpretations of the Hurst coefficient. Moreover, it pioneers the integration of information about the Hurst coefficient and fractal signal classification, to visualise the sample path of the underlying process for inflation in a sub-Saharan African country, to the best of my knowledge.

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Appendix

Inflation Developments with Target Band.