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Does Using Disaggregate Components Help in Producing Better Forecasts for Aggregate Inflation?

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Abstract

This paper analyzes how the information contained in the disaggregate components of aggregate inflation helps improve the forecasts of the aggregate series. Direct univariate forecasting of the aggregate inflation data by an autoregressive (AR) model is used as the benchmark with which all autoregressive (AR), moving average (MA) and vector autoregressive (VAR) models of the disaggregates are compared. The results show that directly forecasting the aggregate series from the benchmark model is generally superior to aggregating forecasts from the disaggregate components. Additionally, including information from the disaggregates in the aggregate model rather than aggregating forecasts from the disaggregates performs best in all forecast horizons when appropriate disaggregates are used. The implication of these results is that better inflation forecasts for Ghana are produce by using information from relevant disaggregates in the aggregate model rather than direct forecasts of the aggregate or aggregating forecasts from the disaggregates.

Keywords: Forecasts, Inflation

JEL Classification: C53, E31

1. Introduction

Central banks all over the world are charged with the responsibility of maintaining low and stable prices in their countries.

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To achieve their goals, the central banks adopt monetary policy frameworks that they believe address local inflation problems. Many of these central banks adopt inflation targeting as their monetary policy framework, which makes accurate inflation forecasts indispensable. Apart from the use of inflation forecasts by central banks and other macroeconomic policy authorities, consumers, businesses, and other policy oriented institutions need inflation forecasts for planning purposes. Additionally, other macroeconomic policies depends, to a great extend, on inflation forecasts. The standard practice, in the literature, is that inflation is calculated for sectors and other disaggregate components but forecasting in many cases has been performed using the aggregate series.

A recent question arising in the literature is whether aggregate inflation forecasts can be improved by using information from the subcomponents. In attempts to answer this question, literature has developed on the use of information from sectoral disaggregates of inflation series (seeAron and Mueller(2008), de Dois Tenaet al.(2010), and Hendry and Hubrisch(2005)). These studies, however, concentrate on disaggregation by product sectors. The concentration of the studies on product categories and the neglect of spatial categories like regions and rural – urban classifications perhaps are based on the implicit assumption of the Law of One Price, which assumes that product markets are efficient. While these assumptions may hold true for the developed economies, spatial heterogeneity in price developments may be significant in developing and emerging market economies where information is asymmetric due to poor road and telecommunication infrastructure.

Although theoretical literature is clear on the conditions under which forecasting aggregate series from the sub-components will outperform the direct forecasting of the aggregate series, empirical studies have reached mixed conclusions. This study extends the previous studies by considering disaggregation across regions, rural – urban as well as product groups and applies the test to data from a developing economy, Ghana. Although previous studies have aggregated forecasts from the disaggregates, this study tests whether including the disaggregates in the aggregate model improves forecasts of the aggregate series. Also, the study investigates which form of disaggregation makes a more significant difference to the aggregate forecast and tests whether pooling forecast from both dimensions can make improve aggregate forecasts.

Apart from using the rural – urban and regional forecasts to compare forecast improvements or otherwise of the series, forecasts of the components are important for regional and business planning.

The rest of the paper is structured as follows; section 2 reviews of the existing literature on the subject. Section 3 discusses the methodologies used in the analysis of the data while section 4 discusses the empirical results. Section 5 states the conclusions and recommendations.

2. Literature Review

The issue of whether micro models explain and/or forecast macro/aggregate series better started with Theil(1954) and expanded later by Grunfeld and Griliches(1960). Series of studies have been done after these pioneering works, which identify three alternatives to using the disaggregate components to improve on the direct forecasts of aggregate series. One approach is to model the subcomponents independently and aggregate the forecast from the independent models based on a weighting scheme. A second approach is to model the subcomponents jointly in a vector autoregression (VAR) and the forecasts of the subcomponents from the VAR are aggregated into an aggregate forecast. A third approach is to use the disaggregate components in the aggregate model and forecast the aggregate directly.

Grunfeld and Griliches(1960)show, by comparing R^2 from OLS regression from aggregate variable and composite R^2 calculated from R^2's of OLS regressions of individual components, that there is no gain in explaining an aggregate variable by aggregating the results of the components. A formal test for Grunfeld and Griliches(1960) procedure for discriminating between the composite model and the aggregate model stated in Pesaran et al.(1989) as choosing the micro models approach if the hypothesis $H_0: e_c'e_c < e_a'e_a$ holds, where $e_c'e_c$ is the composite sum of square error computed from the micro models and $e_a'e_a$ is the sum of square error from the aggregate model. Grunfeld and Griliches(1960)therefore conclude that if the data generating process at the micro level in not known, it is better to forecast the aggregate series directly. Building on this, Pesaranet al.(1989) note that Grunfeld and Griliches(1960) procedure suffers from finite sample bias and develops a choice criterion, and a test of perfect aggregation, for discriminating between aggregate and disaggregate models.

Pesaranet al.(1989)test corrects for the finite sample bias and account for the contemporaneous correlation among the micro models. This test is further generalized by van Garderen et al.(2000) for application in non-linear models.

Pesaranet al.(1989)'s application of their tests to employment functions for the UK economy disaggregated by 40 industries and the manufacturing sector disaggregated by 23 industries find that the disaggregated model fits better than the aggregate model for the whole economy but not for the manufacturing sector. They however interpret the performance of the aggregate model in the case of the manufacturing sector as a misspecification of the aggregate model.

Kohn(1982)andLutkepohl(1984) consider the problem in time series forecasting setting and give a set of conditions under which a linear combination of the components of an aggregate series can forecast the aggregate series from its past. According to these studies, if x_t is a $k-$dimensional (i.e. k components of an aggregate series) stationary process with $y_t = dx_t$ (the aggregate series) where $d = (d_1, d_2 \ldots d_k)$ is a $k-$dimensional vector of weight, let F be an $m \times k$ matrix with rank m and the first row of the $k-$dimensional d, y_t is also stationary and both x_t and $y_t$have MA representations $x_t = \Psi(B)v_t$ and $y_t = \Phi(B)u_t$ respectively where v_t is $k-$dimensional and $u_t$$m-$dimensional vector of white noise. The optimal $h-$ step forecasts, as laid out in Lutkepohl(1984), are $x_{t(h)} = \sum_{i=0}^{\infty} \Psi_{h+i} v_{t-i}$ and $y_{t(h)} = \sum_{i=0}^{\infty} \Phi_{h+i} u_{t-i}$ with their mean square forecast errors $\sum_x(h)$ and $\sum_y(h)$ respectively, generally $\sum_x(h) - F\sum_y(h)F'$ is positive definite and zero if and only if $F\Psi(B) = \Phi(B)F$. These conditions mean that generally, pooling forecasts from sub-components of contemporaneously aggregated series outperforms direct forecast of the aggregate series if the data generating process is known. Kohn(1982)further adds that "if x_t is an ARMA process, then so is y_t and has the same AR and MA orders as x_t and if the moving average polynomial of x_t has all its roots on or outside the unit circle, then the same holds for y_t". In a detailed review of the early literature on combining subcomponent forecasts into aggregate forecasts Clemen(1989) concludes that "forecast accuracy can be substantially improved through the combination of multiple individual forecasts". The later literature, however, is mixed on the subject.

As noted by Hendry and Hubrisch(2010) these methods "focus on disaggregate forecasts rather than disaggregate information" and suggest an approach that uses the disaggregate components in the aggregate model.

They find that forecasting aggregates directly using its past information or including disaggregate information in the aggregate model outperforms aggregate forecasts that are derived from aggregating the forecasts from the individual subcomponents. This supports Zellner and Tobias(2000) who find that aggregating forecasts from disaggregates outperforms direct forecast of the aggregate if the aggregate is not included in the disaggregate model. Hendry and Hubrisch(2010)also recommends dimension reduction by first combining the disaggregate variables and then include the aggregate information in the aggregate model. This reduces estimation uncertainty and mean square forecast error.

While the theoretical literature on the issue of forecasting the aggregate directly or through the subcomponents is conclusive that indirectly forecasting the aggregate series from the subcomponents performs better when the data generating process is known, empirical literature is mixed. In an earlier work, Hubrisch(2003) uses both univariate and multivariate linear time series models to forecast euro area inflation by aggregating the forecasts from the sub components and conclude that aggregating forecasts by component does not necessarily help forecast year-on-year inflation twelve months ahead. Hendry and Hubrsch(2005)) later investigate why forecasting the aggregate using information on its disaggregate components improves forecast accuracy of the aggregate forecast of euro area inflation in some situations, but not in others and conclude that more information can help, more so by including macroeconomic variables than disaggregate components.

Hendry and Hubrisch(2005)find that multivariate models provide little costs or benefits compared to direct forecasts but as the forecast horizon increases aggregating forecasts from the disaggregates performs worst. They also find that including the disaggregates in a VAR with the aggregate series improves the forecasts of the aggregate series. The overall conclusion from Hendry and Hubrisch(2005) is that “the theoretical result on predictability that more disaggregate information does help does not find strong support in this forecasting context”.

Using vector equilibrium correction models Aron and Mueller(2008) evaluate the advantages of forecasting South African inflation data by aggregating projections from different sectors and geographical areas and find that inflation forecast can always be improved by aggregating projections from different sectors and geographical areas.

They, however, emphasize that both levels of disaggregation are required in order to obtain a significantly better inflation forecast. Zellner and Tobias(2000)experiments also provide some evidence that improved forecasting results can be obtained by disaggregation. Benalal et al.(2004)using the euro area inflation find that the direct forecast of the aggregate inflation provides better forecasts than indirectly forecasting from the subcomponents for 12- and 18-steps-ahead forecasts, but the results are mixed for shorter horizons forecasts.

Fritzer et al.(2002)compare forecast performance from independent ARIMA models of the aggregate and disaggregates and VAR models for Australian inflation and find that VAR models outperform aggregation of forecasts from the independent ARIMA models for long-term forecasts horizons. For ARIMA models, they find that the indirect approach of aggregating forecasts from the individual ARIMA models is superior to the direct forecasts from the ARIMA model for the aggregate their results are mixed for the forecasts from the VAR.

3. Methodology

This section outlines the methodologies used in this study. The models for forecasting the inflation series are discussed followed by forecast pooling and evaluation methods and a description of the data and their sources. Finally, the approach used to reduce the data into a smaller number of variables is discussed.

3.1 Models

The method used in selecting which model performs best follows Hendry and Hubrisch(2010) in which five different models are used to forecast the US aggregate inflation series and the forecast performances compared using root mean square forecast error. In this paper, I use the following the models from Hendry and Hubrisch(2010).

i. An autoregressive (AR) model of the aggregate inflation series
ii. A moving average (MA) model of the aggregate inflation series
iii. Aggregating forecasts from independent autoregressive (AR) models of all the subcomponents (regions, sectors and rural-urban components) into aggregate forecasts

iv. Aggregating forecasts from independent moving average (MA) models of all the subcomponents (regions, sectors and rural-urban components) into aggregate forecasts

v. Modeling all the subcomponents jointly in a vector autoregression (VAR) and aggregating the individual forecasts from the VAR into an aggregate forecast.

vi. Including the all subcomponents in a vector autoregression (VAR) with the aggregate series and forecasting the aggregate series form the VAR.

3.2 Granger Causality Tests

This section outlines the procedure used in testing whether the information contained in one series helps in forecasting another series based on Granger(1969). As defined by Judge et al.(1988) “a variable y_{1t} is said to be Granger-caused by a variable y_{2t} if the information in the past and present y_{2t} helps to improve the forecasts of y_{1t} variable”. This definition is operationalized in a bivariate vector autoregression p, VAR(p).

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \sum_{j=1}^{p} \begin{pmatrix} \theta_{11j} & \theta_{21j} \\ \theta_{21j} & \theta_{22j} \end{pmatrix} \begin{pmatrix} y_{1t-j} \\ y_{2t-j} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

y_{1t} does not Granger-cause y_{2t} if and only if $\theta_{21j} = 0 \, (j = 1, ..., p)$ and y_{2t} does not Granger-cause y_{1t} if and only if $\theta_{12j} = 0 \, (j = 1, ..., p)$ (Judgeet al.(1988)).

3.3 The AR and MA Model

Forecasting of the aggregate series using autoregressive (AR) model is set as the benchmark with which all the other models are compared. The autoregressive (AR) representation of a stationary time series y_t assumes that the current level of the series y_t is a weighted average of the previous levels and an error. The general form of an autoregression of order p, $AR(p)$, for a univariate variable y_t is

$$F(L)y_t = d + e_t$$

where $F(L) = 1 - f_1 L - f_2 L^2 - ... - f_p L^p$, L is the lag operator and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

The moving average representation, on the other hand, assumes that y_t is a weighted average of the current and previous errors in the series. The general form of an $MA(p)$ is

$$y_t = m + Q(L)e_t$$

where $Q(L) = 1 - q_1 L - q_2 L^2 - ... - q_p L^p$, L is the lag operator and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$

These general forms of the models are applied to the aggregate inflation series and the subcomponents individually and the optimal lags for the final models are selected based on Akaike Information Criterion (AIC).

3.4 The VAR Models

In order to test if including the disaggregates in a model with aggregate or aggregating forecasts from the disaggregates improve the forecasts of the aggregate, many vector autoregressions are run with the aggregate series and the subcomponents. Let x_t be a k- dimensional vector, an unrestricted VAR(p) specification for x_t is of the form

$$A(L)x_t = m + e_t$$

where $A(L)$ is a $k ´ k$ matrix of coefficients, $A(L) = I - A_1L - A_2L^2 - ... - A_pL^p$ and $\varepsilon_t \sim N(0, \Sigma_\varepsilon)$. Different forms of the VARs are estimated with and without the aggregate and the results compared with the benchmark AR model. Optimum lag selection for the VARs is also based on Akaike Information Criterion (AIC). Granger causality tests are also done to determine predictive information content of the disaggregates in the aggregate. Also, in order to determine how the variables enter the models, unit root test are conducted using Augmented Dickey-Fuller tests.

3.5 Forecast Pooling and Evaluation

The aggregate consumer price index (CPI) is a weighted sum of all its subcomponents. Since the forecasts are performed for the inflation series rather than the consumer price index (CPI), the expenditure weights used in aggregating the CPI are not appropriate for aggregating the inflation series. In the following, I derive time-varying weights that are appropriate for aggregating the subcomponent forecasts for comparison with the direct forecast of the aggregate inflation series.

Let y_t be the aggregate price level (CPI), which is a weighted aggregate of two subcomponents x_{1t} and x_{2t} with constant weights a_1 and a_2 respectively. Then

$$y_t = a_1 x_{1t} + a_2 x_{2t}$$

Inflation is percentage change in CPI over time. Define aggregate inflation as $aggr_t = \frac{\dot{y}}{y}$ and the inflation for subcomponent i as $comp_i = \frac{\dot{x}_i}{x_t}$ where $\dot{y} = \frac{dy_t}{dt}$ and $\dot{x}_i = \frac{dx_{it}}{dt}$ therefore

$$\frac{\dot{y}}{y_t} = \frac{a_1 \dot{x}_1 + a_2 \dot{x}_{2t}}{a_1 x_{1t} + a_2 x_{2t}}$$

$$= \frac{\alpha_1 \dot{x}_1}{y_t} + \frac{\alpha_2 \dot{x}_2}{y_t}$$

$$= \frac{\alpha_1 \dot{x}_1}{y_t}\left(\frac{x_{1t}}{x_{1t}}\right) + \frac{\alpha_2 \dot{x}_2}{y_t}\left(\frac{x_{2t}}{x_{2t}}\right)$$

$$\frac{\dot{y}}{y_t} = \alpha_1\left(\frac{x_{1t}}{y_t}\right)\left(\frac{\dot{x}_1}{x_{1t}}\right) + \alpha_2\left(\frac{x_{2t}}{y_t}\right)\left(\frac{\dot{x}_{2t}}{x_{2t}}\right)$$

$$aggr_t = w_{1t}comp_{1t} + w_{2t}comp_{2t}$$

w_{1t} and w_{2t} are time-varying weights that are shares of each component in the aggregate inflation series and are functions of both the aggregate series and the subcomponent CPIs and $comp_{it}$ is inflation calculated from the ith subcomponent. For a CPI of n sectors

$y_t = \sum_{i=1}^{n} \alpha_i x_{it}$ and the aggregate inflation series is

$$aggr_t = \sum_{i=1}^{n} w_{it}comp_{it}$$

In-sample forecasts are aggregated using the weights derived above. Consistent with Hendry and Hubrisch(2010), out-of-sample forecasts are aggregated using the last weights from the sample since the future weights cannot be known at the time of forecast.

Forecast evaluation of the alternative models, that is, pooled forecasts and direct forecasts, is based on the Root Mean Square Forecast Error (RMSFE) defined as;

$$RMSFE = \sqrt{\frac{1}{F}\sum_{t=1}^{F} e_t}$$

where $e_t = y_{t+h} - \hat{y}_{t+h}$, y_{t+h} and $\hat{y}_{t+h}$ are the actual and forecast series respectively and F is the out-of-sample number of observations retained for forecast evaluation. $\hat{y}_{t+h}$ are obtained from recursive estimation of the models. These RMSFEs is used to judge the models' performance where lower RMSFE means better performance.

3.6 Data Sources and Description

Monthly data on Ghanaian Consumer Price Index (CPI) and inflation series are collected from Prices Section of Ghana Statistical Service. The sector classification of the series is done according to the level 1 of United Nation's "Classification of Individual Consumption by Purpose" (CIOCOP). This is a 12-sector classification that is made up of food and non-alcoholic beverages; alcoholic beverages, tobacco and narcotic; clothing and footwear; housing, water, electricity, gas and other; furnishings, household equipment etc.; health; transport; communications; recreation and culture; education; hotels, cafés and restaurants; and miscellaneous goods and services. This sector classification is further grouped into food and nonfood sectors. The series are also classified into rural-urban and by administrative regions of Ghana.

Two regions, Upper East and Upper West, are merged into one for the purpose of the series publications so that we have nine regions instead of ten. The aggregate series is a weighted index of the subcomponents with the sector, regional and rural – urban weights derived from household expenditure patterns recorded in Ghana Living Standard Surveys (GLSS), a household expenditure survey that is conducted every five years in Ghana.

The sample data for the CPI cover the period 1997:9 to 2011:9 for the aggregate series and the subcomponents, which gives 169 data points. The inflation series cover 1998:9 to 2011:9 giving 157 data points for the study. The starting point of the sample necessitated by data availability from Ghana Statistical Service

3.7 Reduction of the Series

Given the relatively short sample with 12 sector and 9 regions, the estimation of VAR of such dimension will suffer from lack of degrees of freedom, so the estimation for the sector series is done using the two-sector classification of food and nonfood series. The estimation for the urban – rural models is also done using the published series. The problem, however, is with the regional series where there are nine regions. This problem is solved by first pooling the series of contiguous regions to have smaller number of variable in the VARs.

We group the regional data into three zones based on contiguity. South zone is made up of Western, Central, Greater Accra and Volta regions (the regions with coast lines); middle zone is made up of Eastern, Ashanti and BrongAhafo regions; and north zone is made of northern region, upper east and upper west. The series generated for these zones are weighted series based on GLSS expenditure weights used by Ghana Statistical service in aggregating the regional series into the aggregate national series.

4. Empirical Results

This section presents the empirical results of the models developed earlier. It analyzes whether including additional information from subcomponent in modeling aggregate inflation improves forecast results of the aggregate series.

These results are also compared with the results of aggregating forecasts from the subcomponents and the benchmark model. We start with the time series characteristics of the data so as to decide whether the series enter the models at their levels or at their first differences.

4.1 Descriptive Statistics

The descriptive statistics in Table 1 show that the inflation series are not different in terms of the average and volatility. On average, inflation is highest in the non-food sector over the period with the food sector recording the lowest average inflation among all the subcomponents considered. The food inflation series happens to be the most volatile while the non-food series is the least volatile among all the subcomponents.

Table 1: Descriptive Statistics

	AGGR	FOOD	NFOOD	URBAN	RURAL	SOUTH	MIDDLE	NORTH
Mean	18.46	16.91	20.13	18.81	18.13	18.79	17.96	19.07
Std. Dev.	13.54	17.72	10.22	13.05	13.65	13.57	13.85	14.49
Observations	157	157	157	157	157	157	157	157

4.2 Time Series Characteristics of the Series in the Dataset

Since the ways the series are modeled depend on their time series characteristics, I investigate the series for their order of integration.

The characteristics of the series are not clear from the visual examination of the graphs in Figure 1, so Augmented Dickey-Fuller (ADF) tests are used to determine whether the series have unit roots. Table 2.2 shows the results of the ADF tests and apart from the north series, all the series are stationary at 5 percent level of significance. This means that the series enter the models at their levels except the north series. Even though the north series is not stationary, including the first difference in the models do not produce any different result from including it at the level. I therefore treat the north series as all the other series and present the results for the levels of all the series. Similarities of the graphs also suggest that their characteristics should not be different.

Figure 1: Graphs of the Level of the Series in the Dataset

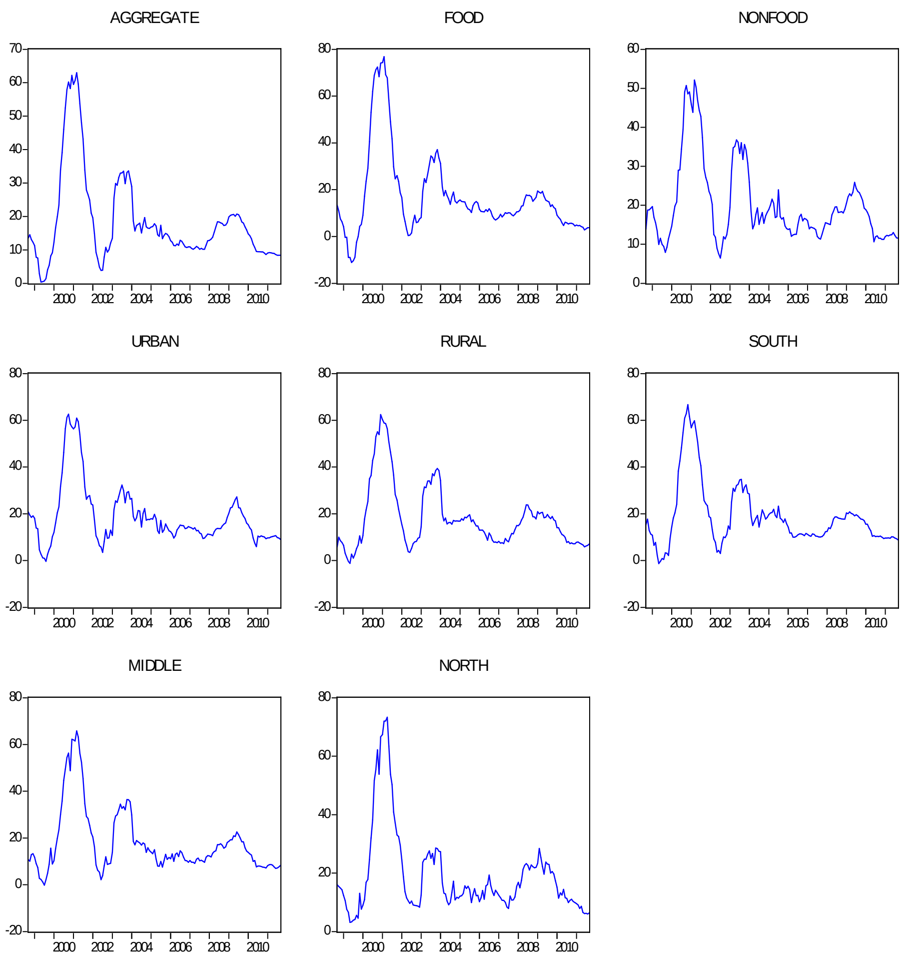

Table 2: Unit Root Tests of the variables in the Data (ADF p-values)

	No. of lags	p-value
Aggregate	12	0.0388
Food	12	0.0301
Nonfood	13	0.0378
Urban	12	0.0223
Rural	13	0.0247
South	12	0.0318
Middle	12	0.0136
North	12	0.1522

4.3 Weights

The published weights from Ghana Statistical Service suggests that the weights are constant over the sample period but analysis of the data shows that aggregating the components with the published weights do not produce the same aggregate series as published. I, therefore, compute average ex-post weight for the sample period. The ex-post weights are regression coefficient from the regression of the aggregate series on respective components corrected for serial correlation. These weights are normalized to sum to 1 and the ex-ante weights are the published weights. Table 3 shows the ex-post weights, normalized ex-post weights and the ex-ante weights. A major observation is the reversal of the weights for the rural-urban series, which weights the urban series more that the rural series ex-ante. The normalized ex-post weights are used in calculating the time-varying weights for aggregating the forecasts. The use of these weights as opposed to the ex-ante weights does not change the results significantly enough to change the conclusions.

Table 3: Weights for Aggregating Forecasts

	Ex-post	Normalized	Ex-ante
Urban-rural			
Urban	0.448850	0.455834	0.535058
Rural	0.535828	0.544166	0.464942
Total	**0.984678**	**1.000000**	**1.000000**
Sectors			
Food And Non-Alcoholic Beverages	0.492863	0.492788	0.449084
Alcoholic Beverages, Tobacco and Narcotic	0.046323	0.046316	0.022299
Clothing and Footwear	0.111954	0.111937	0.112855
Housing, Water, Electricity, Gas and Other	0.059017	0.059008	0.069844
Furnishings, Household Equipment and Rou	0.073029	0.073018	0.078266
Health	0.012603	0.012601	0.043276
Transport	0.054722	0.054714	0.062086
Communications	0.004378	0.004377	0.003133
Recreation and Culture	0.031762	0.031757	0.030439
Education	0.006419	0.006418	0.01597
Hotels, Cafés and Restaurants	0.073856	0.073845	0.082825
Miscellaneous Goods and Services	0.033227	0.033222	0.029924
Total	**1.000153**	**1.000000**	**1.000000**
Regions			
Western	0.115404	0.115448	0.115603
Central	0.066974	0.066999	0.06953
Greater Accra	0.240317	0.240408	0.242125
Eastern	0.093875	0.09391	0.09248
Volta	0.099928	0.099966	0.102775
Ashanti	0.22458	0.224665	0.223353
BrongAhafo	0.077525	0.077554	0.076107
Northern	0.049047	0.049065	0.048918
Upper	0.031973	0.031985	0.02911
Total	**0.999623**	**1.000000**	**1.000000**

4.4 Granger Causality Tests

Table 4 is the result of Eviews' pairwise Granger causality tests that tests whether an endogenous variable can be treated as exogenous in a particular equation. For each equation in the VAR, Table 4 shows chi-square statistics for the joint significance of each of the other lagged endogenous variables in that equation in column 2, degrees of freedom (df) in column 3 and p-values in column 4. The statistics in the last row (All) are for the joint significance of all other lagged endogenous variables in the equation.

The results from Table 4 show that food and nonfood series Granger-cause the aggregate series individually and jointly and there is a feedback from the aggregate series to nonfood but not to food series. The urban and rural series do not Granger-cause the aggregate series either individually or jointly. The aggregate series, however, Granger-cause the urban series. For the regional series, there is a strong joint Granger causality from the disaggregates to the aggregate series but none from the individual series. Feedback runs from the aggregate only to the north series. These results indicate that the food and nonfood series individually and jointly provide much information in forecasting the aggregate series but the urban and rural series do not provide much information in forecasting the aggregate series as the other disaggregates, either individually or jointly. The joint information contained of the regional series helps forecast the aggregate series but the individual series do not provide enough information to forecast the aggregate series.

Table 4: VAR Granger Causality / Block Exogeneity Wald Test between the aggregate and the disaggregate series

Excluded	Chi-sq	df	Prob.
Dependent variable: AGGREGATE			
FOOD	29.60471	12	0.0032
NONFOOD	29.79406	12	0.0030
All	60.55712	24	0.0001
Dependent variable: FOOD			
AGGREGATE	15.17709	12	0.2319
NONFOOD	22.73118	12	0.0301
All	49.19304	24	0.0018
Dependent variable: NONFOOD			
AGGREGATE	27.50577	12	0.0065
FOOD	33.31102	12	0.0009
All	89.18211	24	0.0000
Dependent variable: AGGREGATE			
URBAN	13.71157	12	0.3195
RURAL	16.52092	12	0.1685
All	25.69682	24	0.3687
Dependent variable: URBAN			
AGGREGATE	26.32206	12	0.0097
RURAL	19.85558	12	0.0699
All	50.29478	24	0.0013
Dependent variable: RURAL			
AGGREGATE	12.46291	12	0.4093
URBAN	7.822618	12	0.7988
All	43.4988	24	0.0087

Table 4 (Continued): VAR Granger Causality / Block Exogeneity Wald Test between the Aggregate and the Disaggregate Series

	Chi-sq	df	Prob.
Dependent variable: AGGREGATE			
SOUTH	16.17355	12	0.1834
MIDDLE	17.03393	12	0.1483
NORTH	14.67319	12	0.2598
All	66.27316	36	0.0016
Dependent variable: SOUTH			
AGGREGATE	14.69423	12	0.2586
MIDDLE	15.8875	12	0.1964
NORTH	14.00068	12	0.3007
All	92.91287	36	0.0000
Dependent variable: MIDDLE			
AGGREGATE	11.73318	12	0.4673
SOUTH	12.33768	12	0.4190
NORTH	10.65658	12	0.5586
All	104.3503	36	0.0000
Dependent variable: NORTH			
AGGREGATE	27.12709	12	0.0074
SOUTH	28.88582	12	0.0041
MIDDLE	28.59004	12	0.0045
All	137.462	36	0.0000

4.5 Results of the Various Models and Model Comparison

Three main models are estimated in various forms; an autoregressive (AR) model of the aggregate series and the subcomponents, a moving average (MA) of the aggregate series and the subcomponents and a vector autoregressive (VAR) model of the aggregate and the different subcomponents or all the subcomponents. The VARs are labeled by the variables that enter it, for example VAR_aggr_food means a VAR with the aggregate series and the food series as shown in Table 5. The results from the comparison of the Root Mean Squared Forecast Errors (RMSFE) from Table 5 show that, for all the categories considered, the benchmark autoregressive (AR) model of the aggregate inflation series outperforms aggregate forecasts that are obtained from aggregating forecasts from the subcomponents except for the 1-step-ahead forecasts for the product sectors where aggregating the forecasts from the subcomponents perform marginally better.

For the moving average (MA) models, the direct forecasts are better in all the steps except for the regions where aggregating the forecasts performs better for the 1-step-ahead.

Including additional information from the subcomponents generally performs better for all the models at 1-step-ahead forecasts. The forecasts are, however, less accurate when only food, urban or south series is included in the aggregate model individually, even for the 1-step-ahead forecasts. These results imply that the subcomponents help in producing better short-term forecasts of aggregate inflation if the right subcomponents or their combinations are used in the aggregate model. For the product sector, including the nonfood series improves the forecasts most, while including the rural series improves the forecasts most in the case of the urban-rural classification. In the case of the regional classification, including all the subcomponents improves the forecasts most.

Table 5: Root Mean Square Forecast Error (RMSE) for year-on-Year Inflation*

RMSFE	1-step		6-step		12-step	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Sectors						
AR**	0.137	0.131	0.341	0.739	0.647	1.346
MA	0.188	0.217	1.042	0.810	1.119	0.810
VAR_aggr_food_nonfood	0.077	0.095	0.676	0.706	1.290	1.356
VAR_aggr_food	0.151		0.553		0.755	
VAR_aggr_nonfood	0.061		0.661		1.254	
VAR_food_nonfood		0.093		0.700		1.309
Urban-rural						
AR	0.137	0.158	0.341	0.783	0.647	1.404
MA	0.188	0.207	1.042	0.837	1.119	0.837
VAR_aggr_urban_rural	0.098	0.170	0.736	0.801	1.522	1.708
VAR_aggr_urban	0.190		0.605		0.885	
VAR_aggr_rural	0.067		0.654		1.300	
VAR_urban_rural		0.165		0.747		1.725
Regions						
AR	0.137	0.153	0.341	0.727	0.647	1.308
MA	0.188	0.123	1.042	0.820	1.119	0.824
VAR_aggr_south_middle_north	0.052	0.256	0.670	0.692	1.617	1.760
VAR_aggr_south	0.150		0.491		0.838	
VAR_aggr_middle	0.080		0.670		1.285	
VAR_aggr_north	0.091		0.680		1.422	
VAR_aggr_south_middle	0.065		0.679		1.317	
VAR_aggr_south_north	0.065		0.674		1.309	
VAR_aggr_middle_north	0.065		0.674		1.309	
VAR_south_middle_north		0.088		0.697		1.438

* Direct forecasts are the forecasts of the aggregate series from a particular model, and the indirect forecasts are the aggregate forecasts that are obtained from aggregating forecasts from the disaggregates

**The lag length for the AR varies between 1 and 3 that of the MA varies between 1 and 2

5. Conclusions

This study investigates whether forecasting aggregate inflations series by modeling the subcomponents performs better than forecasting the aggregate series directly, and whether including the disaggregate components in the aggregate model improves the forecasts of the aggregate series. The benchmark model with which all the other models are compared is the univariate autoregressive (AR) of the aggregate series. The aggregate series is also modeled using moving average (MA) models. The subcomponents are modeled either independently as autoregressions (AR), moving average (MA) or jointly as vector autoregressions (VARs) with or without the aggregate series.

The results reveal that direct forecasts of aggregate inflation outperform aggregate forecasts that are derived from aggregating forecasts from the subcomponents for all the steps of the forecasts. Including information from the subcomponents improves on the direct forecasts of the aggregate series for 1-step-ahead forecasts. This, however, depends on the subcomponents or their combinations that are used with the aggregate series. A careful selection of the subcomponents into the models is, therefore, needed to achieve more accurate forecasts. The results for 6-step-ahead and 12-step-ahead forecasts show that direct univariate forecasts are superior to the forecasts from all the models. This result should therefore be taken carefully because a longer sample is needed to evaluate more independent forecasts errors for these steps.

Our findings are similar to that of Hendry and Hubrisch(2010) who find that combining disaggregate information outperforms combining disaggregate forecasts. The results, however, contradict Aron and Mueller(2008) and others who find that aggregating forecasts from disaggregates is superior to direct forecasting of the aggregate series.

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