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ASSESSING VOLATILITY PATTERNS IN FOOD CROPS

(A NON-TECHNICAL SUMMARY)

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AMIS

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Prices of food crops are naturally volatile as their supply depends on unpredictable factors such as weather. While volatility is not a problem per se, excessive price movements in global markets can pose a threat to world food security. Understanding the causes of excessive volatility and constructing indicators to detect market risk is therefore of crucial importance. Against this background, the Agricultural Market Information System (AMIS) conducted research on assessing volatility patterns in food crops.[1] This document is a non-technical summary of this analysis.

Why does volatility matter?

As illustrated by past food price crises, excessive volatility can push people into poverty and hunger. Especially in developing countries, many households are vulnerable to extreme price swings as they lack adequate coping mechanisms such as storage, savings or access to credit. When prices surge unexpectedly these households might have to lower their food intake, take children out of school, save on healthcare services or sell productive assets such as land and livestock. Producers are affected, too. High volatility brings with it considerable downside price risk, which affects planting decisions and undermines agricultural investment where it is needed most.

What is the objective of this study?

While the factors that can influence price movements are firmly established in the literature, relatively little is known about their critical values that would signal market risk. For example, stocks are generally regarded as an effective mechanism to buffer against price shocks. However, what is the critical inventory level that needs to be maintained? Such information is important as it allows policymakers to make better decisions on the allocation of scarce resources for an adequate level of protection. To this end, the study assesses different factors for their impact on price dynamics and identifies specific thresholds that are associated with high or low levels of price volatility.

How are these thresholds established?

The paper examines price volatility for three of the four AMIS commodities: wheat, maize, and soybeans. Rice is excluded because of the overarching importance of domestic policies in price formation. The analysis focuses on monthly price data (covering the period January 2000 to December 2015) for the wheat, maize and soybeans sub-indices of the International Grains Council's "Grains and Oilseeds Index (GOI)" as well as the quotations included in these indices.

In order to assess volatility, a time-series model of these price data is estimated applying a method called "component-wise gradient boosting". The algorithm underlying this technique selects from a range of potentially relevant variables those that best explain observed changes in volatility (for a short overview of the method, please refer to the Box). Four broad classes of variables are considered: (i) market fundamentals, (ii) macroeconomic variables, (iii) financial variables, and (iv) weather-related variables. Table 1 provides an overview of the different variables and the rationale for including them in the analysis.

Which variables seem most relevant?

The boosting algorithm selects variables from several groups as relevant for explaining shifts in the level of volatility. Table 2 summarizes the thresholds that the model estimates for each respective variable. The relevant groups are as follows:

Inventories

Both the global and the US stocks-to-use ratio are associated with changes in the price volatility of all three

[1] Greb, F. and A. Prakash (2016): Assessing volatility patterns in food crops. Food and Agriculture Organization of the United Nations (FAO).

Box: Methodology of the statistical analysis

Modelling framework

The price time series p_t , $t=1 \dots T$, are analysed using a model that sets volatility – the standard deviation of logarithmic returns $r_t = \log p_t/p_{t-1}$ at a certain time in relationship to past months' returns, the time of the year, and the contemporaneous as well as lagged values for a range of other factors. These include market fundamentals, macroeconomic variables, variables related to financialization of commodity markets and variables accounting for weather phenomena.

The sum of these effects, η_t enters the model via an exponential function, which guarantees non-negativity of the term representing volatility, $\exp(\eta_t/2)$ More precisely, price returns and covariates are connected via

$$r_t = \exp(\eta_t/2)\varepsilon_t\ ,$$

$$\eta_t = \beta_0 + \beta_1 t + f_{year}(y_t) + f_{month}(m_t) + \sum_{i=1}^{I} f_i\,(r_{t-i}) + \sum_{j=1}^{J}\sum_{k=1}^{K_j} f_{j,k}(x_{j,t-k})\ ,$$

where ε_t are independent standard normally distributed normal errors. Readers familiar with volatility modelling will recognize this as an exponential ARCH model.

The way in which individual factors influence volatility is described by so-called trees, represented by *f* in the modelling equation. These functions are flexible enough to capture nonlinearities such as abrupt transitions in the dependencies. Trees partition the predictor domain into a number of simple regions characterized by similar effects on the response variable, which are then described by a simple model, a constant in this case. If, as an illustration, only the stocks-to-use ratio impacted food price volatility, partitioning the predictor space would mean segmenting it according to the stocks-to-use ratio being below or above a critical value *c*; or, more generally, its location relative to values $c_1 < \dots < c_n$. For stocks-to-use ratios larger than *c*, predicted volatility would then differ from the prediction for ratios below *c*.

Estimation and variable selection

The model is fitted by means of component-wise gradient boosting. The aim of the boosting algorithm is to estimate a relationship between explanatory variables and a response variable by minimizing the expected loss according to a specific loss function, often (and also in this case) the negative log-likelihood function of the outcome distribution. Boosting relies on stepwise gradient descent techniques to approach the minimum of the observed mean loss, the empirical counterpart of the expected loss. While gradually getting closer to the minimum, at each step the component-wise boosting algorithm determines the best-fitting (in terms of the sum of squared residuals) model component and adds it, multiplied by a small positive shrinkage parameter to regulate the learning speed, to the fit. It is crucial to carefully choose the number of iterations, *m*, the main tuning parameter of the algorithm, to optimize predictive accuracy. Here, *m* is selected based on cross-validation with 250 bootstrap samples of size *T*.

For a tree-based model this iterative procedure implies sequential partitioning of the predictor space. For example, if the stocks-to-use ratio is found to be the most informative covariate in the first iteration, the domain will be partitioned according to whether or not the stocks-to-use ratio is above or below a critical value *c*. If the following ten iterations result in this same variable producing the best fit, the split of the predictor domain in dependence on the stocks-to-use ratio will be reinforced and possibly refined. In the eleventh iteration the oil price might turn out to be the best-fitting component, introducing a segmentation of the predictor space conditional on the oil price being above or below a price *d*. The procedure continues until reaching the final, *m*-th, iteration. Clearly, covariates that have not been selected as the best-fitting component at any step before the algorithm stops, drop out of the model as redundant.

Estimation via component-wise gradient boosting has several distinct advantages. The estimation method allows to consider a very large number of covariates that are suspected to be related to the outcome, even collinear ones. The fitting process includes variable selection, keeping only informative features in the model. In addition, while allowing for considerable flexibility in the shape of the dependencies between response and explanatory variables, contrary to many other methods achieving high predictive accuracy results remain interpretable.

Table 1: Variables considered by the model and the rationale for including them

MARKET FUNDAMENTALS

INVENTORIES

- Global stocks-to-use ratio
- US stocks-to-use ratio
- Major exporters stocks-to-disappearance ratio with the United States
- Major exporters stocks-to-disappearance ratio without the United States

Rationale: Releasing stocks can absorb the supply shock of a bad harvest while the building of stocks can stabilize prices during a bumper crop.

PRODUCTIVITY

- Yield

Rationale: Differential effects of high and low yields on crop prices might lead to changes in volatility.

MARKET THINNESS

- Ratio of world exports to global consumption
- Ratio of world exports to global production

Rationale: A thin market with few buyers and sellers (and thus few transactions) is more susceptible to large price fluctuations.

MARKET CONCENTRATION

- Degree of export concentration

Rationale: High export concentration increases the chance of price volatility from supply shocks in any of the few main exporters.

MACROECONOMIC VARIABLES

INTEREST RATES

- Effective Federal Funds Rate
- 6-Month Treasury Bill

Rationale: Interest rates can affect volatility by determining the opportunity cost of holding stocks and by influencing relative returns of investing in agricultural derivatives markets.

OIL PRICES

- Western Texas Intermediate price
- European Brent price
- Realized and conditional volatility of Western Texas Intermediate price
- Realized and conditional volatility of European Brent price

Rationale: Oil prices may affect crop price volatility by influencing input (processing, fertilizer) and transportation costs as well as through linkages with biofuel.

STOCK MARKET VOLATILITY (AS A PROXY FOR BROAD ECONOMIC RISK)

- Chicago Board Options Exchange's Volatility Index VIX

Rationale: Stock market volatility captures overall economic risk and uncertainty, which might translate into fluctuating crop prices.

FOREIGN EXCHANGE RATES • Index of the foreign exchange value of the US dollar • Realized and conditional volatility of the foreign exchange index Rationale: With international commodities being traded in US dollars, changes in the exchange value of the dollar might impact on crop price volatility by altering demand and supply incentives.	
FINANCIAL VARIABLES	
FINANCIALIZATION OF COMMODITIES • Number of trades in futures contracts • Open interest • Ratio of volume to open interest • Non-commercial long positions • Ratio of long non-commercial to total positions • Ratio of short non-commercial to total positions • Working's speculative index Rationale: Although yet to be confirmed, financialization of commodities might expose crop prices to risks and volatility from outside markets.	
WEATHER VARIABLES	
WEATHER ANOMALIES • FAO's Agricultural Stress Index • Sea surface temperature anomalies (related to El Niño/La Niña) • Oceanic Niño Index (related to El Niño/La Niña) • Southern Oscillation Index (related to El Niño/La Niña) Rationale: Weather variability can cause fluctuations in crop supply and thus prices.	

commodities. For wheat and maize, this also applies to the stocks-to-disappearance ratio for major exporters. In terms of critical thresholds, global inventories below 18 percent (wheat), 17 percent (maize) and 22 percent (soybeans) relative to use prompt higher volatility; for the US stocks-to-use ratio the values are 37 percent (wheat) and 12 percent (maize and soybeans). For the majority of quotations, falling below these thresholds is associated with a significant increase in volatility. The critical change point for the stocks-to-disappearance ratio for major exporters is at around 13 percent (wheat) and 12 percent (maize). Again, a ratio below these thresholds is associated with a significant upward shift of the level of volatility.

Oil prices

Oil prices appear relevant for volatility shifts of wheat, maize, and soybean prices, although more so for the latter two commodities. For European Brent quotations, critical price levels (per barrel) are USD 118 for wheat, USD 105 for maize, and USD 119 for soybeans, all with a three-month lag. The estimated impact of a rise in oil prices beyond these limits is very pronounced in some cases - for certain wheat quotations volatility increases by more than 60 percent. In the case of Western Texas Intermediate (WTI), critical price levels are USD 105 for maize and USD 104 for soybeans; the analysis does not provide evidence for an impact of WTI prices on wheat price volatility.

Stock market volatility

The estimation results suggest the volatility index of the Chicago Board Options Exchange (VIX) to be associated with changes in volatility levels, at least for wheat. This finding would confirm a link between perceived overall risk and uncertainty (as measured by the VIX) and agricultural price volatility. Interestingly, the critical threshold of 23 estimated by the model is close to the value of the VIX that is generally regarded as an indication of extreme market uncertainty.

Foreign exchange rates

The foreign exchange value of the US Dollar seems to explain changes in wheat price volatility; by contrast, it does not appear to be relevant in the case of maize and soybeans. Specifically, wheat price volatility soars by more than 20 percent when the index falls below 101.

Also, rising volatility of the foreign exchange index itself seems to be passed on to commodities. For wheat, levels of 1.3 percent (conditional volatility) and 1.5 percent (realized volatility) appear to be critical. For maize, a level of 1.3 percent (realized volatility) is associated with an increase in volatility.

Financialization

Variables indicating the degree of financialization turn out to be relevant for all three commodities. Looking at wheat, a critical trade volume in futures markets appears to lie between 2,300,000 and 2,900,000 trades per month. Regarding open interest, surpassing a level of around 465,000 to 495,000 contracts corresponds to increased volatility. For maize and soybeans, a growing ratio between the number of trades and open interest is correlated with an increase in volatility.

Weather variability

The boosting algorithm selects variables related to weather variability as relevant for explaining volatility shifts. Estimates show a rise in wheat price volatility associated with episodes of moderate or strong La Niña events (as measured by sea surface temperature anomalies). By contrast, weather-related variables seem to be less important for maize and soybeans. Still, Brazilian maize and US soybean price volatility goes down whenever the Oceanic Niño Index passes a 0.2 and 0.6 threshold, while only the latter seems robust.

What do these findings mean for policymakers?

Among the estimated variables, only a few have clear policy implications. In the case of the stocks-to-use ratio, for example, a general recommendation would be to keep global wheat inventories above a threshold of 18 percent relative to use. However, even for variables that cannot be influenced directly through policies, such as the Oceanic Niño Index, stock market volatility, oil prices or foreign exchange rates, the findings of the paper provide important insights for policymakers to better anticipate and prepare for future crises.

Notably, one important variable that would have immediate policy implications is missing in the study: trade policies. These can have a substantial impact on price movements. A price hike following a shortage of supply on the world market can be exacerbated if a major exporter decides to put in place an export ban in

Table 2: Critical thresholds by commodity

	Wheat	Maize	Soybeans
Global stocks-to-use ratio (percent)	18	17	22
Stocks-to-use ratio (percent)	37	12	12
Major exporters stocks-to-disappearance ratio (percent)	13	12	
Index of the foreign exchange value of the US$	101		
Conditional volatility of the foreign exchange index (percent)	1.3		
Realized volatility of the foreign exchange index (percent)	1.5	1.3	
Chicago Board Options Exchange's Volatility Index VIX	23		
Brent oil price (US$ per Barrel)	118	105	119
WTI oil price (US$ per Barrel)		105	104
Number of trades in futures contracts (thousand)	2 700		
Open interest (thousand)	485		
Ratio of volume to open interest		4.3	8.6
Non-commercial long positions (thousand)	40		
Sea surface temperature anomalies in Niño 3.4 region	-1.0		
Oceanic Niño Index			0.6

order to ensure sufficient domestic supplies. Besides the obvious challenge of having meaningful data for such analysis (export prices usually do not exist when an export ban is in place), assigning numerical values to these policies is troublesome. First, there is not just one type of trade-related policy measure but various, whose relative importance is unclear. Second, their significance has to be seen in the context of the implementing country's overall weight in the trade in the respective commodity. Third, the same measure would have very different domestic and foreign effects. For example, an export tax on wheat implemented by Argentina will effect Argentinian wheat prices differently than if the export tax was applied by the Russian Federation.

Some concluding remarks

The study demonstrates that assessing volatility patterns in food crops can help in selecting the relevant factors and associated threshold levels that would signal market risk. While the boosting algorithm seems a very suitable approach, the model might oversimplify the complex interplay of factors that drives volatility. Also, the analysis might have left out variables, quantified them incorrectly and observed them at a wrong time scale or frequency, in which case the model cannot assess their potential impact on volatility.

It is tempting to infer causation from the results, that is, to interpret variables selected by the boosting algorithm as drivers of volatility. However, unless the channels through which specific variables affect price fluctuations are well understood, such interpretation would not be valid. Among others, this particularly applies to variables related to the level of financialization of commodities markets, where causes and effects can frequently not be distinguished clearly.

Still, awareness of the limitations of the study does not refrain from the recommendation to be diligent when certain variables approach specific thresholds. It is insightful that some of these variables turn out relevant when lagged. This might hint at causality instead of mere association. More importantly, it allows having an indication of possibly elevated future volatility in advance.

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