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Serigne THIAM

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Characterization of the covid-19 crisis on the commodity market using the markov switching variance model

Serigne THIAM[i]

Abstract:

This paper uses Markov Switching Variance Model to detect crises in the commodity market. The crises detected in this market are the COVID-19 health crisis of 2020, the food crisis of 2014, the Greece crisis and the Euro debt crisis between late 2010 and July 2011, the financial crisis of 2008 and and the oil shocks of 1973 and 1979.

The results of the estimation of Markov Switching Variance Model show that the financial crisis of 2008 and the oil shock of 1973 and 1979 plunged the agricultural commodities market into a deep crisis (probability of being in a crisis phase equal to 1), whereas the health crisis more or less caused a crisis on this market (probability of being in a crisis phase equal to 0.7). Also, the crisis caused by the COVID-19 pandemic is shorter than the crises generated by the 2008 financial crisis and the 1973 oil shock.
Also, the pandemic had a greater impact on the energy products market than on the agricultural commodities market.

Keywords: markov Switching Variance Model, health crisis, volatility, commodity market.

Résumé :

Ce papier utilise les modèles à changements de régimes markoviens pour détecter les crises sur le marché des matières premières. Les crises détectées sur ce marché sont la crise sanitaire du COVID-19 de 2020, la crise alimentaire de 2014, la crise de la Grèce et la crise de la dette de l'euro entre fin 2010 et juillet 2011, la crise financière de 2008 et les chocs pétroliers de 1973 et 1979.

Les résultats de l'estimation du modèle markovien hétérocédastique à changement de régime montrent que la crise financière de 2008 et le choc pétrolier de 1973 et 1979 ont plongé le marché des matières premières agricoles dans une profonde crise (probabilité d'être en phase de crise égale à 1) tandis que la crise sanitaire a plus ou moins entrainé une crise sur ce marché (probabilité d'être en phase de crise égale à 0,7). Aussi, la crise provoquée par la pandémie de la COVID-19 est plus courte que les crises générées par la crise financière de 2008 le choc pétrolier de 1973.
Egalement, la pandémie a plus impactée le marché des produits énergétiques que le marché des matières premières agricoles.

Mots clés : modèle markovien hétérocédastique à changement de régime, crise sanitaire, volatilité, marché des matières premières.

[i]PhD in Economics, National Agency for Statistics and Demography (ANSD). Email : morthiam8547@gmail.com

1. INTRODUCTION

Since the financial crisis of 2008, authors have focused on the stability and efficiency of global markets (financial market, commodity market, etc.). Thus, the notion of the efficiency of global markets is more relevant than ever. This notion was initially developed by Fama (1965). Indeed, Fama (1970) defined an efficient market as one "in which stock prices fully reflect available information". He established some important (but not necessary) conditions for efficiency. These conditions include: (i) absence of transaction costs on the exchange of securities, (ii) availability and accessibility of information for all players. Thus, the assumptions of an efficient market require that agents maximise their utility and have rational expectations. Consequently, financial market prices follow a random walk and adapt quickly to information when it becomes available on the market by integrating it into the price, hence a fair price (Fama, 1970; Shiller, 2001).

Lo and MacKinlay (1988) found that stock prices did not follow a random walk. Empirical results suggested that the random walk model was not consistent with the stochastic behaviour of weekly returns. They found positive autocorrelations for both weekly and monthly returns. They stress that the results do not necessarily imply that the market is inefficient or that prices are not rational assessments of "fundamental" values.

Recently, over the last two decades, global markets have been characterised by phenomena that are antagonistic to market efficiency: (i) high price volatility in global markets, (ii) dynamics of market gains, (iii) price dynamics in global markets. These phenomena can be generated by crises, the latest of which is the COVID-19 health crisis.

Emerging in December 2019 in China, the Coronavirus disease has affected every country in the world. Indeed, the pandemic is evolving exponentially around the world (Kuma, 2020). According to WHO, the number of COVID-19 cases is estimated to be 3,157,172 as of April 25, 2020, compared to 147,812,476 as of April 25, 2021. The number of deaths related to COVID-19 is estimated at 211,936 as of April 25, 2020, compared to 3,122,683 as of April 25, 2021. The countries most affected by the pandemic are the United States of America (33,369,192 cases), India (21,485,285 cases) and Brazil (15,009,023 cases).

In addition to the loss of human life, the COVID-19 pandemic has plunged the world economy into a deep crisis. Thus, the world economic growth dropped by 6.0% in 2020 (IMF, 2021). The Eurozone is the most affected, with growth falling by 7.9% in 2020 (IMF, 2021). Sub-Saharan

Africa has not been spared, with economic growth contracting by an estimated 6.1% in 2020 (IMF, 2021).

In addition, restrictions on the movement of people and international travel to contain the spread of the virus are having a significant impact on international trade and global growth. These measures have created both a demand shock (lower consumption) and a supply shock (lower production). Thus, the demand shock results, on the one hand, from the containment measures that paralyzed economic activity through the closure of non-essential activities and, on the other hand, from the disruption of the production chain on an international scale. The supply shock is the result of a reduction in the consumption of certain goods and services at the national level and a drop in foreign demand.

These supply and demand shocks have not spared the world markets; they have led to a decline in most commodity prices. In 2020, world prices for energy products fell by 31.66% compared to 2019 (World Bank, 2020). As for the world prices of base metals, the decrease is estimated at 1.75% (World Bank, 2020). However, an increase of 4.58% is noted for the prices of agricultural products (World Bank, 2020). It should be noted that in 2021, forecasts for world markets indicate a slight increase in world commodity prices (World Bank, 2020).

These favorable forecasts in 2021 are explained by the vaccination campaigns and the gradual reopening of the economies.

This crisis has plunged commodity markets into severe turbulence. Indeed, measuring the extent of this turbulence allows market players and regulators to better distinguish the phases of crisis in order to take the necessary measures. It should be noted that apart from the COVID-19 crisis, other factors have caused turbulence on the world markets. In the oil market, the suspension of cooperation between Saudi Arabia and Russia on production levels, and in the agricultural products market, the Sino-American trade war.

In order to identify turning points and structural changes in world markets, it is necessary to formalize a precise statistical definition of shocks. Thus, both linear and non-linear statistical methods are used. Linear models have been used to study the dynamics of financial and commodity markets. These markets were assumed to be efficient for a long time by Fama (1965, 1970). Currently, the efficiency hypothesis is incompatible with the real functioning of markets because of the heterogeneity of the expectations of market participants, the presence of distinct transaction and information costs and the importance of market imperfections, Dumas (1992), Anderson (1997). Indeed, the rejection of the efficiency hypothesis has revealed the limitations of linear models in the financial domain. These limitations have justified the use of non-linear models to study the dynamics of financial and commodity markets. There are two main categories of non-linear models: models with non-linearity in the mean and models with non-linearity in variance (ARCH-type models). In this study, Markov regime-switching models are used to identify and characterize the COVID-19 crisis in the commodity market.

Markov regime-switching models were first applied in economics by Lindgren (1978). Subsequently, Hamilton (1989) used them in the study of business cycles. He demonstrated that shocks can be captured by a model characterized by Markovian processes. In the same vein, Chauvet et al (2005) used these models to date business cycles in macroeconomic time series.

The aim of this article is to identify the different phases of commodity markets. These phases correspond to periods of crisis and stability. It also determines the dates corresponding to the COVID-19 crisis and evaluates the total duration of this crisis while comparing it to previous crises.

The main contribution of this paper is that Markov Switching Variance Model detect previous crises better than the COVID-19 crisis. Moreover, it shows that the duration of the COVID crisis is shorter than that of previous crises.

Our study is thus structured around three sections. The first section presents the Markovian regime-switching models. The second section proposes a descriptive analysis of the series of world prices on the commodities market. The last section will focus on Markov regime-switching modeling to measure the impact of the COVID-19 crisis on commodity markets.

2. REVIEW OF THE LITERATURE

The theoretical literature on crisis identification is extensive. In general, market events are used to identify crises. Thus, the event method uses logit regression to identify crises. This method has several drawbacks; it identifies crises late and determines the dates of crises in an arbitrary way (von Hagen et al. 2003). These limitations led von Hagen and Ho (2003) to develop a quantitative approach to identifying crises in markets, particularly in banking markets. They construct an index of market pressure. If the index exceeds a predetermined threshold, then they consider the banking market to be in crisis. The determination of the crisis threshold depends on the nature of the data; in particular on the assumption of normality, which is rarely respected. Also, the crisis threshold depends on the characteristics of the sample. One possibility to correct for the above limitations in crisis identification is to endogenise the choice of the crisis threshold and let the data indicate it; this is done by Markov regime-switching models. These models, developed by Hamilton (1989), is used by many researchers such as Calvet and Fisher (2004), Masoud, Hamidreza and Safael (2012), Beckmann and Czudaj (2013), Lux, Morales-Arias and Sattarho (2014), Nguyen and Walid (2014), Aliyu and Wambai (2018).

Thus, Markov regime-switching models have advantages over other methods. First, it endogenises the choice of crisis threshold and crisis duration and thus reduces arbitrariness in identifying the crisis. Second, it allows each endogenously determined crisis duration to vary.

From an empirical point of view, several authors have studied the impact of the COVID-19 pandemic on financial and commodity markets.
Albulescu (2020), estimating an ARDL model to study the relationship between the COVID-19 pandemic and the fall in oil prices, shows that the number of daily COVID-19 infections had a marginal negative impact on oil prices in the long run. Indeed, by causing volatility in financial markets and increasing economic policy uncertainty, the COVID-19 pandemic has strongly affected the dynamics and volatility of world oil prices. Thus, the volatility generated by the pandemic increased from 8% to 22%, Devpura and Narayan (2020).

In the same vein, Gil-Alana and Monge (2020) show that the oil price shocks during the first wave of the pandemic were transitory. This result is obtained through the use of fractional integration techniques. Furthermore, Narayan (2020) in his study finds that the oil price is more influenced by negative oil price news than by the number of daily COVID-19 contamination.

Similarly, using an EGARCH model, Meher et al (2020) indicate that there is a presence of asymmetric volatility in crude oil prices due to the spread of COVID-19. Thus, information related to new cases of COVID-19 contamination has an impact on the volatility of crude oil prices. However, there is no leverage effect of the COVID-19 pandemic on the volatility of natural gas prices.

In addition to the commodity market, Hassan and Riveros Gavilanes (2021) analyse the dynamic impact of the COVID-19 pandemic on financial markets. These authors show that in the short term, the COVID-19 pandemic (the rate of spread of the virus) has a negative impact on the returns of stock market indices. Also, an increase in the rate of spread of the virus led to a decrease in the prices of Brent and WTI by 4.08% and 3.26%, respectively. These results are corroborated by Ahmed et al (2021) who used the conventional Welch's test, the heteroscedastic independent t-test and the GMM multivariate analysis to assess the impact of the COVID-19 pandemic on the performance and sustainability of stock and commodity markets.

Other authors such as Ezeaku, Asongu and Nnanna (2021) estimated a SVAR model and showed that the COVID-19 pandemic, through the oil shock it generated, significantly impacted the market of precious metals (gold and silver) and other base metals (copper and aluminium). Thus, gold and silver prices reacted negatively to the oil shock. For copper, it reacted positively to the oil shock from day 1 to day 130 (end of May 2020), before seeing its world prices decline for the rest of the period. World aluminium prices, on the other hand, reacted positively to the oil shock over the whole period.

Dmytrów et al (2021) use the Dynamic Time Warping (DTW) method to analyse the relationship between the COVID-19 pandemic and commodity prices. Thus, they show that commodities such as heating oil, crude oil, and gasoline are weakly associated with COVID-19. In contrast, natural gas, palm oil, CO2 allowances and ethanol are strongly associated with the development of the pandemic.

In another methodological logic, Jong et al (2021) used Markov regime-switching models to simultaneously determine the impact of COVID-19 and commodity market volatility on the Booking.com stock market. He shows that the disease negatively influenced the performance of the hotel stock market.

Ahmed and Sarkodie (2021) used the same approach to study the switching effect of the COVID-19 pandemic and economic policy uncertainty on commodity prices. The authors consider two regimes: a low volatility regime and a high volatility regime.
Their results also show a high probability that commodity prices remain in the low volatility regime rather than the high volatility regime - due to the market uncertainties attributed to COVID-19.
Also, using the same methodology, Czech and Wielechowski (2021) show that the alternative energy sector appears to be more resilient to COVID-19 than the conventional energy sector.

However, by distinguishing three regimes in the Markov model: the quiet, volatile and turbulent regime. Baiardi et al (2020) show that the quiet regime is the most frequent over the whole period, while the dominant regime is the volatile regime for the 2008 crisis and the turbulent regime for the first four months of 2020.

In a different vein, Benigno et al (2021) in modelling financial crises, use DSGE models. The estimated model fits the data with well-behaved shocks, identifying three crisis episodes of varying duration and intensity: the debt crisis of the early 1980s, the Tequila crisis of the mid-

1990s and the global financial crisis of the late 2000s. The estimated crisis episodes are much more persistent and consistent with the data than traditional models.

From this empirical review of the literature, it can be seen that most authors study the impact of the COVID-19 crisis on the financial and commodity markets. In general, these authors, with a few exceptions, do not characterise the COVID crisis by identifying the different regimes on the markets. This article makes a comparative characterisation of the health crisis on two markets: the energy commodity market and the agricultural commodity market by using a Markovian-Switching Variance Model.

3. BRIEF PRESENTATION OF MARKOVIAN-SWITCHING VARIANCE MODEL

Markov regime-switching models, introduced by Lindgren (1978) and made popular by Hamilton (1989), are used to identify crises and detect turning points in financial markets. This section presents a variant of the Markov change models developed by Kim and Nelson (1999) : Markov Switching Variance Model.

a. Presentation of the model

The Markov Switching Variance Model used in this study is based on the work of Kim and Nelson (1999).

It is assumed that the time series of world prices can be described by the following process:

$$y_t = \sim N(0, \sigma_t^2) \tag{1.1}$$

$$\sigma_t^2 = \sigma_1^2 S_{1t} + \sigma_2^2 S_{2t} + \cdots + \sigma_T^2 S_{Tt} \tag{1.2}$$

where;

T is the number of state;

y_t is the returns on commodity prices in period t;

the commodity price return is modeled using a normal distribution ;

S_{Tt} is an unobserved state variable

σ_T^2 is the variance in state S_{Tt}.

All these equations depend on the state of the model at time t : S_t. This state is detectable using Markov chains. The Markov process is a stochastic process that has the following property: the information useful for predicting the future depends only on the information of today's state.

Hamilton assumes that the state S_t is not directly observable but can be deduced from the observable behavior of the time series of world price returns. Thus, to determine the probability law governing the observations of commodity price returns, a probabilistic model explaining the transition from the state $S_t = i$ to $S_t = j$ is required. It is given by the following transition probability:

$$\Pr(S_t = j/S_{t-1} = i) = p_{ij}, \tag{1.3}$$

i, j=0, 1

$$\sum_{j=1}^{2} p_{ij} = 1 \tag{1.4}$$

$\sigma_1^2 < \sigma_2^2$.

p_{ij} denotes the probability of moving to state j knowing that one is in state i. This probability depends only on today's state and not on the past state. From these equations, we can try to estimate the transition probabilities and the variance of the innovation.

b. Estimation of the model

The maximum likelihood method is used to estimate the parameters of the Markovian switching variance model. For this purpose, the joint density of $\tilde{y}_t$ and $\tilde{S}_t$ the log likeliwood function are written as follow:

$$p\left(\tilde{y}_T, \tilde{S}_T; \theta\right) = p(\left(\tilde{y}_T \middle| \tilde{S}_T; \theta_1\right) \times p(\tilde{S}_T; \theta_2),$$

$$= \prod_{t=1}^{T} p((y_t|S_t; \theta_1) \times \prod_{t=1}^{T}(S_t|S_{t-1}; \theta_2) \tag{1.5}$$

where;

$\theta = [\theta_1' \;\; \theta_2']'$ with $\theta_1 = [\sigma_0^2 \;\; \sigma_1^2]'$, $\theta_2 = [p_{00} \;\; p_{11}]'$

$\tilde{y}_t = [y_1 \;\; y_2 \ldots \; y_T]'$, $\tilde{S}_t = [S_1 \;\; S_2 \ldots \; S_T]'$

By using log function

$$\ln\left(p\left(\tilde{y}_T, \tilde{S}_T; \theta\right)\right) = \sum_{t=1}^{T} \ln\left(p\left((y_t|S_t; \theta_1)\right) + \sum_{t=1}^{T} \ln\left((S_t|S_{t-1}; \theta_2)\right) \tag{1.6}$$

If S_t were observed, θ_2 would be irrelevant and the log likelihood function would be maximized with respect to θ_1 :

$$\frac{\partial \ln\left(p(\tilde{y}_T,\tilde{S}_T;\theta)\right)}{\partial\theta_1} = \sum_{t=1}^{T} \frac{\partial \ln\left(p\left((y_t|S_t;\theta_1\right)\right)}{\partial\theta_1}. \tag{1.7}$$

If $S_t$is not observed, we maximize the expected log likelihood function

$$Q(\theta;\tilde{y}_T,\theta^{k-1}) = \int_{\tilde{S}_T} \ln\left(p\left(\tilde{y}_T,\tilde{S}_T;\theta\right)\right) \times p\left(\tilde{y}_T,\tilde{S}_T;\ \theta^{k-1}\right). \tag{1.8}$$

We obtain

$$\sum_{t=1}^{T}\sum_{S_t=0}^{1} \frac{\partial \ln\left(p\left((y_t|S_t\right)\right.}{\partial\theta_1} p((S_T|\tilde{y}_T;\theta^{k-1}) = 0, \tag{1.9}$$

Where $p((S_T|\tilde{y}_T;\theta^{k-1})$ is the smoothed probability.

By using iteration for equation (1.9), we obtain

$$\ln\left(p\left((y_t|S_t = j;\theta_1\right)\right) = -\frac{1}{2}log2\pi - \frac{1}{2}ln\sigma_j^2 - \frac{1}{2}\frac{y_t^2}{\sigma_j^2}, \tag{1.10}$$

The first order conditions in equation (1.9) give the following result :

$$\sum_{t=1}^{T}\left(-\frac{1}{2}\frac{1}{\sigma_j^2} + \frac{1}{2}\frac{y_t^2}{\sigma_j^4}\right)p(S_t = j|\tilde{y}_T;\theta^{k-1}) = 0, \tag{1.11}$$

Equation 1.11 allows to obtain the estimation of σ_j^{2k}

$$\sigma_j^{2k} = \frac{\sum_t y_t^2 p\left(S_t = j|\tilde{y}_T;\theta^{k-1}\right)}{\sum_t p\left(S_t = j|\tilde{y}_T;\theta^{k-1}\right)}, \tag{1.12}$$

By differentiating the expected log likelihood function in equation (1.12), we obtain p_{jj}^k :

$$p_{jj}^k = \frac{\sum_t p\left(S_t = j,\ S_{t-1} = j|\tilde{y}_T;\theta^{k-1}\right)}{\sum_t p\left(\ S_{t-1} = j|\tilde{y}_T;\theta^{k-1}\right)}. \tag{1.13}$$

4. DESCRIPTIVE STUDY AND STATIONARITY OF THE SERIES

This section presents the data used in the study before making a descriptive analysis of the world market prices of agricultural and energy products.

a. The data

The working data come from the World Bank's Commodity Price Data database. These data relate to the world price indices of agricultural and energy commodities. The agricultural commodity market is composed of raw materials (wood, rubber, etc.), food products (oil, meat, seeds, etc.) and beverages. As for the energy products market, it is composed of oil, natural gas and coal. It should be noted that these data are monthly (12 data per year), they cover the period from January 1960 to February 2021 and concern the market for energy and agricultural products; that is, a total of 734 observations.

Justification of the choice of markets

The commodities market is composed of the energy and non-energy markets. The former includes the coal, natural gas and crude oil markets. The latter is composed of the markets for metals, agricultural products and fertilizer. These markets have different characteristics and do not react in the same way to different crises. For example, the energy products market is more volatile because of crude oil.

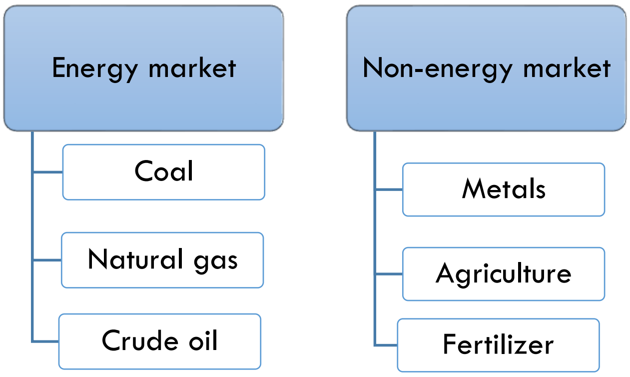
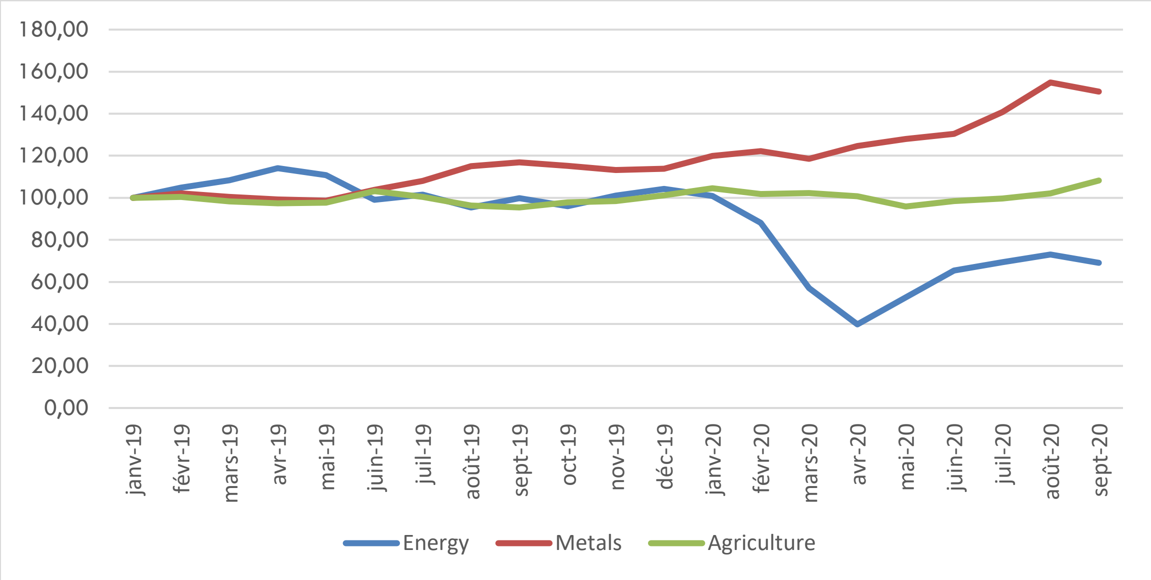


Figure 1: Composition of the commodity market

Source: World Bank Development Prospects Group

Indeed, the COVID-19 pandemic has led to a drop in world prices on the various commodity markets except for the metals market. The fall in prices was more significant on the energy market (60.56% over the period January 2020 to April 2020). Regarding the agricultural commodities market, a decline of 3.71% was recorded over the same period.

However, the metals market, which seems to be resilient to this crisis, has seen an increase in world prices. This could lead to the conclusion that the impact of the COVID-19 crisis was more significant on the energy markets and the agricultural commodities market. This justifies the choice of these two markets.



Source: World Bank Commodity Price Data, 2021

Figure 2: Evolution of world commodity prices

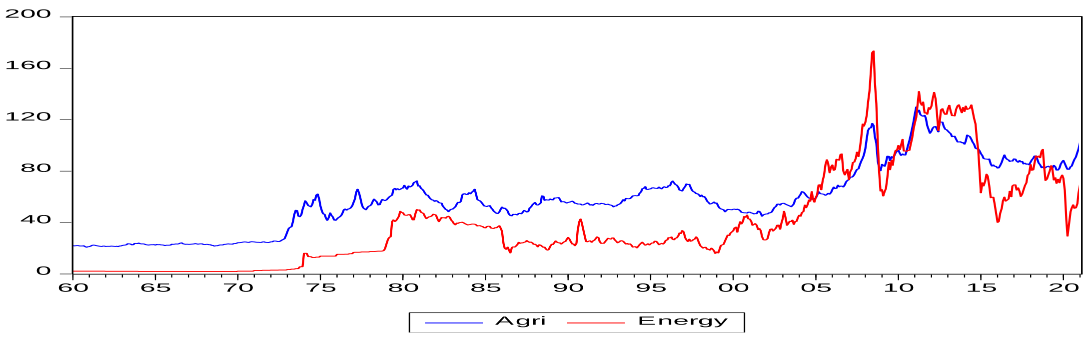
b. Graphical representation of world price indices

The analysis of the graphs of monthly price indices for agricultural and energy products shows a general upward trend marked by three main periods:

- the period 1960-1972 characterized by low and stable world price indices

- the 1973-2005 period marked by high world price indices with moderate fluctuations

- the period 2006-2021, symbolized by very high world price indices with strong fluctuations.



Source: World Bank Commodity Price Data, 2021

Figure 3: Monthly price index for agricultural and energy products

Furthermore, graphical analysis 3 shows that the series experience stochastic shocks that accumulate over time and thus increase the variance of the process over time. This means that the two series represented have little chance of being stationary. Indeed, to confirm the non-stationarity of the series, it is necessary to implement unit root tests.

c. Unit root tests

Unit root tests allow to detect the existence of a non-stationary process. They also help to determine the nature of the non-stationarity (TS or DS process) and therefore the right method to stationaryize the series. Two main methods can be used to test the stationarity of series: the Dickey-Fuller test (1981) and the Philips-Perron test (1988).

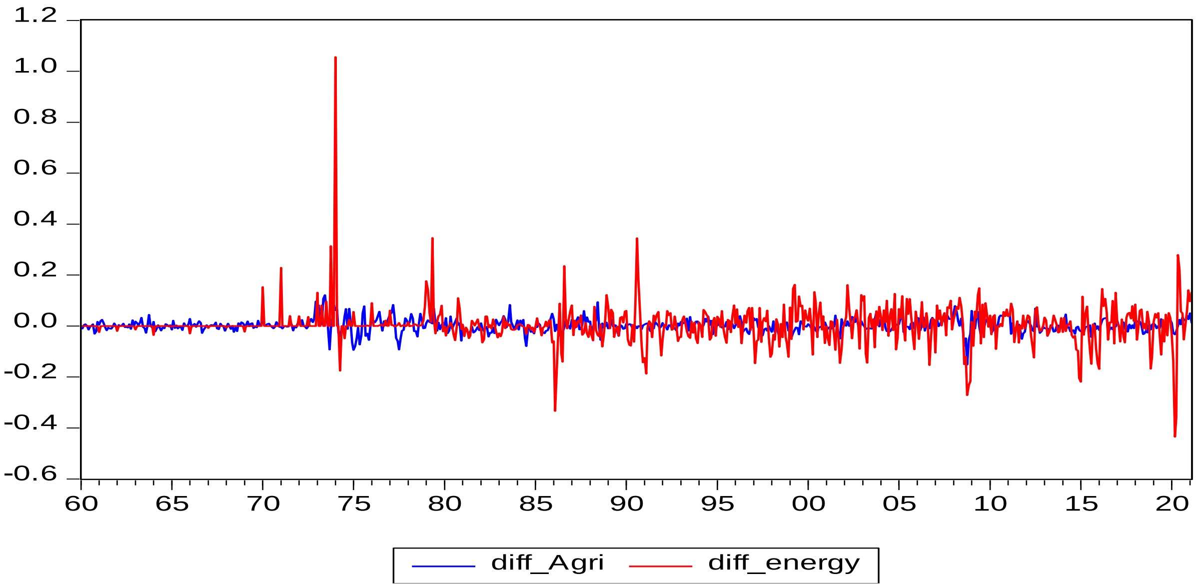
The analysis in Table 1 shows that the majority of the unit root tests conclude at the 5% threshold that both series (Agricultural Commodity Price Indices and Energy Price Indices) are non-stationary. These results validate the hypothesis of non-stationarity made during the descriptive analysis of the series.

Table 1: Unit root test on the monthly price indices of agricultural and energy products

Test	**Statistic**	**Test at level of agricultural commodity price indices**		**Test at level of energy price indices**	
		With constant	With constant & Trend	With constant	With constant & Trend
ADF	t-Stat	-1.3261	-2.9615	-2.1751	-3.7398
	Prob.*	0.6190	0.1440	0.2158	0.0204
Phillips-Perron	t-Stat	-1.1770	-2.6864	-1.9183	-3.2333
	Prob.*	0.6861	0.2426	0.3239	0.0787

Source : Author's calculation

Since these two series are not stationary, we can differentiate them in logarithm. In this case, we obtain the returns of the world prices on the market of agricultural commodities and energy products. Before using these returns in the following, we must ensure that they are stationary. Indeed, if they are not, we differentiate them again, i.e. work in second differences. Note that at first glance, cf. Figure 4, the returns series seem stationary.



Source: World Bank Commodity Price Data, 2021

Figure 4: Monthly returns of agricultural and energy products

The stationarity of the returns shown in Table 2 confirms this conjecture. All unit root tests conclude that the returns series are stationary at the 5% threshold.

Table 2: Unit root test on returns

Test	Statistic	Test at level of returns of agricultural commodity price indices		Test at level of returns of energy price indices	
		With constant	With constant & Trend	With constant	With constant & Trend
ADF	t-Stat	-16.7364	-16.7283	-21.3836	-21.3824
	Prob.*	0.0000	0.0000	0.0000	0.0000
Phillips-Perron	t-Stat	-16.7364	-16.7283	-21.1484	-21.1344
	Prob.*	0.0000	0.0000	0.0000	0.0000

Source : Author's calculation

Before using the returns series in modeling, some summary statistics should be given.

d. Descriptive statistics of the returns

Table 3 gives the descriptive statistics of the returns in the agricultural and energy commodity markets. It can be seen from this table that the distributions of the two series do not follow a normal distribution. Indeed, the Jarque-Bera statistic allows us to reject the null hypothesis of normality. The skewness and kurtosis support the rejection of the null hypothesis of normality. Note that the agricultural market returns are less volatile (standard deviation of 0.4917) than the energy market returns (standard deviation of 4.3389).

Table 3: Descriptive statistics for commodity market returns

	Agricultural market returns	Energy market returns
Mean	0.0021	0.0049
Median	0.0004	0.0000
Maximum	0.1211	1.0557
Minimum	-0.1516	-0.4345
Std. Dev.	0.0259	0.0769
Skewness	0.0983	3.1781
Kurtosis	6.8978	53.7316
Jarque-Bera	465.8328	79947.6800
Probability	0.0000	0.0000
Sum	1.5350	3.6139
Sum Sq. Dev.	0.4917	4.3389
Observations	734	734

Source : Author's calculation

5. MODEL ESTIMATION AND RESULTS

The results of the estimation of the Markov Switching Variance Model allow us to study the volatility of agricultural commodity markets and to characterize their different regimes on the one hand, and to identify and characterize the COVID-19 crisis on the agricultural commodity market and to compare it with the 2008 financial crisis on the other.

a. Volatility of the agricultural commodities market and characterization of the schemes

Table 4 provides the estimation results of the Markov Switching Variance Model. Indeed, the logarithm of the standard deviation of the two regimes is significant at the 5% level. It is estimated at -4.0496 for regime 1 and -3.0706 for regime 2; this corresponds to standard deviations of 0.0174 and 0.0463 for regime 1 and 2 respectively. This confirms the existence of a low volatility regime (regime 1) and a high volatility regime (regime 2). Indeed, regime 2 ("crisis" phase) is almost three times more volatile than regime 1 ("normal" phase). Moreover, the estimation of the parameters of the transition matrix (P11-C and P21-C) reveals that a rise in world price indices on the agricultural market is associated with a high chance of being in a low volatility situation ("normal" phase). This is because when world prices rise, the probability of being in a "crisis" phase is low and the probability of moving from the "crisis" phase to the "normal" phase remains high.

Table 4 : Estimation of model coefficients

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
LOG(SIGMA)	-4.0496	0.0440	-91.8729	0.0000
Regime 2				
LOG(SIGMA)	-3.0706	0.0877	-34.9750	0.0000
Transition Matrix Parameters				
P11-C	4.0647	0.5220	7.7857	0.0000
P21-C	-2.6480	0.5828	-4.5432	0.0000

Source : Author's calculation

Table 5 gives the transition probabilities. It shows that the probability of being in regime 1 ("normal" phase) is estimated at 0.9831 and that of being in regime 2 ("crisis" phase) is equal to 0.9338. These two very high probabilities imply that the two regimes are very persistent. Thus, the normal phase is more persistent than the crisis phase. This is consistent with the results of Kayalidere, et al. (2017). Regarding the duration of the phases, it is given by Table 5. It is noted that the duration of being in a normal phase is 59 months and that of being in a crisis phase amounts to 15 months. In fact, the duration of the normal phase is almost four times longer than that of the crisis phase. Therefore, only an extreme event can cause the agricultural commodities market to shift from regime 1 ("normal" phase) to regime 2 ("crisis" phase). In this study, these extreme events are the oil crisis, the financial crisis, the food crisis and the health crisis related to the COVID-19 pandemic.

Table 5: Transition probability and duration of regimes

Transition probability		
Regime	1	2
1	0.9831	0.0168
2	0.0661	0.9338
Duration of regimes		
Regime	1	2
	59.2522	15.1270

Source : Author's calculation

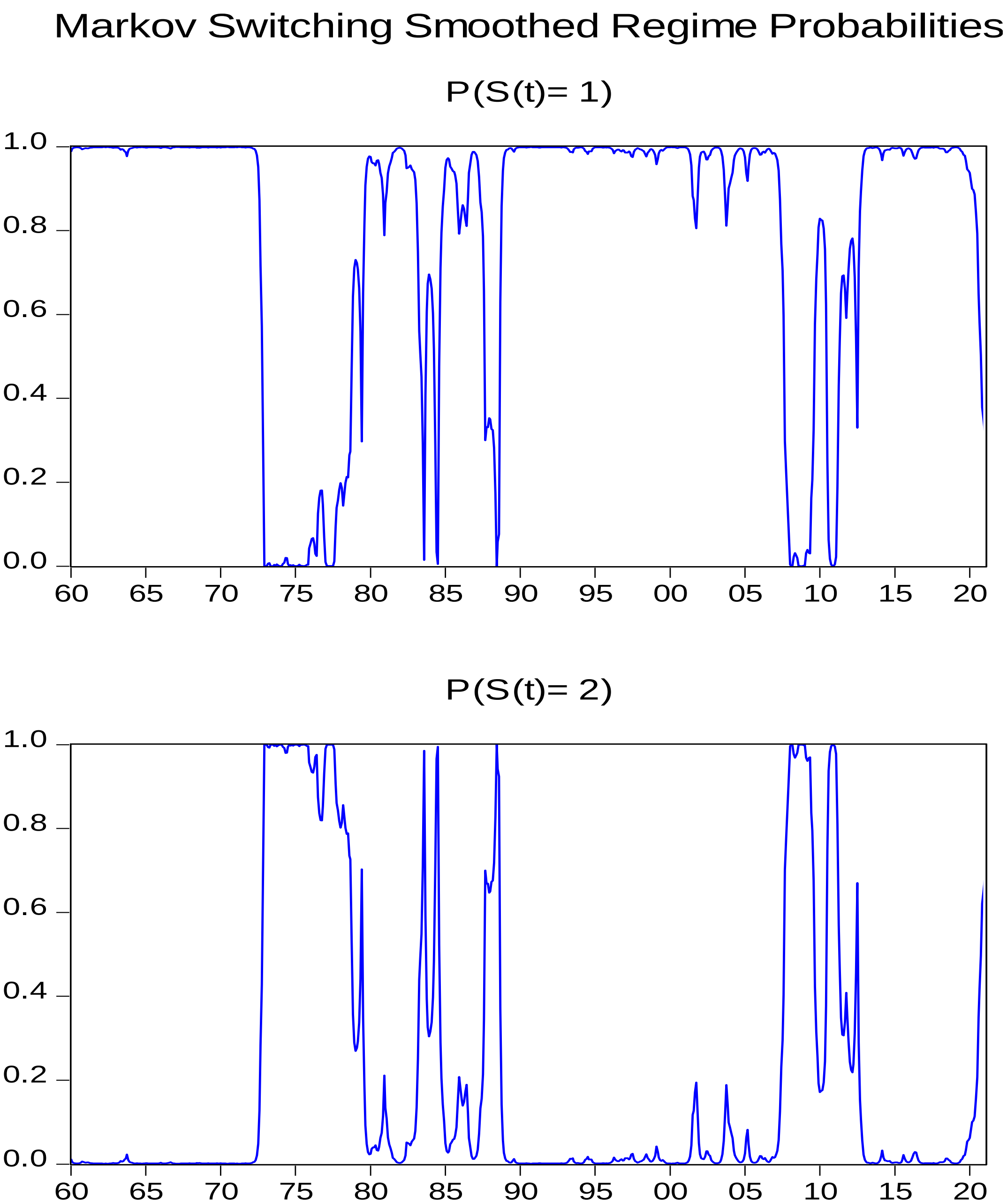
b. Analysis of the impact of COVID-19 on the agricultural commodities market

This section uses Markov Switching Variance Model to identify and characterize the COVID-19 crisis on the agricultural commodities market on the one hand, and to compare the COVID-19 crisis with the 2008 financial crisis on the other hand.

i. Identification and characterization of the COVID-19 crisis in the agricultural commodities market

The analysis and economic interpretation of the Markov Switching Variance Model, through the smoothed conditional probabilities, allows us to identify and characterize the COVID-19 crisis.

Figure 5 below shows the evolution of the probabilities of being in a crisis phase on the agricultural commodities market. Thus, a probability close to 1 corresponds to high volatility over the periods considered. In this case, we think that the agricultural commodities market is facing a crisis. At first glance, we notice the presence of several peaks, but we analyze only those observed during the last two decades; that is, from 2000 to 2021. These peaks are attributable to events such as the health crisis of 2020, the food crisis of 2014, the Greek crisis and the euro debt crisis between late 2010 and July 2011 and the financial crisis of 2008. A more detailed analysis allows us to characterize the health crisis and to compare it with the other crises previously mentioned.



Source: Author's calculation

Figure 5: Smoothed probability estimates by type of regime

The Markov model identified the COVID-19 crisis in the agricultural commodities market. The instability caused by this crisis started in October 2020, but the crisis reached its peak in January 2021, with a smoothed conditional probability close to 0.7. The closer this value is to 1, the more the market is in crisis. A threshold of 0.5 is even chosen by some authors to identify a crisis phase, Majidi (2017).

This health crisis has affected the agricultural commodities market in several ways. Indeed, the global pandemic has profoundly changed production, consumption, exchange and interaction patterns. Thus, the containment measures related to the COVID-19 pandemic have had a surprising impact, Cheval et al. (2020) 1. The pandemic has led to a decline in world prices for agricultural products. Thus, agriculture is used for food and energy. The "sugar" and "corn" sectors, which are heavily used in the production of ethanol (an alternative to petroleum), have seen their prices fall. This decline is accentuated by the spectacular fall in oil prices linked to the COVID-19 pandemic. The same is true of the rapeseed market, where prices are historically low. This drop is directly linked to demand because the closure of bars and restaurants and the cancellation of all sporting and cultural events have led to a decline in demand for beer.

For wheat and rice, the opposite phenomenon is occurring. For these two basic commodities, prices are significantly higher. Uncertainties about supply chains and fears of import restrictions, caused by the COVID-19 pandemic, have pushed prices up. In anticipation of shortages, large importing countries such as Algeria, Morocco, Egypt and Saudi Arabia have increased their demands, which has led to a rise in wheat and rice prices.

ii. Comparison between the COVID-19 crisis and the financial crisis of 2008 and the oil shock of 1973 in the agricultural commodities market

The analysis of the smoothed conditional probabilities in the figure 5 allows us to identify the oil shock of 1973 and the financial crisis and the food crisis of 2008 in the agricultural commodities market. Indeed, for these crises, the smoothed conditional probability is equal to 1. This probability value is higher than that for the health crisis (0.7). In other words, the Markov Switching Variance Model detects the 2008 financial crisis and the oil shock of 1973 better than the health crisis. This could be explained by the fact that the 2008 financial crisis and the oil shock of 1973 had a greater impact on the agricultural commodities market than the health crisis. Also, the analysis of the smoothed conditional probabilities shows that the crisis caused by the COVID-19 pandemic is shorter than the crises generated by the 2008 financial crisis and the 1973 oil shock.

Indeed, in 2008 the already existing food crisis was accentuated by the financial crisis. Its main causes are:

- the increase in the production of biofuels, which led to a decrease in the volume of cereals and oilseeds available for human consumption;

- the increase in consumption demand for food products in China and India;

- natural disasters (drought or excessive rainfall) which reduced production;

- the surge in world oil prices, which has accelerated the production of biofuels.

All these factors have plunged the agricultural commodities market into a deep crisis, which was accentuated by the financial crisis of 2008. Indeed, this financial crisis pushed speculators to redirect their portfolios to the commodities market in the form of index arbitrage contracts, futures contracts and options contracts. This speculation accelerated the volatility and excitement of the agricultural commodities markets.

c. Comparative Analysis of the Impact of COVID-19 on Agricultural and Energy Commodity Markets

The energy market and the agricultural commodities market have different characteristics in terms of volatility. They do not react in the same way to different crises.

i. Comparative analysis of price volatility on the markets

Table A1 in the appendix gives the results of the estimation of the Markov Switching Variance Model. Indeed, on the energy market, we distinguish a normal regime of volatility equal to 0.0436 and a crisis regime that is three times more volatile (0.1267). Overall, the energy market is more volatile than the agricultural commodities market, regardless of the regime. For the normal regime, the level of volatility is 0.0436 on the energy market against 0.0174 for the agricultural commodities market. For the crisis regime, the volatility is almost three times higher on the energy market than on the agricultural commodities market.

Volatility on the energy market depends on the price of oil. The latter evolves according to the production strategy of OPEC countries, geopolitical structural shocks and events on the financial markets.

Since 2000, there has been a financialization of energy commodities, Silvennoinen and Thorp (2010). Thus, the development of paper oil has accompanied the spread of futures contracts, which has led to strong speculation in these markets. This speculation has strongly contributed to the volatility of these markets and has led to a positive correlation between energy commodity prices and those of several other financial assets (CNUCED, 2009, 2011).

In addition, volatility depends on structural geopolitical shocks. For example, geopolitical events have weighed on price fluctuations: the Yom Kippur War, the invasion of Iraq and the Arab Spring.

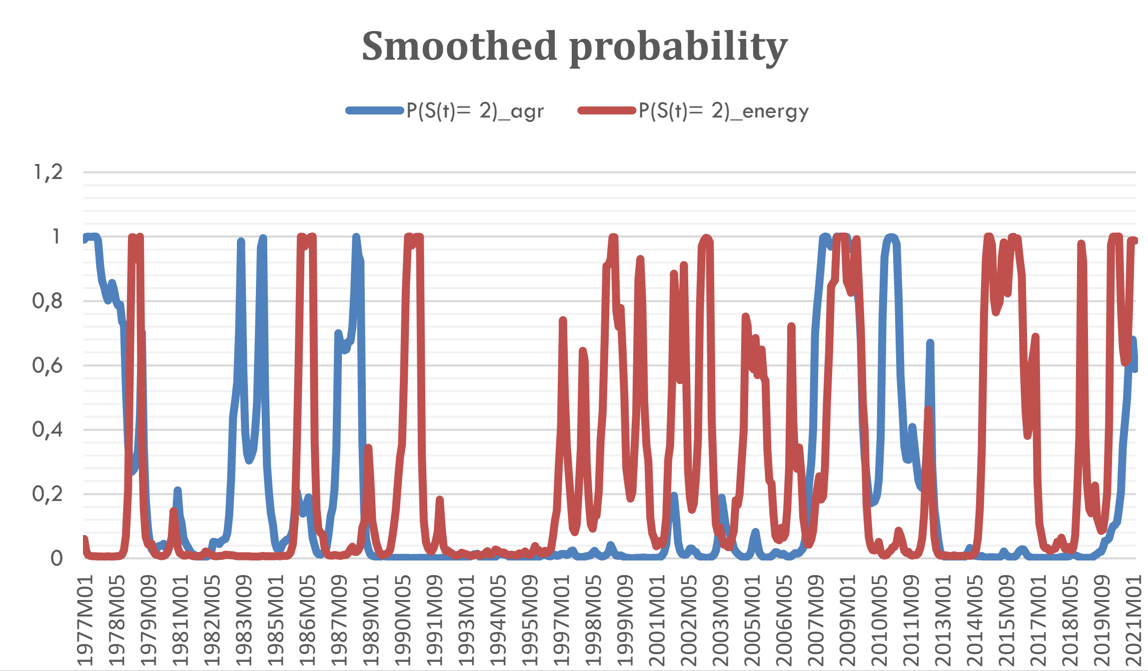
With regard to transition probabilities (see Table A2 in the Appendix), as in the agricultural commodities market, the probability of being in regime 1 ("normal" phase) is much higher than that of being in regime 2 ("crisis" phase) on the energy market. These two very high probabilities (over 85%) are evidence of the persistence of crises in this market. We note that the duration of being in a normal phase is 19 months on the energy market compared to 59 months on the agricultural commodities market, and the duration of being in a crisis phase is 7 months on the energy market compared to 15 months on the agricultural commodities market. In fact, whatever the regime, the durations are shorter on the energy market.

ii. Comparative analysis of the COVID-19 market crisis

Figure 6 gives the comparative evolution of the smoothed probabilities obtained using the Markov Switching Variance Model. Thus, these models were able to detect all the crises on these two markets. We note that crises are more frequent in the energy commodities market. This is due to the high volatility of oil prices. The latter, as mentioned above, depend on geopolitical structural shocks and events in the financial markets. The probability that the COVID-19 pandemic will cause a crisis in the energy products market is equal to unity and it is equal to 0.7 in the agricultural commodities market. In other words, the Markov Switching Variance Model perfectly detects the COVID-19 crisis in the energy commodity market. In other words, the pandemic had a greater impact on the energy products market than on the agricultural commodities market.

Indeed, the containment measures directly affected supply and demand on the energy market and particularly on the oil market. Thus, the COVID-19 crisis has hit hard an oil market already weakened by the rivalry between OPEC member countries (a trade war between Saudi Arabia and Russia). Thus, the COVID-19 pandemic has caused a 30% drop in global demand between January and April 2020 following containment measures. In other words, the shutdown of a large part of the economic activities caused a drop of about 30 million barrels per day Souiki et al (2020).

This oil market crisis has spread to the agricultural commodities market. For example, some agricultural products ("sugar" and "corn") are heavily used in the production of ethanol (an alternative to oil); this is what makes there a strong correlation between oil prices and the prices of agricultural products. Thus, the drop in world oil prices linked to the COVID-19 pandemic has strongly accentuated the drop in agricultural commodity prices.



Source : Author's calculation

Figure 6: Smoothed probability on the commodity market

6. CONCLUSION

The Markov Switching Variance Model is used in this paper to detect crises in the commodity market. The crises detected in this market are named the COVID-19 health crisis of 2020, the food crisis of 2014, the Greece crisis and the Euro debt crisis between the end of 2010 and July 2011 and the financial crisis of 2008.

The study shows that the 2008 financial crisis has more impact on the agricultural commodity market than the COVID-19 health crisis. Indeed, the financial crisis caused speculators to shift their portfolios to the commodity market in the form of index arbitrage contracts, futures contracts and option contracts. This speculation has led to high price volatility in agricultural commodity markets.

It should also be noted that the Markov Switching Variance Model was able to detect all the crises on both markets. Indeed, crises are more frequent on the energy commodities market. This is due to the high volatility of oil prices, which depend on geopolitical structural shocks and the situation of financial markets. The results also show that the pandemic has had a greater impact on the energy commodities market than on the agricultural commodities market. Note that volatility in the agricultural commodities market is positively correlated with the volatility of world oil prices and the financial market. This weakens the agricultural commodity markets, which are already dependent on climatic conditions and the demand of large countries such as India and China.

As a recommendation, we must reduce the volatility of world prices and fight against the instability of prices on commodity markets. This requires good inventory management (stock building and de-stocking). A good ex-ante stock build-up allows for the absorption of supply and demand shocks on these markets; it makes price volatility around the equilibrium price low. Thus, it is necessary to build up stocks in a situation of commodity price instability in order to deal with shocks.

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Annexe

Tableau A1: Estimation of the model on the different markets

Variable	Energy products returns	
	Coefficient	Prob.
Regime 1		
LOG(SIGMA)	-3.1322	0.0000
Regime 2		
LOG(SIGMA)	-2.0659	0.0000
Transition Matrix Parameters		
P11-C	2.8912	0.0000
P21-C	-1.7792	0.0000
	Agricultural products returns	
Regime 1		
LOG(SIGMA)	-4.0496	0.0000
Regime 2		
LOG(SIGMA)	-3.0706	0.0000
Transition Matrix Parameters		
P11-C	4.0647	0.0000
P21-C	-2.6480	0.0000

Source : Author's calculation

Tableau A2 : Transition probability and duration of regimes

Transition probability		
Energy market		
Regime	1	2
1	0.9474	0.0525
2	0.1443	0.8556
Agricultural products market		
Regime	1	2
1	0.9831	0.0168
2	0.0661	0.9338
Duration of regimes		
Energy market		
1		2
19.0165		6.9255
Agricultural products market		
1		2
59.2522		15.1270

Source : Author's calculation