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**Abstract**

*Near-term forecasting of inflation is a critical component of a central bank's forecasting and policy analysis system (FPAS), but there is scanty evidence to inform the selection of appropriate models. While linear univariate models are generally used in near-term inflation forecasting, there is some advantage in including non-linear univariate models especially in economies like Zambia, which are prone to shocks that can induce non-linearities. In this paper, we evaluate the out-of-sample near-term forecasting performance of linear (random walk and auto regressive moving average) models and a non-linear Markov-Switching autoregressive model over the period January 1998 - January 2023. Non-linear models perform better at forecasting overall inflation and food inflation while linear models are better at forecasting non-food inflation. In addition, a combination of forecasts of food inflation from the non-linear model and non-food inflation from the linear model are superior to forecasts from individual linear and non-linear models. We recommend the inclusion of non-linear models in the suite of nearterm inflation forecasting models for Zambia and the combination of forecasts from linear and non-linear models.*

**Keywords**: Near-term; inflation; non-linear; forecasting

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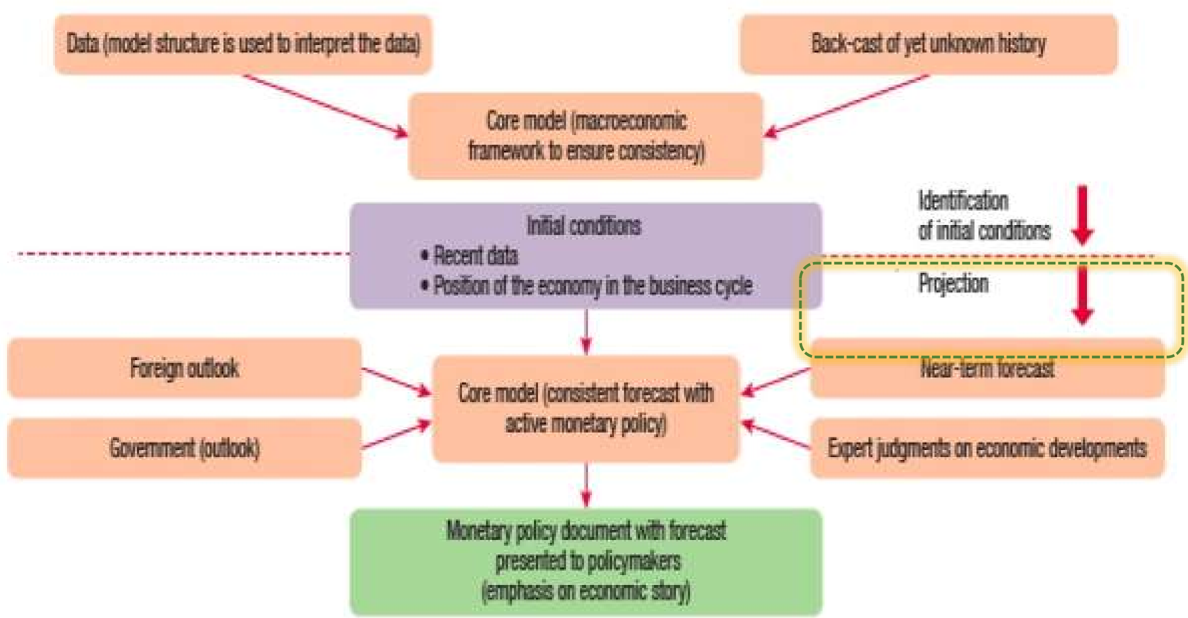
## 1. Background

Near-term forecasting of inflation (i.e. one or two quarters ahead) is a critical part of a forward-looking central bank Forecasting and Policy Analysis System (FPAS). FPAS is a "…system of tools and related processes designed to support forward-looking monetary policy formulation based on economic data and analysis" (Maelhe et al, 2021). In figure 1, the role of near-term forecasts within FPAS, which is to augment medium-term projections from a core macroeconomic forecasting model, is vivid. These near-term forecasts are generated from a set of models different from the core forecasting model. This cocktail of forecasts at different horizons is necessitated by the fact that structural macroeconomic models tend to perform well at longer horizons but poorly at shorter horizons, while the converse is true for near-term forecasting models (Giacomo et al, 2017).

Figure 1: Schematic Diagram of FPAS




Source: Maelhe et al, 2021

In essence, near-term inflation forecasting models exploit high frequency data (weekly, fortnightly or monthly) to distinguish between transitory and persistent inflation by teasing out the underlying inflation trend (Bernanke, 2007). Accurate near-term inflation forecasts are a useful starting point on which medium-term projections pick up from and evolve going forward. Since the focus of near-term forecasting is to get accurate forecasts, univariate models tend to be among the preferred tools for use due to the superior performance they have over structural models at forecasting inflation for horizons less than twelve months (Mitchell et al, 2016; Massimiliano et al. 2003). Most of the univariate models are either linear or non-linear in nature and there is no clear-cut dominant performer among the two in the literature. Among the most common linear univariate models are autoregressive moving average (ARMA), seasonal autoregressive integrated moving average (SARIMA) and random walk (RW) models. The most common non-linear univariate models are the threshold autoregressive (TAR) and Markov switching autoregressive (MS-AR) models. The only guidance on the choice of linear versus non-linear models relates to the underlying data generating process. Broadly, incorrectly assuming non-linearity is worse than if the nonlinearity is ignored altogether (Enders, 2014). However, ignoring non-linearities when present may result in poor out-of-sample forecasting performance due to the inherent misspecification of the model (Stock and Watson, 1999; Ghysels and Marcellino, 2018). For instance, the Bank of England reviewed its previous suite of forecasting models in 2003 which led to the development and inclusion of non-linear models such as the Markov switching and smooth transition autoregression (STAR). A post evaluation of these new suite of models showed that non-linear univariate models did improve the forecasting performance of the Bank of England's near-term forecasts (Kapetanios et al, 2007).

In the literature, it has been established that non-linearities in inflation are a common feature (Kim, 1993; Bredin and Fountas, 2006; Castillo, et al, 2012; Gbadebo and Mohammed, 2015). In a small open economy like Zambia, which is prone to external shocks, inflation forecasting performance may be state-dependent or non-linear (Petrovska et al, 2016). Indeed, Wakumelo (2022) demonstrates that since 1992, inflation in Zambia can be described as having two regimes—low volatility and high volatility. Similarly, Mbao (2023) finds inflation in Zambia to be episodic – exhibiting anti-persistent fractional Brownian motion processes in some periods and persistent in other times. These findings suggest that non-linearities are an important consideration in the modelling and forecasting of inflation in Zambia.

An additional consideration for near-term forecasting is whether the projections should be made on overall inflation or at disaggregated level of food and non-food inflation. Generally, some studies have reported benefits of forecasting at disaggregated levels before aggregation, but this remains an empirical question (Massimiliano et al, 2003). In Zambia, some studies have demonstrated the benefits of analysing inflation at a disaggregated level compared to aggregate level (Chipili, 2021; Chisha et al, 2023). However, these studies are focused on in-sample predictability. While not unique to Zambia alone, the literature concerning near-term inflation forecasting is scanty despite its importance in the FPAS implemented within most central banks.

In a small open economy such as Zambia, is it possible that a non-linear univariate model can out-perform its linear counterparts at forecasting inflation in the near-term? Is there any superior forecasting performance gained by using disaggregated data (food and non-food inflation) as opposed to aggregated data (overall inflation) in near-term inflation projections? These are the questions that this study answers empirically in its contribution to the debate on near-term inflation forecasting in Zambia. To the authors' knowledge, this is the first attempt at a discussion on near-term inflation forecasting for Zambia. Therefore, the results from this study will be useful to practitioners, especially central bankers, who are constantly working to improve near-term forecasting capabilities in highly uncertain environments such as those of an import dependent economy. Accurate near-term forecasts of inflation improve the public's perception about the central bank's ability to discern inflation in the near-term making it more likely that they will believe in the authorities' medium-term projections. This is a small but important channel through which near-term inflation expectations are formed and become the basis for the formation of long-term inflation expectations that reinforce the central bank's credibility with the public.

The study finds non-linear model to perform better than linear models at forecasting overall inflation and food inflation while the linear models are better at forecasting non-food inflation. In addition, a combination of forecasts of food inflation from the non-linear model and non-food inflation from the linear model are superior to both aggregate and disaggregate forecasts from the individual linear and non-linear models. The role of non-linear univariate models in improving near-term inflation forecasting in Zambia is, therefore, found to be important.

The remainder of this paper is structured as follows. The second section presents a review of empirical literature. The methodology and data are covered in sections 3 and 4, respectively, while the presentation and discussion of results constitute section 5. Section 6 presents the conclusion and recommendations.

## 2. Literature Review

In the forecasting literature, there is generally a proposed model(s) that is compared to some chosen benchmark model and evaluated based on some statistical criteria using a so-called pseudo out-of-sample forecasting exercise. Metrics such as the root mean squared error (RMSE), mean absolute error (MAE), and the mean absolute percentage error (MAPE) obtained from loss functions have mostly been used to evaluate forecasts from different models. The RMSE is a measure of the average squared deviation of the forecasted values from actual values while the MAE is an error statistic that averages the absolute deviation of the forecasted values from the actual values. The MAPE represents the percentage of average absolute value of forecast errors relative to the actual forecasts (Draxler, 2014). For each of the criteria described above, the closer the measure is to zero, the better the forecast from the model that generated it. The MAE and MAPE have similar properties, but the MAPE cannot be applied when the variable is already a percentage such as inflation or GDP growth. Hence, the RMSE and MAE are mostly employed in inflation forecast evaluation studies. Although Willmott and Matsuura (2005) suggested that the RMSE might be a misleading indicator compared to the MAE due to its sensitivity to outliers, Chai and Draxler (2014) contend that the proposed avoidance of RMSE and the use of MAE is not the solution to the problem. They demonstrate that the RMSE is not ambiguous in its meaning, contrary to what was claimed by Willmott et al. (2009). Their findings show that the RMSE is more appropriate to represent model performance than the MAE when the error distribution is expected to be Gaussian.

As benchmarks, univariate models have been used frequently with the most common ones being the random walk (RW), autoregressive moving average (ARMA) and seasonal autoregressive integrated moving average (SARIMA) models (Akdogan, 2012) among the linear models and TAR and MS-AR models among the common non-linear approaches. In terms of the actual implementation, pseudo out-of-sample forecasts try to replicate what would have been the information set available to a forecaster at a particular point in time in history. This is usually conducted using rolling (a moving data window of fixed size) and recursive/expanding (an increasing data window) strategies. In a rolling window, the sample size is fixed at a value, say *T,* which is a sub-sample from a full time series of length $N > T$. In the first iteration, the model is estimated over $t = 1, \dots, T$ and out-of-sample forecasts are obtained. In the second and subsequent iterations, both the start and the end estimation dates are consecutively increased by one observation as the model is reestimated each time in order to keep the sample size fixed i.e. $t = 2, \dots, T + 1, t = 3, \dots, T + 2$ *and so on*. In each iteration, $h$-step ahead out-of-sample forecasts are generated and forecast evaluation criteria (RMSE, MAE, MAPE) are computed using the remainder of the sample which has actual values i.e. $N - T$. The recursive/expanding window forecasting strategy on the other hand does not fix the sample size as it uses a growing sample size at each iteration. What is fixed in the expanding window strategy is the start date as all samples will begin at $t = 1$. In the first iteration, the model is run from $t = 1, \dots, T$ and $h$-step ahead forecasts are generated. In the subsequent iterations, the start date is fixed $(t = 1)$ but the end date is increased by one period each time that the model is re-estimated and forecast evaluation criteria are computed (Sahiner, 2022). The rolling window has been used more often in the literature as the results are broadly robust to structural breaks since the parameters are allowed to adopt more quickly especially for high frequency variables like inflation and exchange rates (Rossi, 2013). D'Agostino et al (2006) finds the rolling window strategy to be better suited than the expanding window for evaluating the forecasting performance of different models especially when non-linearities are expected. Unlike expanding windows, rolling windows account for time variation in predictability. Rolling window estimators have the further advantage that they preserve the effect of estimation uncertainty on forecast performance. In contrast, estimation uncertainty vanishes asymptotically for expanding window methods such as recursive estimation schemes (Giacomini and Komunjer, 2005).

Massimiliano et al (2003) find that large multiple-equation models such as vector autoregressive models and traditional structural models are often outperformed by univariate models at near-term forecasting using a rolling window strategy. Stock and Watson (2008) employ the rolling window strategy to compare pseudo out-of-sample forecasts of US inflation generated from multivariate and univariate models based on RMSEs. Their findings show that the performance of short-term forecasts from multivariate models was episodic, sometimes better than and sometimes worse than a good univariate benchmark. Furthermore, they assert that Phillips curve inflation forecasts do not improve upon good univariate benchmark models at short-term forecasting.

Linear autoregressions and their variants have been used in near-term inflation forecasting and while there is no consistent strong performer, ARMA models tend to perform better than

AR models. Nyoni and Mutongi (2019) find an autoregression (AR) to be optimal for modelling and forecasting year-on-year inflation rates for The Gambia using RMSEs and information criteria based on an expanding window. Variants of ARs which incorporate moving averages (i.e. autoregressive moving average (ARMA) models) and heteroscedastic components (i.e., generalized autoregressive conditional heteroscedasticity (GARCH) models) have also been used in near-term forecasting (Petrovska et al 2016; Pufnik and Kunovac 2006; Ekpenyong and Udoudo, 2016; Hanif, 2015; Tahsina, 2013; Sani and Serah 2013; Adjepong et al 2013). Using month-on-month and quarter-on-quarter consumer price index (CPI) changes for Slovenia, Stovicek (2007) demonstrated that ARMA models outperform the simple AR model based on RMSEs when allowing for the same degrees of freedom at near-term forecasting. Nyoni and Nathaniel (2018) used information criteria and Theil's U to compare the forecast performance of ARMA (1, 0, 2), ARIMA (1, 1, 1) and AR (3) – GARCH and found strong evidence in support of the ARMA (1, 0, 2) at forecasting Nigerian inflation. However, Nyoni (2018) repeated this exercise on inflation series for Kenya and found ARIMA to generally perform just as good as the AR-GARCH model.

Among linear univariate models of inflation, the random walk has often been chosen as a benchmark. Using a combination of rolling and expanding window strategies, Hofmann (2008), D'Agostino et al (2006) and Arratibel et al (2009) argue that it is difficult to find models that significantly outperform the benchmark random walk model. Nonetheless, Hanif et al (2015) find contradicting evidence with forecasts from autoregressive distributed lag modelling being better than the random walk model forecasts at short horizons. The random walk model is also found to be inferior in the near-term when compared to models which incorporate more economic information in inflation forecasting such as a Phillips curve motivated time varying parameter model, a suite of VAR and Bayesian VAR models and dynamic factor models (Akdogan, 2012). The choice of the random walk as a good benchmark forecasting model for inflation was reiterated by Huseynov et al, (2014) who used inflation for Azerbaijan to compare forecasts from univariate (mainly the random walk) models and several variants of vector autoregressions (VARs). They find that for different horizons, the random walk is not inferior to the sophisticated models considered.

For countries where inflation is occasionally high and volatile, forecast performance of different models may be state-dependent (Petrovska et al, 2016). As emphasized in Stock and Watson (1996), ignoring non-linearities when they exist can lead to model misspecifications and distort both in-sample and out-of-sample forecasting accuracy. Regime switching models have been used frequently to capture non-linearities in inflation. In line with Stock and Watson (1996), Khadaroo (2005) finds a two-regime self-exciting threshold autoregressive (SETAR) to be superior to the corresponding linear autoregressive (AR) models for inflation rates of India, Singapore, and South Africa over the period 1976 to 2002. Further, the Bank of England improved upon a previous suite of models used in forecasting inflation and GDP by adding non-linear univariate models, including the regimeswitching models to the suite (Pagan, 2003; Bjornland, 2008). In their evaluation of this new suite of models, Kapetanios et al (2007) found that the Markov switching and smooth transition autoregression (STAR) forecasts for GDP growth as well as the Markov switching, STAR and factor model forecasts for inflation performed better than the simple AR over several horizons.

The forecasting performance of linear versus non-linear univariate models has been well addressed by Stock and Watson (1999) for many macroeconomic time series, including inflation. Their results are inconclusive, providing support for linear methods in some cases and non-linear methods in other cases. They, however, point out that in cases where nonlinear forecasts improve upon linear forecasts, the models that do so are relatively tightly parameterized and hence efficient. The superiority of non-linear over linear models has also been established by Fraz et al (2019) who compared inflation forecasts for the non-linear SETAR and MS-AR models with a linear AR for a series of developing and developed countries. They conclude that non-linear models yield better forecasts based on the RMSE, MAE and MAPE in agreement with Crawford and Fratantoni (2003) who compared ARIMA with Markov switching models' forecasting performances and concluded that Markov switching models are a compelling choice for forecasting housing prices in real estate markets that have historically displayed boom and bust cycles.

A Markov switching model that distinguishes periods of high and low inflation and logistic regression models that measure the likelihood of high inflation regimes were employed by Makatjane and Xaba (2016) to build an early warning system (EWS) model for predicting inflation in South Africa. Their results demonstrate the significance of regime switching EWS models based on in-sample and out-of-sample forecasting performance. In a similar exercise, Cruz and Mapa (2013) developed an EWS model for predicting the occurrence of high inflation in the Philippines using Markov switching and logistic regression models. Their results mirror by Makatjane and Xaba (2016), providing support for the significance of the developed EWS based on in-sample and out-of-sample forecasts.

A large strand of literature on inflation in Zambia has investigated the nexus between inflation and key economic variables without paying more attention to its univariate properties overtime (refer to Odhiambo, 2012; Chidothi and Sheefeni, 2013; Roger et al, 2017; Bulawayo et al, 2018 and Chipili, 2021). An exception is Mbao (2023) who employed univariate approaches to examine the dynamics underlying the inflation process in Zambia. The study finds inflation to be episodic – exhibiting anti-persistent fractional Brownian motion processes in sometimes and persistent in other times which provides support for the consideration of non-linearities in inflation modelling and forecasting. There are also studies that have shown the benefits of analysing inflation at disaggregated level compared to aggregate level (Chipili, 2021; Chisha et al, 2023). However, these studies are concerned with in-sample predictability. While not unique to Zambia alone, the literature concerning nearterm inflation forecasting is scanty despite its importance in forward-looking monetary policy decision making within central banks (Chipili, 2022; Chisha et al, 2023). To the authors' knowledge, this is the first attempt at a discussion on near-term inflation forecasts for Zambia.

## 3. Methodology

We follow a 2-step estimation procedure. In step 1, we estimate the linear random walk, ARMA and Markov switching autoregressive models (MS-AR) of month-on-month inflation for Zambia. In the second step, near-term forecasts i.e. over a 6-month horizon are obtained by implementing rolling window and expanding window strategies. A key distinction between these models relates to the specification of the mean and variance of the series. For the random walk and ARMA, both the mean and variance are assumed to be constant across the sample while Markov switching models allow for discrete jumps in both the mean and variance of a time series (Crawford and Fratantoni, 2003).

### 3.1 Random Walk Model

The random walk model of inflation is given as:

$$x_{t+h}^{h} = x_t^h + \varepsilon_{t+h}^{h} \tag{1}$$

where $x_{t+h}^{h}$ is the *h-period* ahead month-on-month change in the consumer price index (CPI). According to the traditional random walk, the inflation forecast for any horizon $h$ is equal to the last realized value of the inflation rate i.e the last realized value of inflation is iterated forward to compute future inflation conditional on information up to time *t.*

### 3.2 ARMA Model

The autoregressive [AR (p)] model of inflation is given by:

$$\pi_t = \sum_{i=1}^{p} \alpha_i \pi_{t-i} + \varepsilon_t \tag{2}$$

where $\pi_t$, the monthly change in the CPI, is regressed on $p$ of its own lags and $\alpha_i \ldots \alpha_p$ are estimation parameters. The error, $\varepsilon_t$, is a purely random process with zero mean and constant variance $\sigma^2$.

The moving average [MA (q)] of inflation is given by:

$$\pi_t = \beta_0 \varepsilon_t + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \tag{3}$$

where $\pi_t$ and $\varepsilon_t$ are as defined earlier and $\beta_0$ … $\beta_q$ are parameters to be estimated. The combination of AR (p) and MA (q) processes results in an *ARMA (p, q)* process (Box and Pierce, 1970). An *ARMA (p, q)* is estimated where $p$ and $q$ refer to the longest lags in the AR and MA processes, respectively. The resulting process is presented as:

$$\pi_t = \sum_{i=1}^{p} \alpha_i \pi_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \qquad (4)$$

According to Alnaa and Ahiakpor (2011), employing the ARMA model yields the best univariate time series predictions. The ARMA model in equation 3 is presented more compactly as:

$$\vartheta\,(L)\pi_t = \gamma(L)\varepsilon_t \qquad (5)$$

where $\vartheta\,(L)$ and $\gamma(L)$ are polynomials in the lag operator of order $p$ and $q$, respectively.

### 3.3 Markov Switching Autoregressive (MS-AR) Model

The steps followed in this section draw on Hamilton (1989). When a time series variable is subject to parameter instability, linear models can lead to substantial estimation bias and a poor forecasting performance (Ghysels & Marcellino, 2018).

In a Markov switching framework, the researcher allows for the possibility of regime shifts in the series but is presumed not to observe these shifts directly even though it is possible to draw probabilistic inference about whether and when they may have occurred based on the observed behavior of the series (Hamilton, 1989). A Markov switching model features regime switches among all or some of the estimation parameters following a Markov process. The model has a state variable, $S_t$, which is assumed to follow a first order Markovchain with transition probabilities given by:

$$P(\,S_t = \text{j} / \,S_t = \text{i}) = P_{ij} \qquad (6)$$

where $P_{ij}$ refers to the probability that inflation transitions to state $j$ given that it was in state $i$ last period (Hamilton, 1989). From an economic point of view, the states of $S_t$ or regimes could describe unobservable conditions of the economy (Ghysels and Marcellino, 2018). In the context of this paper, these could refer to inflation regimes of high and low volatility. The states $S_t$ take integer values {1, 2, … . . , $N$} and the transition probabilities in equation 6 are such that the probability of the current state depends only on the previous state. From the evolution of the inflation series (refer to section 4), a reasonable apriori expectation points to a possibility of two inflation regimes so that $N = 2$. Accordingly, the transition matrix of constant transition probabilities is presented as:

$$P = (P^{11} \quad P_{12}) = ( \quad P \qquad 1 - q) \qquad (7)$$

$P_{21} \quad P_{22} \qquad 1-p \quad q$

The resulting two-state Markov switching autoregressive process of order $m$ is then described by:

$$\pi_t = \begin{cases} \alpha_{11}\pi_{t-1} + \alpha_{12}\pi_{t-2} + \cdots + \alpha_{1m}\pi_{t-m} + \varepsilon_t, & if\ S_t = 1 \\ \alpha_{21}\pi_{t-1} + \alpha_{22}\pi_{t-2} + \cdots + \alpha_{2m}\pi_{t-m} + \varepsilon_t, & if\ S_t = 2 \end{cases} \qquad (8)$$

where $\varepsilon_t \sim N(0, \sigma_i^2)$ and $i = 2$.

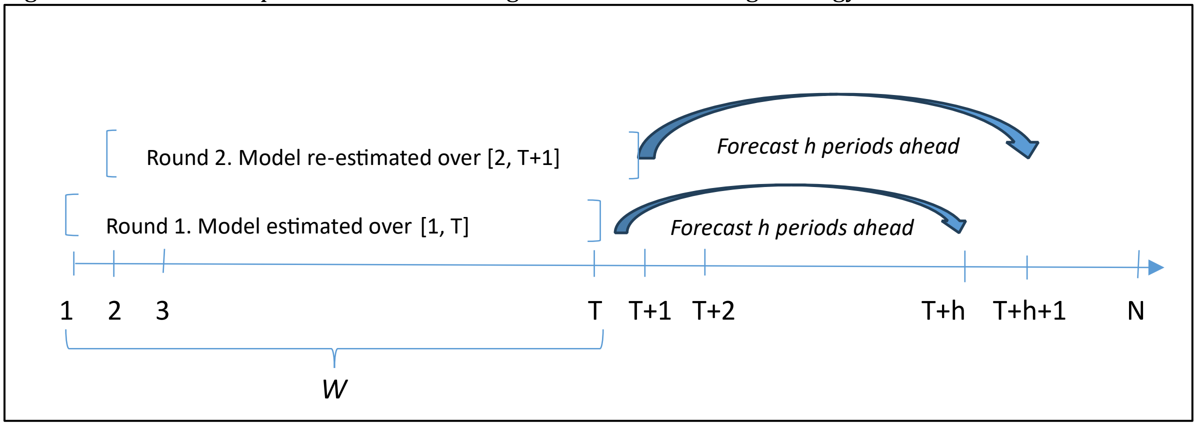
### 3.4 Pseudo Out of Sample Forecasting

Pseudo out-of-sample forecasting exercises are useful in evaluating the forecasting performance of models by replicating as close as possible what the forecaster would have been facing in real time except that this is done retrospectively. The models to be compared are the Markov switching AR model, ARMA and random walk models. The choice of the forecasting strategy, evaluation metric and forecast horizon is not innocuous when it comes to evaluating out-of-sample forecasting performance. In this study, we use both the rolling and expanding window strategies. The rolling window strategy is generally robust to structural breaks as it also includes the most recent information in the estimation especially for high frequency data like inflation. The expanding window strategy, however, tends to keep a much longer history of data and picks up dynamics that would be relevant over the long term for macroeconomic variables that are best analyzed at relatively lower frequencies such as quarterly. Both these approaches are used in the literature and employed in this case, but the rolling window results take prominence.

In the rolling window estimation, the window or sample size $W$ is fixed but there is no formal way to choose the optimal size (Figure 2). The general rule of thumb is that it should be large enough (*i.e. n > 30*) to avoid small sample biases in estimation. The sample size *(n = 157)* we choose is sufficient for the Markov switching model to exploit possible regime switches in inflation.

From a full sample $N$, we take an initial sub-sample of size $T$ and the remainder $N - T + 1$ becomes the basis for the out-of-sample performance evaluation of forecasts, $\hat{y}_t$, with the realized actual values $y_t$. In the first stage, the model is estimated over a sub-sample of the first $T = W$ observations and projections are made for horizon $h$. The sample is then adjusted such that the first observation is dropped, and the end of the sub-sample observation is increased by one. In so doing, the size of the window is maintained at $W$ but the sample shifts in time on data point forward. The *h-month* ahead forecasts are obtained for this new sub-sample and then the model is re-estimated over the next sub-sample, shifted one observation in time and so on.

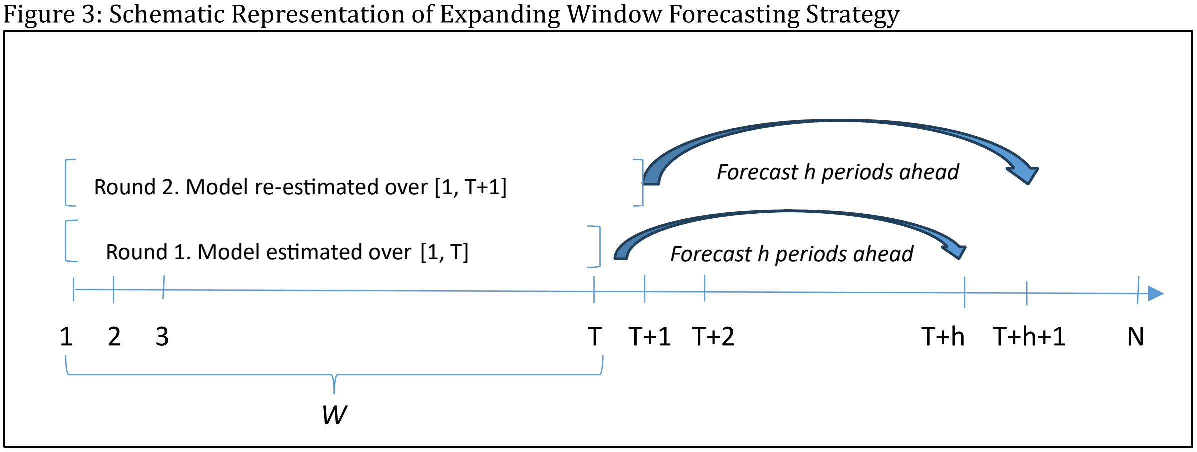
Figure 2: Schematic Representation of Rolling Window Forecasting Strategy




Source: Adapted from IMF Institute for Capacity Building Macroeconomic Forecasting Course

In the expanding window, the sample size is increased with each iteration but the starting point is fixed (Figure 3). In the first instance, the model is estimated over $[1, T]$ and forecasts obtained while in the second and subsequent iterations, the sample size is increased by one i.e. $[1, T+1]$, $[1, T+2]$ and so on (Figure 3).

Figure 3: Schematic Representation of Expanding Window Forecasting Strategy




Source: Adapted from IMF Institute for Capacity Building Macroeconomic Forecasting Course

The evaluation metrics that are employed include the root mean square error (RMSE) and the mean absolute error (MAE). The RMSE is sensitive to outliers since it penalizes larger deviations while the MAE does not. Therefore, there is merit in using both. For each horizon $h$, these evaluation metrics from the three models are calculated and compared. The root mean square forecast error is given as:

$$RMSE^h = \sqrt{\frac{1}{f}\sum_{i=1}^{f}(\hat{y}_t - y_t)^2} \quad (8)$$

where $f$ is the number of forecasts generated. In our case for each horizon, we have and the formula for the mean absolute error is:

$$MAE_h = \frac{1}{f}\sum_{i=1}^{f}|\hat{y}_t - y_t| \quad (9)$$

The model with the lowest RMSE and MAE is the better performing one at that respective horizon.

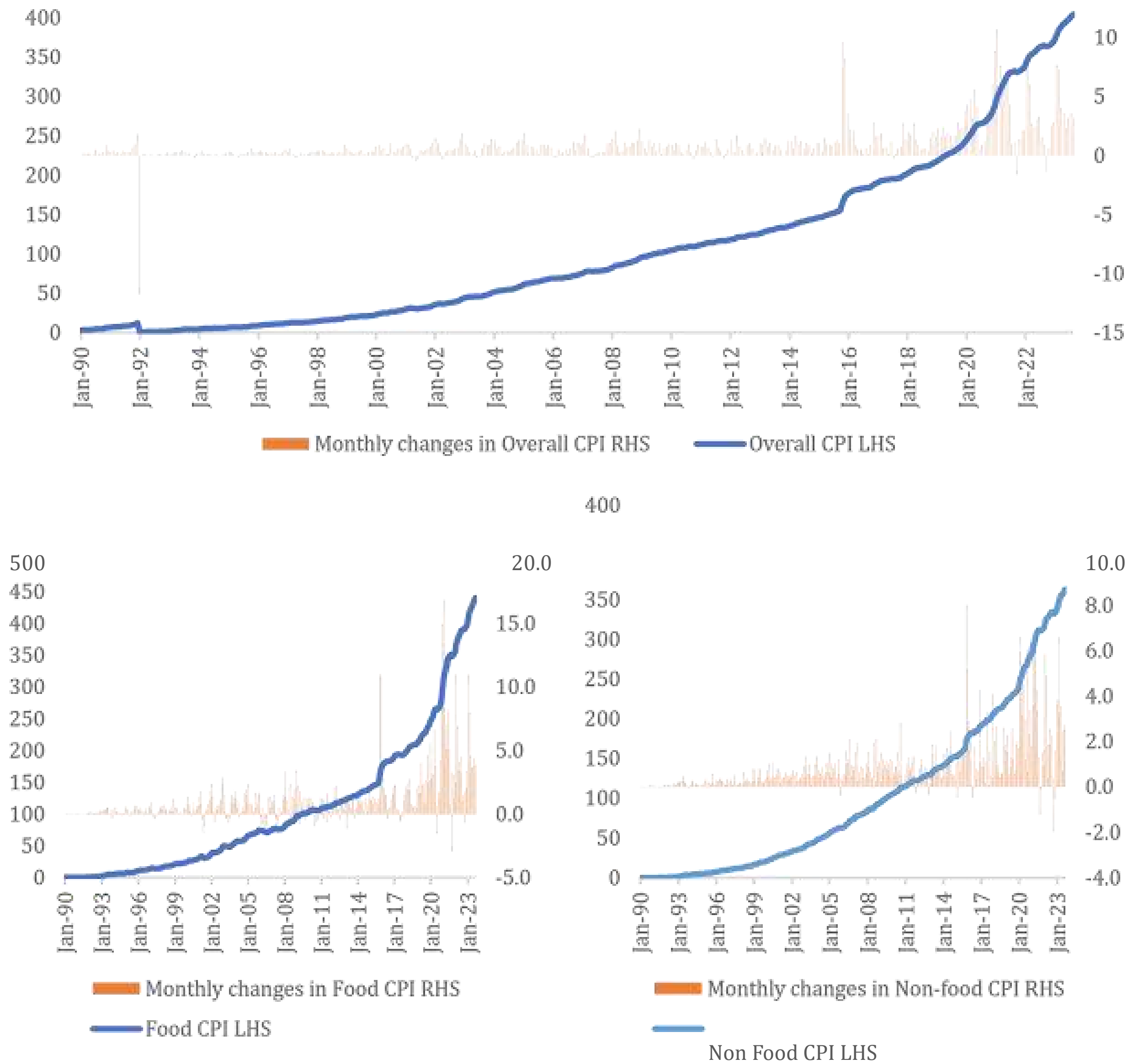
## 4. Data

We use monthly changes in the consumer price index (CPI) to evaluate the out-of-sample forecasting performance of linear (RW and ARMA) models and a non-linear (MS-AR) model. We conveniently adopt a data span January 1998 - December 2012 which is long enough to capture any possible non-linearities in the data generation process for inflation. The period December 2012 to January 2023 is then used for out-of-sample forecasting iterations and evaluation. The choice of monthly changes in the CPI over year-on-year inflation is motivated by the quest to circumvent modelling base effects in the forecasting process that would show up as unwarranted persistence even when inflation is expected to turn around. The data on food, non-food and overall CPI was collected from the Zambia Statistics Agency.

Over the data span, food, non-food, and overall CPI exhibit a persistent upward trend (Figure 4). Monthly changes in all the three series show increasing volatility in the latter half of the data span, giving credence to the possibility of regime switches in inflation volatility. The food CPI trend appears to be steeper than the non-food CPI which signifies that there could be gains from forecasting inflation using disaggregated data.

Figure 4: Evolution of Overall, Food and Non-food CPI

450 15




Source: Zambia Statistics Agency

## 5. Results and Discussion

The ‘*auto arima’* STATA function was used to select the optimal model among candidate ARMA models. This was the basis of the choice of ARMA (2,2) as a benchmark linear model. Similarly, candidate Markov switching models with varying number of autoregressive terms were estimated and the information criteria (Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC)) and log likelihood for each were obtained (Table 1). The optimal model chosen is the one that minimizes the information criteria but maximizes the log likelihood function. Accordingly, the MS-AR (3) model is chosen and estimated. The equation specification for the Markov switching model features a 2-state discrete Markov chain i.e. inflation volatility is allowed to switch between two regimes while the AR parameters are kept equal across regimes. This follows Binner et al, (2004) who found that allowing the autoregressive structure to vary across regimes deteriorates out-of-sample forecasting performance and can be interpreted as 'in-sample overfitting'.

Table 1. Candidate Markov switching Models Properties

| Model | AIC | BIC | Log likelihood |
|---|---|---|---|
| MS-AR 1 | 1376.758 | 1403.921 | -681.379 |
| MS-AR 2 | 1363.364 | 1394.396 | -673.682 |
| MS-AR 3 | 1354.993 | 1389.867** | -669.496** |

** optimal model

Source: Authors' Computation

The results show that using both RMSE and MAE for overall inflation, the MS-AR outperforms linear models (RW and ARMA) across the whole forecast horizon based on 134 iterations when the rolling window strategy is implemented (Table 2).

Table 2: Forecast Evaluation of Overall Monthly Inflation - Rolling Window

| | RMSE | | | MAE | | |
|---|---|---|---|---|---|---|
| HORIZON | ARIMA | MS-AR | RW | ARIMA | MS-AR | RW |
| h=1 | 0.719 | 0.707 | 0.727 | 0.457 | 0.431 | 0.451 |
| h=2 | 0.864 | 0.845 | 0.937 | 0.544 | 0.511 | 0.594 |
| h=3 | 0.899 | 0.863 | 1.017 | 0.594 | 0.532 | 0.665 |
| h=4 | 0.911 | 0.868 | 1.069 | 0.602 | 0.540 | 0.690 |
| h=5 | 0.917 | 0.874 | 1.118 | 0.603 | 0.545 | 0.741 |
| h=6 | 0.916 | 0.881 | 1.146 | 0.603 | 0.550 | 0.782 |

Source: Authors' own computations

However, when an expanding window is used, the MS-AR is outperformed by the ARMA model across all forecast horizons but is not outperformed by the random walk (Table 3). This in a way may imply that the ARMA tends to benefit from using additional information, including distant history, which nonetheless is counterintuitive for inflation that is a relatively high frequency variable and whose future values depend less and less on the distant past. We, therefore, maintain the results on the rolling window to break the tie and conclude that the MS-AR outperforms the linear models.

Table 3: Forecast Evaluation of Overall Monthly Inflation - Expanding Window

| | RMSE | | | MAE | | |
|---|---|---|---|---|---|---|
| HORIZON | ARIMA | MS-AR | RW | ARIMA | MS-AR | RW |
| h=1 | 0.700 | 0.714 | 0.722 | 0.453 | 0.462 | 0.449 |
| h=2 | 0.870 | 0.917 | 0.921 | 0.564 | 0.614 | 0.580 |
| h=3 | 0.925 | 0.980 | 0.997 | 0.605 | 0.689 | 0.648 |
| h=4 | 0.951 | 1.022 | 1.045 | 0.625 | 0.750 | 0.670 |
| h=5 | 0.968 | 1.064 | 1.091 | 0.645 | 0.798 | 0.720 |
| h=6 | 0.972 | 1.092 | 1.118 | 0.647 | 0.839 | 0.761 |

Source: Authors' own computations

At a disaggregated level and for food inflation especially, the MS-AR tends to outperform the ARMA and RW across all forecast horizons in both the rolling window and expanding window strategies (Tables 4 and 5). This is not surprising given that food inflation is relatively more susceptible to shocks than non-food inflation. Therefore, it is intuitive that the non-linear model performs better than a linear counterpart at forecasting food inflation.

Table 4: Forecast Evaluation of Monthly Food Inflation - Rolling Window

| | RMSE | | | MAE | | |
|---|---|---|---|---|---|---|
| HORIZON | ARMA | MS-AR | RW | ARMA | MS-AR | RW |
| h=1 | 1.064 | 1.046 | 1.023 | 0.650 | 0.645 | 0.639 |
| h=2 | 1.185 | 1.178 | 1.274 | 0.717 | 0.695 | 0.789 |
| h=3 | 1.217 | 1.209 | 1.362 | 0.747 | 0.717 | 0.848 |
| h=4 | 1.216 | 1.216 | 1.414 | 0.748 | 0.712 | 0.885 |
| h=5 | 1.219 | 1.210 | 1.448 | 0.752 | 0.723 | 0.938 |
| h=6 | 1.224 | 1.207 | 1.477 | 0.752 | 0.726 | 0.984 |

Source: Authors' own computations

Table 5: Forecast Evaluation of Monthly Food Inflation - Expanding Window

| | RMSE | | | MAE | | |
|---|---|---|---|---|---|---|
| HORIZON | ARMA | MS-AR | RW | ARMA | MS-AR | RW |
| h=1 | 1.011 | 0.990 | 1.002 | 0.689 | 0.629 | 0.968 |
| h=2 | 1.238 | 1.212 | 1.248 | 0.854 | 0.764 | 1.167 |
| h=3 | 1.309 | 1.254 | 1.327 | 0.944 | 0.822 | 1.191 |
| h=4 | 1.361 | 1.268 | 1.380 | 1.015 | 0.853 | 1.201 |
| h=5 | 1.396 | 1.289 | 1.416 | 1.072 | 0.883 | 1.198 |

Table

| | | | | | | |
|---|---|---|---|---|---|---|
| h=6 | 1.419 | 1.305 | 1.450 | 1.106 | 0.913 | 1.199 |

Source: Authors' own computations

Regarding non-food inflation, the ARMA model outperforms the MS-AR and the RW at all forecast horizons using both the rolling and expanding window strategy (Tables 6 and 7). Interestingly, results from the expanding window strategy for non-food inflation are the only set that show the RW outperforming the MS-AR (Table 6).

6: Forecast Evaluation of Monthly Non-food Inflation - Rolling Window

| | RMSE | | | MAE | | |
|---|---|---|---|---|---|---|
| HORIZON | ARMA | MS-AR | RW | ARMA | MS-AR | RW |
| h=1 | 0.692 | 0.700 | 0.749 | 0.500 | 0.499 | 0.512 |
| h=2 | 0.734 | 0.750 | 0.846 | 0.527 | 0.545 | 0.587 |
| h=3 | 0.752 | 0.762 | 0.914 | 0.552 | 0.573 | 0.654 |
| h=4 | 0.753 | 0.770 | 0.952 | 0.545 | 0.583 | 0.676 |
| h=5 | 0.743 | 0.777 | 0.995 | 0.539 | 0.591 | 0.720 |
| h=6 | 0.733 | 0.775 | 1.016 | 0.533 | 0.584 | 0.743 |

Source: Authors' own computations

Table 7: Forecast Evaluation of Monthly Non-food Inflation - Expanding Window

| | RMSE | | | MAE | | |
|---|---|---|---|---|---|---|
| HORIZON | ARMA | MS-AR | RW | ARMA | MS-AR | RW |
| h=1 | 0.693 | 0.728 | 0.748 | 0.500 | 0.499 | 0.715 |
| h=2 | 0.760 | 0.840 | 0.827 | 0.527 | 0.545 | 0.757 |
| h=3 | 0.794 | 0.910 | 0.880 | 0.552 | 0.573 | 0.772 |
| h=4 | 0.812 | 0.973 | 0.908 | 0.545 | 0.583 | 0.768 |
| h=5 | 0.827 | 1.034 | 0.950 | 0.539 | 0.591 | 0.778 |
| h=6 | 0.825 | 1.066 | 0.974 | 0.533 | 0.584 | 0.770 |

Source: Authors' own computations

That the linear models outperform the MS-AR in forecasting non-food inflation supports the idea that non-linearities are more important in forecasting food inflation which is prone to shocks than non-food inflation. To test this assertion further, we compare the forecasts obtained by weighting food and non-food inflation forecasts from the respective MS-AR and ARMA models as well as a hybrid of forecasts of food inflation from the MS-AR and non-food

Table

inflation from the ARMA model[2]. A combination of forecasts from MS-AR and ARMA outperforms forecasts from respective individual models (Table 8). This result brings out an important and useful synergy where a non-linear model can be used to forecast food inflation and a linear model used to forecast non-food inflation and a weighted average of the two is computed as a forecast of overall inflation.

8: Combination Forecasts versus Single Model Forecasts-Disaggregated Approach

| | RMSE | | | MAE | | |
|---|---|---|---|---|---|---|
| HORIZON | ARMA | MS-AR | Combination (MS-ARMA) | ARMA | MS-AR | Combination (MS-ARMA) |
| h=1 | 0.752 | 0.751 | 0.738 | 0.463 | 0.460 | 0.453 |
| h=2 | 0.850 | 0.860 | 0.838 | 0.523 | 0.528 | 0.515 |
| h=3 | 0.879 | 0.886 | 0.869 | 0.553 | 0.554 | 0.533 |
| h=4 | 0.882 | 0.897 | 0.876 | 0.564 | 0.568 | 0.537 |
| h=5 | 0.881 | 0.897 | 0.876 | 0.563 | 0.574 | 0.543 |
| h=6 | 0.875 | 0.901 | 0.881 | 0.549 | 0.577 | 0.548 |

Source: Authors' own computations

To assess whether there are benefits of forecasting at a disaggregated level, the RMSEs from the projection of overall inflation are compared with the RMSEs from the disaggregated approach where food and non-food are forecasted individually and then weighted. In Table 9, we reproduce the RMSEs from Table 2 and Table 8 for comparison. From table 9 below, the ARMA projections using a disaggregated approach outperform the ARMA using overall inflation only. However, this is not the case for the MS-AR as overall inflation projection is strictly better than that from a disaggregated approach. However, a combination of MSARMA from a disaggregated approach yields better forecasts than the ARMA forecasting overall

[2] The Random walk is left out in this comparison given its prior poor performance relative to the ARMA and MS-AR

Table

inflation, but only beats the MS-AR at horizons 2 and 6[3]. Undeniably, the MS-AR does better at forecasting overall inflation but a combination of MS-ARMA is close and can be useful.

Table 9: Disaggregated versus Aggregate Forecasting

| | RMSE- Disaggregated approach | | | RMSE- Overall inflation | |
|---|---|---|---|---|---|
| HORIZON | ARMA | MS-AR | Combination (MS-ARMA) | ARMA | MS-AR |
| h=1 | 0.752 | 0.751 | 0.738 | 0.719 | 0.707 |
| h=2 | 0.850 | 0.860 | 0.838 | 0.864 | 0.845 |
| h=3 | 0.879 | 0.886 | 0.869 | 0.899 | 0.863 |
| h=4 | 0.882 | 0.897 | 0.876 | 0.911 | 0.868 |
| h=5 | 0.881 | 0.897 | 0.876 | 0.917 | 0.874 |
| h=6 | 0.875 | 0.901 | 0.881 | 0.916 | 0.881 |

Source: Authors' own computations

## 6. Conclusion

Near-term forecasting of inflation (i.e. one or two quarters ahead) is a critical part of a central bank's forward-looking Forecasting and Policy Analysis System (FPAS). Univariate models tend to be preferred for use in near-term inflation forecasting due to their simplicity and robustness. Among univariate models, the random walk tends to be particularly hard to beat as a benchmark (D'Agostino et al, 2006) and ARMA models tend to perform better. However,

[3] At four decimal places, the RMSE for combination is 0.8805 while the MS-AR is 0.8815

in small open economies prone to external shocks, such as Zambia, non-linear models may improve near-term inflation forecasting (Petrovska et al, 2016).

This study sought to answer two important questions: whether a non-linear univariate model can out-perform its linear counterparts at near-term inflation forecasting, and whether there is any gain in forecasting performance when disaggregated data as opposed to aggregated data are used. We estimated two linear models (Random walk and ARMA) and a non-linear Markov switching autoregressive model (MS-AR) on which we performed a pseudo out-of-sample inflation forecasting exercise using rolling and expanding windows. The RMSE and MAE were used to compare performance over a 6-month horizon.

Our results show that for overall inflation, the non-linear MS-AR model outperforms linear models (RW and ARMA) across the entire forecast horizon based on 134 iterations when the rolling window strategy is implemented. This result is robust to structural breaks that may be present in the data. At a disaggregated level and for food inflation especially, the nonlinear MS-AR tends to outperform the ARMA and RW across all forecast horizons while the ARMA model outperforms the MS-AR and the RW in forecasting non-food inflation. We interpret this as a reflection of the idea that nonlinearities are more important in forecasting food inflation which is prone to shocks than non-food inflation in Zambia. Our results show that a combination of food inflation forecasts derived from non-linear MS-AR and non-food inflation forecasts from ARMA outperforms forecasts from using respective individual models. These results point to benefits in forecasting inflation using disaggregated data and then aggregating as reported by Massimilano et al (2003). This brings to light an important synergy where a non-linear model can be used to forecast food inflation while a linear model is used to forecast non-food inflation and a weighted average of the two is used as a forecast of overall inflation.

This study has demonstrated that there are benefits to model non-linearities when forecasting inflation in Zambia in the near-term. Hence, we recommend the inclusion of nonlinear (regime-switching) models in the suite of near-term inflation forecasting models used in the Bank of Zambia. This aligns with Mbao (2023) who recommends the inclusion of regime-switching models in the Bank of Zambia suite of forecasting models. Our results also reinforce studies that have shown the benefits of modelling inflation at a disaggregated level compared to aggregate level. In addition, there is additional benefit in using a combination of forecasts from regime-switching models for food inflation and linear models for non-food inflation when forecasting aggregate inflation. If overall inflation is to be projected alone, then a non-linear MS-AR model is strictly better than a projection from a linear model.

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