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International Food Policy Research Institute
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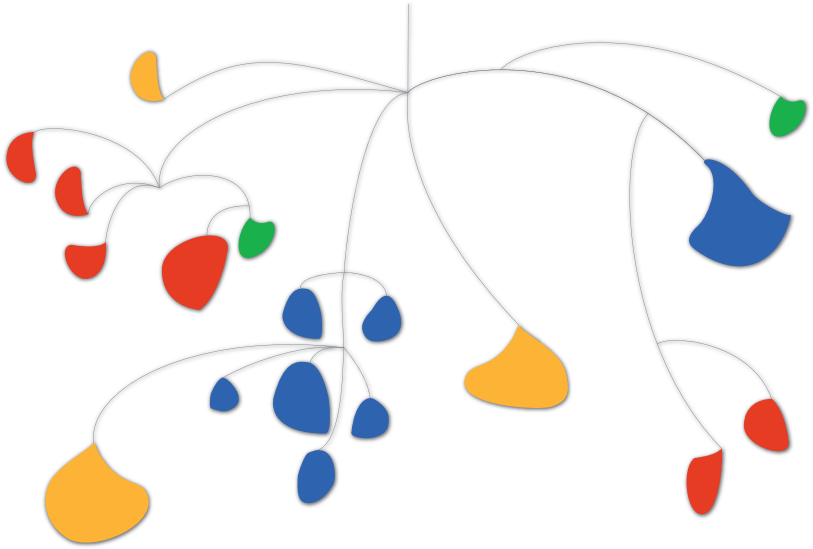
DEVELOPING A SET OF EARLY WARNING GLOBAL MARKET INDICATORS



One of the original goals of the Agricultural Market Information System (AMIS) was to develop a set of early warning global market indicators which could alert AMIS members to detect market conditions that could lead to excessive price volatility. Early meetings of AMIS in 2011 and 2012 considered a variety of measures. Most recently, a technical workshop was held in Washington, DC to consider several global market indicators which could be potentially incorporated into the *AMIS Market Monitor*. This report summarizes the results of the workshop for discussions at the Rapid Response Forum (RRF).

Previous AMIS efforts

At the inaugural AMIS meeting in September 2011, members called for the development of market indicators which could flag emerging market conditions that might lead to excessive price volatility in the face of some exogenous shock and pose a threat to vulnerable people. An exchange of views on the definition of abnormal market conditions and the selection of appropriate indicators took place at an AMIS meeting in December 2011. A paper based on the discussions at that meeting was prepared and presented to the first meeting of the Global Food Market Information Group in Rome in February 2012 (AMIS 2012a).

As articulated in a report on indicators (AMIS 2012b). presented to the Global Food Market Information Group in October 2012, indicators help (i) detect global food market vulnerabilities *ex ante*; (ii) better understand global market developments; and (iii) provide a rigorous basis for communication between the AMIS Secretariat and the RRF. The focus of the research is on drivers and corresponding indicators relevant to the *short-term* global food market outlook, covering one marketing year. These will be used alongside the supply and demand data for the commodities covered by AMIS (wheat, maize, rice and soybeans) to be provided by AMIS countries to the AMIS Secretariat on a monthly basis

Indicators which have been presented to the Information Group include stock-to use ratios, model-based identification of excess food price volatility, different policy indicators related to domestic and trade policies, futures markets indicators and media analyses. In addition to these suggestions, a number of simple indicators are already in general use and have been routinely disseminated through publications such as the FAO Food Outlook. Those include various price indices such as the FAO Food Price Index, the regular FAO cereal balances and relevant information concerning developments in nonagricultural markets – oil price developments, for example - likely to affect food prices.

Over the past 5 years, the *AMIS Market Monitor* has incorporated several measures into its regular reporting including: historical and implied price volatility measures, open trading interest on futures exchanges to track investment flows of commercial interests, swap positions and managed money, and global crop conditions developed by GEOGLAM. In addition, data are presented on the global fertilizer outlook and the US market for ethanol.

Yet while much progress has been made on the development of relevant market indicators in the *AMIS Market Monitor*, work remains on the development of associated threshold levels or of critical ranges of values which, if observed, would signal a need for particular vigilance from the AMIS Secretariat.

To this end, a workshop was held in Washington, DC on November 12-13 to examine a set of market indicators which could be used to monitor price volatility and serve as a forward-looking early warning system for policy makers, producers and consumers. The workshop was hosted by the International Food Policy Research Institute and was attended by a number of AMIS Secretariat members, including FAO, the World Bank and the World Food Program, as well as technical experts from academia and USAID (FEWSNet).

Much of the focus of the first day was spent on global market indicators. IFPRI presented its Excessive Food Price Variability Early Warning System and the World Bank presented its Food Price Crisis Monitor. Both measures were developed following the price crisis of 2007/08 and 2010/11 and are published and updated daily on their respective websites. In addition, FAO presented work on developing a forward looking predictor of commodity prices which could be compiled in real time summarizing market sentiment of investors. Technical background research on the IFPRI and World Bank measures have appeared in peer-reviewed journals. The research on a market sentiment index

is at a more preliminary stage with research currently underway at FAO.

The second part of the workshop concerned local measures of price volatility – thus with a lesser relevance to the work of AMIS. Included was a discussion of the World Food Program's Alert for Price Spikes (ALPS) indicator; FAO's Global Information and Early Warning System (GIEWS), and US Agency for International Development's Famine Early Warning System Network (FEWSnet). In addition, IFPRI presented research on transmission of global volatility to local markets (Ceballos *et al*. 2015) and the World Bank presented research using vegetative indices to identify potential impact on maize prices in Tanzania (Baffes, Kshirsagar and Mitchell 2015).

Global market indicators

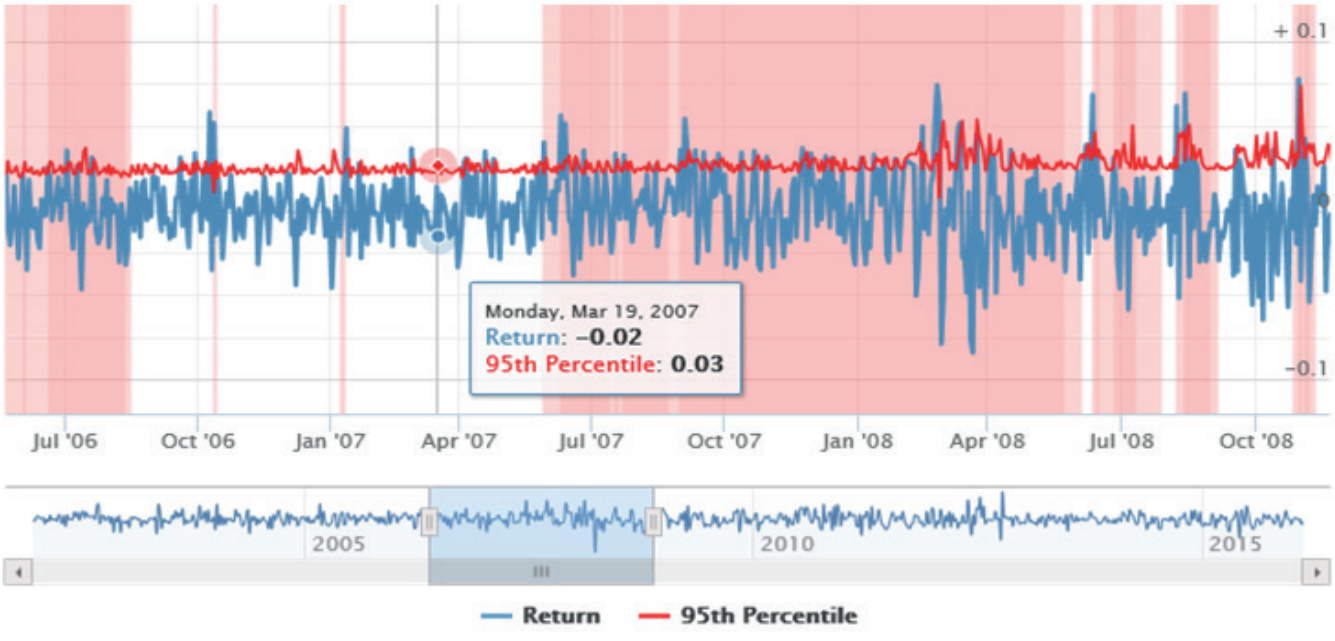
In line with the more global focus of the *AMIS Market Monitor*, both the IFPRI Excessive Food Price Variability Early Warning System and the World Bank Food Price Crisis Monitor track how current price movements in international markets compare with historical movements and seek to identify whether prices movements exceed normal patterns. The IFPRI measure examines daily futures price movements while the World Bank measure examines recent trends in daily or monthly prices compared to long term historical measures. The FAO sentiment index, on the other hand, seeks to measure the prevailing behaviour of investors and other market participants.

IFPRI Excessive Food Price Variability Early Warning System

The IFPRI measure is based on statistical modeling and looks at daily futures price data for four major crops – hard wheat, soft wheat, maize, rice and soybeans.[1] Data for the model are obtained from closing prices of futures contracts traded on the Chicago Mercantile Exchange (CME Group) and, in the case of hard wheat, the Kansas Board of Trade (now also part of the CME Group). The tool presents a visual representation of historical periods of excessive global price volatility from 2000 to present, as well as a daily volatility status.

The blue line in Figure 1 shows daily returns to Hard Red Winter Wheat futures over the period June 2006 to

[1] A more technical description is presented in the appendix.



Data source: Markets, Trade, and Institututions Division

October 2008. The red line indicates a statistical measure of an "excessively" high return (a return that has a probability of occurring less than 5 percent of the time). Thus when the blue line exceeds the red line, that daily return is considered excessive. Note that the observation of a small number of such returns does not necessarily indicate a period of excessive volatility. It is the persistent occurrence of such extreme returns that characterizes periods of extreme volatility. For that measure, the model looks back over the previous 60 days to determine whether the number of extreme price movements is statistically unusual.

IFPRI has developed a further indicator to summarize its price volatility measure with a color system as follows:

- RED or Excessive Volatility: If the probability value is less than or equal to 2.5 percent, we are in a period of an excessive number of days of extreme price returns relative to that expected by the model ; therefore we characterize that date as belonging to a period of excessive volatility.
- ORANGE or Moderate volatility: If the probability value is bigger than 2.5 percent or less than or equal to 5 percent, we are in a period of moderate number of days of extreme price returns relative to that expected; therefore we characterize that date as belonging to a period of moderate volatility.
- GREEN or Low volatility: If the probability value is bigger than 5 percent, the number of extreme price returns is consistent to what is expected from the model; therefore we characterize that date as belonging to is a period of low volatility.

The days in volatility reflects the number of continuous days in the current level of volatility. For example, 20 days of low volatility means that since the last instance of moderate or high volatility, there have been 20 days of low volatility. Table 1 shows the number of continuous days in low volatility as of February 5, 2016.

World Bank Group Food Price Crisis Monitor

The World Bank Group measure of price volatility examines recent price movements relative to a long detrended price series. The methodology was developed using monthly data but more frequent (e.g., daily) data could be used. The goal of the proposed monitoring system is to provide early detection of unfolding food security crises related to prices in the most vulnerable – International Development Association (IDA) – countries. Vulnerability is determined by a country's degree of exposure to domestic food price spikes and limited macroeconomic capacity to mitigate their effects.

Conceptually, the framework is designed at two levels. The first is the global level, which captures global or regional shocks affecting or expected to affect food security. The second is the domestic level (country specific), which focuses on the exposure of each IDA country to the shock, and the country's capacity to manage and withstand the shock's impacts. The presence of two stages does not imply necessarily that both are always closely and inevitably linked. The pass-through of international prices to domestic prices is not automatic, either because national markets are not internationally integrated, or because even when they are, price transmission lags several months on average. Rather, the two stages of the framework ensure that specific countries' vulnerabilities to global shocks are carefully analysed, and also that domestically generated alerts are not overlooked when global prices are calm.

Table 1.
Number of continuous days in the current level of volatility

Commodity	Futures exchange	Volatility level	Number of consecutive days in the current level of volatility
HRW wheat (KC)	CME	Low	1 275
SRW wheat (Chicago)	CME	Low	1 423
Corn	CME	Low	1 292
Soybeans	CME	Low	1 235
Rice	CME	Low	1 277

Source: IFPRI, data as of February 5, 2016.

Operationally, the monitoring framework will generate two types of alerts: top down and bottom up. In the top-down approach, the alert system is activated during the global stage after either or both global food and fuel prices exceed some predefined threshold. Then, domestic indicators are analysed to determine the severity of each IDA country's vulnerability to the global alarm. The bottom-up approach focuses on domestic vulnerability and sounds the alarm – even in the absence of global crisis – when two or more countries in a region or subregion exceed their domestic price and macroeconomic triggers.

As outlined in the paper by Cuesta, Htenas and Tiwari (2015), the calibration exercise that predicts the 2008 and 2011 price spikes show that the best performing triggers are:

(i) Global food price index (FOPI) exceeds 3 standard deviations (SD) from the detrended historical mean of 1960–2006 (2005=100).
(ii) Domestic food staple prices increase at least 15 percent during a period of five months for two or more countries from a same (sub)region.
(iii) All those countries in the region or subregion that exceed the staple price trigger have at least one macroeconomic vulnerability (as defined by debt, current account, fiscal, and foreign reserves triggers).

With regards to price levels defining a crisis, the Bank research points out that there is no analytical work that relates price increases to food insecurity deterioration. The justification for the 15 percent figure is that the average annual increase for years in which the global food price index increased since 1960 is 12 percent; the average price changes for years without price spikes is 8 percent. The average increase among the five years in the series with serious price spikes is 42 percent. Arguably, a 15 percent increase in five months implies a 3 percent monthly increase in prices, which is close to the increase for those years with price spikes. The monthly price increase that is considered unusually high is adjusted to a five-month period consistent with the consecutive period criterion discussed above. Then, the 15 percent food price increase is analysed for five consecutive months, and for five months relaxing the condition of consecutive price increases observed in all five months.

Finally, unusual prices are defined statistically as levels exceeding 3 standard deviations with respect to the historical trend before the increasing price trend since January 2000. It is important to caveat this choice with the fact that the standard deviation of a nominal series over a four decade period is simplistic, not least because each of the series considered may have undergone structural breaks. However, this crude tool is an initial starting point. One step further is to replicate the exercise after detrending the series in an attempt to get rid of potential seasonality effects, that is, of predictable, recurrent and transitory effects. In addition, the benchmark period of 1960–2006 is determined by the fact that available food and fuel price series go all the way back to 1960. Furthermore, the year 2007 marks the onset of a price increase sustained trend after two disparate periods, 1960–72, and 1973–2006, of stable and volatile global prices, respectively.

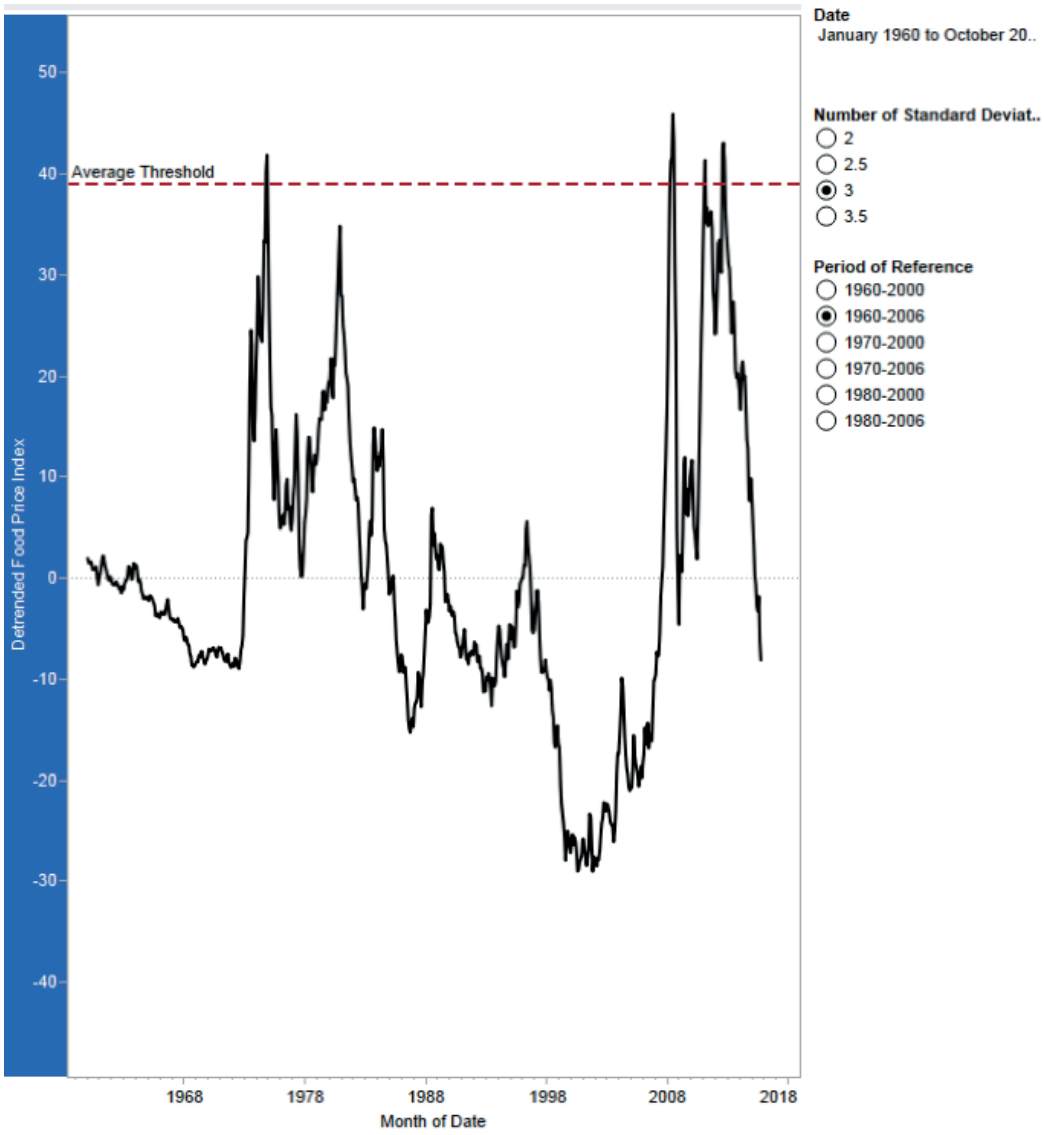
The Price Crisis Monitor was developed based on monthly commodity price data as reported in the World Bank's Pink Sheet. Figure 2 (next page) shows analysis based on the World Bank Food Price Index but similar charts could be constructed based on other indices (for example, using the World Bank energy index or fertilizer index). Moreover, the methodology could be applied to other price series such as the FAO Food Price Index, the FAO Food Commodity Price Indices or the IGC Grains and Oilseed Index.

Table 2 (next page) shows recent index values, recent movements of the index and whether current levels are "abnormally" high (determined as being greater than 3 standard deviations of the detrended historical mean).

FAO Market Sentiment Index

At the workshop, FAO presented work on developing a forward looking predictor of commodity prices which can be compiled in real time summarizing *market sentiment* of investors and others (Pozzi 2015). The ongoing research seeks to fill a gap in the paucity of forward-looking indicators that portends high prices and high uncertainty, and hence volatility, in the AMIS monitored commodities of wheat, maize, rice and soybeans. An important class of indicators that purports to be predictive relates to market sentiment. Simply put, market sentiment refers to the "general prevailing attitude of investors as to anticipated price

Figure 2.
World Bank Food Crisis Monitor



Title: "Crisis Monitor - Global" http://www.worldbank.org/en/topic/poverty/food-price-crisis-observatory
Source: World Bank Group
Note: Baseline 2010=100
Disclaimer: As explained throughout this site, there is no official consensus on the definition of a food crisis. The information, interpretations and conclusions presented in this tool are for informational purposes only and shall not be used or relied on by the user, including to define or declare global or national food crises in any formal way. Nor shall this tool be construed as providing investment advice. Although the World Bank Group makes reasonable efforts to ensure all the information presented in this tool is correct, its accuracy and integrity cannot be guaranteed. Use of this tool is at the user's own risk and under no circumstances shall the World Bank Group be liable for any loss, damage, liability or expense incurred or suffered which is claimed to result from the use of this tool. This tool and the data it contains do not imply any opinion, judgment or endorsement on the part of the World Bank Group, and the findings, interpretations and conclusions expressed in the data are those of variou..

Table 2.
World Bank Price Monitor

Index	January 2016	Change from previous month (%)	Change over past 5 months	Consecutive months of increase/decrease	Exceeds 3 SD of detrended historical mean
Global Food Price Index	84.49	-1.1	-3.9	3 ↓	No
Global Grain Price Index	82.13	-0.4	-2.0	3 ↓	No
Energy Price Index	40.50	-15.3	-31.8		
Fertilizer Price Index	85.98	-5.1	-9.33	2 ↓	No

Source: World Bank Pink Sheet
The Crisis Monitor is available here: http://www.worldbank.org/en/topic/poverty/food-price-crisis-observatory#1

development in a market … [which] is the accumulation of a variety of fundamental and technical factors, including price history, economic reports, and national and world events."[2] Sentiment analysis then measures the market's propensity to risk and hence the expected volatility in prices. Indicators of market sentiment have proven their worth in equity and foreign exchange markets. Traditionally derived from realized quantitative information, they are widely used to assess future market direction, especially in the context of "contrarian indicators" – identifying market peaks and troughs.[3]

With new forms of information flow, especially social media (e.g. Twitter), blogs and dedicated news services, there is a growing wealth of additional information that can be harvested and exploited to assess where markets might be headed. *News analytics* and *social network-embedded prediction models* are widely known to be used in financial modeling,[4] particularly in quantitative and algorithmic trading. Other than *IFPRI's Food Security Media Analysis System*, which allows users to scan for news events from predetermined sources and to cross tabulate them on food prices, there are no such prediction models applied in commodity markets, at least in the public domain.[5]

The overarching objective is to construct and disseminate (via the AMIS website) real-time sentiment indices for the AMIS set of commodities in the framework of news analytics and social network-embedded prediction. Technologies for text mining, e.g. web scraping, harnessing web services and APIs, as well as a sentiment dictionary will be established, supported with semantic analysis to infer meaning. The (past) predictive performance of the indices will also be assessed giving confidence to users.

[2] http://en.wikipedia.org/wiki/Market_sentiment

[3] For example, CNN's "Fear and greed index"; Acertus Market Sentiment Indicator (AMSI), The Investors Intelligence Survey, SWFX Sentiment Index. See www.sentimentrader.com/indicators for more examples

[4] As an example of their predictive performance, forecasting stock returns from Twitter sentiments, was found to have a R2 of 0.952, with a low maximum absolute percentage error of 1.76 percent (see "Twitter Sentiment Analysis How To Hedge Your Bets In The Stock Markets" (http://arxiv.org/abs/1212.1107))

[5] Such indicators in commodity markets may well exist but are likely to be proprietary, and integral to firms' private trading strategies and investment decisions

Summary

The IFPRI Excessive Price Volatility measure and the World Bank Group Food Price Crisis measure are complementary indicators. While the World Bank indicator measures recent price movements and price levels, the IFPRI indicator provides a measure of market price volatility over the past 60 days. Neither of the measures is forward looking in a predictive sense but they are best thought of as measures that indicate whether recent price movements are "abnormal" in a statistical sense.

The FAO research on a market sentiment index seeks to develop a more forward-looking indicator that could anticipate price developments. Work remains preliminary at this point and will be reported on in the future.

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Appendix

Technical Description of the IFPRI Excessive Food Price Variability Early Warning System

The IFPRI measure is based on the Nonparametric Extreme Quantile Model (NEXQ). A more technical description can be found in Martins-Filho, Torero and Yao (2010) and Martins-Filho, Yao and Torero (2011).

NEXQ is implemented in three sequential steps. First it estimates a model of the dynamic evolution of daily returns based on historical data going back to 1954. This model is then combined with extreme value theory to estimate conditional higher-order quantiles of the return series, allowing for classification of any particular realized return (that is, effective return in the futures market) as extremely high or not. Note that the observation of a small number of such returns does not necessarily indicate a period of excessive volatility. It is the persistent occurrence of such extreme returns that characterizes periods of extreme volatility. The second part of the model implementation identifies periods of excessive volatility based on a statistical test applied to the number of times extreme values occur in a window of 60 consecutive days.

Any model that tries to explain the evolution of returns over time has to be flexible enough to incorporate all of the salient characteristics of the time series of returns that are observed. So first a flexible, fully nonparametric location scale model is developed that explains the evolution of returns through time. This model has two important characteristics. The first is that the mean and the variance of returns through time can vary with time because they are functions of past returns and other important variables that condition the mean and the variance. The second important characteristic of this model is that these functions that describe the mean and the variance for the process are not specified as belonging to any specific parametric class of functions; that is why we call this a nonparametric model. This is important because it allows the data to speak freely about the structure of these functions.

The second part is to devise a consistent way of defining what extreme values of returns are, i.e. what extreme price variability is. The way this is done is by combining the nonparametric estimation of the model with extreme value theory. To do this, one must approximate the tails of the distribution of the model which were estimated in the first step. "Tails" refers to the part of the distribution that is associated with very high or low levels of the variable of interest. Taking advantage of the fact that the tails of any distribution can be approximated by a function called Generalized Pareto Function or Generalized Pareto Distribution, the nonparametric location scale model estimation in the first step is combined with the Generalize Pareto distribution approximation of the tails to estimate this high order conditional distribution of the quantiles.

Thus one can determine what level of return will give us probabilities of exceedances that are above that value that occur with very low probability (i.e. 5 percent, 2 percent or 1 percent). In summary, this allows one to estimate quantiles of the return series, which one can then classify any particular daily return as being "large". Any quantile can be used to help define "large," but the 95 percent percent quantile was selected, i.e. any daily return that exceeds the estimated 95 percent quantile is classified as a very high return.

As mentioned above, it is important to note that the identification of any particular return does not allow for identifying a period characterized by very high price volatility or an unusually high number of occurrences of high price volatility.

The third part of NEXQ implementation tries to resolve this by using a statistical test that identifies periods of increased price variability. This is done retrospectively, i.e. for any particular day where one observes a return, we look at the previous 60 trading days that preceded that return; within that period of time, we have an estimated number of returns that exceeds the quantile that we estimate with our model. Then we compare that count of the number of returns that exceed the quantile with the expected number of returns that should have exceeded it. A statistical test is then developed to verify whether the discrepancy between the count we have of the exceedances over the quantile and the expected number of excedances is high. If it is statistically significantly high, that particular day is characterized as a day belonging to a period of excessive volatility. This 60 day window is then moved through the entire past history of returns and construct the periods of excessive price volatility. (see for example http://www.foodsecurityportal.org/policy-analysistools/excessive-food-price-variability-earlywarning-system).