**A Markov Regime Switching Approach for Estimating Commodity Prices Changes with Location of the Change-Points**

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**Abstract**

The rapid changes in commodity prices lead to remarkable consequences for many developing countries whose revenues strongly rest on exporting these products. For the purpose of forecasting prices against supply shocks, knowledge of their estimate is needed. Monthly data on commodity prices over the period 1989-2013 are used. We use a Markov switching model introduced by Hamilton (1989) to analyze the prices changes and to locate the change-points. The results show existence of two regimes for commodity prices estimated, with a persistence of the regime one in three commodities. The probability of being in regime 1 varies from 0.68 to 0.98 and the duration of all regime goes from 1 to 53 months. In addition, the change-points depend on the type of commodities. The Markov Switching Model provided very interesting results for the countries that export these commodities. In each date, it is possible to predict in the next date, the most likely regime. These results will allow countries to take appropriate measures and reduce the adverse effects associated with a gross fall of prices in the economy. In the context of commodity volatility prices, it is important that public policies use good techniques to forecast and analyze the prices.

**Keywords:** commodity prices; Markov switching model.

## 1. Introduction

The rapid changes of commodity prices lead to remarkable consequences for many developing countries whose revenues still depend on exporting these products. Exports of commodities are a primary source of income for most African countries, particularly those of the West African Economic and Monetary Union (WAEMU). The prices of these different commodities are mainly determined on the world market and are influenced by fluctuations occurring through the supply and demand shocks. For the purpose of forecasting prices against supply shocks, knowledge of their estimate is needed.

Markov Switching Modeling seeks to study the changes of regime intervened in a series. The use of these models in macroeconomics has largely been developed in Hamilton (1989). These models have been popularized in the econometric literature to consider some type of non-stationarity present in many economic and financial series. Since the work of Hamilton, a large number of theoretical and empirical studies have been proposed for this type of econometric model. The model is interesting because it provides at any time a probability of occurrence of a certain unobserved variable, which is assumed to follow a Markov Switching chain with K states. In the economy, the increase in the price of many commodities dominated the discussion and into production, commodities are an important input. Authors show that the best strategy to model the dynamics of commodity prices is to consider each commodity case by case.

Authors such as Ferrara and Anas (2002) developed an economic index to detect in real time the entry and exit dates of recession for the United States. This indicator is based on a Markov Switching Model proposed by Hamilton (1989) and applied to different sets of representative American classic cycle. The filtered probabilities obtained from these series are combined while taking into account the risk of false signals to output an instantaneous probability of recession. Yuan (2011) proposed an exchange rate forecasting model which combines the multi-state Markov-switching model with smoothing techniques. Otherwise, several authors (Deng, 2000; de Jong, 2005; and Chen and Forsyth, 2008), building on the seminal work of Hamilton (1989), have used Markov Switching Approach. Chen and Insley (2008) investigates a regime switching model of stochastic lumber prices and they show that the land value and critical harvesting prices are found to be significantly different depending on which price model is used. Simon (1996) uses a Markov Switching model to analyze inflation in Australia. The results suggest that inflation is reasonably well represented by relatively simple functions of past inflation and an output gap term. Other author (Weron et al., 2004) analyzes the electricity prices by using Markov Switching model.

The observation of changes in commodity prices suggests that the generator sets process is influenced by an unobserved random variable called state or regime. This study aims to estimate, to study and to forecast the prices changes in four commodities namely cocoa, coffee, cotton and peanut, through the use of Markov Switching Model. The remainder of this paper is organized as follows. The section 2 discusses the data and methodology, section 3 presents the results and discussions. In a last section, we propose a conclusion.

## 2. Data and Methods

We use monthly time series on commodity prices provided by AFRISTAT[1]. These are economic data on the evolution of commodity prices and concern the indicative prices of four commodities: coffee, cocoa, cotton and peanut. The data cover the period 1989-2013. The seasonal test was conducted in all series. All four series are not affected by seasonal variations at 5% level.
In this paper, we use a Markov Switching Autoregressive Model (MS-AR). The Markov Switching Model approach is a method that can detect changes in trend of series by providing the conditional probability and the conditional mean of the process on each date t.

The basic assumption is that, a time series can be modeled in different structures or different models according to an unobserved process and finite value. In general, this unobserved process is a Markov chain whose states are called different "regimes", while the observed series follows a linear autoregressive model whose coefficients depend on the current regime.

Having observed that this type of series often had breaks in their mean, the idea of Hamilton was to model this non-stationarity using piecewise linear process. In a Markov Switching Model, the dynamics of variables change potentially of regime in each period of time depending on the economic condition. The model is specified as follows:

$$y_t = \mu(s_t) + \sum_{i=1}^{p} \phi_i(s_t) y_{t-1} + \sigma_{s_t} \varepsilon_t \qquad (1)$$

where $y_t$ is a stationary measure of the commodity prices. It is important to note that, the parameters model depend on a unobserved variable $s_t$ reflecting the state of the economy. In the Markov Switching Model, we suppose that the variable $s_t$ follows a Markov process of first order with M states with constant transition probabilities.

The probability that $s_t = 1$ knowing $I_{t-1}$ (all information available on the date $t-1$ with predictive power on $s_t$ ) is therefore determined only by the current value of $s_{t-1}$. Formally, $s_t$ satisfies the following property:

$$\Pr(s_t = j \setminus s_{t-1} = i, I_{t-1}) = \Pr(s_t = j \setminus s_{t-1} = i) = p_{ij} \quad \forall\, i \; et \; j = 1,2,\dots,M \quad (2)$$

where $p_{ij}$ is the probability of being in state $j$ in the date $t$ knowing that it was in the state $i$ in the date $t-1$. These transition probabilities satisfy the following relationship:

[1] Observatoire Economique et Statistique d'Afrique Subsaharienne (www.afristat.org)

$$\sum_{j=1}^{M} p_{ij} = 1 \; \forall \, i = 1, 2, ..., M \qquad (3)$$

In the case of two regimes (M = 2), the model is written as :

$$y_t = \mu_1 + \sum_{i=1}^{p} \phi_{1i} y_{t-i} + \sigma_1 \varepsilon_t \quad when \; s_t = 1 \qquad (4)$$
$$y_t = \mu_2 + \sum_{i=1}^{p} \phi_{2i} y_{t-i} + \sigma_2 \varepsilon_t \quad when \; s_t = 2$$

In this model, the parameters of the autoregressive part and intercept are dependent of the regime at time t. Regime 1 describes the periods of downtrend of prices and regime 2 denotes the periods of uptrend of prices.

In this case, the transition matrix takes the form:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{bmatrix} \qquad (5)$$

From measurements of the persistence of regimes, $p_{11}$ and $p_{22}$, we can obtain an estimate of the average duration of the regimes.

If we note $d_t^i$ the random variable representing the duration of the process in the regime i, knowing that the original regime is i, then this random variable follows a geometric distribution with parameter $1-p_{ii}$, i.e., for all $n > 0$ :

$$\Pr\left(d_t^i = 1\right) = p_{ii}^{n-1}\left(1-p_{ii}\right) \qquad (6)$$

Therefore, the average duration of the regime i, is given by $E\left(d_t^i\right) = 1/\left(1-p_{ii}\right)$.

In practice, it is often useful to consider the ergodic probabilities to be in a specific regime.

It can be shown (Hamilton, 1994) that:

$$P\left(s_t = 1\right) = \left(1-p_{22}\right)/\left(2-p_{22}-p_{11}\right) \qquad (7)$$
$$P\left(s_t = 2\right) = \left(1-p_{11}\right)/\left(2-p_{22}-p_{11}\right)$$

The estimate coefficients depend on the state of the regime. The authors suggest to determine the number of delay series through the two criteria (AIC and SC). These two criteria are used to select two delays (p = 2) for the four series of commodities that we studied. The result of this work will be devoted to the estimation of a MS (2)-AR (2) model for the four series. In other words, in this paper, our procedure is based on estimating a model with two regimes as explanatory variables, the dependent variable lagged of order 1 and 2.

**Locating the Change-Points in the series**

Markov Switching Modeling of a time series allows the detection of breakpoints. The hypothesis is that the series is completely observed, the breakpoints are calculated a posteriori. Mathematically, the model can be written as follows: we consider the function $\left(y_y\right)_{t=1...T}$ and we suppose that it change abruptly. Lavielle et Teyssière (2006) suppose that there is an integer $k^*$ and a sequence of changes-points $\gamma^* = \left(\gamma_1^*, ..., \gamma_{k^*}^*\right)$ with $\gamma_0^* = 0 \prec \gamma_1^* \prec ... \prec \gamma_{k^*}^* = T$ such as $\left(\lambda_k, \sum_k\right) \neq \left(\lambda_{k+1}, \sum_{k+1}\right)$ where $\lambda_k = E\left(y_t\right)$ and $\sum_k = Var\left(y_t\right)$, $\gamma_{k-1}^* + 1 \leq t \leq \gamma_{k^*}^*$.

### 3. Results and discussions

The last line of the table 1 gives the log-likelihood for each model on each series. Each of Figures 2-4 show respectively the filtered and smoothed probabilities, conditional mean and standard deviations for cocoa, coffee, cotton and peanut.

Table 1 : Markov Switching Model Estimation for cocoa, coffee, cotton and peanut

| Parameters | Regime1 | Regime2 | Regime1 | Regime2 | Regime1 | Regime2 | Regime1 | Regime2 |
|---|---|---|---|---|---|---|---|---|
| | Cocoa | | Coffee | | Cotton | | Peanut | |
| Constant | -0.008 | 0.006 | -0.003 | 0.011 | 0.001 | 0.100 | -0.005*** | 0.012* |
| | (0.006) | (0.005) | (0.004) | (0.019) | (0.004) | (0.301) | (0.002) | (0.007) |
| $y_{t-1}$ | 1.270*** | 1.148*** | 1.154*** | 2.282*** | 1.489*** | 0.830 | 1.493*** | 1.373*** |
| | (0.161) | (0.081) | (0.053) | (0.441) | (0.074) | (1.046) | (0.057) | (0.083) |
| $y_{t-2}$ | -0.221 | -0.186** | -0.161*** | -1.328*** | -0.460*** | -0.127 | -0.509*** | -0.391*** |
| | (0.177) | (0.079) | (0.055) | (0.434) | (0.076) | (0.969) | (0.056) | (0.083) |
| Ergodic probabilities | 0.29 | 0.71 | 0.83 | 0.17 | 0.87 | 0.13 | 0.56 | 0.44 |
| Duration of regime | 3.08 | 7.66 | 4.74 | 1.00 | 52.95 | 7.93 | 12.23 | 10.38 |
| Transition Probabilities Matrix | 0.68 | 0.13 | 0.79 | 1.00 | 0.98 | 0.13 | 0.92 | 0.10 |
| | 0.32 | 0.87 | 0.21 | 0.00 | 0.02 | 0.87 | 0.08 | 0.90 |
| Sigma ( $\sigma_{S_t}$ ) | 0.028*** | 0.064*** | 0.053*** | 0.094*** | 0.066*** | 0.236 | 0.015*** | 0.068*** |
| | (0.006) | (0.004) | (0.004) | (0.014) | (0.006) | | (0.002) | (0.005) |
| Observations | 291 | | 291 | | 291 | | 291 | |
| Likelihood Log | 416.748 | | 383.656 | | 424.850 | | 561.001 | |

Source: Our calculations based on AFRISTAT's data

The results are analyzed in the following paragraphs. The estimated transition probabilities show that the two regimes are persistent as the probabilities are greater than 0.5. But the persistence of a regime depends on the type of commodities. The results of different commodities are interpreted in the same way.

#### Estimating Cocoa Prices Changes

Regarding cocoa, the transition matrix shows low persistence of regime 1 and greater persistence of regime 2. Indeed, the probability of being in regime 2 at time t knowing we were in the same regime at t-1 is very high (estimated at 0.87). On the other side, the probability of being in regime 1 at time t knowing we were in the same regime at t-1 is relatively lower and 0.68. In addition, the estimation of ergodic probabilities shows that 29% of price observations should be located in regime 1 and 71% in regime 2. One rising month in cocoa prices is followed in 87% of cases by one rising month in prices and one declining month in cocoa prices is followed in 68% of cases by one declining month in prices. Similarly, the transition from the decline regime to the rising regime occurs with a probability of 32%, which explains why the average duration of the decline regime is 3 months. On the other side, the transition from the rising regime to the decline regime occurs with less probability (13%), which explains why the average duration is longer in the regime (about 8 months). Thus we can expect that, on average, a period of high volatility lasts more than 3 months. The review of autoregressive coefficients estimated by regime shows an autoregressive process away for cocoa prices for each regime. Figure 1 illustrates the evolution of filtered and smoothed probabilities for the two states.

#### Estimating Coffee Prices Changes

Regarding coffee series, the transition matrix shows a persistence of regime 1 and a virtual absence of regime 2. Indeed, the probability of being in regime 1 at time t knowing we were in the same regime at t-1 is 79%. In addition, the estimation of ergodic probabilities shows that 83% of the price observations should be located in regime 1 and 17% in regime 2. Thus, one decline month in coffee prices is followed in 79% of cases by one decline month. The transition from the decline regime to the rising regime occurs with a probability of 21%, which explains that the average duration of the decline regime to the rising regime is approximately 5 months. The transition from the regime 2 to the regime 1 operates with a total probability of 100%, which explains that the average duration in the regime scheme is very short (1 month). In addition, when we examining the autoregressive coefficients estimated by regime, we noticing an autoregressive process specific by regime for the coffee series. Figure 2 illustrates the evolution of filtered probabilities and smoothed for the two states.

Figure 1 : Filtered and Smoothed Probabilities, Fitted Conditional Mean and Standard Deviation for

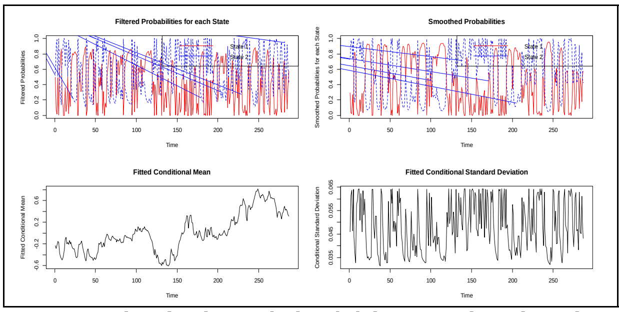



Figure 2 : Filtered and Smoothed Probabilities, Fitted Conditional Mean and Standard Deviation for Coffee

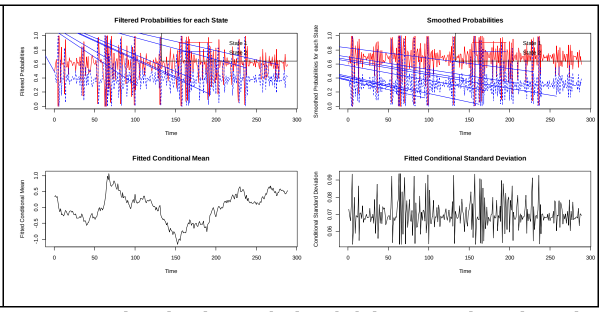



Figure 3 : Filtered and Smoothed Probabilities, Fitted Conditional Mean and Standard Deviation for Cotton

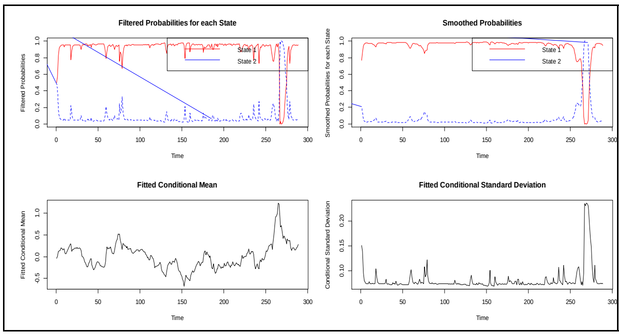
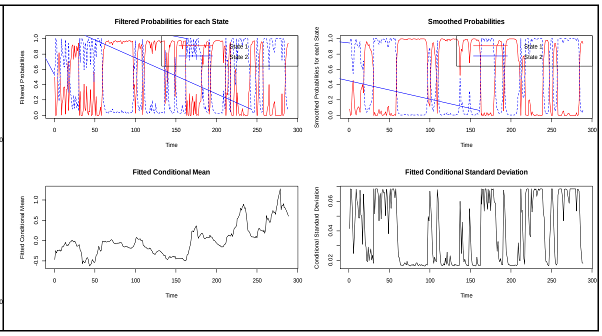



Figure 4 : Filtered and Smoothed Probabilities, Fitted Conditional Mean and Standard Deviation for Peanut




## Estimating Cotton Prices Changes

Estimates on cotton prices show that, the transition matrix shows a persistence of both regimes with a dominance of regime 1. Indeed, the probability of being in regime 1 at time t knowing we were in the same regime at t-1 is 98%. For regime 2, the probability of being at time t in this regime while you are there at time t-1 is 87%. In addition, the estimation of ergodic probabilities shows that 87% of the price observations should be located in regime 1 and 13% in regime 2. Thus, one declining month of cotton prices followed in 98% of cases by another declining month. One rising month is followed in 87% by one rising month. The transition from the regime 1 to the regime 2 occurs with a probability of 2%, which explains that the average duration of the decline regime to the rising regime is 53 months.

On the other side, the transition from the regime 2 to the regime 1 occurs with a probability 13%, which explains the average duration of the rising regime is shorter (8 months). Figure 3 illustrates the evolution of filtered probabilities and smoothed for the two states.

## Estimating Peanut Prices Changes

The estimating of transition matrix for peanut prices changes highlights persistence of two regimes with a dominance of regime 1. Indeed, the probability of being in regime 1 at time t knowing we were in the same regime at t-1 is 92%. For regime 2, the probability of being at time t in this regime while you are there at time t-1 is 90%. In addition, the estimation of ergodic probabilities shows that 56% of the price observations should be located in regime 1 and 44% in regime 2. It is observed that the two regimes seem to share almost equally the information contained in prices. One declining month in peanut prices followed in 92% of cases by one declining month while, one rising month is followed in 90% by one rising month. The transition from the regime 1 to the regime 2 occurs with a probability of 8%, which explains why the average duration of the rising regime is greater than 12 months, whether more than one full year. On the other side, the transition from the regime 2 to the regime 1 occurs with a probability of 10%, which explains why the average duration of this regime is lower (10 months) than the above. Figure 4 illustrates the evolution of filtered probabilities and smoothed for the two states.

**Estimating Commodities Change-Points**

When applying the algorithm of Lavielle and Teyssière (2006), the changes-points are obtained for the different commodities series. These changes-points are someway the exact date or period where the tendency of different series changes. The goal is to forecast the future trend of the series, taking into certain assumptions and known information generating process. It is interesting to observe the history of a variable to discover regularities. It is here to assume that the same causes produce the same effects and to establish robust forecasts on sudden ruptures and non-anticipatable changes. Through these various changes-points, it is given the exact year and month in the series trend. The cocoa series shows 12 changes-points between 1990 and 2010. The coffee and cotton series give 10 changes-points, while there were 11 changes-points in the peanut series.

## 4. Conclusions

The results show existence of two regimes for commodity prices estimated, with a persistence of the regime one for coffee, cotton and peanut but the persistence of regime two for cocoa. The probability of being in regime 1 varies from 0.68 to 0.98 and the probability of being in regime 2 varies from 0 to 0.90. The duration of all regimes goes from 1 to 53 months. In addition, the change-points depend on the type of commodities. The Markov Switching Model provided very interesting results for the countries that export these commodities. In each date, we can predict in the next date, the most likely regime. These results will allow countries to take appropriate measures and reduce the adverse effects associated with a gross fall of prices in the economy. In the context of volatility of commodity price in most WAEMU countries, it is important that public policies use good techniques and adequate price forecasting. This allows them to reach decisions that are in the direction of a better process and generator prices. It is also important that public policies implement structures that ensures analyze daily commodity prices and make recommendations from studies of the context of international market.

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