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Measuring Food Price Volatility

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Table of Contents

List of Tables

List of Figures

Abstract

Over the past two decades, the prices of agricultural commodities have experienced large and unpredictable fluctuations that have attracted the attention of researchers, policymakers and the media to better understand the mechanisms that govern this phenomenon. It is therefore important to acquire basic tools to assess the level of price volatility to warn of abnormal movements. The main objective of this technical note is to provide an overview of this literature in constant evolution, and tools for measuring food price volatility. The tools developed in this technical note help understand the complexity of measuring volatility and the caution required in their use. Thus, the application of these tools requires their adaptation to the nature of the data generating process and the use of appropriate tests and criteria in order to choose the best approach.

I. Introduction

Since 2006, agricultural commodity prices have experienced wide and unpredictable fluctuations that have attracted much attention from researchers, policymakers and the media to better understand the mechanisms that guide this phenomenon and to find measures to control it. In 2011, a group of experts from several agencies (FAO, IFAD, IMF, OECD, UNCTAD, WFP, WB, WTO, IFPRI and the United Nations High-Level Task Force (UN-HLTF)) prepared a policy report on food price volatility and agricultural markets.

In that report, they define price volatility in a purely descriptive sense. In simple terms, volatility refers to price changes. Thus, not all price changes are problematic, for example when prices move in a smooth and well-established trend reflecting market fundamentals or when they show a typical and well-known seasonal pattern. However, price changes become problematic when they are large and unpredictable and create a level of uncertainty that increases risks for producers, traders, consumers, and governments and can lead to sub-optimal decisions.

The particular focus on price volatility rhymes with its adverse consequences for economic welfare. It has been argued that price volatility generates uncertainty about the true price levels for producers and consumers, and therefore production and consumption decisions can lead to sub-optimal outcomes compared to those obtained under more stable price conditions, (Kalkuhl et al., 2016). However, it is important to distinguish between volatility and high or low price levels. On the one hand, high price levels negatively affect vulnerable and poor households that allocate more than 60% of their income to food consumption, (FAO et al., 2011). On the other hand, producers are more concerned about low price levels that threaten their return on investment and the long-term viability of their farms. This refers to the traditional policy dilemma, (Timmer et al., 1983): high prices support production and low prices support consumption. However, the effects of high or low prices are more complex for households that are both producers and consumers of agricultural products, especially small African producers.

Referring to FAO's 2012 background paper, the causes of price volatility can be grouped into three non-exclusive fundamental parameters. First, natural shocks such as weather phenomena (drought, floods, etc.), pests, and crop diseases that negatively affect the supply of agricultural products. Second, product supply and demand are inelastic in the short term even though stocks are an alternative response to supply shocks. Thirdly, the time taken to cover the supply gap and rebuild stocks is often long. These combined effects were decisive during the price surge over the period 2007-2008. In addition, other complex phenomena may play a fundamental role in price fluctuations. These are particularly climate change, production areas exposed to high risks of natural shocks, the energy market, government intervention, and exchange rate fluctuations. To these we must add the complex phenomenon of speculation, whose impact is the most controversial.

However, it is important to acquire the basic tools to assess the degree and transmission of food price volatility in order to warn of its potential negative impacts. To achieve this, this technical note aims to analyze and develop three fundamental aspects. These are the processes that generate price data, the degree of food price volatility and the standard tools for assessing food price volatility. Furthermore, volatility transmission measurement tools constitute a much broader field needed to be presented separately in other technical note for analyzing the transmission of volatilities between interdependent markets. Interest in the latter is motivated by the fact that agricultural commodity markets are close substitutes for demand, have similar input costs, compete for limited natural resources, and share common market information, (Gardebroek and al., 2014).

This technical note presents in the first part the tools to measure food price volatility. This part discusses the analysis of data-generating processes, the tools to measure the degree of price volatility, and the standards tools to assess food price volatility. The second part is devoted to the presentation of data and the results of the different theoretical approaches studied in the first part.

II. Tools to measure food price volatility

a. *Analysis of data generating process*

After the 1980s, time series analysis underwent many developments. These were aimed on the one hand at questioning the fundamentals of the study of time series, and on the other hand at proposing more general and more efficient alternatives (Granger & Newbold (1974), Cuddy & Della Valle (1978)). To this end, the problem of spurious regression raised by Granger & Newbold (1974) was the most widespread problem. In simply put, this refers to a situation in which two unrelated and not all stationary series can show a significant relationship through the application of linear regression. This leads to the need to test the hypothesis of series stationarity, which is the basis of classical time series analysis. To achieve this, it is important to define the notion of stationarity and to distinguish between deterministic and stochastic non-stationarity.

i. Definition and types of processes

1. Definition

The stationarity of a time series refers to a principle of temporal invariance of these order moments. This temporal invariance of the order moments, referred to as strong stationarity, is restricted to a notion of weak stationarity at moments of order less than or equal to two, also called second-order stationarity, which is applied in econometrics. Theoretically, it is defined as follows: A process (x_t, t ∈ ℤ) is said to be stationary in the weak sense if it satisfies the following three conditions:

1. $\forall\, t \in \mathbb{Z}:\ \mathrm{E}(x_t{}^2) < \infty$

2. $\forall\, t \in \mathbb{Z}:\ \mathrm{E}(x_t) = \mu$
3. $\forall\, (t,h) \in \mathbb{Z} * \mathbb{Z}$: $\mathrm{Cov}(x_t, x_{t+h}) = \mathrm{E}[(x_{t+h} - \mu) * (x_t - \mu)] = \gamma(h)$

2. Types of processes

There are two types of processes according to Nelson and Plosser (1982). These are mainly the TS process associated with deterministic non-stationarity and the DS process corresponding to stochastic non-stationarity.

- TS (Trend Stationary) process

A TS process is a process that can be written as a sum of a deterministic function of time and a stationary stochastic process. Technically (x_t, $t \in \mathbb{Z}$) is a TS process if it can be written in the following form:

$$x_t = f(t) + \varepsilon_t \qquad (1)$$

f(t) is a deterministic function of time, ε_t is a stationary stochastic process.

The fundamental property of these processes is the non-persistence of shocks, also called the absence of hysteresis. Economically, this one translates that the long-term trajectory of the process is not affected by the short-term fluctuations.

- DS (differency stationary) process

In contrast to TS processes, DS processes have a non-deterministic component, also known as the stochastic component. Technically, (x_t, $t\in \mathbb{Z}$), a non-stationary process, is a DS process of order d if $(1 - L1)^d x_t$ is stationary. The fundamental property of these processes is the persistence of shocks. That is, shocks have a permanent effect on the process in question.

ii. Unit root tests or stationarity tests

Unit root tests are crucial in time series analysis. They help guide the choice of the most appropriate econometric model. The difficulty in implementing unit root tests lies in the complexity of formalizing the processes. A priori, it is impossible to define the type of process and therefore it is not simply a test directly involving the rejection or non-rejection of the null hypothesis. Rather, they are test procedures involving different types of specifications in a well-established order. These procedures include the Dickey and Fuller test (1976, 1981), the Phillip and Perron test (1986, 1987, 1988), the KPSS test, and the Dolado et al. test (1990). Extensive documentation of these tools is available. In particular, a good testing procedure is provided by Dolado et al (1990).

1 Lag operator

iii. What should be avoided and retained?

Care must be taken not to consider a DS process in place of a TS process and vice versa. Chan, Hayya, and Ord (1977) and Nelson and Kang (1981, 1984) were the first to address these issues. In the case of a random walk (DS process), the extraction of a trend on the latter creates a positive autocorrelation of the residuals. Similarly, the difference filter of an affine TS process is supposed to eliminate the deterministic trend component, whereas it creates an artificial perturbation of the residuals (autocorrelation).

It should be remembered that there is no single standard procedure for unit root testing. Referring to Ertur (1998), three important aspects should be retained. Firstly, it is necessary to make a graphic diagnostic of the considered series in order to detect any form of non-linearity and possible major structural changes. Second, the testing strategy should start with the most general model possible regarding the specification of the deterministic component. Third, it is necessary to juggle several tests while limiting overly restrictive assumptions about the residuals and the deterministic component to ensure the robustness of the results, since unit-root tests have very low powers and tend to reject H1 (Schwert, 1989; Cochrane, 1991; Blough, 1992).

This brief presentation on stationarity tests is an important element in understanding the harmful effects of not taking stationarity into account and in orienting the choice of the most appropriate tool for measuring the degree of volatility.

b. Tools to measure the degree of food price volatility

In this section, the objective is to present the tools for measuring price volatility. They can be classified in two categories: standard tools and tools derived from the econometric approach. However, it is important to recall the considerations used to measure the degree of price volatility. In the case of food products, it can be measured at the producer, wholesaler, or retailer level. Minot (2012) pointed out that in Africa, most of the available price data on food prices are those from the wholesaler or retailer. In addition, most of the structures in charge of collecting statistical data take this consideration into account and often collect monthly price data.

i. Standard tools

The standard tools to measure volatility depend on the assumption made about the stationarity of the price series.

1. Case of stationary series

In this case the mean and variance of the series are assumed to be constant. Two standard measures can be derived from these two indicators.

- Standard deviation

The standard deviation is a statistical tool for measuring the dispersion of values in a series relative to the mean. It represents the root of the variance. The advantage of the standard deviation over the mean is that it is easily interpreted. Its formula is defined below:

$$\boldsymbol{\sigma} = \sqrt{\frac{\sum_{t=1}^{T}(P_t - \bar{P})^2}{T-1}}; \text{ with } (P_t,\ t=1\ldots T), \text{ the price series.} \quad (2)$$

The problem with the standard deviation is that it does not allow comparing the volatility of two distributions of values with different scales or units of measurement. For this reason, the coefficient of variation is used.

- Coefficient of variation

The coefficient of variation, the ratio of the standard deviation to the mean, is a measure of relative dispersion. It is often expressed as a percentage and tells us that the higher the coefficient, the greater the dispersion of values around the mean. In the context of price volatility analysis, the coefficient of variation is useful for assessing the degree of price volatility and for comparing price volatility among several products that do not have the same units or scales of measurement. The formula for the coefficient of variation is defined below:

$$CV = \frac{\sigma}{\bar{P}} \quad (3)$$

2. Case of non-stationary series

In general, price data are often non-stationary. In this case, it is important to determine the process that generates the data. This may be a TS process or a DS process.

- Case of a TS process

The trend-adjusted coefficient of variation is best suited. Indeed, if the process is a first-degree polynomial, then the average explodes over time, leading to a low coefficient of variation. However, the nature of the deterministic component (affine, quadratic, exponential, ...) must be well defined before the extraction of the trend. Here, we assume that the process is affected by a deterministic trend defined as follows:

$$P_t = \alpha + \beta \times trend + \varepsilon_t \ (E) \quad (4)$$

The trend-adjusted coefficient of variation is given by:

$$CV^* = CV\sqrt{(1-\bar{R}^2)} \text{ ; with } \bar{R}^2 = 1 - \left[(1-R^2)\left(\frac{T-1}{T-k}\right)\right], \quad (5)$$

R^2, the explanatory power of the model (E).

- Case of DS processes

In the presence of a unit root, the usual volatility measurement tools become non relevant. In this case, we have no control over the variance of the process. It is therefore relevant to choose other volatility measurement tools that consider the stochastic nature of the trend. Two generally used transformations allow the presence of the stochastic trend to be considered. They are shown below:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}},\ r_t = log\,\frac{P_t}{P_{t-1}} \tag{6}$$

They represent Net returns and log returns, respectively. For small variations, the two transformations are similar.

Sometimes, the Z-statistic proposed by is also used, (Baffes, 2004). It is presented as follows:

$$Z = \sqrt{\frac{\sum_{t=1}^{T}(P_t - P_{t-1})^2}{T-1}} \tag{7}$$

ii. Tools from the econometric approach

The tools for measuring price volatility presented in the standard tools do not take into account cases where the process presents a mixed (deterministic and stochastic) trend. On the other hand, other approaches make it possible to model the conditional volatility of the price process.

1. Process with a mixed trend

This econometric approach to calculating volatility aims to extract the mixed trend and calculates the relative dispersion of the distribution of values around the predicted value. It is defined as follows:

$$\tau = 100\sqrt{\frac{1}{T-1}\ \sum_{t=1}^{T}\left(\frac{P_t - \widehat{P_t}}{\widehat{P_t}}\right)^2} \tag{8}$$

With $\widehat{P}_t$, the predicted value from $P_t = \alpha + \beta * trend + \gamma * P_{t-1} + \varepsilon_t$.

2. Processes with non-constant volatility

Up to now, the tools used to measure the volatility assume that volatility is homoscedastic (constant). This is not often the case for commodity and asset prices, (Bollerslev and al, 1994). The family of ARCH (Autoregressive Conditionally Heteroscedastic) models introduced by Engle (1982) are based on an endogenous parameterization of the conditional variance and make it possible to model this type of property. In this technical note, the modelling of ARCH and GARCH[2] processes are presented.

The idea behind these two processes is that they allow us to estimate the volatility of the process based on past values of volatility. Technically, their major difference lies in the fact that the ARCH process uses the MA model to estimate volatility, whereas the GARCH process generalizes the ARCH process by using the ARMA model to take into account the persistent memory effect of volatility.

[2] Generalized Autoregressive Conditionally Heteroscedastic

The ARCH(q) process introduced by Engle (1982) is defined by the following equation:

$$r_t = a_o + \sum_{i=1}^{q} a_i r_{t-1} + \varepsilon_t \;\; ; avec \; \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + v_t \qquad (9)$$

With the constraints ($\alpha_0 > 0$, $\alpha_i > 0, 1 \ldots q$) which guarantee the strict positivity of the conditional variance.

The GARCH(p,q) process, developed by Bollerslev (1986), allows to take into account a long memory process. It is represented as follows:

$$r_t = a_o + \sum_{i=1}^{q} a_i r_{t-1} + \varepsilon_t \;\; ; avec \; \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + v_t \qquad (10)$$

With $\alpha_0 > 0,\; \alpha_i > 0, i = 1 \ldots q;\;\; \beta_j \geq 0$*, j=1…p*

The validity of this model is based on the validity of the following relationship:

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1 \qquad (11)$$

If $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j = 1$, the IGARCH model would be much more suitable.

However, it is important also to consider asymmetric GARCH models. The objective of these models is to improve the consideration of volatility asymmetry in the response of conditional variance to an innovation. In particular, the EGARCH process gives a form of asymmetry that takes into account the positivity and negativity of the signs of innovation, but also the scale of the impact. The EGARCH model is presented below:

$$z_t = \omega + \sigma_t \varepsilon_t$$

$$log(\sigma_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_i z_{t-i} + \sum_{i=1}^{q} \gamma_i |z_{t-i}| + \sum_{j=1}^{p} \beta_j \, log(\sigma_{t-j}) + v_t \qquad (12)$$

iii. A Standard tool for assessing food price volatility: FAO Tool (GIEWS):

The main goal of measuring food price volatility is to monitor the dynamics of food price variations in order to alert to potential crises that could compromise the proper functioning of the market and the well-being of the economy. However, it is not easy to appreciate the degree of price volatility. Indeed, like any indicator, we are always confronted with type I and type II errors. The first error occurs when reporting that there is an alert when the markets are functioning normally. The second arises when no alert goes unreported when the markets are falling apart. Which of both is better? What is clear is who seeks to flee one, wishes to run into the other. It is then sufficient to find a balance between type 1 error and type II error.

However, there are standard tools to guide decision-making. These are mainly statistical methods for determining critical areas that trigger alarms. In this technical note, we will limit ourselves to the methodology proposed by FAO.[3]

1. Definition and objective of FAO tool: Indicator of Food Price Anomalies

The Indicator of Food Price Anomalies developed by the Global Information and Early Warning System (GIEWS) of the Food and Agriculture Organization of the United Nations (FAO) is used to identify serious market disruptions. It is also used as one of the indicators for monitoring Goal 2 of sustainable development (Zero Hunger)[4]. This indicator, proposed by Baquedano (2015), is based on a weighted moving average of two composite growth rates (QCGR, ACGR)[5]. Indeed, this idea is motivated by the consideration of seasonality and the trend often observed in price evolution. The compound growth rate is a geometric mean that assumes that the variable grows at a constant rate and is also less sensitive to outliers compared to the arithmetic mean. It is defined as follows:

$$XCGR = \left(\frac{P_{t_n}}{P_{t_0}}\right)^{\frac{1}{t_n - t_0}} - 1 \qquad (13)$$

With:

XCGR: the compound annual or quarterly growth rate.

P_{t_n}: the price at the end of the period.

P_{t_o}: the price at the beginning of the period.

t_n-t_o: the number of months between the beginning and the end of the period.

Therefore, the annual and quarterly Indicator of Food Price Anomalies (IFPA) are defined as follows:

[3] A tool is proposed by IFPRI as well on its Food Security portal. Given the complexity of this tool its inclusion of goes beyond the scope of this Note (cf. Conclusion).
[4] End hunger, achieve food security and improved nutrition and promote sustainable agriculture
[5] Quarterly Compound Growth Rate (QCGR) and an Annual Compound Growth Rate (GR)

$$X\_IFPA_{yt} = \frac{XCGR_{yt} - \overline{XCGR_t}}{\hat{\sigma}_{XCGR_t}} : \begin{cases} X\_IFPA_{yt} \geq 1 & Abnormally\ High \\ 0.5 \leq X_{IFPA_{yt}} < 1 & Moderately\ High \\ -0.5 \leq X\_IFPA_{yt} < 0.5 & Normal \end{cases} \quad (14)$$

$XCGR_{yt}$ is the quarterly or annual composite growth rate of month t for year y.

$\overline{XCGR_t}$ is the average of the quarterly or annual composite growth rate for month t across years y.

$\hat{\sigma}_{XCGR_t}$ is the standard deviation of the quarterly or annual composite growth rate.

X_IFPA_{yt} is the annual or quarterly Indicator of Food Price Anomalies.

These indicators give an idea of the dynamics of price change. Thus, monitoring them makes it possible to signal potential serious market disturbances. Following the same logic as Araujo et al (2012), Baquedano (2015) also considered the standard deviation of the compound growth rate (annual or quarterly) as a relevant threshold for giving alerts. Indeed, when the deviation of the compound growth rate (annual or quarterly) from historical trends exceeds its standard deviation, the situation is considered alarming. On the other hand, when it falls short of its standard deviation and exceeds half of it, the market disruption is considered moderate.

It is important to understand that the indicators defined above do not provide an understanding of the dynamics of price changes. Taken in isolation, they do not allow a clear conclusion to be drawn on the functioning of the market because other exogenous variables independently fundamental to the market may affect the dynamics of price change. Therefore, the results need to be weighted with other available information on market fundamentals, the macroeconomic context, and external shocks.

However, the IFPA aggregates the two indicators of the composite growth rate to provide a tool for assessing the level of price volatility. It is defined as follows:

$$IFPA_{yt} = \gamma * Q\_IFPA_{yt} + (1 - \gamma) * A\_IFPA_{yt} \quad (15)$$

A critical component of this indicator is the value of γ. It should be determined by applying principal component analysis. Indeed, γ is the weight of the quarterly dimension on the variation in the composite indicator.

2. Proposals to reduce Type I and Type II errors

Baquedano (2015) proposed two amendments to reduce type I and type II errors, respectively. The first consists of deflating the two components of the IFPA by price volatility (standard deviation of returns) over the same period. This reduces the deviation of the composite growth rate from the estimated composite growth rate and thus the probability of Type I error. This transformation is represented as follows:

$$vXCGR_{yt} = \left(1 - \sigma_{r_{yt}}\right) * XCGR_{yt} \quad (16)$$

$vXCGR$: the composite growth rate adjusted for price volatility

r_t =log(p_t)-log(p_{t-1})

$\sigma_{r_{yt}}$: standard deviation of returns

The second change seeks to reduce Type II error by changing the calculation of the mean and standard deviation of the compound growth rate. This consists of associating weights to the months over the period considered. Indeed, an early period of high and volatile prices should not have the same weight as a more recent period of declining and volatile prices. Therefore, if one wishes to minimize the type II error, it is better to associate greater weights to more recent periods. Thus, the weights used are increasing time weights.

The weighted average of the composite growth rate is defined as follows:

$$\overline{vXCGR_{wt}} = \frac{1}{\sum_{y=1}^{Y} w_y} \sum_{y=1}^{Y} w_y * vXCGR_{yt} \tag{17}$$

$\overline{vXCGR_{wt}}$ is the weighted average of the compound growth rate (annual or quarterly) adjusted for volatility in month t.

The weighted standard deviation of the composite growth rate is represented by the following relationship:

$$\hat{\sigma}_{vXCGR_{wt}} = \sqrt{\frac{\sum_{y=1}^{Y} w_y \left(vXCGR_{yt} - \overline{vXCGR_{wt}}\right)^2}{\sum_{y=1}^{Y} w_y - 1}} \tag{18}$$

w_y is the weight of the year or quarterly y.

Once the composite annual and quarterly growth rates are calculated, it is possible to calculate the IFPA taking into account the above considerations:

$$IFPA_{yt} = \gamma * Q\_IFPA_{yt} + (1-\gamma) * A\_IFPA_{yt} \tag{19}$$

With : $X\_IFPA_{yt} = \frac{vXCGR_{yt} - \overline{vXCGR_t}}{\hat{\sigma}_{XCGR_{wt}}}$

The main challenge in calculating the IFPA is the availability and quality of the data. The IFPA is sensitive to both issues. At least a 60-month series is needed to ensure the calculation of the indicator, (Baquedano, 2015).

III. Data and Results

a. Data

In this technical note, the Senegal's Food Price Index (FPI) from FAOSTAT is used to apply the tools to measure food price volatility developed in this note. Monthly indices from 2000 to 2018 have been used. As a result, the analysis of the volatility of this index also focuses on taking into account trend and seasonality. This consideration is also valid for other monthly price indicators (FPI, food prices).

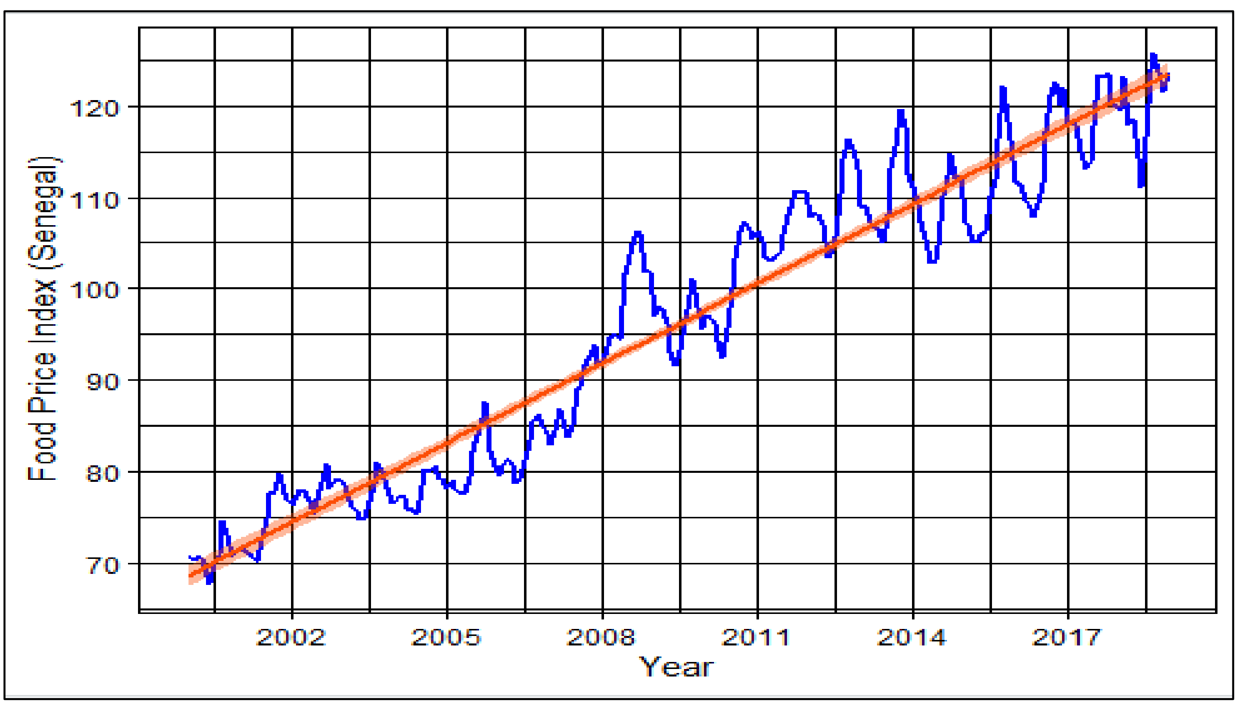
b. Results

i. Descriptive analysis

1. Graphical analysis

Graphic representation is a milestone in the analysis of a time series. It is an indication of the nature of the process, the presence of a trend, seasonality, and periods of high volatility. Figure 1 shows the Food Price Index (FPI) over the period 2000 to 2018. An overall trend emerges. This is the existence of a deterministic trend and seasonality. Econometric tools make it possible to validate this observation and to take it into account.

Figure 1: Evolution and trend of the Food Price Index (FPI) (2000-2018)



Source: Authors

2. *Numerical analysis*

This part quantifies price volatility. The two flagship measures presented are the standard deviation and the coefficient of variation. The standard deviation is used to determine the dispersion of the Food Price Index around the mean and the coefficient of variation is used to assess the extent of the dispersion. In addition of both standard measures, trend and seasonality effects are considered to determine the adjusted coefficient of variation. Thus, Table 1 presents the standard tools to measure Senegal's Food Price Index volatility. The fundamental result is that the FPI volatility is almost explained by trend and seasonality. Once both are taken into account, the coefficient of variation remains relatively low. Therefore, it is fundamental to take these effects into account to better understand the dynamics of price changes.

Indeed, the trend and seasonal adjusted coefficient of variation reduced volatility by nearly 16% compared to the simple coefficient of variation. Considering seasonality allowed a volatility increase equal to 0.92 compared to the indicator τ corresponding to the gamma trend equal to 0.66. All this shows the need to analyze these tools with caution.

Table 1 : Standards tools to measure food price volatility

	Sd[6]	**CV**[7] **(%)**	**Adj_CV_trend** [8]**(%)**	**Adj_CV_Tr_Sea (%)**[9]	**Gamma_trend (%)**[10]	**Gamma_Tr_Sea (%)** [11]
FPI (Senegal)	16.59	17.27	1.27	0.86	0.66	1.58
Net returns	0.02					
Log Returns	0.02					

Source: Authors

ii. Econometric results

The tools to measure food price volatility presented in the descriptive analysis allow us to understand the dispersion of volatility. However, this can only be identified if the disruptive effects (trend and seasonality) are properly considered. The results in Table 1 confirm that taking these effects into account provides a more accurate picture of the volatility of the considered series. However, other specific effects may occur. These are the volatility clustering modeled using the ARCH and GARCH models.

Therefore, this section presents the volatility dynamics using ARCH and GARCH modelling.

Two specifications have been retained. These are the Senegalese Food Price Index and the returns of the FPI. This makes it possible to analyze the volatility of the price index from two different ways.

[6] Standard deviation
[7] Coefficient of variation
[8] Adjusted coefficient of variation from trend adjusted
[9] Adjusted coefficient of variation from trend and seasonality adjusted
[10] Gamma from the process with a mixed trend
[11] Gamma from the process with a mixed trend and seasonality

1. Modeling the volatility of the FPI

The analysis of stationarity and seasonality was able to show that the FPI is affected by trend and seasonality. Indeed, FPI is trend stationary. This leads to consider the FPI series with removed trend. Based on this, the SARIMA (p, d, q) $(P, D, Q)_{12}$ model is used to extract seasonality. Once these have been extracted, volatility modeling is done using one the more adapted GARCH (p, q) model.

- Choice of SARIMA orders and the most adapted GARCH model

To avoid subjective choice based on correlation and partial autocorrelation, the use of the BIC criteria made it possible to select the optimal model. The selected model is as follows: SARIMA (1, 0, 0) $(2, 0, 0)_{12}$+GARCH (1, 1).

- Diagnosis of residuals: normality, autocorrelation, and heteroscedasticity

The residuals tested are those resulting from the application of the SARIMA (1, 0, 0) $(2, 0, 0)_{12}$ model. Thus, Table 2 presents the normality (Jarque-Bera), autocorrelation (Ljung-Box) and heteroskedasticity (ARCH-Test) tests. The normality test concludes that the hypothesis of normality is rejected (p-value>0.05). With a delay order of 12, the Ljung-Box autocorrelation test allows the null hypothesis of non-autocorrelation to be retained. However, the ARCH test leads to the rejection of the null hypothesis of homoscedasticity.

Table 2: Diagnosis of residuals

	Jarque-Bera	**Ljung-Box**	**ARCH-Test**
P-value	0.00	0.34	0.00

Source: Authors

- Estimation results of the most adapted GARCH model: EGARCH (1,1)

Table 3 presents the parameters of the EGARCH model (1, 1). Five parameters are presented in the table. The first parameter (omega=0.09), not significant, reflects the unconditional variance, also called the unconditional volatility. It represents the minimum variance threshold below which the conditional variance does not fall. The third parameter (alpha1=+0.05), representing the impact of past volatility shocks. This coefficient is relatively small and significant. The fourth parameter (beta1=+0.95) is used to detect the persistence of volatility. It is very close to 1 and remains significant. The last parameter (gamma1=+0.11) confirm the significant and positive presence of the asymmetry effect. This implies that a positive shock has more impact than a negative shock.

Table 3: EGARCH (1, 1) model parameters estimated

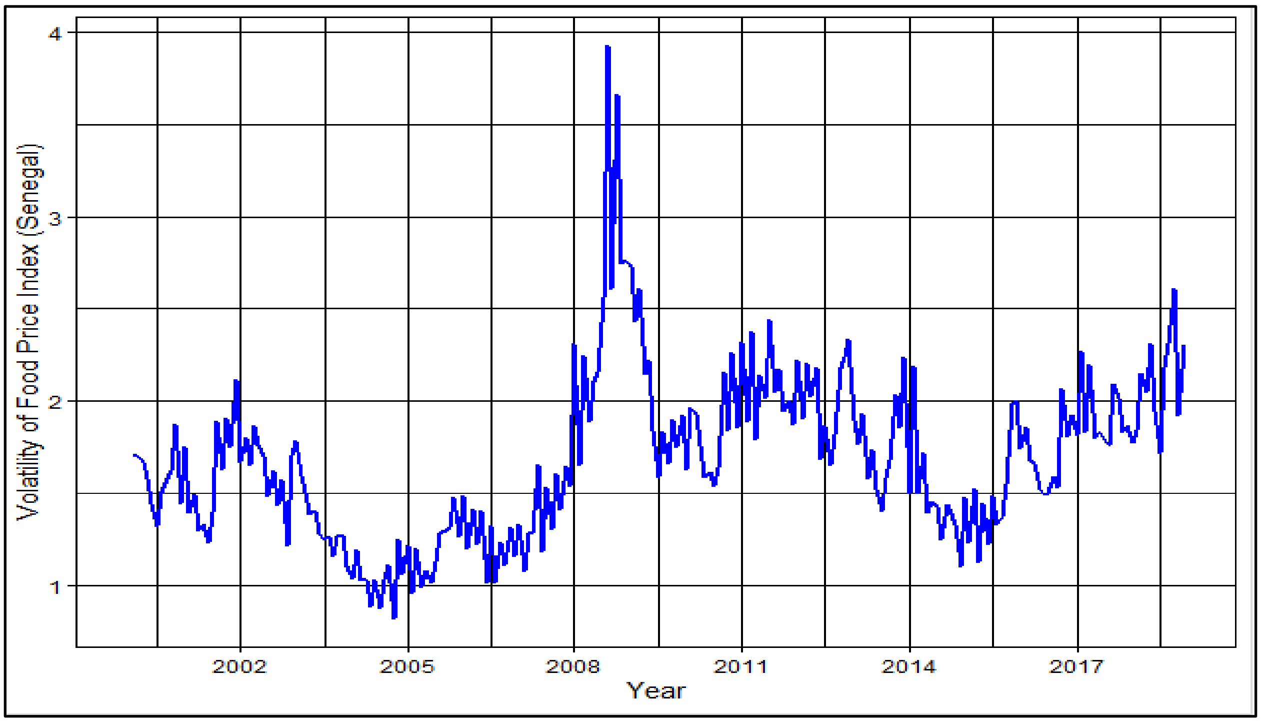
	Estimate	Std, Error	t value	Pr(>|t|)
omega	0,05	0,03	1,58	0,11
Alpha0	0	0,1	-0,02	0,98
alpha1	0,16	0,05	3,34	0
beta1	0,95	0,03	35,82	0
gamma1	0,11	0,04	2,55	0,01

Source: authors

- Trend of the conditional volatility

Figure 2 shows the dynamics of Food Price Index volatility over the period 2000-2018. Periods of high volatility have been detected, notably from 2008 to 2011 and throughout 2018. This representation is important for understanding that Senegal's Food Price Index is sometimes highly volatile compared to the normal trend.

Figure 2: Volatility of Food Price Index (FPI)



Source: Authors

2. FAO tools for assessing the volatility of Food Price Index

The Indicator of Food Price Anomalies (IFPA) assesses price growth in each month over many years by considering the seasonality of agricultural markets and inflation. It provides an early warning of periods of high volatility.

The results in Table 4 show the proportions of alerts (Alert/watch) given by the application of the Indicator of Food Price Anomalies and the Indicator of Food Price Anomalies adjusted and weighted to the Food Price Index (FPI) of Senegal. The proportion of alerts given by the weighted method is much higher than that given by the unweighted method. However, it is difficult to compare the relevance of these two indicators. It is best to observe the composite indicators and combine them with the quarterly and annual sub-indicators and the available information to better appreciate the results before reaching any questionable conclusions. Indeed, the results of this tool are very sensitive to extreme values and do not have criteria for selecting the optimal indicator or even a criterion for assessing the indicator. Similarly, no objective technique has justified the choice of weightings, which consist of giving more importance to recent data.

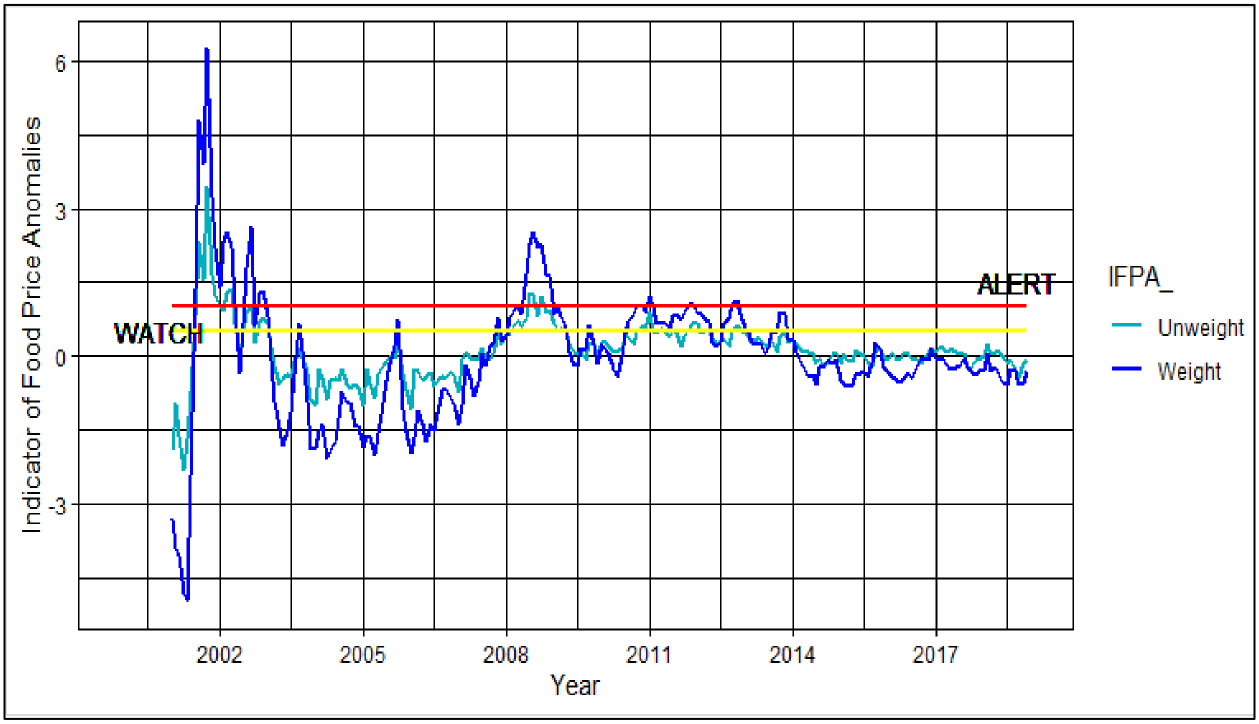
Table 4: Comparison of weighted and un-weighted Indicator of Food Price Anomalies warnings

	IFPA_Unweight	**vIFPA_Weight**
Number of Alerts	14	33
Proportion of Sample with an Alert (p)	0.06	0.14
N obs	227	226
Standard deviation	3.62	5.31

Source: Authors

Table 4 presents some comparative statistics that are often reductive of the information available on the indicators. Observation of the two indicators in Figure 3 shows that from the point of view of the information available, the weighted indicator presents 33 alerts, and the unweighted indicator presents 14 alerts mostly over the period 2001-2003 and over the period 2008 -2011. These results seem to be consistent with the periods of high volatility observed in recent years. Thus, based on the weighted indicator, we reduce the type II error (do not alert when there is indeed an alert). Which is confirmed by the results. The important thing to remember is that even though weighting and fitting is presented as a type II error reducer, it should be analyzed with relevance and always link these alerts to the information available in order to avoid false alerts.

Figure 3 : Indicators of Food Price Anomalies (simple and weighted)



Source: Authors

IV. Conclusion

The analysis of volatility has become fundamental in a context where the disruptive uncertainties of investment, production and consumption decisions are recurrent. However, the implementation of coherent and rapidly applicable tools is of paramount importance. To this end, this technical note provides a review of tools to measure food price volatility and the application of those tools to Senegal's Food Price Index. It also presents the standard tools for measuring and assessing volatility, namely the FAO tool, developed by Baquedano (2015).

The tools developed in this technical note help to understand the complexity of volatility measures and the caution required in applying these tools. Thus, the application of this tool requires its adaptation to the nature of the data generating process and the use of appropriate tests and criteria in order to choose the best model.

However, it is also noted that the use of the FAO tool developed by Baquedano (2015) as a warning tool of the potential serious disruptions in the functioning of the market, but it requires particular caution as it is based on very sensitive (mean, standard deviation) and subjective (weighting, threshold) considerations. This means that the results of this tool are often debatable and require the use of backtesting to verify its adequacy to reality.

As a result, the tool proposed by IFPRI in collaboration with the European Commission in 2010 to set up an early warning system called the Food Security Portal to mitigate the effects of rising and increasingly volatile food prices, offer an econometric approach based on non-parametric estimation developed by Martins-Filho, Torero and Yao in 2010. This tool allows to identify periods of excessive price variability (i.e., price variability that exceeds a pre-established threshold). This approach is supposed to be the most general and provides a more coherent and reliable analytical framework.

Moreover, the tools developed in this technical note focus on Senegalese food price index volatility independently of the interrelationships that food product price volatilities may coexist between them. The analysis of market interrelationships in terms of price volatility can give a better insight into the dynamic price relationships between different markets. The results of the application of the tools in this technical note would be much more interesting if we considered the analysis of volatility and transmission of food product prices instead of the aggregate food price index.

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