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Forecasting inflation under varying frequencies

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This paper seeks to determine the impact of monthly and annual data frequencies on the accuracy of inflation forecasts attainable via econometric and subspace-based methods. The application considers food inflation across short and long run horizons in Colombia, a country with an inflation targeting regime. The data includes all 54 components of the food consumer price index (CPI) in Colombia from Jan. 1999 Oct. 2012, and the study forecasts the food CPI, and inflation using the parametric and nonparametric techniques of ARIMA, Exponential Smoothing (ETS), Holt-Winters (HW) and Singular Spectrum Analysis (SSA). We find that when forecasting the index, ARIMA forecasts are on average best, whilst for monthly inflation forecasting SSA is comparatively better and for annual, the results vary between SSA and ARIMA. These statistically significant findings give policy makers an option to select an apt forecasting model which suits their requirements.

keywords: Food inflation; Forecasting; Singular Spectrum Analysis; ARIMA; Exponential Smoothing; Holt-Winters.

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1 Introduction

Nations around the world continue to experience economic hardships which have negative impacts on the incomes of mass populations. Accordingly, it is important to keep a close watch over food inflation rates so that governments can take precautionary measures to curb and ensure the masses will not be left starving as a result of escalating food prices and inability to afford. Throughout the 1970s and 1980s, the Colombian economy exhibited an inflation rate of more than 20% per year which, following the terminology advocated in Dornbusch and Fischer (1993), made Colombia a "moderate-inflation country par excellence". In 1991, a new Political Constitution radically modified the structure and functions of the Central Bank in Colombia (Banco de la República), with the purpose of creating an institution independent from the central government. The new Political Constitution stated that the main objective of the Central Bank was to control inflation, and that it had to coordinate its monetary, exchange and credit policies with the macroeconomic policies implemented by the government. Following the introduction of the new constitution, the Board of Directors of the Central Bank began to announce a quantitative inflation target, although the official adoption of a fully-fledged inflation targeting regime only occurred several years later, in 2001. As indicated in Agénor (2000), the distinguishing feature of an inflation targeting regime is that inflation becomes the primary goal of monetary policy (instead of output or unemployment), and as a result of that, the central bank has to develop (econometric) models to predict the future behavior of prices, giving it the opportunity to adjust its policies so that actual inflation does not significantly deviate from the target inflation rate (or range).

In a recent paper, Gómez et al. (2012) compare models for forecasting food inflation in Colombia. This is clearly a relevant and useful exercise for developing country central banks operating inflation targeting regimes, such as the Colombian one, because of the large share of the households income that is typically spent on food products, and in Dessus et al. (2008) it is estimated that this share is about 30% in developing countries. Gómez et al. (2012) employed flexible least squares methods in the presence of structural breaks to forecast inflation in three main food categories, namely away-from-home, processed and fresh, and found that forecast accuracy can be improved by combining the forecasts from the individual models.

The aim of this paper is to compare the performance of four forecasting techniques which represents econometric and subspace-based methods belonging to both parametric and nonparametric forecasting approaches, as applied to the 54 food prices that make up this category of the Colombian CPI as well as to the overall CPI on food. The analysis of price data at such a highly disaggregated level clearly constitutes a valuable source of information for policymakers who are engaged in sectorial analysis. Indeed, given the wide spectrum of products involved in the analysis, it becomes particularly useful to determine if a forecasting method is outperforming the other ones, and if this extends to all the forecasting horizons under consideration. As to the forecasts of the overall CPI on food, they are clearly a valuable tool of information for the analysis at the macroeconomic level. Given that the Colombian central bank relies on inflation targeting and in general developing countries are known for spending over 30% of household income on food (Gómez et al., 2012), the importance and necessity of considering forecasting food inflation is justified. Furthermore, as mentioned in Von Braun (2008), commodity prices continue to increase and thus adds to the renewed interest in food inflation for developing countries.

At this juncture, it is important to note that the mandate of this paper is not to compare and contrast between all inflation forecasting techniques. A distinguishing feature of the analysis is the examination of the subspace-based Singular Spectrum Analysis (SSA) technique as a method to forecast food inflation at different time horizons, as compared to three other commonly used econometric forecasting methods known as ARIMA, Holt-Winters (HW) and Exponential Smoothing (ETS). Given the distinction between econometric and subspace-based methods, it is pertinent to briefly comment upon these. Econometric techniques such as ARIMA, HW, and ETS are concerned with modelling a given data set and forecasting with both the signal and noise inclusive. However, subspace-based methods such as SSA not only seeks to extract signals (i.e., trend and seasonal variation in data), but also filters the noise in a time series prior to forecasting. As such, in the event that SSA succeeds in outperforming the econometric models it would mean that practitioners can achieve more out of a given data set (in addition to accurate forecasts) as the technique enables them to extract and study in depth the trend and seasonal fluctuation in food inflation which can help explain and understand the impact, behaviour and changes in overall food inflation. The study also seeks to determine how the frequency impacts inflation forecasting accuracy by considering both monthly and annual data.

ARIMA represents parametric forecasting techniques whilst ETS, HW and SSA represent nonparametric forecasting techniques. Applications of ARIMA, ETS and HW models for inflation forecasting can be found in Junttila (2001), Bos et al. (2002), Ang et al. (2007), Mihaela (2012), Moser et al. (2007), Benalal et al. (2004), He et al. (2012). It is useful to briefly comment on the consideration of both HW and ETS techniques in the forecasting exercise. We do so because these two models are optimised based on different criterion. The HW approach uses heuristic values for the initial states and then estimates the smoothing parameters by optimizing the MSE, whilst ETS estimates both the initial states and smoothing parameters by optimizing the likelihood function (Khandakar and Hyndman, 2008). As such, it makes sense to evaluate which approach results in comparatively superior forecasts. The SSA technique too has experienced a rapid increase in popularity over the recent past with a number of successful applications for modelling and forecasting in a variety of fields (Silva et al., 2018; Hassani and Gupta (2017); Hassani et al., 2017; Hassani et al., 2009; Hassani et al., 2013a; Hassani et al., 2013b). Notably, the SSA technique was initially adopted for inflation forecasting by Hassani et al. (2013b) where its performance was compared against other methods such as Autoregressive processes and SSA was found to be superior.

In general, we find that if forecasting the index itself is the target, then the econometric ARIMA forecasts are on average better than the competing models. Likewise, for monthly food inflation forecasting the subspace-based SSA forecasts are comparatively more accurate, whilst for annual food inflation forecasting the results vary between SSA and ARIMA depending on the horizon of interest. The findings indicate that for monthly food inflation data, noise reduction can help improve the accuracy of forecasts. The data and the findings undergo various statistical tests for normality, stationarity and statistically significant differences between forecasts, and these have been discussed in detail below.

The remainder of this paper is organized as follows. The theory underlying the forecasting models are presented in Section 2. Section 3 presents the data and introduces the measures used to analyse the forecasting accuracy between the selected models. Section 4 reports the empirical results and the paper ends with some conclusions in Section 5.

2 Forecasting Models

2.1 Autoregressive Integrated Moving Average (ARIMA)

This study uses the optimal version of the Box et al. (2015) ARIMA model, referred to as Automatic-ARIMA. It is made available through the forecast package for the *R* statistical software as one of the automatic forecasting techniques. See, Khandakar and Hyndman (2008) for a detailed description of the algorithm and the optimality of Automatic-ARIMA. Here, we summarize the algorithm, and in doing so we mainly follow Khandakar and Hyndman (2008). At the first stage, the algorithm uses Kwiatkowski−Phillips−Schmidt−Shin (KPSS) unit root tests from Kwiatkowski et al. (1992) in order to calculate the required number of differences d. Thereafter, minimization of the Akaike information criterion (AIC) enables the determination of the values of p and q. In the following step, the optimal model is selected and it is the model which records the smallest AIC. In order to perform the task of selecting the optimal model,the following combinations are evaluated, namely, ARIMA*(2,d,2)*, ARIMA*(0,d,0)*, ARIMA*(1,d,0)*, and ARIMA*(0,d,1)*. Finally, the decision on whether or not to include a constant c is made depending on the value of d, whereby if d=0, then c is included and if $d \geq 1$ the constant is set at zero. Furthermore, this version of ARIMA automatically considers the seasonality aspect when modelling the data (for more on this, see Hyndman and Athanasopoulos, 2013).

2.2 Holt-Winters (HW)

The Holt-Winters model is a popular nonparametric time series forecasting technique. Here we use the HW model which is provided through the forecast package for the *R* software. For a detailed description of the underlying algorithm see Khandakar and Hyndman (2008). According to Hyndman and Athanasopoulos (2013), the HW function uses heuristic values for the initial states and thereafter optimizes the MSE to to estimate the smoothing parameters. One key difference between the Automatic-ARIMA and HW models (in addition to Automatic-ARIMA being a parametric technique) is that the HW process involves minimizing the Bayesian Information Criterion (BIC) as opposed to minimizing the AIC.

2.3 Exponential Smoothing (ETS)

The ETS technique is yet another automatic forecasting model which is made available via the forecast package for the *R* software. This particular exponential smoothing model overcomes an inherent limitation in the earlier models which failed to provide a straightforward calculation of prediction intervals Makridakis et al. (2008). A detailed description of ETS can be found in Hyndman and Athanasopoulos (2013). In brief, the ETS model is one which considers the error, trend and seasonal components of a given time series. ETS then goes on to choose the optimal exponential smoothing model from over 30 possible options. This is done by optimizing initial values and parameters using for example, the MLE, and selecting the best model based on the AIC.

2.4 Singular Spectrum Analysis (SSA)

The SSA technique has two variations known as Vector SSA and Recurrent SSA. In this study we adopt the most basic version of Vector SSA only as there is overwhelming support for its forecasting capabilities in Hassani et al. (2017). A detailed description on the theory which underlies the SSA technique can be found in Golyandina et al. (2001). The SSA technique seeks to decompose a given time series and extract the trend and seasonal components, and reconstruct a less noisy time series which can then be used for forecasting. SSA is also renowned for its ability of extracting and modelling seasonal components in a time series (see, Chen et al., 2013), and this aspect is of great importance when forecasting food inflation. Below, we provide a brief explanation of the process involved and in doing so we mainly follow Hassani et al. (2013b).

Consider the real-valued nonzero time series $Y_T = (y_1, \ldots, y_T)$ of sufficient length T. Let $K = T - L + 1$, where L $(L \leq T/2)$ is some integer called the window length. The first stage is known as decomposition. Here, we define the matrix $\mathbf{X} = (x_{ij})_{i,j=1}^{L,K} = [X_1, ..., X_K]$, where $X_j = (y_j, ..., y_{L+j-1})^T$. In doing so we are transforming a one dimensional time series into a multidimensional time series which is referred to as the embedding step. At the next step, singular value decomposition (SVD) of $\mathbf{XX^T}$ provides us with the collections of L eigenvalues $(\lambda_1 \geq \lambda_2 \geq \ldots \lambda_L \geq 0)$ and the corresponding eigenvectors $U_1, U_2, \ldots, U_L$, where U_i is the normalized eigenvector corresponding to the eigenvalue λ_i $(i = 1, \ldots, L)$. In the second stage which is known as reconstruction, we first group the eigenvalues in order to reduce the noise level in the original noisy series. To do this, we select r singular values from L. Finally, in order to convert the matrix of selected components into a time series we perform diagonal averaging. This provides an approximation of the original series with less noise which can be used to forecast new data points. The forecasting algorithm of SSA can be applied to any time series that approximately satisfies the linear recurrent formulae (LRF) (Golyandina et al., 2001). The series Y_T satisfies a LRF of order d if there are numbers $a_1, \ldots, a_d$ such that $y_{i+d} = \sum_{k=1}^{d} a_k y_{i+d-k}, 1 \leq i \leq T - d$. To obtain the coefficients $a_1, \ldots, a_d$ we use $U_1, U_2, \ldots, U_L$ obtained from the SVD step (Golyandina et al., 2001).

The two choices of the SSA technique are L and r. In this paper, we use the optimal values of L and r to forecast the Colombian food CPI, monthly and annual food inflation.

We select these optimal values based on the Root Mean Squared Error (RMSE) criterion which is explained in the next section. In simple terms, we look for the combination of L and r which provides the lowest RMSE and use the related L for decomposition and the r for reconstruction of the less noisy time series which is then used for forecasting. A detailed description of the optimal SSA forecasting algorithm can be found in Hassani et al. (2015).

3 The Data

The Colombian CPI for food is made up of 54 components. The data consists of the seasonally unadjusted, monthly CPI on food from January 1999 to October 2012, for a total of T=166 time observations. The source of the data is the Departamento Administrativo Nacional de Estadística (DANE). In this paper, we forecast the index and then use the index to compute monthly and point-by-point (annual) inflation forecasts for each of the 54 components using four different forecasting techniques, in order to identify the best model for forecasting Colombian food inflation in the future. In all instances we use approximately $\frac{2}{3}^{rd}$ of the observations for training the respective models and set aside the remaining $\frac{1}{3}^{rd}$ for testing the accuracy of the forecasts. We forecast the index and inflation at horizons of $h = 1$, 3, 6 and 12 steps ahead. Figure 1 illustrates the time series for the 54 components of the monthly Colombian food CPI. It is clear that the CPI in general illustrates an upward sloping trend.

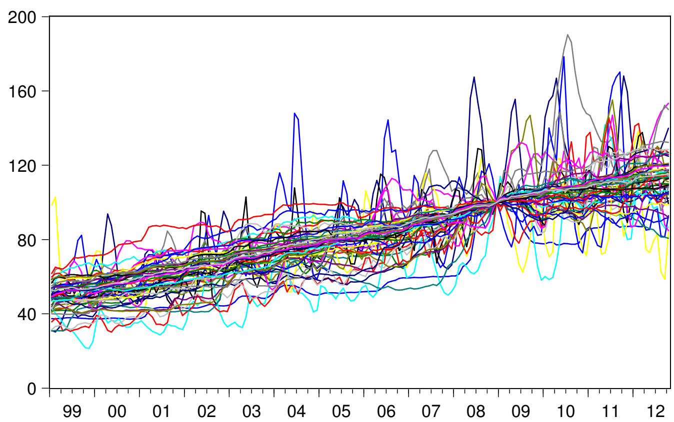

Figure 1: Monthly Colombian food CPI components Jan. 1999- Oct. 2012.

Figure 2 shows the time series for all 54 components which makes up the Colombian Food CPI as monthly inflation estimates. It is evident from Figure 2 that in order to be successful at accurately forecasting food inflation in Colombia, the models will have to succeed at forecasting time series with varying volatility.

Figure 3 shows the time series for all 54 components of the Colombian Food CPI as

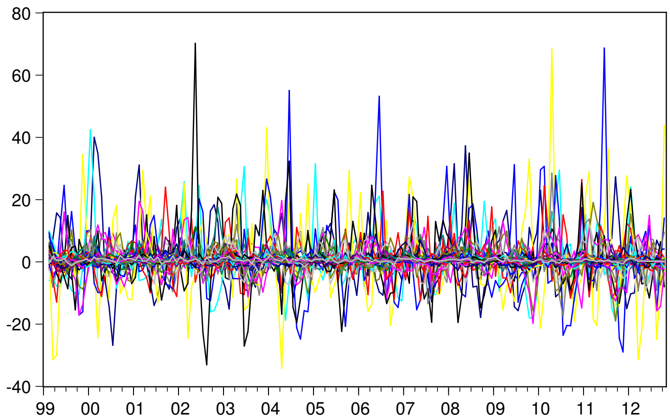

Figure 2: Monthly Colombian food inflation time series Feb. 1999- Oct. 2012.

annual inflation estimates. First and foremost, we can see a startling difference between the Colombian food CPI, monthly food inflation and annual inflation time series. This further justifies the approach adopted by this study for analysing, modelling and forecasting the food index, monthly and annual inflation separately. In simple terms, as a result of the differing variations visible in Figures 1-3, it is likely that a model which succeeds in outperforming the other methods at forecasting monthly food inflation accurately might not be optimal when it comes to providing annual food inflation forecasts for Colombia.

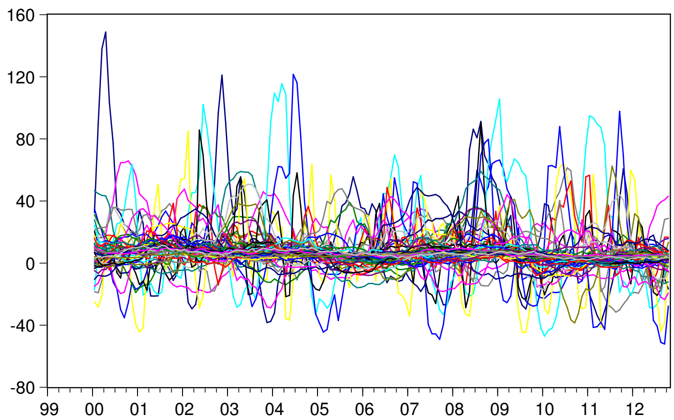

Figure 3: Point-by-point Colombian food inflation time series Dec. 1999- Oct. 2012.

In order to extract more information regarding the data, we analysed the descriptives by considering the entire sample for each of the 54 components which make up the monthly and annual food inflation in Colombia. Table 1 presents some descriptives of the monthly inflation components. The first observation from the minimum values is that between 1999 and 2012, each component has experienced deflation in at least one month. During a point in this time period, the price of carrots was the worst affected by deflation in terms of the magnitude. Furthermore, it is clear that on average over time period in question, food prices in Colombia has shown an increase. Potatoes report the highest average monthly inflation reported during this period whilst the maximum monthly inflation reported during this period is attributable to Onions and the minimum monthly inflation reported out of all components is the deflation for Tomato's. However, when analyzing each time series it is important to consider the median as a measure of central tendency except where the components are normally distributed. Accordingly, based on the median, it is Fresh Vegetables that report the highest monthly price change in the Colombian food CPI. The standard deviation confirms the high volatility between monthly inflation reported for each component and confirms that an appropriate forecasting model should be able to model and predict this volatility to be provide the most accurate monthly food inflation forecast for Colombia. We also report the skewness statistic for each time series and confirm whether the distributions are normally distributed via the Shapiro-Wilk normality test. It is important to assess the distribution of the time series as we employ two parametric techniques which assumes a normal distribution. Normality testing confirms that out of the 54 time series only 5 of the components are normally distributed. As a result, when forecasting using the parametric techniques, Box-Cox transformations were used to meet the normality assumption. It is a well known fact that such transformations result in unrealistic estimates, and this suggests that a nonparametric model is likely to be the best option for forecasting monthly Colombian inflation as a majority of the components fails to meet the assumption of normality sans transformations. An analysis of the kurtosis shows that we are dealing with time series which have both Leptokurtic and Platykurtic distributions which increases the difficulty for modelling and forecasting this information. Finally, we test the monthly inflation time series for stationarity using a unit root process. In this case, the results indicate that all 54 components are stationary at a p-value of 0.01.

Next, we examine some descriptive statistics for annual food inflation in Colombia. Table 2 reports these descriptives. It is clear from Table 2 that if we limited our analysis to point-by-point food inflation alone, we would not be able to capture the deflation reported in the monthly inflation figures over a 12 month period. This would have implications on the well being of farmers and producers as there is a major difference between the inferences which could be made from monthly and point-by-point food inflation figures in Colombia as evident from Tables 1 and 2. For example, when analysed on a monthly basis, Table 1 picks up the worst deflation that has occurred during a particular month and all components have experienced deflation during this period. However, on an annual basis, we are unable to pick up the deflation in all components and so it would give an idea of an overall well-being of the related producers when in reality they could be experiencing grave price related difficulties during a given year. In terms of average annual food inflation between 1999 and 2012, Onions record the highest average year-on-year increase in price at 14.2% whilst Potatoes come in a close second with

13.1% average annual inflation. Interestingly, the average monthly inflation reported for potatoes (see, Table 1) is very modest at just 1.45%. The maximum year-on-year inflation during this period is reported by Carrots which records a 130.2% increase in price during a particular year whilst Tomatoes have experienced the lowest year-on-year price increase with a deflation of 49.6%. If we consider the median for the non-normally distributed components, the highest median annual price change is once again recorded by Fresh Vegetables. As seen with monthly food inflation descriptives, the point-by-point too illustrates a high volatility between the 54 components as reported by the standard deviation with the lowest year-on-year volatility being reported by Canteen Drinks. The skewness statistic suggests that we are faced with both positively and negatively skewed distributions. Normality testing showed that except for time series relating to the price change of eggs, fish, other fruits, other groceries, other non-alcoholic drinks, other roots and tomato, all other components of the CPI are not normally distributed when analysed on an annual basis. The kurtosis analysis for point-by-point food inflation in Colombia shows that we are faced with distributions both with a high and low probability for extreme values, as seen in the monthly inflation case. Finally, we once again test all time series for a unit root problem. The results indicate that for annual food inflation in Colombia, a majority of the time series are in fact non-stationary. This is a major difference in comparison to what was experienced for monthly food inflation. Furthermore, the non-stationarity has implications on parametric forecasting models. However, the nonparametric technique of SSA is known to be able to handle both stationary and non-stationary time series. As such, it would be interesting to see how well the SSA model performs in comparison to the other techniques at forecasting the non-stationary time series accurately.

Table 1: Descriptive statistics for monthly food inflation in Colombia.

Series	Min	Median	Mean	Max	SD	Skewness	Kurtosis	S-W (p-val.)	ADF
Bananas	-4.68	0.46	0.45	6.42	1.62	0.08	0.64	0.61*	-6.78
Beef	-3.39	0.27	0.45	9.40	1.30	3.12	17.7	0.00	-5.91
Bread	-1.12	0.49	0.54	4.70	0.85	1.77	6.30	0.00	-5.80
Burger in Bun	-1.04	0.45	0.53	2.47	0.57	0.53	1.27	0.00	-4.74
Canned Vegetables	-0.83	0.36	0.48	5.55	0.72	3.01	15.8	0.00	-6.35
Canteen Drinks	-0.83	0.36	0.46	3.27	0.53	1.42	5.54	0.00	-5.18
Carrots	-29.0	-1.33	1.26	68.7	14.2	1.38	3.97	0.00	-9.99
Cassava	-4.06	0.05	0.67	9.38	2.66	1.12	1.23	0.00	-4.62
Cereals	-1.72	0.39	0.60	9.58	1.15	3.16	21.1	0.00	-7.35
Cheese	-8.67	0.43	0.43	5.01	1.41	-1.46	10.8	0.00	-8.75
Chicken	-3.13	0.33	0.40	3.88	1.13	0.25	1.22	0.00	-8.91
Chocolate	-7.42	0.27	0.69	8.67	1.85	1.48	7.17	0.00	-6.33
Coffee	-3.19	0.27	0.74	11.0	1.81	3.21	12.9	0.00	-6.35
Cold Fast Food	-1.24	0.43	0.48	2.19	0.61	0.24	0.20	0.46*	-5.21
Eggs	-5.82	0.33	0.48	9.32	1.99	0.98	4.31	0.00	-9.12
Fats	-2.95	0.35	0.62	6.35	1.60	0.88	1.62	0.00	-4.53
Fish	-2.21	0.34	0.51	4.89	0.90	1.01	3.30	0.00	-6.48
Flour	-1.25	0.41	0.59	3.98	0.95	0.81	0.66	0.00	-5.08
Fresh Vegetables	-13.0	0.85	1.05	26.4	7.65	0.66	0.70	0.00	-10.7
Hot Fast Food	-0.69	0.46	0.54	2.88	0.55	0.80	1.43	0.00	-4.91
Juices	-3.15	0.26	0.40	5.12	0.87	0.95	7.98	0.00	-7.07
Kidney Beans	-8.85	0.44	0.54	11.3	2.96	0.22	1.41	0.01	-9.42
Milk	-3.80	0.35	0.57	6.10	1.13	1.95	8.08	0.00	-6.03
Mulberry	-17.6	0.60	0.50	28.5	5.09	0.71	5.63	0.00	-10.5
Oils	-3.03	0.04	0.47	7.94	1.76	1.48	3.07	0.00	-6.14
Onions	-18.8	-0.83	0.94	42.4	10.5	0.99	1.38	0.00	-8.65
Oranges	-19.0	0.80	0.71	19.0	5.63	-0.10	0.79	0.35	-10.1
Other Bakery	-1.30	0.44	0.59	5.60	0.93	1.54	4.80	0.00	-6.72
Other Cereals	-2.86	0.41	0.59	8.03	1.16	2.07	10.1	0.00	-6.07
Other Condiments	-0.53	0.39	0.52	6.56	0.74	3.90	26.2	0.00	-6.37
Other Dairy	-3.92	0.14	0.47	8.17	1.36	2.96	12.5	0.00	-8.45
Other Dried Veg.	-3.09	0.05	0.62	17.5	2.80	2.85	11.4	0.00	-5.31
Other Fish	-2.30	0.29	0.50	8.19	1.50	1.60	4.78	0.00	-7.63
Other Fruits	-9.31	0.93	0.90	12.7	4.47	0.07	-0.58	0.31*	-12.5
Other Groceries	-2.41	0.44	0.52	6.18	0.89	2.13	12.4	0.00	-6.44
Other Meats	-3.69	0.10	0.41	7.89	1.39	2.79	10.3	0.00	-8.33
Other Non Alcoholic	-1.88	0.29	0.52	5.51	0.97	2.03	7.04	0.00	-6.53
Other Roots	-10.7	0.22	0.68	16.1	4.37	0.31	0.27	0.30	-6.76
Panela	-2.86	0.23	0.60	8.86	1.92	1.28	2.23	0.00	-5.40
Pasta	-4.92	0.25	0.62	5.75	1.52	0.98	2.93	0.00	-5.71
Peas	-33.1	-0.90	1.12	70.2	12.5	1.10	4.89	0.00	-11.4
Plantain	-6.55	-0.06	0.52	11.5	3.12	0.59	0.64	0.00	-8.82
Pork	-3.94	0.43	0.36	4.35	1.43	-0.01	1.18	0.92*	-6.95
Potato	-26.8	-0.32	1.45	40.0	10.6	0.94	1.69	0.00	-8.32
Restaurant Meals	-1.06	0.31	0.44	2.40	0.53	1.51	2.85	0.00	-5.15
Rice	-5.81	0.13	0.64	18.2	2.84	3.00	15.3	0.00	-9.18
Salt	-1.71	0.48	0.54	4.00	0.87	0.60	1.39	0.01	-5.47
Soft Drinks	-0.74	0.30	0.59	4.35	0.96	2.03	4.17	0.00	-6.43
Soups and Creams	-2.86	0.33	0.45	9.29	1.09	3.20	25.0	0.00	-7.36
Sugar	-4.13	0.14	0.52	8.10	1.85	1.21	2.91	0.00	-5.58
Tomato	-34.3	-1.01	1.01	68.4	15.3	0.84	1.96	0.00	-10.4
Tree Tomato	-19.8	0.26	0.57	20.0	7.09	-0.02	0.19	0.91*	-7.17
Various Jams	-3.08	0.43	0.44	9.99	1.52	1.79	9.72	0.00	-9.58
Various Sauces	-5.60	0.21	0.38	5.54	1.20	0.68	6.53	0.00	-7.59

Note:* indicates a normal distribution based on the Shaprio-Wilk (S-W) test at $p = 0.05$.
† indicates non-stationarity based on an Augmented Dickey–Fuller (ADF) test for unit roots at $p = 0.01$.

Table 2: Descriptive statistics for point-by-point food inflation in Colombia.

Series	Min	Median	Mean	Max	SD	Skewness	Kurtosis	S-W (p-val.)	ADF
Bananas	-9.95	3.75	5.75	29.5	9.10	0.87	0.24	0.00	-1.56†
Beef	-9.18	4.55	5.46	25.4	7.12	0.96	1.28	0.00	-2.11†
Bread	-1.76	6.23	6.01	19.7	4.27	0.81	0.61	0.00	-1.62†
Burger in Bun	2.02	5.91	5.99	10.8	1.74	0.46	0.22	0.02	-0.64†
Canned Vegetables	1.13	4.41	5.17	13.1	2.62	1.14	0.58	0.00	-1.22†
Canteen Drinks	2.71	5.06	5.14	8.72	1.26	0.42	-0.47	0.00	-0.97†
Carrots	-51.9	5.69	9.01	130.2	37.2	0.73	0.52	0.00	-5.93
Cassava	-19.3	2.31	8.88	66.5	19.8	0.84	-0.12	0.00	-2.98
Cereals	0.26	6.20	6.20	19.2	3.72	0.54	-0.08	0.00	-1.49†
Cheese	-4.49	5.11	5.40	14.0	3.24	0.14	0.70	0.00	-1.99†
Chicken	-3.99	5.06	4.77	19.1	4.18	0.38	0.49	0.02	-2.22†
Chocolate	-6.50	4.87	7.88	50.4	10.7	2.23	5.45	0.00	-1.92
Coffee	-5.57	5.34	9.28	47.3	11.2	1.52	1.47	0.00	-2.76
Cold Fast Food	1.22	5.48	5.54	11.8	2.11	0.22	-0.60	0.04	-0.65†
Eggs	-8.11	5.67	5.45	19.6	5.59	-0.04	-0.42	0.72*	-3.10
Fats	-10.4	4.95	7.91	38.2	10.6	1.03	0.66	0.00	-1.91†
Fish	-2.87	6.15	6.00	15.7	3.80	0.11	-0.52	0.31*	-1.56†
Flour	-5.72	6.62	6.77	19.7	6.20	-0.01	-0.79	0.02	-2.07†
Fresh Vegetables	-16.2	7.95	11.0	53.8	13.6	0.72	0.37	0.00	-4.92
Hot Fast Food	3.41	5.82	6.00	9.68	1.58	0.33	-1.04	0.00	-0.99†
Juices	-6.48	5.07	4.31	12.4	4.27	-0.64	-0.19	0.00	-1.63†
Kidney Beans	-19.4	3.94	5.93	40.2	12.5	0.57	0.16	0.00	-3.62
Milk	-0.13	6.36	6.56	18.1	4.17	0.45	-0.34	0.00	-1.23†
Mulberry	-21.3	4.65	4.75	39.8	8.69	0.41	2.16	0.00	-6.39
Oils	-8.26	3.32	6.45	35.0	10.8	0.76	-0.21	0.00	-2.28†
Onions	-48.92	5.22	14.2	120.1	37.1	0.65	-0.35	0.00	-4.14
Oranges	-37.8	7.09	7.68	69.9	15.8	0.34	1.95	0.00	-5.21
Other Bakery	0.61	5.67	6.75	19.4	4.02	1.07	1.01	0.00	-1.25†
Other Cereals	-3.87	5.45	6.14	26.7	5.92	0.60	0.17	0.00	-2.05†
Other Condiments	1.31	4.70	5.19	16.8	2.38	1.67	3.95	0.00	-1.35†
Other Dairy	-2.75	5.53	5.26	10.9	3.42	-0.46	-0.51	0.00	-1.68†
Other Dried Veg.	-14.8	-1.11	7.97	58.9	20.4	1.23	0.19	0.00	-3.35
Other Fish	-2.73	2.90	5.04	17.6	5.80	0.76	-0.86	0.00	-1.48†
Other Fruits	-19.3	10.3	9.93	43.5	11.3	0.20	0.52	0.11*	-3.86
Other Groceries	-3.34	5.74	5.53	14.7	3.10	0.12	0.39	0.06*	-1.36†
Other Meats	-2.72	4.59	4.97	15.2	4.47	0.47	-0.73	0.00	-1.85†
Other Non Alcoholic	1.60	6.38	6.05	15.1	3.25	-0.13	-0.43	0.13*	-2.13†
Other Roots	-30.4	9.28	8.38	63.0	17.7	0.16	-0.14	0.30*	-2.75
Panela	-10.3	4.77	8.39	45.3	14.6	0.69	-0.48	0.00	-2.05†
Pasta	-8.98	5.34	7.45	35.3	9.27	1.20	0.98	0.00	-2.65
Peas	-33.7	4.58	7.49	91.4	21.7	1.24	2.26	0.00	-8.79
Plantain	-9.19	6.01	6.62	36.8	9.31	0.51	0.02	0.00	-3.52
Pork	-8.00	3.27	4.55	19.9	6.28	0.59	-0.53	0.00	-1.99†
Potato	-37.7	7.31	13.1	117.9	33.1	1.14	1.09	0.00	-4.72
Restaurant Meals	1.68	5.00	5.05	7.85	1.36	0.03	-0.45	0.04	-0.34†
Rice	-22.7	4.70	7.73	65.5	15.1	1.57	4.15	0.00	-3.10
Salt	0.16	6.05	6.32	15.3	3.44	0.52	0.05	0.00	-1.92†
Soft Drinks	-0.12	6.85	6.77	16.1	3.90	0.09	-0.83	0.00	-1.93†
Soups and Creams	-2.70	3.74	4.61	17.3	4.23	0.89	0.19	0.00	-1.19†
Sugar	-17.5	4.29	7.01	41.8	12.5	0.64	0.20	0.00	-3.46
Tomato	-49.6	5.70	6.62	85.1	27.7	0.19	-0.57	0.15*	-7.36
Tree Tomato	-27.5	3.79	5.57	44.3	17.6	0.12	-1.10	0.00	-3.49
Various Jams	-6.65	3.39	3.72	25.8	4.42	0.67	2.63	0.00	-2.60
Various Sauces	-7.19	2.64	3.76	19.4	4.80	0.67	0.59	0.00	-1.91†

Note:* indicates a normal distribution based on a critical value, $p = 0.05$.

† indicates non-stationarity based on an Augmented Dickey–Fuller test for unit roots at $p = 0.01$.

3.1 Measures for Evaluating the Forecasting Accuracy

Root Mean Squared Error (RMSE)

The RMSE is now a popular measure of forecasting accuracy and frequently cited in forecasting literature (see, for example, Hassani et al., 2009, Silva et al., 2018, Zhang et al., 1998).

$$\text{RMSE} = \left(\sum_{i=1}^{N} (\widehat{y}_{T+h,i} - y_{T+h,i})^2 \right)^{1/2},$$

where, $\widehat{y}_{T+h}$ is the h-step ahead forecast obtained by a forecasting model, N is the number of the forecasts and y_{T+h} is the actual value. The lower the RMSE, the lower the forecasting error. Accordingly the model with the lowest RMSE is said to outperform the rest in terms of forecasting accuracy.

Score

The score is a measure of the number of times where each forecasting technique outperforms the other, and is reported at each horizon. This calculation was earlier used in Hassani et al. (2009). The percentage is calculated as *Score÷ Total no. of CPI components* and shows the capability of the forecasting model at accurately forecasting a majority of the food inflation components in Colombia. The Sig. Score records the number of statistically significant outcomes which make up the total score.

Direction of Change (DC)

We use the DC criterion to measure the percentage of accurate direction of change predictions achieved by each forecasting model. The DC metric is important as it shows whether in the event of the actual series illustrating an upwards trend, the forecast correctly predicts this upward trend and vice versa. In general, a model is said to have a better DC prediction than a random walk if it records a DC greater than 50% (Altavilla and De Grauwe, 2010). For a detailed description of the DC criterion see (Altavilla and De Grauwe, 2010). In brief,

$$\text{DC} = \left(\frac{1}{T} \sum_{t=1}^{T} \phi \Delta_{t+h}^{e} = \Delta_{t+h} \right),$$

where Δ_{t+h} and Δ_{t+h}^{e} are the actual and predicted direction of change in the variable of interest h steps ahead, and ϕ equals 1 if $\Delta_{t+h} = \Delta_{t+h}^{e}$ and 0 otherwise.

4 Empirical Results

Initially we explore forecasting the Colombian consumer price index (CPI) for food. The results are shown in Table 3. First and foremost, the results indicate that out of a total of 54 time series which make up the food CPI in Colombia, only 7 of them can be forecasted using a single forecasting technique at all horizons if we wish to obtain the most accurate forecasts. Accordingly, we can conclude that ARIMA outperforms HW, ETS and SSA at all horizons in forecasting the Colombian CPI for Bread, Plantain and Potato. Likewise, HW outperforms the rest at all horizons when forecasting the Colombian Cold Fast Food, Pork and Restaurant Meal indices while ETS is able to outperform the other models at all horizons in forecasting the Salt index. However, the basic Vector SSA model is unable to outperform ARIMA, ETS or HW models at all horizons for any given component in the Colombian food CPI. Secondly, the score and percentage shows that if we consider the forecasting performance based on individual components of the Colombian food CPI, then, the ARIMA model is able to provide a majority of the most accurate forecast of the Colombian food CPI in the short run as it records the highest individual and combined score at $h = 1$ and 3 steps ahead. In the long run ($h = 6$ and 12 months ahead), based on the combined score we can see that the ETS model provides the majority of most accurate forecasts for the Colombian food CPI. However, a closer look at the results show that both ARIMA and ETS appear to be indifferent in terms of majority accurately forecasted at $h = 6$ steps ahead. At $h = 12$ steps ahead which is the one year ahead forecast, based on the score and percentage it is possible to identify that the HW model provides a majority of accurate forecasts by accounting for 35% of the components. Thirdly, the percentage values also suggest that a combination of ARIMA and SSA models could provide a very good approximation for one month ahead forecasts of the Colombian food CPI as it is collectively able to accurately forecast 74% of the CPI food components. For obtaining accurate annual forecasts, the percentage statistic suggests that a combination of HW and ETS models would be optimal as it is able to capture accurately the future index movements for 65% of the overall components which make up the Colombian food CPI. Interestingly, once again the analysis thus far based on the score and percentage suggests the SSA model is least favourable in this case. We go a step further and test the best outcomes for statistical significance using the modified Diebold-Mariano test found in Harvey et al. (1997). In this case, the results were appalling as only a very minimal outcomes were statistically significant in comparison to the forecasts from the remaining three models. This suggests that majority of the forecasts for the Colombian food CPI are likely to be chance occurrences.

Presented in Table 4 are the results for DC predictions of each model at each horizon in terms of forecasting the Colombian CPI for food. Here we also test each of the outcomes for statistical significance. Based on the score we can see that ARIMA outperforms the rest of the models in terms of accurately predicting the DC for majority of the components in the CPI food index at horizons of 1 and 3 steps ahead. However, in the long run, the ETS model provides the best score at horizons of 6 and 12 steps ahead and outperforms the rest in terms of accurately predicting the DC for a majority of the components. Furthermore, the results indicate that at 1 and 3 steps ahead, ARIMA reports the highest number of significant outcomes within the score whilst the ETS model is able to report the highest number of significant outcomes at $h = 6$ and 12 months ahead. We also report the total number of significant DC outcomes but it should be noted that having a higher total number in this case does not imply a model is predicting the DC better than any other given model. This is because the total significant outcomes would include both good and bad DC predictions which could still be significant. However if one is interested in figuring out which model is able to provide the most statistically significant outcomes for DC then we can conclude that at $h = 1$ step ahead, ARIMA provides the most statistically significant results and that ETS reports the most statistically significant outcomes $h = 3$, 6, and 12 steps ahead. Finally, we calculate the average DC predictions for each model at each horizon. Here we are able to identify that on average, the ARIMA model provides the most accurate DC prediction for the Colombian food CPI forecasts at all horizons reporting accuracy levels of over 70%. As such, based on the results for RMSE and DC, we can conclude that the ARIMA model is best for obtaining Colombian food CPI forecasts at $h = 1$ and 3 steps ahead, whilst both ARIMA and ETS are indifferent at $h = 6$ steps ahead, and finally, in order to obtain forecasts for the index at $h = 12$ steps ahead, the HW model can outperform the rest based on both the RMSE and DC. Furthermore, if we are only interested in $h = 1$ step ahead forecasts of the index, a combination of ARIMA and SSA models might be able to provide better results as both these models report identical average DC at $h = 1$ step ahead and SSA is able to provide the second best forecast at $h = 1$ step ahead for the CPI. However, once we consider the statistical significance of the forecasts, as reported in Table 3, it is more appropriate to conclude that there is likely to be no major difference between the forecasting accuracies of the models evaluated here and that an exceedingly high majority of the RMSE results are in fact chance occurrences.

Table 3: RMSE for out-of-sample Colombian food CPI forecasts.

	ARIMA				Holt-Winters				SSA				ETS			
Series	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Bananas	1.53	2.71	**2.78**	**3.41**	**1.46**	**2.52**	3.40	5.61	1.79	5.68	3.66	9.66	1.54	2.90	3.78	4.87
Beef	0.91	**1.68**	**3.69**	**5.79**	0.95	2.34	5.20	11.7	**0.90**	2.33	4.61	7.87	0.96	2.08	3.99	6.44
Bread	**0.88**	**1.27**	**1.71**	**3.00**	1.02	1.71	2.01	3.23	1.04	2.12	4.61	5.93	0.96	1.59	2.02	3.07
Burger in Bun	0.56	0.96	1.38	2.49	**0.48**‡	**0.79**	**0.91**	**1.31**	0.58	1.11	1.54	2.07	0.55	0.85	1.05	1.91
Canned Vegetables	0.44	0.73	1.11	1.85	0.50	0.78	0.90	**0.87**	0.46	0.87	1.15	1.30	**0.42**	**0.65**	**0.79**‡	0.91
Canteen Drinks	0.33	0.62	0.98	1.57	0.35	0.55	0.64	0.59	**0.29**	0.61	0.82	1.17	0.31	**0.48**	**0.54**‡	**0.51**
Carrots	**15.0**	**22.3**	**24.6**‡	29.9	17.2	25.0	32.9	32.1	17.4	29.2	28.9	**25.5**	19.9	30.6	44.8	54.1
Cassava	2.48	**5.81**	**8.53**	15.3	2.68	6.13	12.4	20.0	2.56	5.87	9.29	**10.1**‡	**2.47**	5.92	8.88	16.0
Cereals	1.00	1.65	2.14	3.15	0.96	1.49	**1.70**	**1.59**	0.99	1.61	2.05	3.55	**0.93**	**1.46**	1.79	2.03
Cheese	**1.06**	2.13	2.79	4.78	1.21	**1.93**	2.75	2.58	1.07	2.17	**2.53**	**2.52**	1.12	2.13	2.74	2.63
Chicken	1.00	**2.21**	3.94	4.92	1.23	2.29	4.48	6.08	**0.85**	2.38	**3.73**	**3.82**	1.17	2.22	4.20	4.91
Chocolate	**0.80**	**1.20**	1.94	3.62	1.00	1.25	1.97	5.15	0.82	1.72	2.29	3.49	0.84	1.29	**1.63**	**2.85**
Coffee	0.92	**1.76**	**2.40**	4.73	1.26	2.10	3.00	4.86	0.91	2.55	3.94	5.56	**0.90**	1.77	3.15	**4.72**
Cold Fast Food	0.53	0.84	1.33	2.34	**0.47**	**0.66**	**0.87**	**1.33**	0.59	1.03	1.32	2.08	0.50	0.96	0.91	1.32
Eggs	**1.80**	3.09	4.15	4.06	1.91	**2.81**	**4.04**	**3.76**	2.15	3.96	4.26	4.89	1.87	2.92	4.27	3.99
Fats	1.58	**2.30**	2.81	5.97	1.48	2.68	4.14	**4.8**	**1.29**	2.74	4.45	6.63	1.55	2.42	**2.58**	5.80
Fish	0.58	1.22	2.16	3.96	0.69	1.26	2.25	2.79	**0.50**	1.35	2.71	4.88	0.54	**0.94**	**1.60**	**1.66**
Flour	**0.71**	**1.74**	**2.90**	6.44	1.10	2.04	2.96	6.66	0.81	2.55	3.64	**4.11**	0.72	1.92	4.18	10.9
Fresh Vegetables	**8.70**	13.8	15.2	22.0	9.15	13.9	15.3	21.0	9.56	**11.5**	**12.6**	**13.6**	8.96	14.2	14.7	20.3
Hot Fast Food	0.44	0.86	1.42	2.51	**0.35**	**0.49**	0.65	**0.68**‡	0.37	0.77	1.01	1.54	0.40	0.57	**0.62**	0.71
Juices	**0.41**	0.87	1.52	3.03	0.71	0.85	**0.99**	**1.72**	0.43	0.96	1.41	2.50	0.43	**0.84**	1.31	2.62
Kidney Beans	**1.49**	**3.37**	4.92	6.98	2.28	4.52	7.38	6.95	1.72	4.69	5.64	7.57	1.64	3.65	**4.52**	**5.46**
Milk	0.61	1.28	2.29	4.36	0.84	1.88	2.50	4.27	**0.55**	1.27	2.33	3.92	0.56	**0.95**‡	**1.96**	**2.82**
Mulberry	**7.04**	9.83	11.6	13.5	8.70	**9.00**	10.5	**11.3**	8.78	11.9	12.2	12.4	7.87	9.15	**10.2**	11.9
Oils	0.90	1.72	3.07	6.05	0.95	1.98	4.00	**3.39**	**0.86**	2.86	5.75	10.6	0.90	**1.61**	**2.04**‡	4.01
Onion	**8.39**	**14.8**	24.0	29.2	9.30	15.4	22.9	27.1	8.66	16.1	**17.5**	**16.2**	10.2	19.3	32.3	63.4
Oranges	7.27	**18.6**	29.2	26.3	8.99	19.1	30.9	**23.2**	**7.23**	21.4	**22.9**	24.8	8.73	20.3	33.0	31.5
Other Bakery	0.67	1.05	1.47	3.44	0.62	0.98	1.30	**2.00**	0.61	1.29	2.10	2.88	**0.54**	**0.80**	**1.14**	2.59
Other Cereals	**0.78**	1.66	2.91	5.89	1.02	**1.63**	**1.99**	**3.04**	0.81	2.43	3.17	4.73	0.84	1.85	2.92	3.59
Other Condiments	0.58	1.08	1.36	2.24	0.56	0.77	**0.88**	**0.98**	**0.54**	**0.72**	0.95	1.39	0.55	0.96	1.41	2.58
Other Dairy	0.71	1.48	2.42	3.66	1.03	2.02	3.33	3.69	**0.50**	1.13	1.96	4.00	0.54	**1.06**	**1.68**	**2.05**

Other Dried Veg.	**1.58**	**2.24**	3.64	6.48	1.77	3.01	3.84	8.13	1.60	3.57	6.07	12.2	1.68	2.93	**3.03**	**3.26**
Other Fish	1.45	1.97	**1.66**	2.07	1.44	1.98	2.44	2.95	**1.08**	**1.44**	2.05	2.80	1.21	1.52	1.81	**1.89**
Other Fruits	**3.52**	8.22	**10.1**	12.5	4.07	**7.87**	14.9	14.1	3.63	10.1	11.4	**10.6**	5.04	9.80	10.5	12.5
Other Groceries	0.67	1.12	2.07	2.99	0.82	4.85	**1.54**	**1.55**	0.65	1.37	1.68	2.37	**0.63**	**0.94**	1.57	1.79
Other Meats	0.87	1.53	1.88	3.48	0.98	1.58	**1.52**	**2.06**	**0.80**	1.63	2.10	3.07	0.82	**1.45**	1.55	2.41
Other Non Alcoholic	**1.08**	**2.05**	3.03	3.45	1.39	2.54	3.32	4.52	1.27	2.11	**2.17**	**1.99**	1.15	2.09	2.83	3.88
Other Roots	**5.24**	**11.5**	23.6	29.3	6.15	12.3	26.3	25.8	5.90	12.8	**18.1**	22.4	5.33	12.6	25.2	**20.5**
Panela	**1.25**	2.75	4.80	9.03	1.49	2.86	6.03	10.9	1.55	3.96	7.81	12.7	1.37	**2.65**	**4.55**	**7.45**
Pasta	**0.95**‡	**1.50**	2.36	3.48	1.18	2.20	3.10	2.78	1.17	3.17	4.26	6.16	1.04	1.66	**2.21**	**2.17**
Peas	**7.36**	**11.3**	**11.8**	12.9	13.9	17.0	15.3	15.8	7.89	13.5	12.7	**11.6**‡	10.0	15.8	16.3	16.0
Plantain	**2.77**	**4.03**	**7.93**	**9.88**	3.45	6.03	8.17	10.4	2.84	7.01	8.68	10.2	3.21	8.52	13.5	20.3
Pork	1.30	2.72	4.72	7.59	**1.29**	**2.59**	**4.29**	**5.93**	1.51	3.68	5.41	7.53	1.39	3.17	6.43	9.02
Potato	**11.0**	**19.8**	**20.2**	**17.7**	14.8	26.5	32.3	32.0	13.2	27.7	23.8	23.2	12.9	30.9	38.5	68.5
Restaurant Meals	0.42	0.61	0.83	1.61	**0.25**	**0.40**‡	**0.58**	**0.93**	0.28	0.60	0.94	1.19	0.46	0.61	0.68	1.06
Rice	**3.40**	10.2	18.6	13.1	4.29	10.6	20.7	18.1	4.78	**8.52**	**12.7**	12.6	4.14	12.8	33.8	**10.7**
Salt	0.97	1.50	2.17	3.32	1.07	1.68	2.34	2.39	0.99	1.91	2.60	3.95	**0.95**	**1.47**	**2.02**	**2.30**
Soft Drinks	0.80	**1.63**	2.19	**2.21**	1.14	1.93	2.54	2.89	**0.79**	1.82	**1.95**	2.80	0.87	1.85	2.31	2.68
Soups and Creams	1.10	**1.58**	**1.92**	3.16	1.04	1.61	2.45	3.94	1.10	1.79	2.71	3.59	**1.00**	1.60	2.02	**2.84**
Sugar	**1.50**	**3.02**	**5.26**	7.94	2.27	4.63	9.71	19.6	1.90	5.35	7.46	**6.64**	1.60	3.48	6.25	9.72
Tomato	12.9	**18.1**	20.4	21.4	16.2	22.6	28.3	31.0	**12.6**	20.2	**20.1**	**19.1**	15.8	21.2	27.5	33.0
Tree Tomato	**6.23**	11.9	**15.7**	12.7	6.88	**11.8**	16.6	**12.5**	6.73	13.0	17.6	18.3	7.64	17.8	34.9	24.7
Various Jams	1.40	**1.70**	3.05	3.28	1.41	1.80	**2.67**	2.76	**1.30**	2.42	2.68	3.29	1.46	1.81	2.72	**2.63**
Various Sauces	0.75	1.03	**1.77**	2.56	0.98	1.46	1.98	2.68	**0.73**	1.36	2.00	**2.27**	0.76	**1.01**	1.99	2.94
	ARIMA				Holt-Winters				SSA				ETS			
h	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Score	**24**	**24**	**16**	6	6	12	12	**19**	16	4	10	13	8	14	**16**	16
Sig. Score	**1**	0	1	0	**1**	**1**	0	1	0	0	0	**2**	0	**1**	**3**	0
Percentage	**44%**	**44%**	**30%**	11%	11%	22%	22%	**35%**	30%	7%	19%	24%	15%	26%	**30%**	30%

‡ indicates a statistically significant difference between the RMSEs of the model with minimum RMSE (shown in Bold) and each of the other models for each respective horizon, using the modified Diebold-Mariano test at $p = 0.10$.

Table 4: DC: out-of-sample Colombian food CPI forecasts.

	ARIMA				Holt-Winters				SSA				ETS			
Series	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Bananas	0.59	0.72	0.84	0.87	0.61	0.72	0.78	0.80	0.52	0.52	0.63*	0.64*	0.59*	**0.72**	0.80*	0.78*
Beef	0.70*	0.79	0.84	0.76	0.64	0.76*	0.80*	0.76*	0.73	0.72	0.73	0.47	0.70	0.78	0.80	0.78*
Bread	0.63	0.72	0.84*	0.91*	0.55	0.70*	0.80*	0.73*	0.54	0.70*	0.63	0.87*	0.63	0.69	0.80*	0.73*
Burger in Bun	0.89*	0.90*	1.00*	1.00*	0.89*	0.93*	1.00*	1.00*	0.79	0.91*	1.00*	1.00*	0.89*	0.91*	1.00*	1.00*
Canned Vegetables	0.85*	0.93*	0.98	1.00*	0.82	0.93*	1.00*	1.00*	0.84	0.96*	0.98*	1.00*	0.86*	0.93*	1.00*	1.00*
Canteen Drinks	0.96*	1.00*	1.00*	1.00*	0.77	0.94	1.00*	1.00*	0.96*	1.00*	1.00*	1.00*	0.96*	1.00*	1.00*	1.00*
Carrots	0.59	0.63	0.82*	0.78*	0.50	0.81	0.78	0.80	0.50	0.81	0.78	0.80	0.59	0.56	0.73	0.82*
Cassava	0.73*	0.74	0.65*	0.64	0.61	0.61	0.57	0.67*	0.68*	0.85*	0.69	0.71	0.73*	0.74	0.65*	0.64*
Cereals	0.70	0.69*	0.86*	0.98*	0.70	0.72*	0.94*	0.98*	0.73	0.76*	0.88*	0.96*	0.79*	0.74*	0.92*	0.98*
Cheese	0.66	0.74*	0.82*	1.00*	0.64	0.72	0.78*	1.00*	0.73*	0.69*	0.69	1.00*	0.68*	0.69	0.78*	1.00*
Chicken	0.57	0.69	0.76	0.84*	0.63	0.69*	0.76*	0.84*	0.70	0.59	0.71	0.84*	0.57	0.65*	0.73	0.84*
Chocolate	0.73*	0.89*	0.98*	1.00*	0.64	0.83	0.94*	1.00*	0.70	0.85*	0.86*	0.98*	0.64	0.81*	0.98*	1.00*
Coffee	0.77*	0.89	0.94*	1.00*	0.71	0.80*	0.82	1.00*	0.77	0.78*	0.96*	1.00*	0.73	0.81	0.80	1.00*
Cold Fast Food	0.77	0.94	0.98	1.00	0.73	0.96	0.98	1.00	0.68	0.93	0.98	1.00	0.77	0.89	0.98	1.00
Eggs	0.55	0.69	0.57	0.80*	0.63	0.72*	0.55	0.80	0.66	0.57	0.57	0.71	0.50	0.69*	0.57	0.80
Fats	0.66*	0.74	0.84*	0.93*	0.59	0.63	0.65	0.69	0.77*	0.70	0.78*	0.93*	0.64	0.81	0.86*	0.89
Fish	0.71*	0.74	0.73*	0.87*	0.64	0.70	0.63*	0.87*	0.70	0.67	0.69*	0.82	0.71*	0.78*	0.71	0.67
Flour	0.68*	0.80	0.80	0.80*	0.54	0.78	0.86	0.84	0.73	0.69	0.90*	0.93*	0.77	0.91*	0.90*	0.96*
Fresh Vegetables	0.59	0.66	0.66	0.70	0.52	0.69	0.63	0.62	0.64*	0.78*	0.75*	0.76	0.45	0.69	0.61	0.62
Hot Fast Food	0.88*	0.98*	1.00*	1.00*	0.85	0.98*	1.00*	1.00*	0.79	0.94*	1.00*	1.00*	0.88*	0.98*	1.00*	1.00*
Juices	0.77*	0.78*	0.82*	0.87*	0.64	0.81*	0.80*	0.82*	0.71	0.83*	0.84*	0.73*	0.73	0.78	0.78*	0.87*
Kidney Beans	0.70	0.74*	0.61	0.71	0.39*	0.52	0.55	0.73	0.71*	0.74	0.73	0.58	0.70*	0.81*	0.82*	0.78*
Milk	0.71	0.85*	0.88	1.00*	0.68	0.76	0.94	0.80	0.77	0.80*	0.84*	1.00*	0.73	0.77	0.94*	1.00*
Mulberry	0.57	0.72	0.75*	0.76*	0.50	0.80*	0.84	0.78	0.64	0.80	0.82	0.71	0.43	0.78	0.82*	0.71
Oils	0.71	0.65	0.69	0.49	0.68	0.74	0.76	0.87	0.71	0.63	0.47	0.47	0.71	0.72	0.73	0.73
Onion	0.68	0.76	0.71	0.64	0.52	0.76*	0.75	0.64	0.64	0.72*	0.76	0.78	0.57	0.78*	0.80*	0.51
Oranges	0.63	0.69	0.65*	0.73	0.64	0.76	0.73*	0.80	0.71	0.50	0.61	0.73	0.39	0.63	0.65	0.53
Other Bakery	0.59	0.83*	0.96*	1.00*	0.63	0.81	0.94*	1.00*	0.63	0.80	0.94*	0.93	0.66*	0.85*	0.92*	1.00*
Other Cereals	0.61	0.70	0.75*	0.67	0.64	0.69	0.73*	0.69*	0.61	0.56	0.88*	0.80	0.63	0.69	0.57	0.69
Other Condiments	0.71*	0.85	0.92	0.93	0.68	0.93*	1.00*	1.00*	0.71*	0.93*	1.00*	1.00*	0.71	0.87*	0.96*	0.96
Other Dairy	0.77*	0.85*	0.86*	0.80*	0.55	0.63*	0.65	0.80*	0.80*	0.81*	0.80	0.73	0.77*	0.89*	0.88	0.80*

Other Dried Veg.	0.66	0.85*	0.73	0.67	0.57	0.83	0.78*	0.64	0.71	0.72*	0.71	0.62	0.66	0.85*	0.75	0.71
Other Fish	0.43	0.54	0.69	0.64	0.55	0.61*	0.69	0.62	0.64	0.59	0.53	0.64	0.50*	0.61*	0.69	0.67*
Other Fruits	0.71	0.72*	0.69*	0.78	0.66	0.74	0.67	0.84*	0.66	0.65*	0.69	0.82*	0.57	0.63*	0.73	0.82*
Other Groceries	0.73	0.89	0.84*	1.00*	0.57	0.80*	0.84*	1.00*	0.75*	0.87*	0.86*	1.00*	0.77*	0.84*	0.89*	1.00*
Other Meats	0.57	0.67	0.80*	0.91*	0.55	0.65*	0.78*	0.91*	0.59	0.61	0.75*	0.78	0.59	0.65	0.78*	0.91*
Other Non Alcoholic	0.82	0.91*	0.88*	1.00*	0.57	0.83	0.86	1.00*	0.66	0.80	0.86*	1.00*	0.80*	0.85	0.88*	1.00*
Other Roots	0.63	0.61	0.67	0.73*	0.63	0.76	0.71*	0.76*	0.73	0.76*	0.75	0.73	0.68	0.69*	0.73*	0.82*
Panela	0.86	0.89	0.86*	0.78	0.77*	0.81	0.82	0.82*	0.82	0.76*	0.75	0.62*	0.86*	0.85*	0.90*	0.82*
Pasta	0.68*	0.83*	0.88*	1.00*	0.66*	0.76*	0.84	0.93*	0.61	0.74*	0.86*	1.00*	0.64	0.80*	0.90*	0.91*
Peas	0.73	0.81*	0.78	0.67	0.54	0.76*	0.73	0.69	0.70	0.67	0.80*	0.76*	0.39	0.69	0.73	0.67
Plantain	0.66*	0.70	0.55	0.80	0.63	0.72	0.71	0.84*	0.55	0.44	0.59	0.56	0.64	0.72	0.63	0.84*
Pork	0.73*	0.69	0.63	0.44	0.77	0.81	0.75	0.44	0.77*	0.54	0.49	0.33	0.70	0.69*	0.61*	0.44
Potato	0.79	0.85	0.80	0.91	0.52	0.63	0.59	0.78	0.71	0.70	0.71*	0.69	0.79	0.80	0.86*	0.71
Restaurant Meals	0.98*	1.00*	1.00*	1.00*	0.98	1.00*	1.00*	1.00*	0.98	1.00*	0.96*	1.00*	0.98*	1.00*	1.00*	1.00*
Rice	0.71	0.69	0.69	0.64	0.57	0.70	0.78	0.69	0.32*	0.52	0.61*	0.84	0.71	0.83*	0.86*	0.69
Salt	0.68*	0.85*	0.88*	1.00*	0.57	0.80	0.88*	1.00*	0.70	0.78*	0.88*	1.00*	0.68*	0.85*	0.88*	1.00*
Soft Drinks	0.82*	0.87*	0.92*	1.00*	0.52	0.81	0.90*	1.00*	0.79	0.67	0.86*	0.98	0.80*	0.81	0.92*	1.00*
Soups and Creams	0.64	0.74*	0.80*	0.96*	0.73*	0.76*	0.75	0.96*	0.66	0.72*	0.72*	0.89*	0.68	0.72	0.75	0.96*
Sugar	0.70	0.70	0.80	0.78*	0.64	0.72*	0.78*	0.82*	0.57	0.41	0.55	0.80*	0.66	0.72	0.82	0.82*
Tomato	0.71*	0.85*	0.75*	0.82	0.55	0.69	0.69*	0.64	0.71	0.78*	0.71	0.82*	0.36	0.81*	0.63	0.73
Tree Tomato	0.80*	0.89	0.88	0.78	0.82*	0.93*	0.88*	0.80	0.75	0.87	0.82	0.71	0.77	0.76	0.61	0.69
Various Jams	0.55	0.87	0.69	0.76	0.61	0.87	0.69	0.76	0.70*	0.69	0.76	0.67	0.63	0.89	0.63	0.64
Various Sauces	0.57*	0.81*	0.84	0.98	0.61	0.74	0.76	0.96	0.68	0.74	0.80*	1.00*	0.61*	0.78	0.84	0.93
	ARIMA				Holt-Winters				SSA				ETS			
h	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Score	**26**	**24**	23	30	8	20	19	32	24	12	16	22	20	18	**26**	**34**
Sig. Score	**14**	**13**	16	25	3	12	12	23	9	10	11	17	11	**13**	**19**	**29**
Total Sig. Outcomes	**23**	23	29	30	6	23	26	31	12	26	29	27	20	**27**	**31**	**34**
Average DC	**0.70**	**0.79**	**0.81**	**0.84**	0.64	0.77	0.77	**0.84**	**0.70**	0.73	0.78	0.82	0.68	0.78	**0.81**	0.83

* indicates DC predictions are statistically significant based on a t-test at $p = 0.10$.

Next, we forecast monthly food inflation in Colombia. The forecasting results for monthly food inflation are reported in Table 5. The highlighted RMSE values indicates the lowest forecasting error reported for each CPI food component at each horizon. The score indicates that for monthly food inflation forecasting, the SSA model reports the highest score both in the long and short run. Accordingly, we can infer that the SSA model reports the lowest error for forecasting majority of the monthly food inflation components in Colombia. At 1 month ahead, the SSA model provides the best forecast for 69% of the components, 78% of the components at 3 and 6 months ahead and an impressive 96% of the components at 12 months ahead. Furthermore, the results indicate that the optimal ARIMA model, HW and ETS models experience a deterioration in their performance based on the score as the horizon increases from 1 month to 12 months ahead. However, the SSA model's performance at forecasting a majority of the monthly inflation components most accurately, increases along with the horizons. This result not only indicates that the performance of the SSA model can outperform the rest of the models considered in this study in both the short and long run horizons, but also that the SSA model can provide the best performance in the long run. This result is crucial for policy makers as accurate long and short run forecasts for inflation can enhance the efficiency of policy decisions. The unit root test performed earlier showed that the time series for Onions is non-stationary. Interestingly, the SSA technique outperforms all other techniques at all horizons at forecasting most accurately the monthly inflation in Onions. The study also finds that the ETS model is unable to outperform any of the other forecasting techniques considered here for forecasting monthly Colombian food inflation at $h = 1$ month ahead and $h = 12$ months ahead. Furthermore, the HW model is unable to outperform the competing techniques at $h = 12$ months ahead. Once again, we test the best outcomes for statistical significance using the modified Diebold-Mariano statistic in Harvey et al. (1997). Here, the SSA model reports the highest number of significant outcomes. Interestingly, even though the other models report the best outcomes for certain CPI food components, except for one instance at $h = 3$ steps ahead for ARIMA, none of the other reported best outcomes are found to be statistically significant. Thus we are able to conclude that the forecasting accuracies attainable for monthly food inflation in Colombia using SSA is more stable and reliable than those reported by ARIMA, ETS and HW models.

We also test the ability of the the forecasts to correctly predict the actual direction of change in the monthly food inflation. The results shown in Table 6 indicates that the SSA model is superior in comparison to ARIMA, HW and ETS based on the DC criterion. In fact, on average, the SSA model reports DC results of over 70% at all horizons. In order to ensure the results are not solely chance occurrences, we test the DC output for statistical significance. The SSA model once again provides the most number of statistically significant outcomes at all horizons. The ARIMA model is able to provide an equivalent number of statistically significant outcomes to that of SSA at $h = 3$ steps ahead, but the average DC prediction for ARIMA here is less than that of SSA. As such, we are able to conclude that the SSA model can provide the best DC prediction for monthly food inflation forecasts in Colombia in comparison to ARIMA, ETS and HW.

Table 5: RMSE for out-of-sample monthly Colombian food inflation forecasts.

	ARIMA				Holt-Winters				SSA				ETS			
Series	1	3	6	12	1	3	6	12	1	3	6	12	1	3	6	12
Bananas	1.50	1.63	1.52	1.52	1.54	**1.57**	1.53	1.60	**1.48**	1.69	**1.46**	**1.46**	1.55	1.67	1.58	1.61
Beef	0.94	1.08	1.19	1.30	0.95	1.12	1.37	1.60	**0.89**	**0.96**	**0.98**	**0.91**	0.99	1.33	1.53	1.86
Bread	0.90	0.76	0.73	0.76	1.01	0.90	0.77	0.71	**0.88**	**0.67**	**0.66**	**0.67**	0.98	0.87	0.72	0.74
Burger in Bun	0.51	0.53	0.54	0.51	**0.45**	**0.47**	**0.48**	0.45	0.49	0.50	0.49	**0.44**	0.52	0.54	0.54	0.50
Canned Vegetables	0.41	0.43	0.44	0.41	0.48	0.49	0.44	0.41	**0.40**	**0.41**	**0.35**	**0.32**‡	0.42	0.42	0.43	0.39
Canteen Drinks	0.32	0.34	0.30	0.30	0.30	0.30	0.34	0.24	**0.26**‡	**0.26**‡	**0.21**	**0.21**‡	0.31	0.31	0.29	0.29
Carrots	**13.9**	**14.6**	**16.1**	17.1	16.1	16.3	16.8	15.1	14.9	15.21	16.2	**14.2**‡	16.1	16.3	16.5	17.3
Cassava	2.17	2.48	2.51	2.71	2.24	2.79	2.73	2.80	**2.04**	**2.21**	**2.28**	**2.33**	2.19	2.63	2.68	2.71
Cereals	1.00	0.98	0.94	0.94	1.00	0.99	0.94	0.96	**0.90**	**0.85**	**0.83**	**0.83**	0.93	0.90	0.86	0.87
Cheese	0.99	1.02	1.02	1.05	1.04	1.08	1.09	1.00	**0.93**	**0.96**	**0.95**	**0.93**	1.01	1.02	1.03	1.06
Chicken	0.94	1.14	1.12	1.18	1.02	1.16	1.23	1.39	**0.83**‡	**0.95**	**0.91**	**0.95**	1.08	1.11	1.12	1.15
Chocolate	0.73	0.74	**0.74**	0.80	0.81	0.85	1.00	0.94	**0.72**	**0.73**	**0.74**	**0.77**	0.77	0.81	0.86	1.01
Coffee	**0.83**	0.90	0.92	0.96	1.09	1.19	1.36	1.15	0.84	**0.87**	**0.83**	**0.71**	0.85	0.97	1.17	0.87
Cold Fast Food	0.50	0.51	0.50	0.48	0.47	0.48	0.47	0.49	**0.46**	**0.46**	**0.45**	**0.42**	0.50	0.50	0.50	0.48
Eggs	1.88	1.94	1.82	1.65	2.02	2.08	1.97	1.74	**1.85**	**1.91**	**1.74**	**1.51**	1.96	1.94	1.81	1.61
Fats	1.43	1.30	1.23	1.36	1.34	1.44	1.67	1.44	**1.18**	**1.18**	**1.14**	**1.11**‡	1.49	1.50	1.37	1.79
Fish	0.61	0.69	0.71	0.68	0.61	0.63	0.67	0.62	**0.44**‡	**0.49**	**0.51**	**0.51**	0.57	0.58	0.59	0.60
Flour	**0.71**	0.94	1.05	1.08	0.84	1.00	1.11	1.48	0.75	**0.92**	**0.92**	**0.75**	0.77	1.07	1.47	1.80
Fresh Vegetables	7.96	7.98	**8.05**	8.40	8.80	8.86	8.71	8.66	**7.02**	**7.65**	8.18	**7.94**	8.33	8.36	8.37	8.50
Hot Fast Food	0.43	0.47	0.47	0.42	**0.33**	**0.33**	**0.33**	0.32	0.34	0.34	**0.33**	**0.28**‡	0.42	0.42	0.43	0.38
Juices	0.40	0.43	0.43	0.46	0.49	0.47	0.48	0.50	**0.38**	**0.39**	**0.36**	**0.35**	0.39	0.42	0.40	0.40
Kidney Beans	**1.50**	1.73	1.75	1.92	2.04	2.22	2.17	2.14	**1.50**	**1.60**	**1.60**	**1.63**	1.73	2.07	1.95	2.36
Milk	0.55	0.59	0.63	0.62	0.61	0.62	0.69	0.71	**0.48**	**0.47**	**0.46**‡	**0.45**	0.54	0.60	0.81	0.87
Mulberry	**5.99**	**6.54**	7.09	7.37	6.99	7.07	7.18	7.48	6.42	6.87	**7.08**	**6.48**‡	6.79	6.90	**7.08**	7.46
Oils	0.93	1.03	1.06	1.21	1.11	1.30	1.56	1.17	**0.87**	1.08	0.99	**0.94**	1.03	**0.96**	**0.95**	1.18
Onion	8.94	10.0	10.7	10.5	10.5	10.8	12.8	12.3	**8.85**	**8.89**‡	**9.20**‡	**8.77**‡	10.9	11.8	13.3	17.0
Oranges	6.12	7.64	7.72	7.67	7.62	9.07	8.34	7.61	**6.00**	**6.81**	**6.63**	**7.28**	6.45	9.31	9.88	10.7
Other Bakery	0.66	0.66	0.59	0.61	0.58	0.56	0.56	2.56	**0.50**‡	**0.51**	**0.47**	**0.47**	0.58	0.58	0.55	0.59
Other Cereals	**0.79**	0.88	0.92	0.87	1.02	1.11	1.14	1.15	0.84	**0.80**	**0.65**	**0.61**	0.91	0.94	0.91	0.88
Other Condiments	0.53	0.57	0.51	0.51	0.51	0.51	0.51	0.51	**0.43**‡	**0.43**‡	**0.43**	**0.42**	0.47	0.49	0.45	0.47
Other Dairy	0.67	0.69	0.66	0.63	0.65	0.67	0.67	0.63	**0.43**‡	**0.46**‡	**0.53**	**0.48**	0.55	0.56	0.57	0.55

Other Dried Veg.	1.80	1.58	1.69	1.71	2.00	2.54	1.69	1.86	**1.56**	**1.48**	**1.39**	**1.24**	1.83	1.99	1.39	1.23
Other Fish	1.45	1.35	1.23	1.22	1.31	1.31	1.33	1.38	**1.14**‡	**1.13**‡	**1.12**‡	**1.09**‡	1.42	1.34	1.33	1.48
Other Fruits	3.42	3.92	4.06	3.81	3.55	4.03	4.30	4.61	**3.36**	**3.76**	**3.71**	**3.46**	4.70	4.89	5.46	5.75
Other Groceries	0.62	0.64	0.65	0.67	0.67	0.70	0.70	0.72	**0.55**‡	**0.55**	**0.54**‡	**0.54**‡	0.61	0.62	0.61	0.63
Other Meats	0.88	0.89	0.89	0.75	0.95	0.97	0.98	0.92	**0.77**‡	**0.79**‡	**0.81**	**0.60**‡	0.86	0.87	0.88	0.74
Other Non Alcoholic	**0.92**	**0.97**	**0.99**	1.03	1.07	1.10	1.11	1.15	0.96	0.99	1.02	**0.89**	1.01	1.00	1.02	1.04
Other Roots	3.92	4.64	5.00	5.04	3.86	4.21	4.50	4.28	**3.68**	**3.93**	**3.85**	**3.97**	4.31	5.54	5.92	4.64
Panela	**1.21**	**1.30**	**1.46**	1.78	1.53	1.56	1.57	2.03	1.29	1.40	1.53	**1.54**	1.28	1.33	1.65	1.93
Pasta	**0.95**	**0.81**	0.84	0.91	1.60	1.45	1.44	1.28	1.01	0.90	0.83	**0.80**	1.02	1.02	**0.80**	0.87
Peas	**7.68**	**7.80**‡	**7.89**	7.96	11.4	10.6	9.37	9.00	8.20	9.40	8.27	**7.46**	10.0	9.69	8.48	8.28
Plantain	**2.67**	3.16	3.10	3.23	3.37	3.50	3.69	3.77	2.74	**2.74**	**2.79**	**3.03**	3.23	3.61	4.16	4.56
Pork	1.39	1.56	1.66	1.65	1.39	1.47	1.59	1.53	**1.30**	**1.28**	**1.33**‡	**1.42**	1.60	1.90	2.42	2.19
Potato	9.43	9.43	**8.24**	**8.98**	12.3	14.0	13.2	15.1	**8.50**	**9.11**	8.45	9.17	10.8	13.0	15.0	16.7
Restaurant Meals	0.37	0.39	0.42	0.42	**0.23**	**0.24**	**0.25**	0.27	0.24	**0.24**	0.26	**0.26**	0.42	0.42	0.44	0.43
Rice	**4.00**	5.62	4.88	**2.81**	4.82	6.60	7.72	4.12	4.52	**4.68**	**3.45**	3.08	5.01	6.42	6.93	3.77
Salt	0.88	0.89	0.89	0.94	0.98	1.03	0.98	1.01	**0.84**	**0.83**	**0.86**	**0.85**	0.88	0.89	0.91	0.95
Soft Drinks	**0.74**	0.83	0.85	0.82	0.95	0.97	1.00	0.95	0.77	**0.82**	**0.82**	**0.78**	0.82	0.84	0.85	0.82
Soups and Creams	1.08	1.09	1.01	1.00	1.06	1.11	1.09	1.06	**0.98**	**0.99**	**0.93**	**0.95**	1.03	1.07	1.01	1.01
Sugar	**1.41**	**1.58**	**1.88**	**1.53**	1.86	2.10	2.23	2.87	1.77	1.95	1.96	**1.53**	1.60	1.93	2.45	2.57
Tomato	15.8	17.1	17.7	18.5	19.8	20.2	20.1	21.2	**15.5**	**16.8**	**17.6**	**16.7**‡	18.3	18.6	18.6	19.6
Tree Tomato	5.50	5.72	5.91	5.97	5.71	5.74	5.77	5.93	**5.27**	**5.35**	**5.09**	**5.12**‡	7.33	8.40	9.42	8.48
Various Jams	1.43	1.39	1.42	1.40	**1.26**	**1.26**	**1.21**	1.32	1.32	1.29	1.23	**1.21**	1.47	1.41	1.36	1.42
Various Sauces	0.72	0.73	0.75	0.78	0.77	0.78	0.82	0.79	**0.68**	**0.70**	**0.69**	**0.71**	0.72	0.74	0.73	0.76
	ARIMA				Holt-Winters				SSA				ETS			
h	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Score	14	7	7	2	4	5	4	0	**37**	**42**	**42**	**52**	0	1	3	0
Sig. Score	0	1	0	0	0	0	0	0	**9**	**6**	**5**	**12**	0	0	0	0
Percentage	26%	13%	13%	4%	7%	10%	7%	0%	**69%**	**78%**	**78%**	**96%**	0%	2%	6%	0%

‡ indicates a statistically significant difference between the RMSEs of the model with minimum RMSE (shown in Bold) and each of the other models for each respective horizon, using the modified Diebold-Mariano test at $p = 0.10$.

Table 6: DC: out-of-sample monthly Colombian food inflation forecasts.

	ARIMA				Holt-Winters				SSA				ETS			
Series	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Bananas	0.63*	0.72	0.75	0.64	0.63	0.80*	0.84*	0.56	0.61	0.74	0.82*	0.69	0.55	0.72*	0.80*	0.56
Beef	0.64	0.78	0.73	0.71	0.75	0.74	0.73	0.60	0.73	0.83	0.80*	0.69	0.57	0.76	0.80	0.62
Bread	0.70	0.76	0.75*	0.69*	0.71*	0.78	0.73	0.67	0.73	0.76	0.75*	0.73*	0.71*	0.81*	0.73	0.69
Burger in Bun	0.61	0.63	0.71	0.60	0.77	0.72	0.88	0.69*	0.68	0.67	0.82	0.76	0.61	0.63	0.71	0.58
Canned Vegetables	0.68	0.63	0.65	0.69	0.59	0.67	0.65	0.69	0.64	0.67	0.75*	0.64	0.70	0.67	0.71	0.73
Canteen Drinks	0.61	0.70	0.73	0.64	0.77*	0.83*	0.80*	0.64	0.70	0.81	0.88	0.80*	0.68	0.72*	0.76*	0.62
Carrots	0.71	0.83*	0.69*	0.71	0.63	0.81*	0.73*	0.87*	0.73*	0.87*	0.75	0.76*	0.75	0.83*	0.76*	0.71
Cassava	0.71	0.70*	0.73	0.67	0.64*	0.69	0.65	0.69	0.68	0.74	0.82	0.78	0.64	0.65	0.65	0.69
Cereals	0.59	0.70	0.73	0.73	0.57	0.67	0.67	0.67	0.68	0.80	0.75	0.87*	0.63	0.72	0.73*	0.76
Cheese	0.64	0.78	0.84	0.69	0.64	0.81	0.75	0.60	0.77	0.81*	0.90*	0.73	0.70	0.78	0.90	0.69
Chicken	0.64	0.80*	0.78	0.71	0.57	0.69	0.75	0.62	0.66	0.83*	0.80	0.78*	0.63	0.81*	0.78	0.69
Chocolate	0.59	0.80	0.67	0.67*	0.66	0.76	0.76	0.62	0.70	0.83*	0.71	0.67	0.63	0.69	0.63	0.58
Coffee	0.57	0.74	0.71	0.71*	0.54	0.54	0.59	0.60	0.61	0.72	0.80	0.78*	0.57	0.69	0.67	0.67
Cold Fast Food	0.63	0.80*	0.73	0.71	0.68*	0.69	0.84*	0.69*	0.63	0.76	0.82*	0.73	0.63	0.80*	0.75	0.69
Eggs	0.64	0.76	0.69	0.62	0.61	0.74*	0.65	0.60	0.71*	0.76*	0.73	0.58	0.64	0.76	0.69	0.62
Fats	0.66*	0.69	0.75	0.56	0.68	0.67	0.71	0.67	0.80*	0.70	0.71	0.62	0.61	0.76	0.73*	0.56
Fish	0.61	0.57	0.71	0.67*	0.64	0.67	0.82*	0.62	0.68	0.78	0.82	0.78	0.70*	0.65*	0.73	0.71
Flour	0.52	0.80*	0.76*	0.71	0.57*	0.67	0.73	0.38	0.61*	0.74*	0.76	0.80	0.48	0.72	0.65	0.51
Fresh Vegetables	0.80	0.78*	0.75	0.73	0.84*	0.80	0.78	0.80*	0.79	0.83	0.73	0.73*	0.80	0.78	0.71	0.69
Hot Fast Food	0.52	0.70	0.73*	0.53	0.75	0.85	0.86	0.78*	0.77*	0.83	0.88	0.73	0.61	0.80*	0.69	0.82
Juices	0.66	0.65	0.69	0.62	0.64	0.74	0.73	0.73	0.63	0.80*	0.71*	0.78	0.61	0.70	0.67	0.62
Kidney Beans	0.73	0.70	0.80	0.69*	0.66	0.81	0.78*	0.58	0.77	0.83*	0.80*	0.82	0.52	0.72	0.88	0.67
Milk	0.55	0.61	0.80*	0.67	0.66	0.72*	0.78	0.60	0.61	0.72	0.86*	0.78	0.54	0.69	0.71	0.60
Mulberry	0.68	0.81	0.76	0.67	0.59	0.74	0.73	0.60	0.77	0.78*	0.75	0.76	0.64	0.80	0.76	0.64
Oils	0.54	0.65	0.71	0.64	0.50	0.70	0.63	0.73	0.57	0.78*	0.67	0.56	0.63	0.81	0.71	0.76*
Onion	0.68	0.70	0.78	0.78	0.57	0.59	0.75	0.62	0.66*	0.80	0.84*	0.80*	0.63	0.63	0.69	0.51
Oranges	0.73*	0.87*	0.80*	0.62	0.71*	0.80	0.78	0.64	0.75	0.87*	0.80*	0.73*	0.46	0.70	0.69	0.49
Other Bakery	0.68	0.72	0.71	0.62	0.73	0.74*	0.80	0.51	0.80	0.74	0.80	0.67	0.77	0.77	0.78*	0.62
Other Cereals	0.59	0.70	0.73	0.64	0.59	0.65	0.73	0.69	0.75*	0.69	0.84	0.82*	0.71	0.72	0.75	0.78
Other Condiments	0.66*	0.72	0.69	0.67	0.66	0.78	0.75*	0.62	0.77*	0.85	0.80	0.67	0.70	0.76	0.75	0.67
Other Dairy	0.67	0.72	0.65	0.71*	0.66	0.70	0.67*	0.71	0.77*	0.72*	0.63	0.80	0.64	0.74*	0.61	0.71

Other Dried Veg.	0.55	0.70	0.69	0.71	0.61	0.69	0.65	0.78*	0.71*	0.69	0.78	0.82*	0.66	0.69	0.63	0.82
Other Fish	0.75*	0.67	0.75	0.78*	0.73	0.69	0.76	0.67	0.79	0.74*	0.80	0.82	0.75	0.70*	0.76*	0.67
Other Fruits	0.82	0.85*	0.73*	0.78	0.82*	0.83	0.73	0.67	0.71	0.87*	0.73	0.71	0.50	0.78	0.65	0.62
Other Groceries	0.77	0.70	0.65	0.69	0.71	0.65	0.63	0.67*	0.73	0.72	0.80	0.69	0.75	0.74	0.75	0.67
Other Meats	0.57	0.65	0.59	0.62	0.61	0.67*	0.59	0.62	0.75	0.70	0.75	0.69	0.59	0.63	0.57	0.62
Other Non Alcoholic	0.66	0.74	0.63	0.82*	0.63	0.70*	0.65	0.69	0.70	0.70	0.71	0.76*	0.66	0.70	0.65	0.82*
Other Roots	0.79*	0.67	0.75	0.67	0.75*	0.85*	0.86*	0.80	0.79	0.76	0.55	0.82	0.54	0.69	0.67	0.67
Panela	0.63	0.69	0.63	0.62	0.66	0.76	0.73	0.49*	0.61	0.67	0.76*	0.84	0.54	0.59	0.65	0.49
Pasta	0.63	0.74	0.65	0.62	0.59	0.61	0.69	0.67	0.59	0.69	0.88*	0.69	0.61	0.65	0.78*	0.62
Peas	0.91	0.90	0.84	0.50	0.66	0.74	0.78*	0.84*	0.75	0.72*	0.78*	0.80	0.66	0.78*	0.76*	0.73*
Plantain	0.63	0.81*	0.75	0.73*	0.63	0.76	0.78	0.64	0.70	0.81	0.86	0.73	0.61	0.80*	0.76*	0.67
Pork	0.66	0.65	0.80*	0.80	0.75	0.83	0.86	0.73	0.86*	0.69	0.84	0.76	0.64	0.69	0.63*	0.67
Potato	0.68	0.78*	0.94*	0.80	0.48	0.63	0.78	0.53	0.61	0.80	0.94*	0.80	0.43	0.59	0.75	0.62
Restaurant Meals	0.79	0.76	0.73	0.56	0.80*	0.74	0.80	0.51	0.71*	0.78	0.80*	0.60	0.66	0.72	0.75	0.53
Rice	0.63	0.81*	0.73	0.78	0.48	0.67	0.76	0.62	0.61	0.63	0.63	0.78	0.55	0.70	0.65	0.56
Salt	0.68*	0.74*	0.75	0.64	0.71	0.70	0.67	0.62	0.70	0.69	0.78	0.69	0.70	0.70	0.75	0.64
Soft Drinks	0.68*	0.69*	0.67	0.69*	0.66	0.74*	0.57*	0.76	0.73	0.69	0.71	0.73	0.68*	0.67*	0.67	0.69*
Soups and Creams	0.63	0.78	0.73	0.73	0.63	0.72	0.69	0.69	0.77	0.80	0.75	0.67*	0.73*	0.76	0.75	0.71
Sugar	0.64	0.80*	0.86	0.71	0.59	0.76	0.78*	0.58	0.50	0.70	0.76*	0.73	0.56	0.70	0.75	0.60
Tomato	0.75	0.78	0.73	0.78	0.64	0.81*	0.69	0.73	0.79*	0.74	0.75*	0.80*	0.66	0.81	0.73	0.78
Tree Tomato	0.68	0.83*	0.94*	0.69	0.71	0.87	0.92*	0.69	0.73	0.85*	0.86*	0.73*	0.43	0.59	0.80	0.53
Various Jams	0.79	0.81	0.78	0.64	0.82	0.76*	0.75	0.60	0.82*	0.74	0.82*	0.62	0.84	0.76	0.78	0.64
Various Sauces	0.75	0.85*	0.71	0.64	0.71	0.78	0.71	0.69*	0.75*	0.80	0.71	0.71	0.77*	0.72	0.73	0.69
	ARIMA				Holt-Winters				SSA				ETS			
h	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Score	13	16	11	13	11	13	14	5	**29**	**24**	**35**	**39**	5	11	7	8
Sig. Score	2	8	6	3	5	6	5	3	**11**	**10**	**13**	**12**	1	3	1	2
Total Sig. Outcomes	8	**16**	10	10	10	12	13	10	**15**	**16**	**20**	**15**	5	13	11	4
Average DC	0.67	0.74	0.74	0.68	0.66	0.73	0.74	0.66	**0.71**	**0.76**	**0.78**	**0.77**	0.63	0.72	0.72	0.65

* indicates DC predictions are statistically significant based on a t-test at $p = 0.10$.

Finally, we consider SSA, ARIMA, HW and ETS models for forecasting point-by-point food inflation in Colombia. Table 7 reports these results. Looking at the score we can easily observe that the HW model is least favourable for providing point-by-point food inflation forecasts in Colombia as it reports the worst performance and is unable to forecast any of the CPI components accurately over the other models at $h = 1$ and 6 steps ahead. The score also suggests that ETS is the third best model out of the four available options for annual food inflation forecasting in Colombia. As seen with the monthly food inflation forecasting results, both ETS and HW models continue to remain the least favourable for obtaining point-by-point food inflation forecasts as well. In the long run (that is at $h = 6$ and 12 steps ahead), we can see that the SSA model performs best with scores of 40 and 26. For point-by-point food inflation forecasts at 6 and 12 steps ahead, SSA is able to provide the most accurate forecast for 48% and 61% of the food inflation components. However, the lack of statistically significant outcomes at 6 steps ahead suggests this result could be attributable to a chance occurrence. In the short run, we can see that SSA is best for providing point-by-point food inflation forecasts at 1 step ahead with a score of 40 which corresponds to accurately forecasting 74% of the Colombian food inflation components. However, at 3 steps ahead, the optimal ARIMA model is best in this case with a score of 31 which has a corresponding percentage of 57%. Thus we can conclude that the SSA model is best for providing point-by-point food inflation forecasts for Colombia in the very short run and the long run whilst the ARIMA model should be used if we are interested in obtaining 3 step ahead point-by-point food inflation forecasts. As seen earlier, a majority of the time series is non-stationary in the case of point-by-point food inflation in Colombia. We find, as expected, that the SSA technique is able to provide the most accurate forecast for the non-stationary time series at the different horizons in comparison to the optimal ARIMA model, ETS and HW. As before, we use the modified Dieblod-Mariano test in Harvey et al. (1997) to test the best outcomes for statistical significance. We find that once again (as experienced with the food CPI forecasts) majority of the forecasting results do not have a statistically significant variation in comparison to all three competing models. Whilst this method of testing for the best outcome whereby it is only indicated as statistically significant if the outcome from a particular model is found to be statistically significant in comparison to all three other models is rigorous, we noticed that at monthly inflation forecasting the results were more stable and significant in comparison to this scenario. It is noteworthy that both HW and ETS models were unable to report a single statistically significant best outcome (where applicable) at point-by-point food inflation forecasting in Colombia.

The DC results for point-by-point inflation forecasts are presented in Table 8. From the DC results it is clear that SSA provides the best DC predictions at horizons of $h = 1$ and $h = 12$ steps ahead. Furthermore, at $h = 12$ steps ahead, SSA provides a DC score of 81% with a majority of statistically significant outcomes. At $h = 3$ and 6 steps ahead, ARIMA is able to provide the best DC prediction in terms of the percentage.

Table 7: RMSE for out-of-sample point-by-point Colombian food inflation forecasts.

	ARIMA				Holt-Winters				SSA				ETS			
Series	1	3	6	12	1	3	6	12	1	3	6	12	1	3	6	12
Bananas	2.17	**3.48**	**3.90**	**7.12**	3.20	4.91	5.43	9.14	**2.07**	4.49	6.53	10.3	2.29	3.50	3.94	7.46
Beef	1.25	2.82	5.60	8.35	2.23	4.00	6.30	10.6	**1.01**‡	**2.78**	**3.97**	**3.71**	1.30	2.81	5.67	7.74
Bread	1.31	**1.91**	**2.98**	2.68	1.50	2.27	3.39	**1.40**	**1.30**	2.84	3.90	4.21	1.34	2.17	3.49	1.82
Burger in Bun	0.72	**1.06**	0.90	1.02	0.75	1.35	1.30	1.15	0.72	**1.06**	1.19	1.32	**0.71**	**1.06**	**0.83**	**0.82**
Canned Vegetables	0.57	**0.74**	0.83	1.04	0.80	1.10	1.25	1.61	**0.50**	0.86	**0.77**	**0.78**	0.61	0.77	1.11	1.59
Canteen Drinks	0.39	0.60	0.84	1.10	0.50	0.70	1.02	0.81	**0.30**	**0.58**	**0.81**	1.00	0.36	0.53	0.69	**0.70**
Carrots	20.6	**29.8**	**29.6**	**34.7**	27.0	42.2	46.7	72.8	**19.1**	38.4	36.1	35.0	26.8	39.0	41.4	63.2
Cassava	2.76	**5.37**	**8.75**	**7.69**‡	6.93	15.1	23.7	51.6	**2.61**	6.10	11.0	13.5	2.96	6.22	10.6	16.6
Cereals	1.30	**1.64**	1.87	2.31	1.54	2.16	2.54	2.89	**1.08**	1.78	**1.59**	**2.27**	1.27	1.79	2.30	3.20
Cheese	1.29	**1.75**	**1.80**	**2.18**	2.02	2.97	1.64	4.04	**1.19**	2.19	2.40	2.39	1.35	2.01	1.85	3.18
Chicken	1.24	2.55	3.94	5.59	1.82	3.24	4.87	6.14	**1.06**	**2.52**	**3.59**	**4.13**‡	1.45	2.63	4.02	5.61
Chocolate	**1.03**	**1.48**‡	**1.61**	**2.14**	2.03	3.41	4.62	6.88	1.11	1.74	2.92	4.06	1.10	1.82	2.49	4.38
Coffee	1.30	**2.50**	4.40	4.56	3.38	5.92	7.17	8.26	**1.21**	3.00	**3.78**	**3.09**‡	1.28	2.64	5.87	10.6
Cold Fast Food	**0.64**	**0.88**	**1.04**	1.42	0.80	1.11	1.46	1.93	0.69	1.00	1.15	**1.28**‡	0.66	0.89	1.09	1.42
Eggs	2.87	**3.88**	**5.47**	6.71	3.55	4.84	6.78	9.44	**2.84**	5.71	6.00	**5.86**	3.07	4.32	6.40	7.88
Fats	1.86	**2.31**	**2.89**	5.60	1.79	2.71	2.98	7.54	**1.52**	2.94	5.22	**4.68**	1.94	2.50	3.31	5.42
Fish	0.72	1.29	2.12	4.51	1.16	1.99	3.25	5.59	**0.57**‡	1.26	2.44	**3.75**	0.73	**1.23**	**1.97**	4.22
Flour	0.95	**2.10**	2.92	4.73	1.61	3.21	4.83	6.35	**0.88**	2.52	**2.72**	**2.22**	0.99	2.32	3.96	3.49
Fresh Vegetables	**11.9**	16.1	17.9	18.2	14.8	20.1	24.7	22.6	12.3	**15.6**	**14.8**	**16.0**	13.0	17.5	21.7	20.5
Hot Fast Food	0.54	0.82	0.97	0.86	0.60	0.92	0.88	0.65	**0.53**	0.88	0.88	0.97	0.55	**0.78**	**0.84**	**0.58**
Juices	0.57	1.08	1.61	2.53	1.23	2.48	2.72	4.27	**0.48**	**0.89**	**1.24**	**1.56**	0.57	**0.89**	1.27	2.46
Kidney Beans	**1.64**	**3.68**	4.46	5.14	3.24	5.53	8.79	7.40	1.90	3.96	**4.40**	**4.19**	2.02	5.10	7.91	13.6
Milk	0.67	**1.22**	1.69	2.66	1.30	1.96	2.52	2.10	**0.63**	1.43	1.86	2.47	0.73	1.35	**1.47**	**1.71**
Mulberry	8.26	**10.26**	12.8	13.6	12.0	14.0	14.0	16.7	**8.01**	11.80	**11.2**	**11.5**	9.97	13.4	13.1	16.2
Oils	1.55	3.27	**3.46**	**4.84**	2.17	4.31	7.73	16.8	3.77	3.77	7.21	9.64	**1.40**	**2.94**	3.87	7.47
Onion	**12.6**	**17.4**	27.0	24.7	20.4	33.8	48.6	60.5	12.8	17.6	**20.1**	**16.6**‡	14.4	25.7	51.2	40.8
Oranges	**8.09**	**17.3**	**24.0**	**27.9**	14.1	24.1	36.0	53.0	9.07	25.2	29.1	31.1	10.7	26.2	43.8	74.6
Other Bakery	0.96	1.09	1.63	1.71	1.27	1.89	2.31	2.18	**0.80**	1.14	**1.21**	**1.31**	0.84	**1.06**	1.58	1.61
Other Cereals	1.11	**2.44**	3.81	6.30	2.69	7.51	14.2	24.0	**0.98**	2.55	**3.59**	**4.96**	1.30	2.89	4.32	6.62
Other Condiments	0.73	0.94	1.11	1.22	0.94	1.41	2.09	2.01	**0.60**	1.02	1.11	**0.73**	0.69	**0.85**	**1.03**	1.55
Other Dairy	0.92	1.69	2.54	4.21	1.43	1.96	2.73	4.74	**0.63**	1.40	2.33	**3.55**	0.77	**1.28**	**2.12**	4.36

Other Dried Veg.	3.05	5.97	**5.41**	7.98	4.03	9.70	17.1	34.4	**2.84**	**5.31**	7.79	7.35	3.36	5.99	5.56	**5.18**
Other Fish	1.67	1.76	1.74	2.64	1.60	1.97	1.99	2.55	**1.19**‡	**1.38**	1.64	**1.31**‡	1.49	1.59	**1.63**	2.46
Other Fruits	5.76	11.7	13.9	15.9	6.67	**11.0**	18.1	39.7	**5.68**	12.8	**13.2**	**11.43**	6.62	14.1	19.2	25.0
Other Groceries	0.90	**1.43**	2.11	2.54	1.29	2.13	3.23	3.16	**0.79**	1.44	**1.84**	**1.42**	0.91	1.45	2.10	2.58
Other Meats	1.15	1.65	2.13	2.31	1.41	1.96	2.38	4.07	**1.07**	1.78	**1.99**	**2.01**	1.11	**1.50**	1.94	2.91
Other Non Alcoholic	1.46	**2.40**	**3.18**	3.38	1.88	3.06	4.46	5.36	**1.31**	2.65	3.26	**3.05**	1.76	3.29	5.01	5.55
Other Roots	6.13	**11.4**	18.4	22.7	7.76	14.1	23.1	44.9	**5.56**	13.1	**18.3**	**15.5**	6.36	12.6	22.3	47.5
Panela	1.85	**2.79**	**3.86**	**4.90**	2.52	4.33	7.95	11.6	**1.66**	3.88	8.02	10.6	1.93	3.25	6.36	10.2
Pasta	**1.45**	**2.92**	**4.38**‡	**3.40**	2.84	3.80	7.55	14.4	1.56	4.35	6.13	6.28	1.66	3.84	5.85	8.33
Peas	9.62	14.9	16.2	15.0	23.6	28.9	25.7	22.6	**9.26**	**14.4**	**14.0**	**14.5**	14.9	21.8	22.4	22.9
Plantain	3.08	**5.79**	7.22	7.38	6.32	11.3	13.8	17.7	**3.02**	6.53	**7.04**	**7.29**	3.66	6.48	8.47	8.37
Pork	1.68	**2.23**‡	**3.47**	**2.63**	2.02	3.50	6.94	13.3	**1.53**	3.43	4.90	5.03	1.78	3.04	5.21	6.75
Potato	**10.4**	**18.8**	21.9	27.1	16.5	32.5	51.8	79.0	10.8	20.3	**18.8**	**19.6**	13.1	31.0	51.2	72.0
Restaurant Meals	0.52	**0.68**	**0.83**	**1.14**	0.40	0.59	0.83	1.13	**0.35**	0.78	1.15	1.45	0.52	0.67	0.83	1.14
Rice	**4.91**	11.6	**18.6**	11.6	6.61	14.5	20.7	35.2	7.84	17.4	37.6	46.6	6.23	**11.1**	19.5	**9.83**
Salt	1.16	1.83	2.99	3.57	1.49	2.33	3.16	4.06	**1.06**	1.84	2.53	**3.56**	1.14	**1.77**	**2.42**	3.60
Soft Drinks	1.20	2.55	3.10	5.07	1.78	3.19	4.22	5.98	**1.00**	**2.14**	**2.18**	**2.09**	1.33	2.60	3.16	5.16
Soups and Creams	1.12	1.63	2.41	**1.10**	1.21	2.23	3.40	4.23	**1.08**	**1.54**	**1.89**	1.21	1.16	1.75	2.52	1.10
Sugar	**2.04**	**3.79**	**4.47**	**6.66**	3.95	10.4	20.5	39.4	2.18	6.30	8.42	7.46	2.25	4.86	4.84	10.2
Tomato	**18.7**	**24.0**	30.4	30.9	29.2	43.0	57.6	60.1	19.5	25.9	**27.0**	**27.3**	22.9	30.9	44.9	52.3
Tree Tomato	7.59	13.7	15.4	21.5	9.19	14.9	20.3	30.8	**7.28**	**12.6**	**13.9**	**13.8**‡	8.29	13.6	17.8	27.2
Various Jams	1.66	**1.76**	2.64	2.76	1.85	2.61	3.21	3.30	**1.46**	2.17	**2.48**	**2.28**	1.59	1.86	2.68	3.02
Various Sauces	**0.87**	1.48	**1.70**	1.68	1.34	2.15	3.22	2.48	0.91	1.74	2.14	2.26	0.93	**1.46**	1.79	**1.66**
	ARIMA				Holt-Winters				SSA				ETS			
h	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Score	12	**32**	20	12	0	1	0	1	**40**	12	**26**	**33**	2	12	8	7
Sig. Score	0	**1**	**1**	1	0	0	0	0	**3**	0	0	**6**	0	0	0	0
Percentage	22%	**57%**	35%	22%	0%	1.85%	0%	1.85%	**74%**	22%	**48%**	**61%**	3.70%	22%	14.8%	13%

‡ indicates a statistically significant difference between the RMSEs of the model with minimum RMSE (shown in Bold) and each of the other models for each respective horizon, using the modified Diebold-Mariano test at $p = 0.10$.

Table 8: DC: out-of-sample point-by-point Colombian food inflation forecasts.

	ARIMA				Holt-Winters				SSA				ETS			
Series	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Bananas	0.64	0.83	0.89	0.77	0.44	0.67	0.69	0.67	0.70	0.75	0.78	0.74*	0.34	0.71*	0.82*	0.72
Beef	0.68	0.63	0.56	0.46	0.56	0.73*	0.58	0.62*	0.76*	0.65	0.78*	0.82	0.64*	0.75	0.69	0.62
Bread	0.50	0.73	0.71	0.77	0.32	0.78*	0.73	0.77	0.70	0.44	0.40	0.74	0.50	0.73	0.62	0.72
Burger in Bun	0.60	0.60	0.71	0.74*	0.56	0.54	0.69	0.69	0.66	0.58*	0.64	0.64	0.58	0.56	0.49	0.74
Canned Vegetables	0.56	0.83	0.80	0.69	0.36	0.56	0.62	0.77	0.66*	0.71	0.71	0.85	0.60	0.85	0.71	0.67
Canteen Drinks	0.48	0.65	0.62	0.64	0.62	0.60*	0.58	0.72*	0.74	0.73	0.49*	0.46	0.42	0.69	0.67	0.82*
Carrots	0.74	0.79	0.82*	0.95*	0.52	0.69	0.64	0.77	0.72	0.81	0.76	0.90	0.30	0.69	0.73	0.72
Cassava	0.76*	0.81	0.93*	0.97*	0.58	0.75*	0.71*	0.56	0.76	0.75	0.80	0.85	0.68	0.79	0.71	0.87*
Cereals	0.66	0.63	0.76	0.85*	0.54	0.60	0.62	0.77	0.74	0.77	0.78*	0.79	0.44	0.60	0.64	0.67
Cheese	0.52	0.67	0.82*	0.85*	0.52	0.58	0.64	0.56	0.60	0.64*	0.76	0.92	0.50	0.65	0.64	0.79
Chicken	0.74	0.79	0.73	0.67	0.40	0.54	0.69	0.72*	0.70	0.73	0.87*	0.82*	0.28	0.67	0.78	0.72
Chocolate	0.50	0.81	0.82	1.00*	0.48	0.67	0.64	0.64	0.68*	0.60	0.82*	0.87	0.56*	0.79	0.82*	1.00*
Coffee	0.70	0.77	0.80	0.74*	0.48	0.56	0.58	0.77	0.68	0.79	0.80	0.82	0.68	0.77*	0.80	0.69
Cold Fast Food	0.58	0.60	0.71*	0.69	0.40	0.54	0.51	0.62	0.58	0.63	0.67	0.72	0.48	0.56	0.67	0.69
Eggs	0.68	0.85*	0.93*	0.64	0.44	0.67	0.69*	0.59	0.66	0.69*	0.73	0.74*	0.36*	0.75	0.73	0.54
Fats	0.56	0.65	0.73	0.56	0.74	0.85	0.87*	0.69*	0.72	0.67	0.69	0.87*	0.62	0.81*	0.87*	0.69*
Fish	0.60*	0.81*	0.87	0.59	0.50	0.69	0.64	0.49	0.72*	0.77*	0.76	0.64	0.42*	0.71	0.73	0.64
Flour	0.80	0.77	0.84*	1.00*	0.54	0.67	0.71	0.79*	0.64*	0.63	0.87*	0.97*	0.74	0.75	0.80*	1.00*
Fresh Vegetables	0.62	0.71	0.78	0.85	0.50	0.67	0.73*	0.74	0.68	0.69	0.82	0.95	0.46	0.67	0.69	0.79*
Hot Fast Food	0.56	0.63	0.67	0.82	0.54	0.65	0.76	0.77	0.70	0.65*	0.56	0.64	0.48	0.63*	0.71	0.85
Juices	0.58	0.65	0.80*	0.56*	0.50	0.54	0.53	0.56	0.78	0.60	0.71	0.90*	0.56	0.73*	0.82*	0.77*
Kidney Beans	0.78	0.77	0.84*	0.87*	0.54	0.69	0.73*	0.72*	0.78	0.90*	0.91	0.90	0.74*	0.71*	0.80	0.82*
Milk	0.64	0.77*	0.71	0.82*	0.46	0.63	0.71	0.82	0.72	0.60	0.76	0.79*	0.26	0.71	0.78	0.90
Mulberry	0.64	0.79	0.71	0.85*	0.54	0.71*	0.69*	0.72	0.68	0.77*	0.73	0.85*	0.44	0.77	0.71	0.72
Oils	0.66	0.79	0.80	0.77	0.66*	0.75	0.82*	0.82*	0.76	0.73	0.73	0.67	0.76*	0.81*	0.80	0.59
Onion	0.72	0.85	0.91*	0.95	0.48	0.67	0.67	0.79	0.80*	0.85*	0.93*	0.97*	0.72	0.85*	0.73	0.92
Oranges	0.72	0.77*	0.73	0.72	0.40	0.54	0.49	0.54	0.62	0.50	0.64	0.90*	0.38*	0.63	0.51	0.67
Other Bakery	0.42	0.69	0.64	0.90*	0.40	0.67	0.62	0.77*	0.68	0.71	0.82*	0.90	0.50	0.71	0.71	0.87
Other Cereals	0.64	0.71	0.71	0.67	0.60	0.65	0.73*	0.56	0.70	0.63	0.60	0.82	0.74*	0.81	0.84*	0.74
Other Condiments	0.54	0.63	0.82*	0.77	0.50	0.58*	0.53	0.46	0.76	0.67*	0.67	0.79	0.42	0.65	0.76	0.77*
Other Dairy	0.34	0.67*	0.64*	0.62*	0.42	0.56	0.60	0.54	0.72*	0.65	0.64*	0.77*	0.30	0.73	0.64	0.46

Other Dried Veg.	0.50	0.79	1.00*	0.87*	0.54	0.69	0.60	0.38	0.60	0.79*	0.80	0.54	0.50	0.81*	0.98*	0.90*
Other Fish	0.42	0.58	0.64	0.64	0.54	0.60*	0.62	0.64	0.66	0.67	0.64	0.90*	0.60	0.71	0.69	0.72
Other Fruits	0.66	0.73	0.76	0.90*	0.70	0.85*	0.73*	0.74	0.62	0.73	0.80*	0.95*	0.38	0.73	0.73	0.69
Other Groceries	0.58	0.75	0.64	0.69	0.42	0.50	0.56*	0.56	0.42	0.63*	0.62*	0.64*	0.66	0.63	0.76	0.97
Other Meats	0.54	0.63	0.60	0.59	0.54	0.63	0.60	0.62	0.62	0.67	0.62	0.77*	0.50	0.73	0.76	0.62
Other Non Alcoholic	0.68	0.73*	0.82*	0.87*	0.46	0.65	0.73*	0.72	0.74	0.77	0.71	0.77	0.44	0.71	0.64	0.64
Other Roots	0.74	0.88*	0.84	0.87	0.56	0.65*	0.67	0.62	0.70	0.81*	0.87*	0.90*	0.54	0.71	0.73	0.64
Panela	0.68	0.83*	0.69	0.82	0.58	0.79	0.76	0.82*	0.80	0.54	0.64	0.85*	0.74	0.88	0.80	0.74
Pasta	0.76	0.73	0.80*	0.90*	0.42	0.56	0.64	0.62	0.72	0.69	0.73	0.56	0.70	0.73	0.76*	0.77
Peas	0.80*	0.88	0.71	0.79	0.50	0.67	0.62	0.79*	0.82*	0.83*	0.80	0.85*	0.28	0.69	0.62	0.72
Plantain	0.74	0.73	0.82	0.79*	0.44	0.54	0.73	0.54	0.72	0.71	0.84*	0.82*	0.38	0.67	0.62	0.74
Pork	0.64	0.77*	0.87	0.90*	0.54	0.73*	0.89*	0.77	0.72	0.63	0.69	0.77*	0.52	0.71*	0.91*	0.82*
Potato	0.74	0.79	0.84*	0.77	0.48	0.77	0.73	0.49	0.66	0.75	0.91*	0.95	0.66	0.75	0.71	0.49
Restaurant Meals	0.40	0.58	0.69	0.87	0.50	0.71	0.87*	0.64	0.72	0.60	0.76	0.87*	0.28*	0.60	0.67	0.90
Rice	0.74	0.79	0.80*	0.87*	0.58	0.69	0.78	0.74*	0.78	0.75	0.31	0.90	0.74*	0.81	0.76	0.79
Salt	0.58	0.75*	0.71	0.79	0.46	0.60	0.58	0.67*	0.52	0.67	0.73	0.82*	0.52	0.65	0.64	0.79
Soft Drinks	0.68	0.65	0.82	0.72	0.42	0.52	0.71	0.64	0.70	0.73	0.87*	0.92*	0.30	0.60	0.76*	0.69
Soups and Creams	0.54	0.65*	0.73	0.85	0.52	0.50	0.53	0.69	0.60	0.73	0.71	0.79	0.44	0.65	0.71	0.79
Sugar	0.72*	0.77	0.89*	0.79	0.60	0.60	0.58*	0.41	0.74	0.69	0.78	0.85*	0.74	0.77*	0.91*	0.69
Tomato	0.72	0.83	0.78	0.87*	0.50	0.60	0.56	0.69	0.70	0.83*	0.87*	0.90	0.40	0.73	0.60	0.77
Tree Tomato	0.64*	0.71	0.82*	0.74*	0.50	0.56	0.62	0.59	0.70	0.81*	0.84	0.95*	0.44	0.71	0.73	0.69
Various Jams	0.50	0.79	0.64	0.67	0.52	0.69*	0.71*	0.67	0.64	0.71	0.80*	0.87*	0.56	0.71	0.62	0.72
Various Sauces	0.64	0.63	0.91*	0.74	0.62	0.67*	0.78*	0.77	0.68	0.65	0.71	0.49	0.46	0.73	0.78	0.77
	ARIMA				Holt-Winters				SSA				ETS			
h	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*	*1*	*3*	*6*	*12*
Score	15	**25**	20	14	2	6	5	3	**38**	15	**22**	**34**	4	15	14	11
Sig. Score	1	**7**	12	11	1	3	3	1	**7**	6	**15**	**20**	2	5	6	4
Total Sig. Outcomes	5	11	**19**	23	1	12	16	12	8	**15**	17	**26**	**10**	11	11	12
Average DC	0.63	**0.73**	**0.77**	0.78	0.52	0.64	0.67	0.66	**0.69**	0.70	0.73	**0.81**	0.51	0.72	0.73	0.73

* indicates DC predictions are statistically significant based on a t-test at $p = 0.10$.

As the subspace-based method of SSA was found to be most appropriate for monthly food inflation forecasting, it is important to point out other benefits of such an approach. As an example in Figure 4 we have considered the monthly inflation for Tree Tomatoes. The actual monthly inflation figure for Tree Tomato (shown in black) looks somewhat chaotic to the naked eye. However, SSA based decomposition enables practitioners to extract the 12 month seasonal variation in Tree Tomato inflation (shown in red) which is otherwise masked. Having extracted this signal SSA also enables practitioners to forecast the extracted signal on its own in order to predict the future seasonal variation in Tree Tomato inflation.

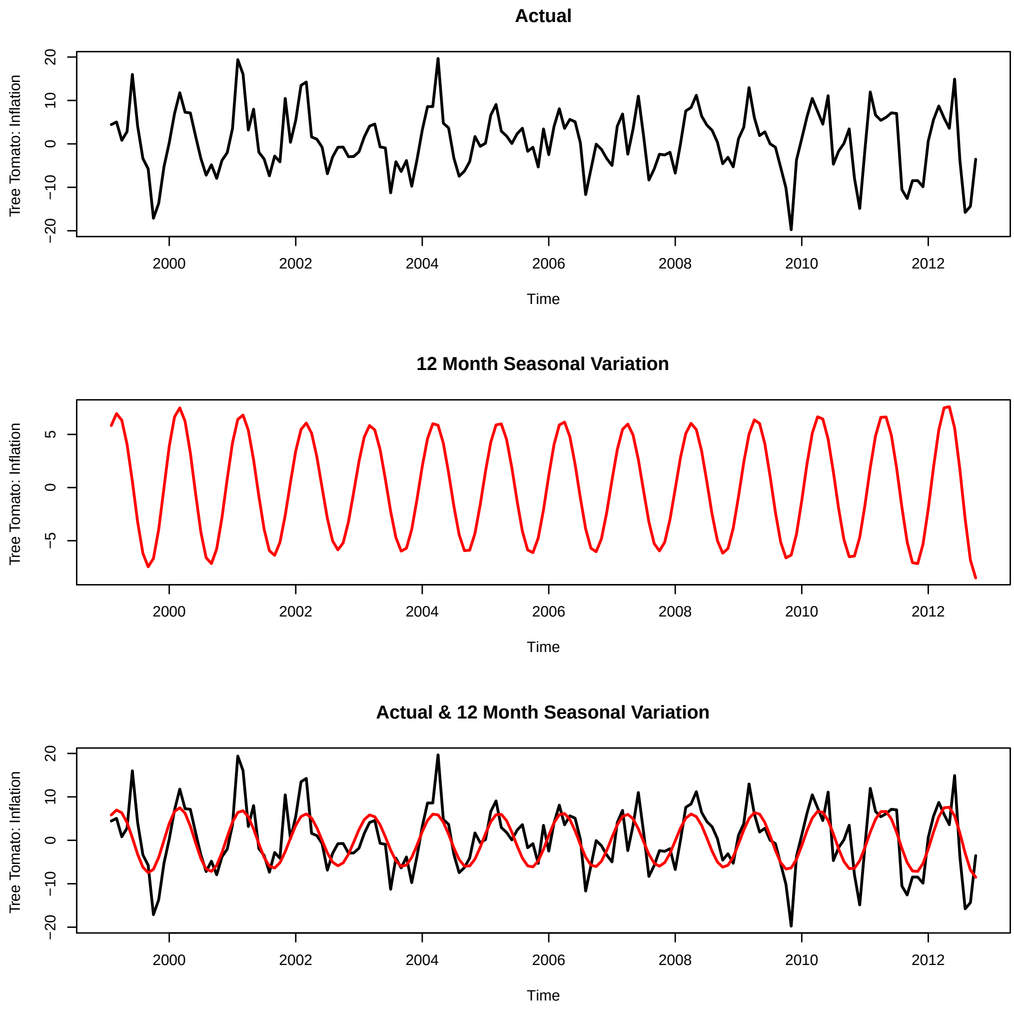

Figure 4: Signal extraction with SSA.

5 Conclusion

This paper begins with the objective of determining whether econometric or subspace-based forecasts are best for predicting inflation via an application which considers forecasting the Colombian food CPI, followed by monthly and annual food inflation. The econometric models are represented via the popular forecasting techniques of ARIMA, HW, and ETS whilst SSA is used to represent subspace based methods. In addition these models also cover both parametric and nonparametric forecasting techniques.

The results show ARIMA and ETS models to be best for forecasting the Colombian food CPI based on the lowest RMSE. However, the differences in the forecasting accuracies are not statistically significant in a majority of the cases. The DC predictions in this case are more reliable and indicates that on average, ARIMA provides the best DC predictions for the Colombian food CPI. Yet, the DC results reported for the SSA model are also over 70% on average. Based on the RMSE and the best outcomes it is pertinent to conclude that majority of the forecasting accuracies reported for the index are chance occurrences, and therefore there exists no real difference between these four models at forecasting the food CPI in Colombia.

Next, we evaluate forecasting monthly food inflation and find that the optimal ARIMA model, ETS and HW models are easily outperformed by the basic Vector SSA model at all horizons. Interestingly, in this case, the SSA model also provides the best DC predictions at all horizons with a majority of statistically significant outcomes. Finally, we evaluate the performance of the models at providing annual food inflation forecasts for Colombia. The results suggest that the basic Vector SSA model is best in the very short run ($h = 1$ step ahead) and the long run ($h = 6$ and 12 steps ahead) whilst the optimal ARIMA model is found to be best for providing point-by-point food inflation forecasts at $h = 3$ steps ahead. The DC results are consistent with the RMSE results obtained by SSA and ARIMA at the respective horizons. This paper also finds that ETS and HW models are the least favourable for forecasting monthly or point-by-point food inflation in Colombia.

The findings also show the importance of considering different frequencies when evaluating for an appropriate forecasting model for any variable of interest. This is because a model that produces the most accurate forecasts at a particular frequency for a given variable will not necessarily produce accurate forecasts for that same variable at a different frequency. This paper has shown that in terms of food inflation forecasting, when the frequency of interest is monthly, then subspace-based methods such as SSA which can filter noise and extract signals are likely to perform better than both classical and relatively new econometric techniques. At the same time, the findings are clear that when dealing with annual food inflation forecasting, classical econometric techniques can provide a more accurate outlook than subspace-based methods.

In general, this study provides policy makers with options to select the most suitable forecasting technique based on their requirement of either maintaining the lowest forecast error and highest direction of change, or a combination of both. An overall analysis of the results indicate that should the Colombian Central Bank be interested in using a sole model for forecasting the food index, monthly and point-by-point inflation, then the SSA model can perform this task relatively well in comparison to the other models. This is because, firstly, for monthly inflation forecasting SSA is optimal and is also the only model which is able to provide the best score at all horizons in at least one of the given scenarios. Secondly, for food CPI forecasting the results strongly suggest there is no actual difference between these forecasting models. Given that the SSA technique is known for its ability to handle both stationary and non-stationary time series, the SSA model is more reliable. Furthermore, on average, across all horizons, the SSA model can provide a DC prediction of over 75% for the Colombian food CPI. Thirdly, for point-by-point inflation forecasting, the SSA model is already best at $h = 1$ and 12 steps ahead. Even though ARIMA outperforms SSA at horizons of 3 and 6 steps ahead, a closer look at the results and comparing them with those obtained at $h = 1$ and 12 steps ahead indicates that the results for ARIMA are more likely to be chance occurrences due to the low number of statistically significant outcomes recorded within the best outcomes. Furthermore, if we are to consider the average DC across all horizons for point-by-point inflation forecasting, SSA is able to outperform ARIMA marginally.

This study opens up further research avenues in the field of food inflation forecasting and the results indicate strongly that the Colombian authorities could greatly benefit by considering the use of a multivariate SSA model for obtaining monthly and annual forecasts of food inflation in the future. Furthermore, it would be interesting to evaluate the performance of the basic Recurrent SSA model and compare it against the results obtained herewith. Finally, the findings here indicate that future research should consider evaluating the forecasting accuracy of a hybrid model combining ARIMA and SSA as ARIMA was found to be the only model which could present some form of competition to SSA at monthly and point-by-point inflation forecasting. The results from this study will be of great significance to the Colombian Central Bank and other government statistical agencies around the world, especially developing nations where food inflation continues to remain a key aspect, in addition to the attention it will receive from academics and researchers globally.

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