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Now-casting Regional Consumer Food Inflation

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Abstract

Consumer price indices (CPI) are disseminated by countries with a lag that typically varies from 1 to 4 months. Global CPI datasets, such as those maintained by the International Labour Organization (ILO), the United Nations' Statistics Division (UNSD) or the International Monetary Fund (IMF), have a longer average lag because of the time needed to collect, compile and publish the data provided by countries. In order to monitor current trends in food inflation, forecasting (or nowcasting) price changes to the current period is therefore necessary. This paper presents the methodological framework used by FAO's Statistics Division to now-cast consumer food inflation at regional level. Hybrid ARIMA-GARCH models are estimated for each region, with additional explanatory variables constructed from a large and high-frequency dataset. The out-of-sample analysis indicates a satisfactory performance of the models at predicting the overall variability in prices as well as the sign and direction of price changes.

Key words: Nowcasting; Regional food consumer prices; ARIMA-GARCH models

JEL codes: C53, Q11

1. Introduction

Real-time data is required for policy makers to anticipate or react in a timely manner to possible tensions on retail food markets. One of the only sources of near real-time information on food prices are price quotations of major agricultural commodities traded on international spot and futures markets. These price quotations are summarized in indices such as the FAO Food Price Indexes (FPIs)[1] or other commodity price indices produced by international organizations such as the World Bank or the International Monetary Fund.

These indices are a useful source of information to monitor current trends in food inflation. However, relying exclusively on them is both insufficient and, in certain circumstances, flawed. First, while a certain degree of transmission exists between price signals on international agricultural commodity markets and retail food markets, the pass-through from one to the other is incomplete, lagged and highly variable across regions (Cachia, 2014). Price trends in certain regions might even be completely decorrelated from international markets and depend only on internal drivers. For example, prices at country or local level may be affected by the sudden release of massive public food stocks, leading to a fall in local prices, while leaving international prices unchanged because the country or region is neither a major exporter nor importer of the commodity released. An absence of or a very low transmission may also reflect an economy which is structurally isolated from international price shocks because of buffer mechanisms provided by governments.

Up-to-date information on food prices at consumer-level is therefore necessary in order to monitor real-time developments of food security in countries and regions. Since August 2013, FAO's Statistics Division is compiling and disseminating estimates of consumer food inflation for different regions of the world and at the global level[2]. They complete the country Consumer Price Indices (CPIs), also published on FAOSTAT, based on data from the International Labour Organization (ILO).

The publication lag at country-level and the additional time needed by international organizations such as the ILO or the United Nations' Statistics Division (UNSD) to compile and harmonize country data inevitably reduces the timeliness. Currently, given these constraints, regional and global estimates are disseminated on FAOSTAT with a lag of 3 months. For example, for the data release of July 2014, CPI indices were published up to April 2014. This working paper presents a possible approach to estimate these 3 months of lacking information using an econometrically sound and flexible methodology.

The remaining sections of this paper are organized as follows: the second section presents the econometric approach used to construct the regional forecasting models and defines the

[1] Details at http://www.fao.org/worldfoodsituation/foodpricesindex/en/
[2] The analysis and underlying data are available at: www.fao.org/economic/ess/ess-economic/cpi/en/

statistics employed to test their performance out-of sample; section 3 presents the data and explanatory variables used; An illustration for one region, North Africa, is provided in section 4. The final section concludes and discusses the possible future improvements of the approach. Annexes provide additional details on the data and results.

2. Forecasting strategy

a. Econometric modeling

Main model

Monthly changes in food prices for each of the sub-region[3], measured by the corresponding CPIs, are predicted using linear regressions with ARMA/GARCH disturbances (also referred to as hybrid ARIMA-GARCH models)[4]. The equations are given below.

Let P_t be the food CPI for a given region measured in t, P_t^* a measure of international agricultural commodity prices, such as the FPIs, $\boldsymbol{X}_t$ a set of other explanatory variables (exchange rates, economic activity data, etc.) assumed to be exogenous and ε_t an independently and identically distributed random error term. Variables in low-cases represent natural logarithms, and growth rates or first log-differences when dotted. Vectors are in bold. The regression equation is:

$$[Reg]:\ \dot{p}_t = \mathrm{a} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \varphi_{\mathrm{i}}\, \dot{p}_{t-i} + \sum_{\mathrm{j}=0}^{\mathrm{k}} \beta_{\mathrm{j}}\, \dot{p}^*_{t-j} + \sum_{\mathrm{l}=0}^{\mathrm{m}} \boldsymbol{\gamma}_{\mathrm{l}} \dot{\boldsymbol{x}}_{t-l} + \varepsilon_t$$

The presence of autocorrelation in the residuals and of "volatility clustering" of the residuals, when large changes tend to follow large changes and small changes follow small changes, is a distinctive feature of commodity prices in general and food prices in particular, even for highly aggregated indices such as food CPIs. This was well evidenced in the food price crisis of 2008-2009, with several episodes of price spikes followed by a period of easing.

To accommodate for residual autocorrelation and volatility clustering, $[Reg]$ can be estimated using a procedure that allows for the residuals to follow an ARMA-GARCH process. The ARMA component represents the autocorrelation structure of the residuals, while the GARCH process reproduces the structure of this autocorrelation in unexpected shocks. The resulting model is:

[3] FAO's Food Consumer Price Indices are available at country, sub-regional (e.g. South-Eastern Asia), regional (Asia) and global. Annex 3 provides the country composition of the different sub-regions.
[4] AR(I)MA stands for Auto-Regressive (Integrated) Moving Average and GARCH for Generalized AutoRegressive Conditional Heteroscedasticity.

$$[M]: \begin{cases} [Reg] \\ [ARMA]:\ \varepsilon_t = \mathrm{b} + \sum_{\mathrm{i}=1}^{\mathrm{P}'} \mu_{\mathrm{i}}\, \varepsilon_{t-i} + u_t + \sum_{\mathrm{i}=1}^{\mathrm{q}'} \theta_{\mathrm{i}}\, u_{t-i} \\ [GARCH]:\ \ \sigma_{\mathrm{t}}{}^2 = c + \sum_{i=1}^{Q} \tau_i u_{t-i}{}^2 + \sum_{j=1}^{P} \rho_j \sigma_{\mathrm{t-j}}{}^2 + \vartheta_{\mathrm{t}} \end{cases}$$

where ϑ is an independently and identically distributed random term and σ the conditional standard error of u. $[M]$ can be estimated using a four-step procedure well described in Ruppert (2011):

- Step 1: estimate $[Reg]$ using ordinary least squares and determine the structure of lags $\mathrm{S(p)} \subseteq \{1, \dots, \mathrm{p}\}, \mathrm{S(k)} \subseteq \{1, \dots, \mathrm{k}\}$ and $\mathrm{S(m)} \subseteq \{1, \dots, \mathrm{m}\}$;
- Step 2: estimate an ARMA for the residuals of $[Reg]$;
- Step 3: compute the conditional variance of the Step 2 residuals using a GARCH equation; and
- Step 4: re-estimate $[Reg]$ using weighted least squares, with the weights equal to the reciprocal of the conditional variances computed in step 3.

Benchmarking models

The forecasting accuracy of $[M]$ is assessed against two basic models. Failure of $[M]$ to outperform the benchmarking models indicates that the forecasting methodology is not appropriate or, in other words, that the information generated by the explanatory variables and the way it is used does not significantly improve the forecasting of food inflation compared to models with no additional information and with a simple structure. The following models are used for the benchmarking:

$$[AR1]:\ \dot{p}_t = \mathrm{c} + \varphi \dot{p}_{t-1} + \varepsilon_t$$
$$[AR0]:\ \dot{p}_t = \mathrm{c} + \dot{p}_{t-1} + \varepsilon_t$$

Where ε is an independently and identically distributed random term. $[AR1]$ is a simple autoregressive model of degree one and $[AR0]$ is generally referred to as a random walk process.

b. Measuring forecasting accuracy

The different models will be assessed on their capacity to accurately forecast monthly food price changes, using the following metrics:

Root Mean Square Error (RMSE)

The RMSE measures the average magnitude of the forecasting error. It is expressed in the same unit as the endogenous variable and is therefore directly interpretable. Its mathematical expression is the following:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\dot{p}_t - \widehat{\dot{p}_t}\right)^2} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\varepsilon}_t)^2}$$

Where $\widehat{\dot{p}_t}$ is the out-of-sample prediction of $\dot{p}_t$. One of the drawbacks of this measure is that it gives equal weight to overestimation and underestimation. This is also a purely quantitative indicator, which does not inform on other dimensions of forecasting accuracy, such as the capacity to anticipate changes in the sign of the variation (inflation or deflation, in our case) and its direction.

Sign of variation (Sign)

The capacity to adequately predict increases or decreases should be one of the essential properties of any model attempting to forecast economic time-series such as food prices. The best models are those that minimize the risk of wrongly forecasting inflation or deflation. Two statistics, $Sign^+$ and $Sign^-$ measure, respectively, the share of episodes of inflation and deflation accurately predicted by the model. $Sign$, the weighted average of the two, measures the average share of inflation and deflation episodes accurately forecasted. These statistics are computed using the following formulae:

$$\begin{cases} Sign^+ = \sum_{t=1}^{T} 1\{(\widehat{\dot{p}_t} \geq 0) \cap (\dot{p}_t \geq 0)\} \Big/ \sum_{t=1}^{T} 1\{(\dot{p}_t \geq 0)\} \\ Sign^- = \sum_{t=1}^{T} 1\{(\widehat{\dot{p}_t} < 0) \cap (\dot{p}_t < 0)\} \Big/ \sum_{t=1}^{T} 1\{(\dot{p}_t < 0)\} \\ Sign = \frac{\sum_{t=1}^{T} 1\{(\dot{p}_t \geq 0)\}}{T} Sign^+ + \frac{\sum_{t=1}^{T} 1\{(\dot{p}_t < 0)\}}{T} Sign^- \end{cases}$$

Where $1(a) = \begin{cases} 1 \; if \; the \; condition \; a \; is \; met \\ 0 \; if \; else \end{cases}$

Time-series of month-on-month changes in food consumer prices are generally stationary around a positive mean because prices tend to exhibit a positive trend. Consequently, it will be easier for the models to accurately predict positive variations than negative ones.

Direction of variation (Dir)

In addition to the sign of the change, it is also key for the models to accurately predict the direction of the change. It is important for policy-makers, investors and other economic actors to minimize the risk of anticipating or betting on an easing of inflation pressures, for example, when inflation is in fact accelerating. Mathematically, the direction of the change is the slope of the growth rate or, in other terms, to the variation of the variation. For

example, if the inflation rate goes from -1% to -0.5%, there is a relative increase in inflation or, symmetrically, a decrease in the pace of deflation. Mathematically: $d\dot{p}_t = -0.5\% - (-1\%) = 0.5\% > 0$, where $d\dot{p}_t = \dot{p}_t - \dot{p}_{t-1}$. The different statistics, Dir^+, Dir^- and Dir are computed analogously to the sign statistics, replacing $\dot{p}_t$ by $d\dot{p}_t$.

3. Data

a. Dependent variables: FAO's Food Consumer Price Indices (CPI)

FAO's Global and Regional Food CPIs measure food inflation for a group of countries at different geographical scales: sub-regional (e.g. South America), regional (e.g. Americas) and global (world, all countries). The country composition of these sub-regions is provided in Annex 3. The Global Food CPI covers approximately 150 countries worldwide, representing more than 90% of the world population. The source of data for the country CPIs is the ILO, the UNSD and websites of national statistical offices or central banks.

The aggregation procedure is based on the use of population weights. Population weights better reflect the impacts on households of regional food inflation, while using the Gross Domestic Product (GDP) or any other measure of national income better reflect the impact on the economy as a whole. Using GDP would also mean giving a higher weight to countries less exposed to food insecurity, because households in countries with higher GDP tend to be richer, spend a lower proportion of their income on food and benefit from lower and less volatile consumer price inflation.

The first log-difference of the monthly sub-regional food CPIs are the dependent variables of the econometric models. Taking logarithms of the original variables has several advantages with respect to the econometric estimation: it linearizes relationships that might be multiplicative and improves the homogeneity of the variance. First log-differences are good approximations of simple growth rates (in this case, month-on-month) when variations are not too high (e.g. in the range of -10% to 10%), which tends to be the case for aggregated indices such as the Food CPIs.

b. Explanatory variables

Appropriate explanatory variables with the most up to date data are used. Relying on "hard" data for the most recent months (the ones for which forecasts of the dependent variable are needed) is key in improving the overall forecasting performance. To maximize the timeliness, daily information was used whenever possible. A description of the explanatory variables and of their importance in forecasting consumer-level food inflation is provided below.

International agricultural commodity prices The measures used in this study are FAO's Food Price Indices (FPI) disseminated each month by the Trade and Markets Division of FAO. The indices for the five major commodity groups are used: cereals,

vegetable oils, meat, dairy and sugar. They are disseminated with a lag of between one and two weeks, i.e. indices for the previous month are published at the beginning of the current month. To be used in the forecasting, the FPI for the current month is predicted using an ARIMA-GARCH approach and daily agricultural commodity prices as explanatory variables. For example, the Cereals FPI for the current month is predicted using daily data up to the last available day (in the case of the July 2014 release, data up to July 17th was used) for the spot price of corn (Central Illinois No. 2 Yellow), oats (No. 2 Milling Minneapolis) and wheat (No. 1 Soft White, Portland). The methodology and data used for now-casting FPIs are described in greater detail in Annex 1.

Currency exchange rates Daily quotations to the USD for a total of 14 of the world's major currencies from developed and developing countries are used. Changes in exchange rates affect inflation in many ways: for example, currency appreciations contribute to reduce food inflation through the reduction in the value, expressed in local currency, of imported commodities. The set of exchange rates (number of currency units for one US Dollar) is the following: Euro, Brazilian Real, Yen, Thai Bath, G-B Pound, Argentinian Peso, Mexican Peso, Russian Ruble, Ukrainian Hryvnia, South-African Rand, Central African Franc, Yuan, Viet Nam Dong and Nigerian Naira.

Stock market indices Stock market indices are used as a proxy of economic activity data, in the absence of information on GDP or any other measure of domestic production and income with the appropriate frequency (monthly) and timeliness. Daily quotations for 11 major stock markets in both developed and developing countries are used. These variables are used to control for the effect of the economic cycle on inflation trends: bullish episodes on stock markets tend to be correlated with higher economic growth and the latter with higher inflation. The following stock market indices have been used: Shanghai Composite Index (China), Nikkei (Japan), S&P 500 (USA), DAX (Germany), Bovespa index (Brazil), S&P BSE Sensex (India), RTSI Index (Russia), CAC 40 (France), IPC Index (Mexico), All Ordinaries Index (Australia) and JKSE Index (Indonesia).

Oil prices Through their impact on production costs across the economy, oil prices affect retail prices and, through second-round effects, wages. Furthermore, developments in oil and food markets are now more and more intertwined, given the increasing use of agricultural commodities to produce bio-diesel and ethanol. The following quotations were used: WTI Crude Oil Spot Price and the Europe Brent Crude Oil Spot Price.

Given the high number of variables in most of the groups, especially for exchange rates and stock market indices, a principal component analysis was used to extract a reduced number of explanatory factors. Details of the principal component analysis are provided in Annex 2.

4. Results

a. Forecasting framework

Forecasting horizon FAO's Regional and Global Food CPIs are computed and disseminated every quarter, according to a pre-defined calendar (Table 1). If the release is in month m, official country data is collected up to m-3 and regional inflation estimates produced up to this date, while the in-between months (m-2 to m) are forecasted.

Table 1 FAO's Regional and Global Food CPIs – Release calendar

Release month	Last month with official data	Months to be forecasted
January	October	November, December, January
April	January	February, March, April
July	April	May, June, July
October	July	August, September, October

Geographical level The econometric models provide forecasts for the different sub-regions. Forecasts for higher geographical groupings (regions, global) are computed by aggregation of sub-regional forecasts.

Forecasting procedure The forecasting equation given by $[M]$ is:

$$[F]: \quad \widehat{\dot{p}_t} = \hat{a} + \sum_{i \in S(p)} \widehat{\varphi}_i \dot{p}_{t-i} + \sum_{j \in S(k)} \widehat{\beta}_j \, \dot{p}^*_{t-j} + \sum_{l \in S(m)} \widehat{\boldsymbol{\gamma}}_l \dot{\boldsymbol{x}}_{t-l}$$

Where

- The structure of lags $S(p)$, $S(k)$ and $S(m)$ is determined by the AIC-based stepwise procedure applied to $[Reg]$; and
- The parameters $(\hat{a}, \widehat{\varphi}_i, \widehat{\beta}_j, \hat{\gamma}_l), \forall i \in S(p), \forall j \in S(k), \forall\, l \in S(m)$ are determined by the four-step procedure described in 2.a.

Assume that country food CPIs have been collected up to t and that forecasts for regional indices are required for the following three months, i.e. for $t + h, \forall h = 1,2\ and\ 3$. This is the situation faced each quarter for the release of the regional food CPIs. For the last forecasted month ($h = 3$), if the right hand-term of the equation includes contemporaneous terms in the explanatory variables, i.e. $0 \in S(m)$ and/or $0 \in S(k)$, the values $\dot{p}^*_{t+3}$ and $\dot{\boldsymbol{x}}_{t+3}$ will also be forecasts. $\dot{p}^*_{t+3}$ is determined through the procedure described in 3.a and Annex 1 and $\dot{\boldsymbol{x}}_{t+3} \equiv \frac{1}{s}\sum_{i=1}^{s} \dot{\boldsymbol{x}}_i$, where s is the number of available days with data for $\dot{\boldsymbol{x}}$ in month $t + 3$.

Additionally, if $h > i$, the previous period forecast will be used in the right-hand side of $\lfloor F \rfloor$ (dynamic forecasting). For example, for $i = 1$ and $h = 2$, $\dot{p}_{t-i+h} = \widehat{\dot{p}_{t+1}}$.

Real-time forecasting The accuracy of the forecasting models is determined on the basis of out-of-sample predictions, .i.e. in real forecasting conditions, for each of the horizons. The procedure is as follows: first, $[M]$ is estimated on a fixed period, say $\mathrm{H}_0 = [1, \dots, t_0]$. $[F]$ is then used to compute the h step-ahead predictions of food inflation, namely $\widehat{\dot{p}^{\mathrm{H}_0}_{t_0+h}}$, $\forall h = 1,2\ and\ 3$. The same procedure is repeated for $\mathrm{H}_1 = [1, \dots, t_0, t_1]$, yielding $\widehat{\dot{p}^{\mathrm{H}_1}_{t_1+h}}$ and so on until the end of the estimation period is reached, $\mathrm{H}_T = [1, \dots, t_0, t_1, \dots, T]$. This process yields three time-series of out-of-sample forecasts, one for each forecasting horizon. These series are used to compute the statistics defined in 2.b.

b. Model estimation

Estimation procedure The procedure used to estimate $[M]$ is described in details below.

<u>Step 1</u>

1a $[Reg]$ is estimated with $\mathrm{p} = \mathrm{k} = \mathrm{m} = 6$. The choice of the maximum number of lags to estimate the "full" model (the model with the maximum number of autoregressive terms and lagged explanatory variables) depends on many factors: the pattern of time dependency in the data, model parsimony, the ease of interpretation of the results and, of course, the predictive accuracy of the model. Time series of consumer prices are known to be highly auto-correlated, but the structure of autocorrelation is not necessarily straightforward because of the multiplicity of factors at play: seasonal effects, price stickiness, delay of economic agents in adapting to shocks and changing market conditions (e.g. a weather event reducing harvest and leading to persistently high prices before supply picks up and prices fall back), etc. Given these characteristics of price time-series, assuming that current price changes depend to some degree on market conditions that prevailed over the past 6 months seems reasonable.

1b The "optimal" model, i.e. the optimal structure of lags $\mathrm{S(p)}, \mathrm{S(k)}$ and $\mathrm{S(m)}$, is determined from the full model using a stepwise search based on the Akaike Information Criteria (AIC).

The AIC is a measure of the relative quality of a statistical model, for a given dataset. As such, it provides a means to select the optimal model within a set of candidate models, optimality here being understood as the best compromise between the quality of the model fit and its simplicity (or parsimony). It is computed in the following way: $AIC = 2k - 2ln(L)$, where:

- k is the number of parameters; and
- L the maximized value of the likelihood of the model

Other model selection criteria exist, such as the BIC (Bayesian Information Criterion), but it has been showed that the AIC or the $AICc$ (the corrected version of the AIC for finite samples) has many advantages over alternative measures: besides its theoretical advantages (the AIC is grounded on information theory, the BIC is not), it has been shown that the AIC is asymptotically optimal in selecting the model with the least mean squared error, under the assumption that the exact "true" model is not in the candidate set (as is virtually always the case in practice), which is not the case of the BIC. For more details on the comparisons between the AIC and other information criterion, refer to Burnham & Anderson (2002 and 2004) and to Yang (2005).

The stepwise search procedure allows adding and deleting variables/lags and evaluates, in each step, each subset of models using the AIC. This procedure is path dependant and therefore not exhaustive[5] but it is known to be quite effective as it combines the advantages of the backward and forward procedures.

The parameters are estimated by maximization of the likelihood function. All the statistical operations necessary for this analysis have been programmed in *R*[6], with the help of pre-defined functions. For this task in particular, the *stepAIC* function from the *MASS* package is used.

<u>Step 2</u>
An ARMA model is fitted to the residuals of the model selected in step 1 in order to capture the possible autocorrelation in the error terms. The R function *auto.arima* (*Forecast* package) is used to estimate the ARMA and determine the number of AR and MA terms through a stepwise search based on the $AICc$.

<u>Step 3</u>
The conditional variance of the estimated residuals of step 2 is estimated using a GARCH equation (see 2.a), with $P = Q = 1$. The GARCH(1,1) is the most simple but also the most robust of the family of volatility models (Engle, 2001). Its statistical properties have been well studied in the literature and it has been shown that it reproduces adequately the volatility process of most economic and financial time-series. Higher-order GARCH processes are useful when a long time-span of data is used, like several decades of daily data (Engle, 2001), which is not our case in this study that considers monthly data over a period of 15 years.

The estimation of the conditional variance is done iteratively, using as a starting estimate the observed variance of the residuals, and maximizing the likelihood function with respect to the parameters c, τ and ρ. A Quasi-Newton optimizer is used to determine the maximum likelihood estimates of these parameters. The *R* function that performs this analysis is *garch (MASS* package).

[5] The evaluation of all possible subset of models would represent a highly computationally intensive task.
[6] www.r-project.org.

Step 4

The parameters of the optimal model determined in *1b* are re-estimated using weighted least squares, with the weights vector being the reciprocal of the conditional variance $\widehat{\sigma_t}^2$ estimated through the GARCH procedure in step 3: $\widehat{W} = \left(\frac{1}{\hat{\sigma}_1{}^2}, \dots, \frac{1}{\hat{\sigma}_t{}^2}, \dots, \frac{1}{\hat{\sigma}_T{}^2}\right)$. This estimation procedure ensures that the conditional heteroskedasticity of the residuals is well taken into account and that the resulting estimates $\hat{a}$, $\widehat{\varphi_l}$, $\hat{\beta}_j$ and $\hat{\boldsymbol{\gamma}}_{\mathbf{l}}$ are convergent**.**

If none of the GARCH parameters are statistically different from 0, the conditional variance is very close to the observed variance, the weights are almost fixed and correspond to the reciprocal of the observed variance and the weighted regression is equivalent to an ordinary least squares regression.

c. Results of the estimation for the main model ($[M]$)

To illustrate the methodology, estimation results are presented and discussed for North-Africa. Results for the other sub-regions are provided in Annex 4[7].

All groups of explanatory variables except oil prices are statistically significant in explaining changes in food consumer prices for North Africa (Table 2). The variables with a contemporaneous impact on food prices are the exchange rates and the stock market indices. The former are logically associated with negative coefficients in the regression (first and second fourth factors). On the contrary, one would expect positive coefficients for stock market indices, as they are assumed to proxy economic activity. The fact that this variable is associated with negative coefficients may indicate that stock market indices, given their regional composition, do not appropriately reflect economic conditions in North African countries.

Agricultural commodity prices are present with the first and second factors extracted from FAO's FPIs. The majority of the coefficients have a positive sign, which was expected. The coefficients associated with the FPIs enter the regression equation with high lags (3 to 6 months) reflecting the delay in transmission of food price signals from international commodity markets to domestic consumer markets.

The autoregressive structure is complex, with a relatively low month-to-month persistence (the coefficient associated with the first lag is 0.23, well under 1), corrective effects in the second and third lags (negative coefficients) and positive effects for the sixth and final lag.

All the variables are statistically significant at the 15% threshold. The F-Statistic close to 6 indicates that the model is globally valid. The model explains 35% of the total variance in food prices (adjusted R-squared) which, given the high volatility in price series and

[7] For the sake of parsimony, the results for the other 20 sub-regions are limited to plots of the observed values vs. 1 step-ahead forecasts. Detailed estimation results are available upon request to the author (franck.cachia@fao.org)

compared with regressions on similar monthly macroeconomic series, is an acceptable result[8]. Changes in consumer prices are predicted with an average error of 1.06% (residual standard error), slightly lower than the observed variability of the time series (1.12%).

The stepwise AIC procedure leads to the selection of a relatively high number of variables (18 in this case, including the autoregressive terms). The model could have been more parsimonious if the maximum number of lags was lower and/or if a more restrictive information criteria had been chosen (such as the BIC). However, given the high degree of freedom of the regression (145), the gain in robustness would not likely be significant.

Table 2 Model estimates and regression statistics

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.006	0.0011	5.5	1.9e-07
Exchange rate, Factor 3, lag 0	0.0015	0.00066	2.3	0.023
Exchange rate, Factor 4, lag 0	-0.002	0.00075	-2.7	0.0071
Stock Market,Factor 1, lag 0	-0.00065	0.0003	-2.2	0.03
Endogenous variable, lag 1	0.23	0.076	3.1	0.0026
Endogenous variable, lag 2	-0.24	0.074	-3.2	0.0014
Endogenous variable, lag 3	-0.16	0.074	-2.1	0.035
Endogenous variable, lag 6	0.2	0.069	2.9	0.005
Commodity prices, Factor 1, lag 4	0.0015	0.00064	2.4	0.02
Commodity prices, Factor 1, lag 6	-0.0021	0.00076	-2.8	0.0062
Commodity prices, Factor 2, lag 3	-0.0013	0.00074	-1.8	0.074
Commodity prices, Factor 2, lag 4	0.0018	0.00075	2.3	0.022
Commodity prices, Factor 2, lag 5	0.0013	0.00076	1.8	0.082
Exchange rate, Factor 1, lag 6	-0.0019	0.00049	-3.9	0.00014
Exchange rate, Factor 2, lag 6	-0.0013	0.00062	-2.1	0.039
Exchange rate, Factor 3, lag 2	0.001	0.00068	1.5	0.13
Exchange rate, Factor 4, lag 3	-0.0012	0.00075	-1.6	0.11
Stock Market,Factor 1, lag 1	-0.00055	0.00029	-1.9	0.06
Stock Market,Factor 1, lag 6	-0.00067	0.00034	-2	0.052

Regression statistics
Standard error of the endogenous variable: 1.12
Residual standard error: 1.06
Multiple R-squared: 0.43
Adjusted R-squared: 0.35
F-Statistic: 5.97
Degrees of freedom: 145

Source: author

d. Forecasting performance

The out-of-sample analysis clearly indicates that the best model for predicting month-on-month changes in food prices for North-Africa is the ARIMA-GARCH (Table 3 and Figure 1). It ranks first with respect to the overall forecasting performance (lower RMSE) and is also better at predicting the sign of the change (inflation or deflation) and much more precise at anticipating its direction: the model successfully predicts the direction of food inflation in 61% of the cases, compared to 45% and 41% respectively for the AR(1)

[8] As a point of comparison, adjusted R-squared for models forecasting trade variables (quarterly data) are rarely above 40%.

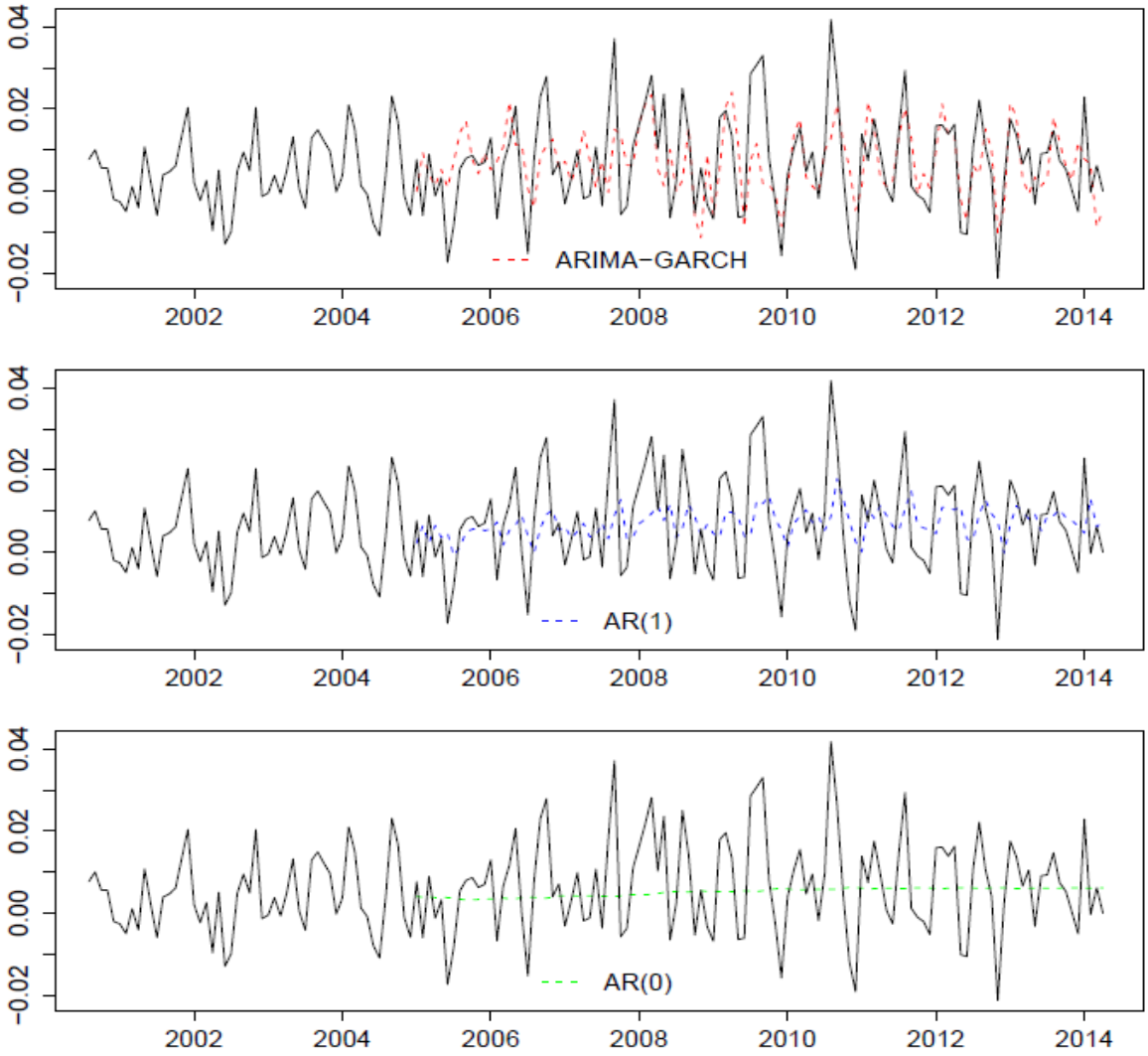
and AR(0). It is also the only model able to forecast deflation episodes in a significant number of cases, while the others are completely unable to do so.

Table 3 Out-of-sample forecasting accuracy statistics (in %)

	ARIMA-GARCH	AR(1)	AR(0)
RMSE	1.1	1.2	1.2
Sign	72	70	71
Sign < 0	33	3	0
Sign > 0	89	97	100
Direction	61	45	41
Dir < 0	63	44	33
Dir > 0	59	46	47

Source: author

Figure 1: 1-step ahead out-of-sample forecasts vs. observed Food CPIs (m-on-m changes)



Source: author

5. Conclusion

The objective of this working paper was to describe the methodology used by FAO's Statistics Division to nowcast food inflation for consumers. The approach is econometrically sound and allows for ARMA/GARCH dynamics in the residuals of the regression equations, which is a feature often found in high frequency economic and financial time-series in general and in food prices in particular.

The approach yields satisfactory results for most of the sub-regions. The illustration for North Africa indicated that the model performed satisfactorily at predicting changes in the sign (inflation or deflation) and direction (acceleration, deceleration) of price changes (respectively, 72% and 61% of good predictions). These measures of forecasting accuracy are often overlooked in comparing models.

Given the intrinsic difficulty in predicting macroeconomic time-series, especially on a monthly basis, and the high level of volatility in price series, predictions always have to be interpreted with caution and with reference to the upside and downside risks that may affect the outlook. In this respect, work still needs to be undertaken to determine robust confidence intervals for the predictions in order to quantify some of the underlying uncertainty affecting the forecasts.

An effort was made to allow the maximum level of flexibility in the forecasting procedure: for example, the order of the GARCH as well as the maximum number of lags of the regression equation can be parameterized in the *R* function, additional explanatory variables can be added without having to change the script, forecasts can be automatically updated each day on the basis of new information for the explanatory variables (automatically sourced using APIs[9]). The procedure is also relatively easy and fast to use: the computations, storage of the results and generation of publication-ready outputs for 21 sub-regions take less than 5 minutes to run. These characteristics of the procedure are important given the frequent and recurrent nature of the forecasts. Major modifications or additions to the methodology have to be made in such a way that the portability of the system, its ease of use and efficiency are the least affected.

[9] Application Programming Interface (APIs) are used to retrieve data directly from online databases (quandl.com, yahoo!Finance, etc.)

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Annexes

1. Now-casting FAO's Food Price Indices (FPIs)

a. Econometric approach

Linear regressions with ARMA/GARCH disturbances are used to forecast the current month of the FPIs. The procedure is described below.

The first step consists in fitting the following equation using ordinary least squares:

$$eq1:\ \dot{fpi}_t = \mathrm{a} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \varphi_{\mathrm{i}}\, \dot{fpi}_{t-i} + \boldsymbol{\gamma}\dot{\boldsymbol{x}}_t + \ \varepsilon_t$$

Where:

- $\dot{\mathrm{fpi}}$ is the month-on-month growth rate of one of the five major commodity group indices (cereals, sugars, vegetable oils, meat and dairy);
- $\dot{\mathbf{x}}$ a matrix of month-on-month growth rates for different basic commodities likely to be good predictors of $\dot{\mathrm{fpi}}_{\mathrm{t}}$; and
- ε a random error term.

In a second step, an $ARMA$ model is fitted to the residuals of $eq1$:

$$eq2:\ \hat{\varepsilon}_t = \mathrm{b} + \sum_{\mathrm{i}=1}^{\mathrm{p}'} \varphi_{\mathrm{i}}\, \hat{\varepsilon}_{t-i} + u_t + \sum_{\mathrm{j}=1}^{\mathrm{q}'} \theta_{\mathrm{i}}\, u_{t-i}$$

Where:

- $\hat{\varepsilon}$ is the time-series of residuals from $eq1$; and
- u a random term identically and independently distributed.

The autoregressive and moving average structures in $eq1$ and $eq2$ (p, q′ and q′) are determined on the basis of a stepwise procedure using the Akaike Information Criterion (AIC) in its corrected form, i.e. adapted to finite samples. The maximum number of lags is 5, i.e. $p \leq 5$, $\mathrm{p}' \leq 5$ and $\mathrm{q}' \leq 5$.

The third step consists in using a GARCH(1,1) to estimate the conditional variance of u:

$$eq3:\ \sigma_{\mathrm{t}}{}^2 = c + \tau u_{t-1}{}^2 + \rho\sigma_{\mathrm{t}-1}{}^2 + \vartheta_{\mathrm{t}}$$

Where:

- σ^2 is the conditional variance of u; and
- ϑ a random term identically and independently distributed.

The time-series $W = \left(\frac{1}{\sigma_1{}^2}, \dots, \frac{1}{\sigma_t{}^2}, \dots, \frac{1}{\sigma_T{}^2}\right)$ is then be used as a weighting variable to re-estimate *eq1* using weighted regression (Generalized Least Squares).

b. Data

For each of the commodity group indices to be forecasted, a set of explanatory variables are used to improve the predictions. These variables are daily quotations of futures contracts or cash prices for commodities assumed to be closely related to the group indices (cf. Table).

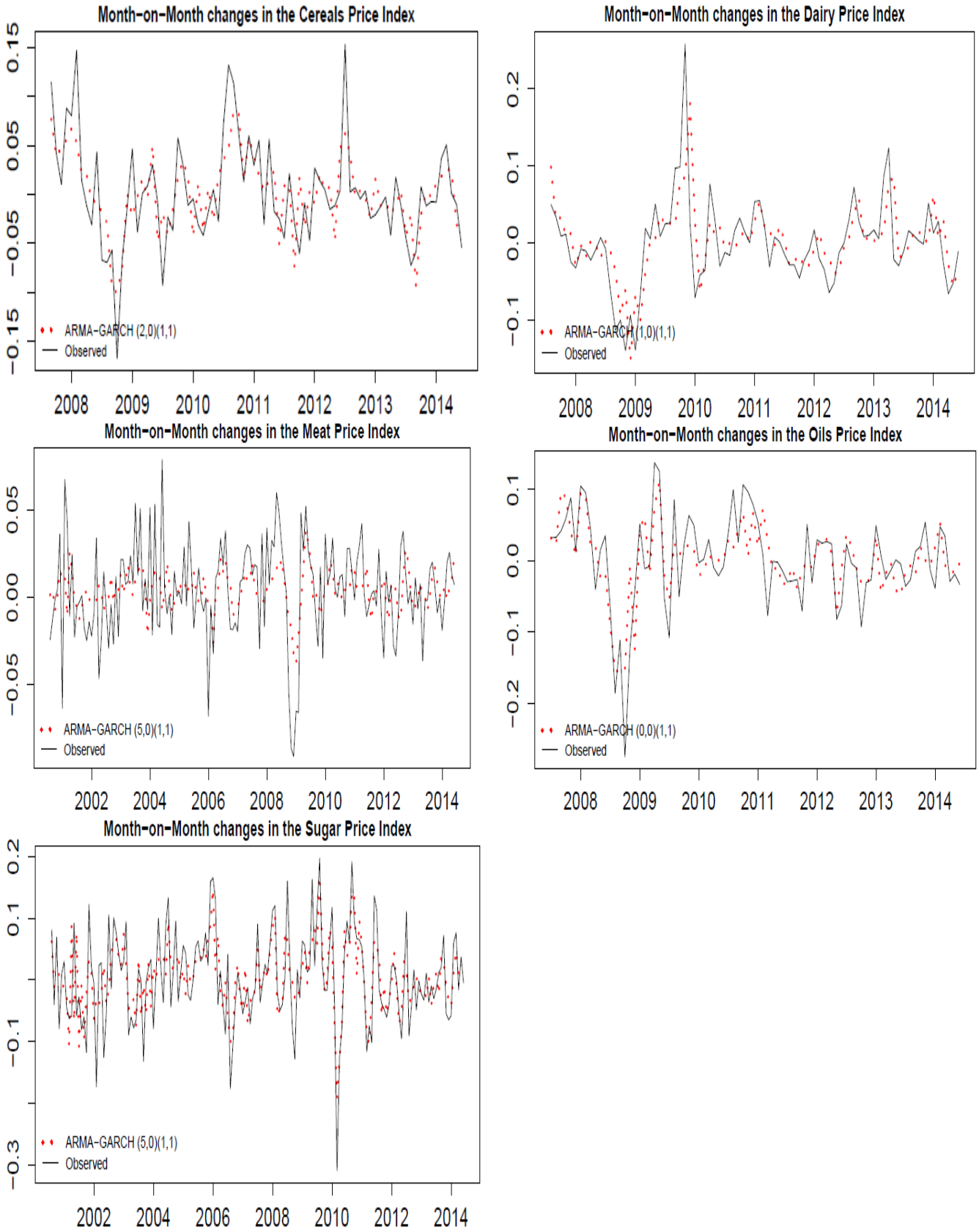
Table FAO Food Price Indices and possible explanatory variables

Index to be forecasted	**Explanatory variables**	
	Commodity	***Description***
Cereals Price Index	Corn, No. 2 Yellow, Central Illinois	Cash commodity price in $ per bu. Source: USDA
	Oats, No.2 Milling, Minneapolis	
	Wheat, No. 1 Soft White, Portland OR	
Sugar Price Index	Sugar No. 11 Futures , Continuous Contract #1	Non-adjusted price based on spot-month continuous contract calculations. Raw futures data from Intercontinental Exchange (ICE) United States.
Meat Price Index	Live Cattle Futures, Continuous Contract #1.	
	Lean Hogs Futures, Continuous Contract #1	
Oils Price Index	Corn Oil, Crude Wet/Dry Mill	Cash commodity in cents per lb. Source: USDA
Dairy Price Index	Milk, Non-Fat Dry	Cash commodity price in $ per lb. Source: USDA.
	Cheddar Cheese, Blocks, Chicago	

Source: http://www.quandl.com

c. Results

Figure: Observed vs. fitted values for the five commodity group indices



d. Forecasting

FPIs referring to the previous month are published in the first or second week of the current month. Forecasts of the FPI for the current month are given by:

$$\widehat{\dot{fpi}}_m = \hat{a} + \sum_{i=1}^{p} \hat{\varphi}_i \, \dot{fpi}_{m-i} + \hat{\gamma}\hat{x}_m$$

Where:

- m is the current month
- p is determined through the first estimation of eq1;
- $\hat{a}$, $\hat{\varphi}_i$ and $\hat{\gamma}$ are determined by the weighted regression; and
- $\hat{x}_m$ is the average of the quotations (futures contract or cash price depending on the commodity) from the first day of the month up to the day when the forecast is made. As regional food CPI estimates are generally disseminated during the third week of the month, data for at least half of the current month is generally available for the forecasting.

2. Results of the Principal Component Analysis for the explanatory variables

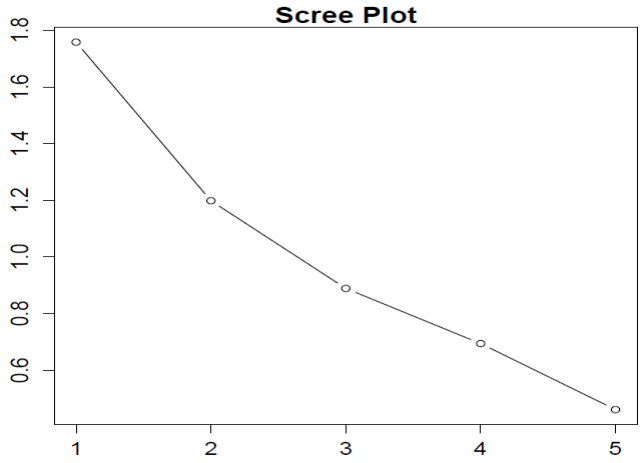
A principal component analysis is used to reduce the number of explanatory variables for each of the groups of variables – Food Price Indices, exchange rates, stock market indices and oil prices. The main results of this analysis are provided for the first three groups. As only two variables are used to measure oil prices, the first factorial axis, which contributes to over 90% of the total variance, is selected. This analysis has been carried out using the *R* package *nFactors*. For more information on this package and its functionalities, refer to http://cran.r-project.org/web/packages/nFactors/nFactors.pdf.

a. FAO Food Price Indices (FPIs)

Table 1 Statistics on the principal component analysis for FPIs (selected factors highlighted)

Factors	Eigenvalues	Proportion of total variance	Cumulative variance
1	1.8	0.35	0.35
2	1.2	0.24	0.59
3	0.89	0.18	0.77
4	0.69	0.14	0.91
5	0.46	0.092	1

Figure 1 Eigenvalues

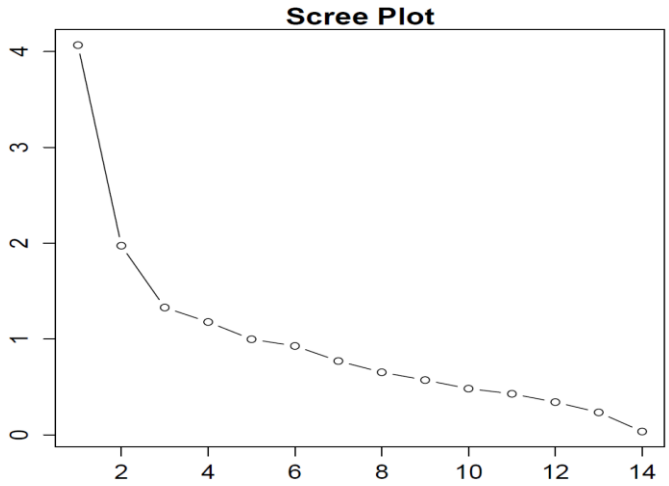


b. Exchange rates against the US dollar

Table 2 Statistics on the principal component analysis for FPIs (selected factors highlighted)

Factors	Eigenvalues	Proportion of total variance	Cumulative variance
1	4.1	0.29	0.29
2	2	0.14	0.43
3	1.3	0.095	0.53
4	1.2	0.084	0.61
5	1	0.071	0.68
…	…	…	…
14	0.036	0.0026	1

Figure 2 Eigenvalues

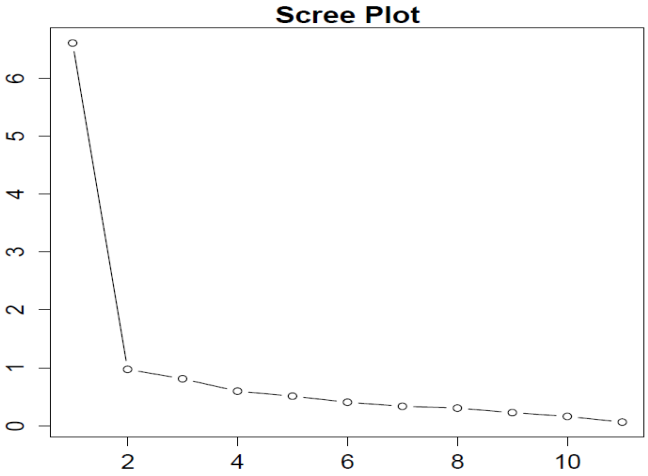


c. Stock market indices

Table 3 Statistics on the principal component analysis for stock market indices

Factors	Eigenvalues	Proportion of total variance	Cumulative variance
1	6.6	0.60	0.60
2	0.97	0.089	0.69
3	0.81	0.074	0.76
…	…	…	…
11	0.063	0.0058	1

Figure 3 Eigenvalues



3. Composition of macro-regions used for the Food CPIs

Northern America: United States of America, Canada, Bermuda
Central America: Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama
South America: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Suriname, Uruguay, Venezuela
Caribbean: Antigua and Barbuda, Aruba, Barbados, Cayman Islands, Dominican Republic, Grenada, Haiti, Jamaica, Puerto Rico, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Trinidad and Tobago

Europe[10]: all EU-27 countries, Albania, Iceland, Latvia, Norway, Switzerland, Island of Man, Republic of Moldova, Serbia

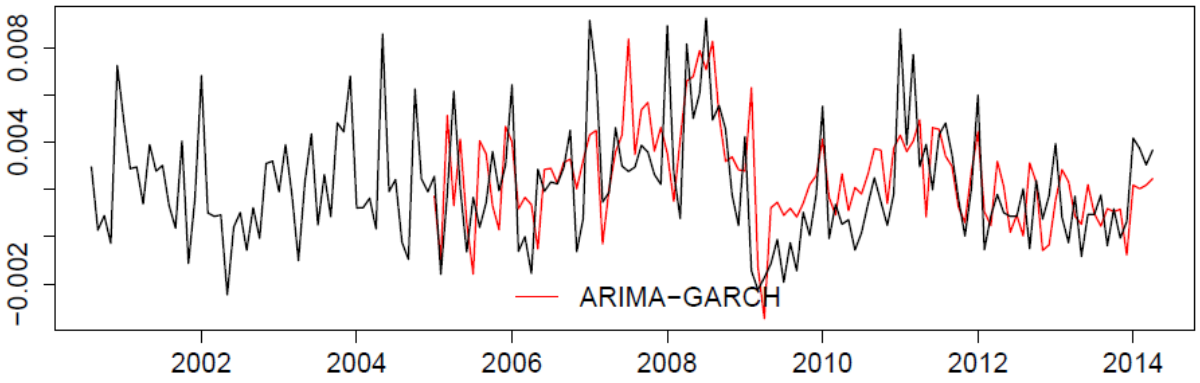
Western Asia: Armenia, Bahrain**,** Cyprus**,** Israel**,** Jordan**,** Kuwait**,** Oman**,** Saudi Arabia**,** Syrian Arab Republic**,** Turkey
South-Eastern Asia: Brunei, Cambodia, Indonesia, Lao, Malaysia, Myanmar, Philippines, Singapore, Thailand
Southern Asia: Bangladesh, India, Iran, Maldives, Nepal, Pakistan, Sri Lanka
Eastern Asia: China, Hong Kong SAR, China, Macao SAR, China (mainland), Japan, Republic of Korea

Northern Africa: Algeria, Egypt, Morocco, Tunisia
Western Africa: Benin, Burkina Faso, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Cameroon Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone
Eastern Africa: Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Seychelles, Uganda, Tanzania, Zambia
Southern Africa: Botswana, Lesotho, Namibia, South Africa
Central Africa: Angola, Cameroon, Congo, xxGabon

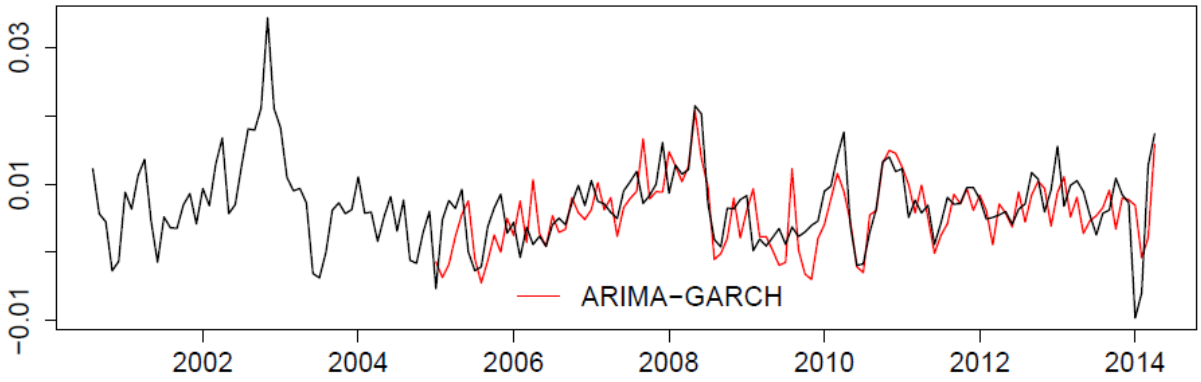
[10] Sub-divided into Northern, Southern, Western and Eastern Europe.

4. Observed vs. 1 step-ahead month-on-month Food CPI forecasts

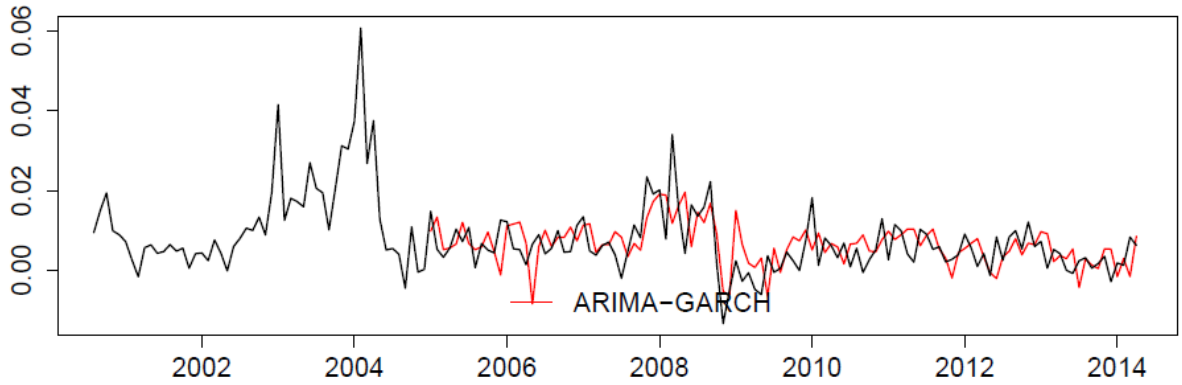
Northern America



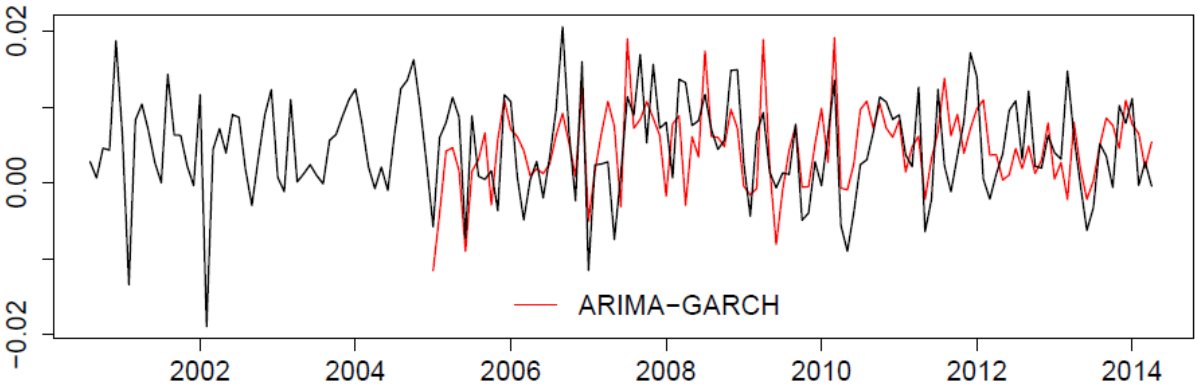
Southern America



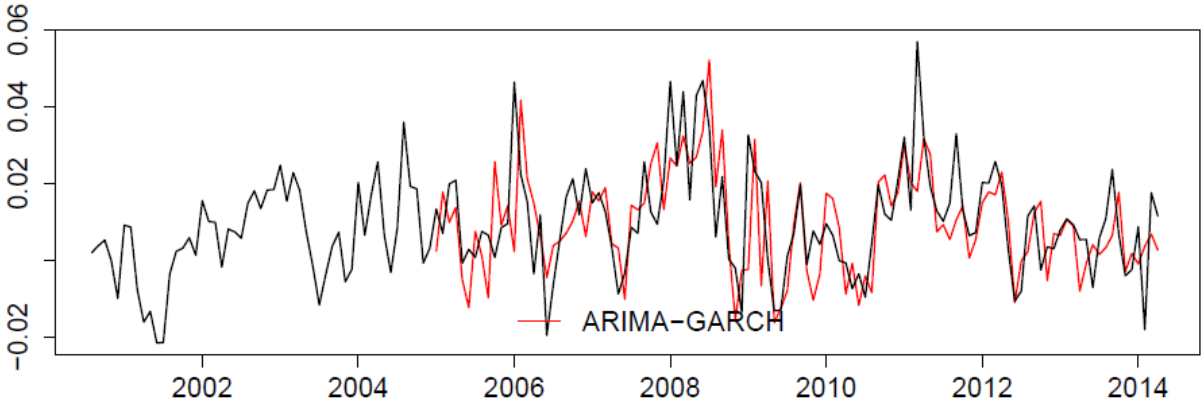
Caribbean



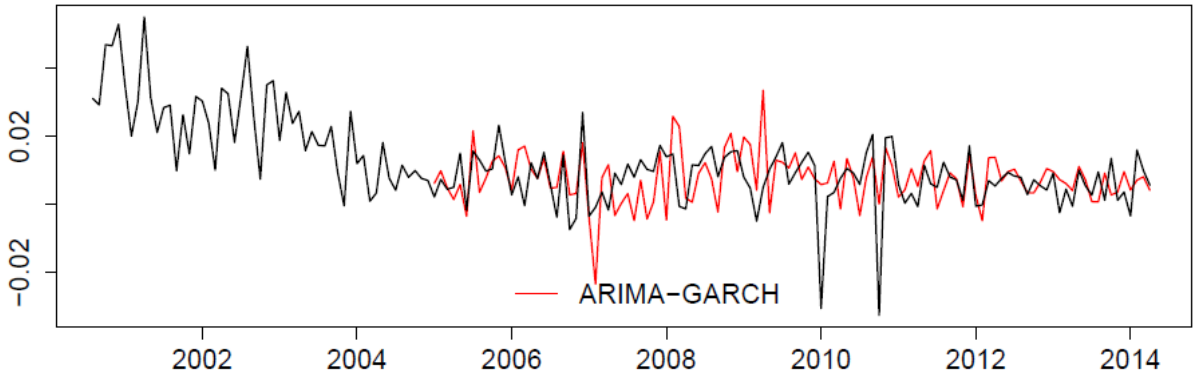
Central America



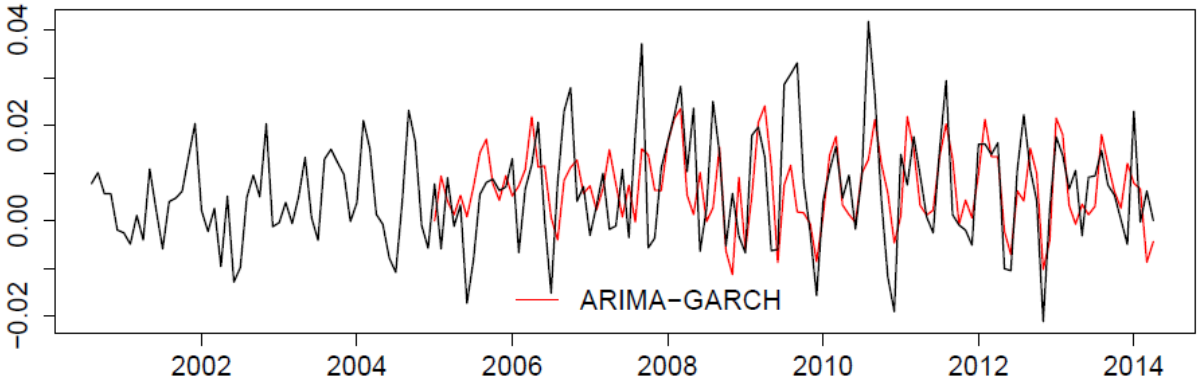
Eastern Africa



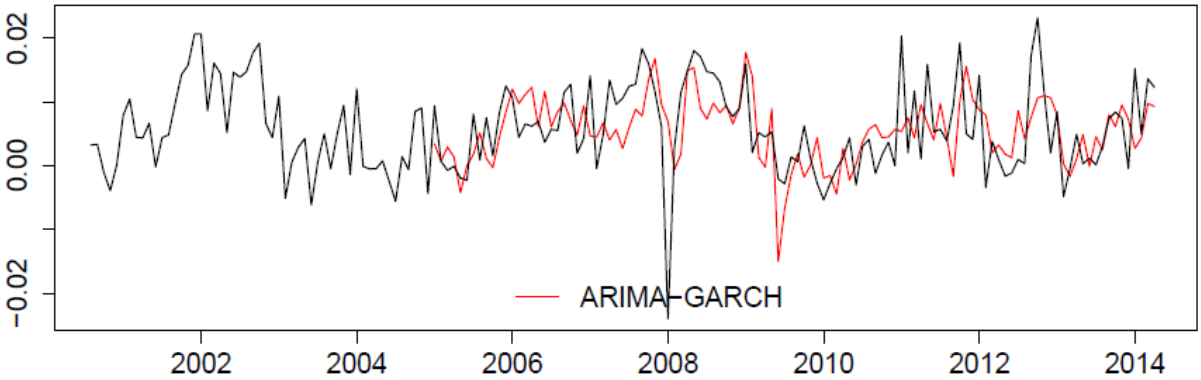
Central Africa



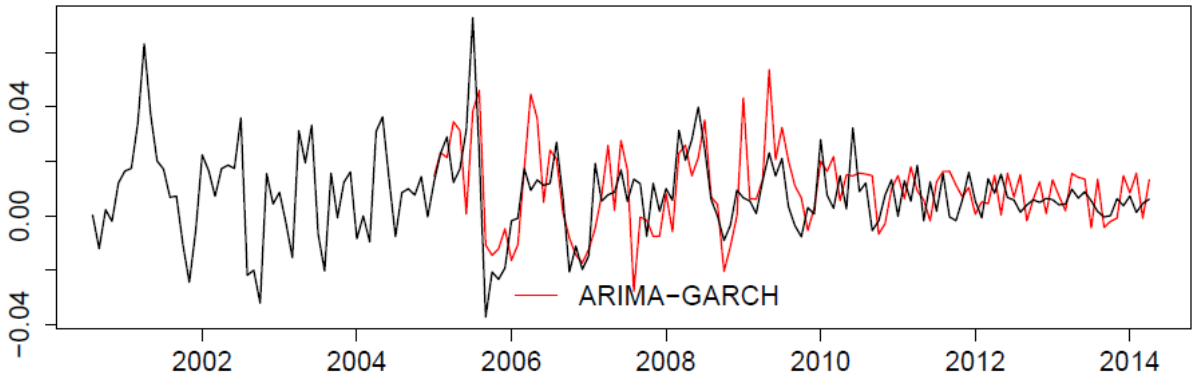
Northern Africa



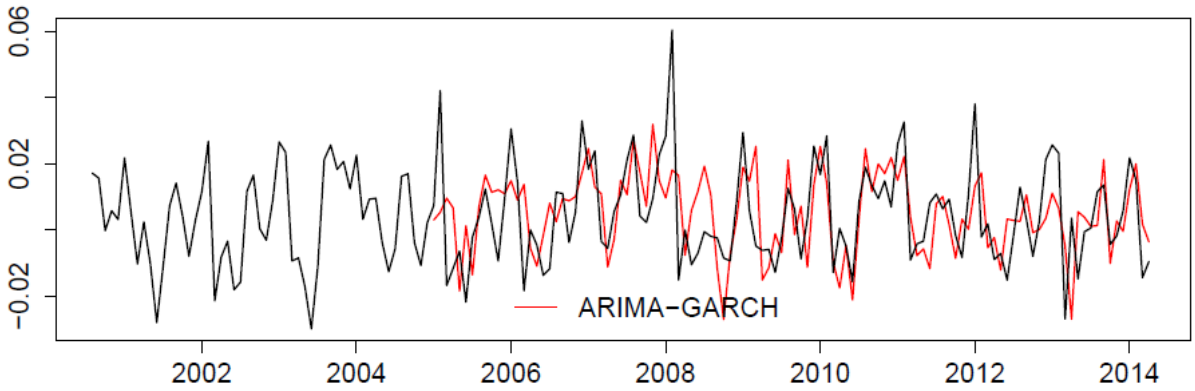
Southern Africa



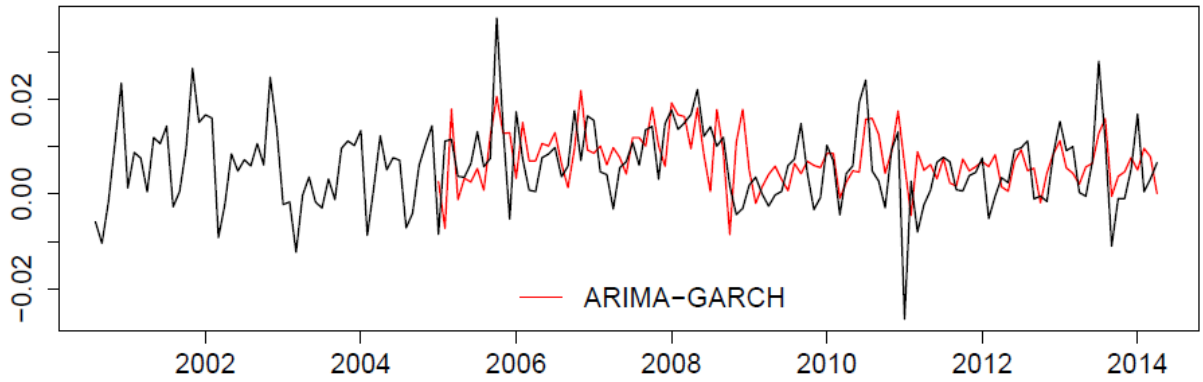
Western Africa



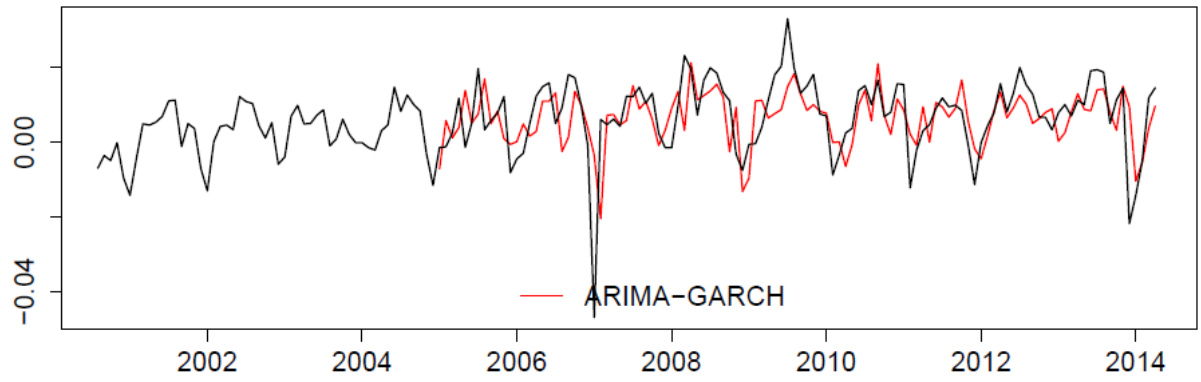
Eastern Asia



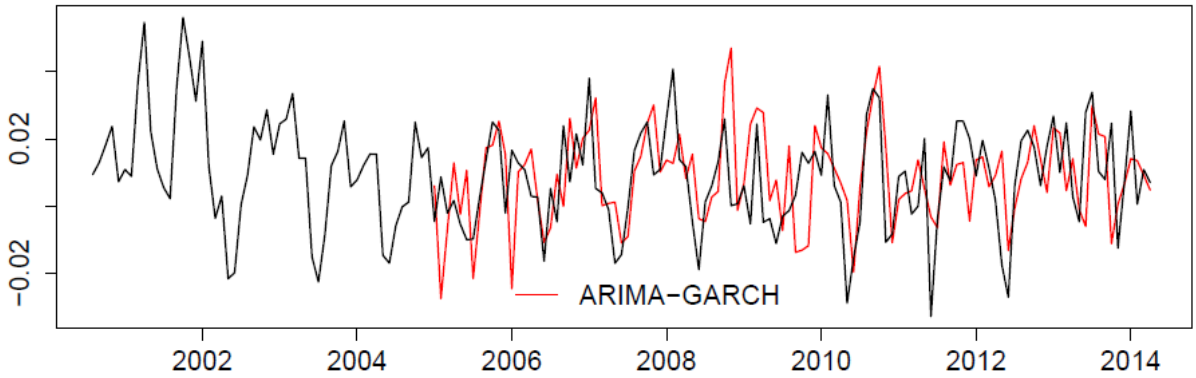
South-Eastern Asia



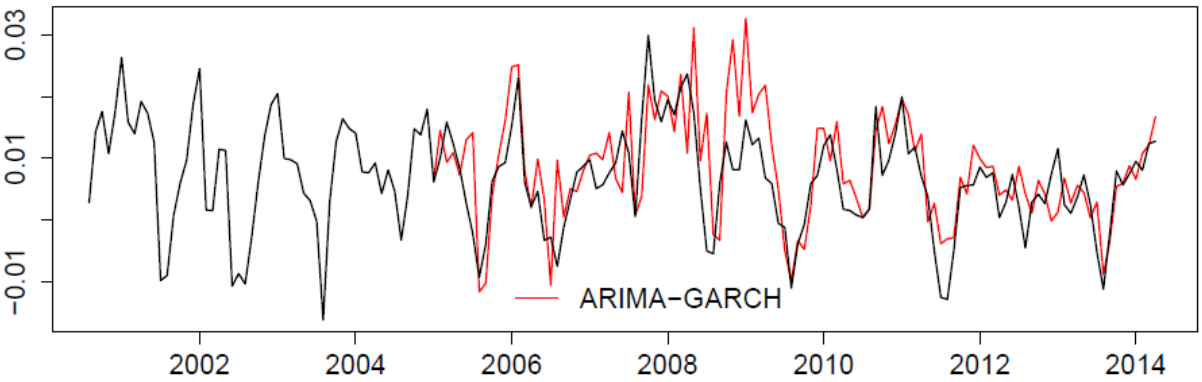
Southern Asia



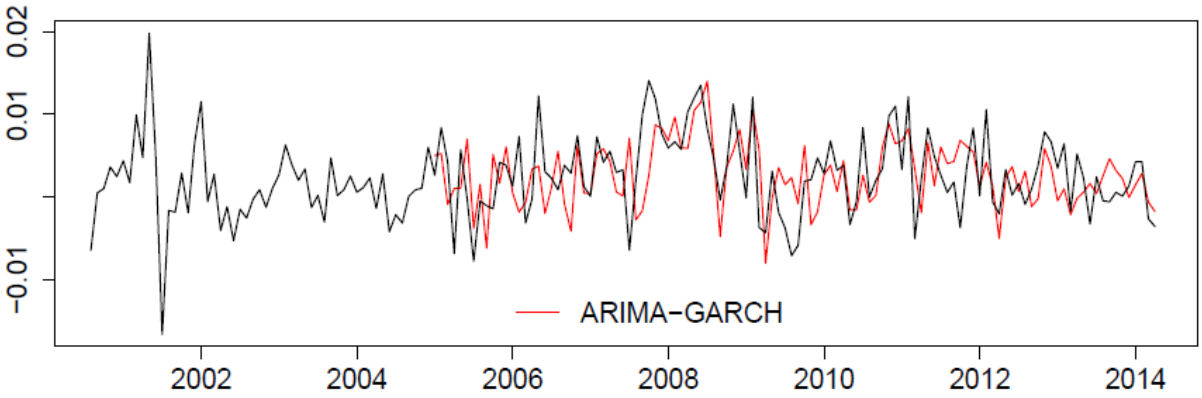
Western Asia



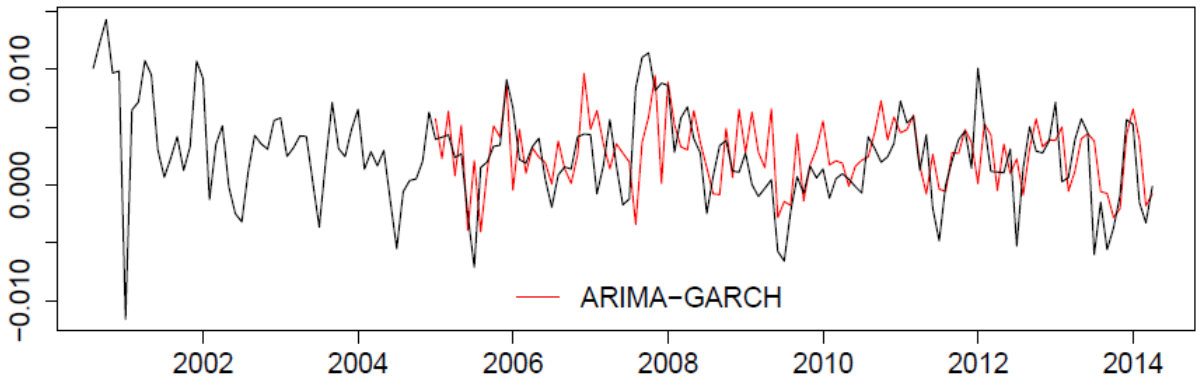
Eastern Europe



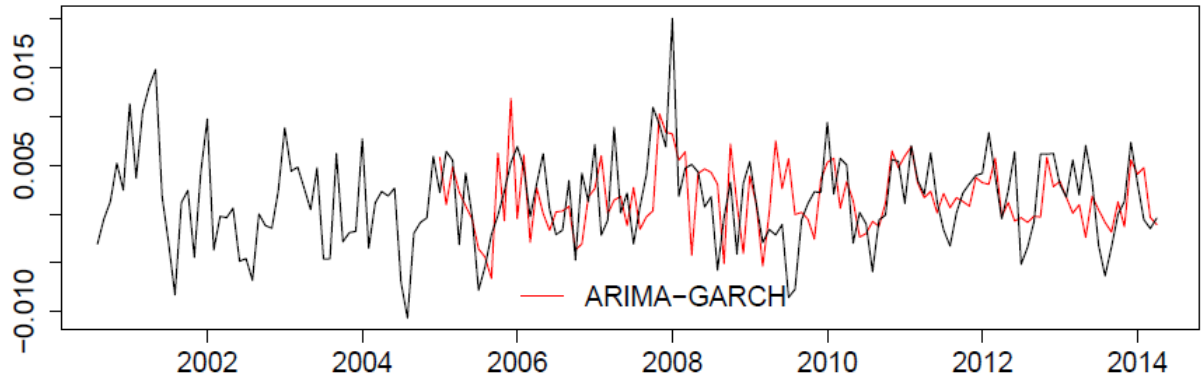
Northern Europe



Southern Europe



Western Europe



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