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Excessive Food Price Variability Early Warning System

Incorporating Fertilizer Prices[1]

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1 Introduction

Low adoption of improved land management practices, including fertilizer use, is one of the main factors for low agricultural productivity in many developing countries. Rising agricultural productivity in many countries has been accompanied by greater fertilizer use. For example, sub-Saharan African countries, characterized by low agricultural productivity, have a very low fertilizer application rate, averaging 10 kilograms per hectare (kg/ha) of nutrients of arable land, compared to 288 kg/ha in a high-income country (Hernandez and Torero, 2011). Considering the essential role that agriculture plays in the rural economy of many developing countries, many policies have been implemented to encourage sustainable fertilizer adoption. The effectiveness of different mechanisms remains though a topic of discussion. Hernandez and Torero (2013) and Hernandez and Torero (2018), for instance, note that fertilizer prices are generally higher in more concentrated markets at the global and local level. The authors argue that better understanding the dynamics of fertilizer prices in international markets can help in designing policies that promote sustainable fertilizer use in developing countries, which are increasingly dependent on imported fertilizer.

Price spikes or shocks in the fertilizer market, especially excessive price shocks, can be detrimental to fertilizer adoption and farmer's productivity, particularly among vulnerable smallholders in developing countries who lack effective risk-sharing mechanisms. Properly and timely monitoring abnormal price fluctuations (volatility) on fertilizer global markets is thus relevant to inform appropriate and timely responses and attenuate potential projected negative effects on production decisions and rural incomes.

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On this regard, the Excessive Food Price Variability Early Warning System (hereafter Early Warning System), maintained by IFPRI's Food Security Portal (https://www.foodsecurityportal.org/), identifies unusual periods of excessive price variability for a variety of commodities. The tool is based on nonparametric estimators for conditional value-at-risk (CVaR) and conditional expected short- fall (CES) associated with conditional distributions of the modeled price returns series, as in Martins-Filho et al. (2015) and Martins-Filho et al. (2018). The unusual periods of excess price variability are identified when the return of the underlying price series exceeds the estimated CVaR, providing an early warning system for farmers, traders, processors, and consumers worldwide. The agricultural products monitored include maize, hard and soft wheat, rice, soybeans, coffee, cocoa, sugar, and cotton. Recently, energy products were incorporated, including crude oil and natural gas. The price information for all these products is available on a daily basis, which offers a rich dataset for model estimation and hypothesis testing.

The objective of this note is twofold. First, we aim to extend the Early Warning System to start monitoring fertilizers prices, particularly potash, urea, ammonia, and di-ammonium phosphate (DAP) prices from the US Gulf. These price series are available on the weekly basis, as opposed to the other commodities with daily price data. We discuss the challenges involved to incorporate these series, with a notably smaller sample size, and illustrate the predictive performance of estimators in terms of identifying periods of excessive volatility using these series. Second, drawing on the literature in extreme value theory, we propose alternative estimators for the CVaR, which are relatively easy to implement.

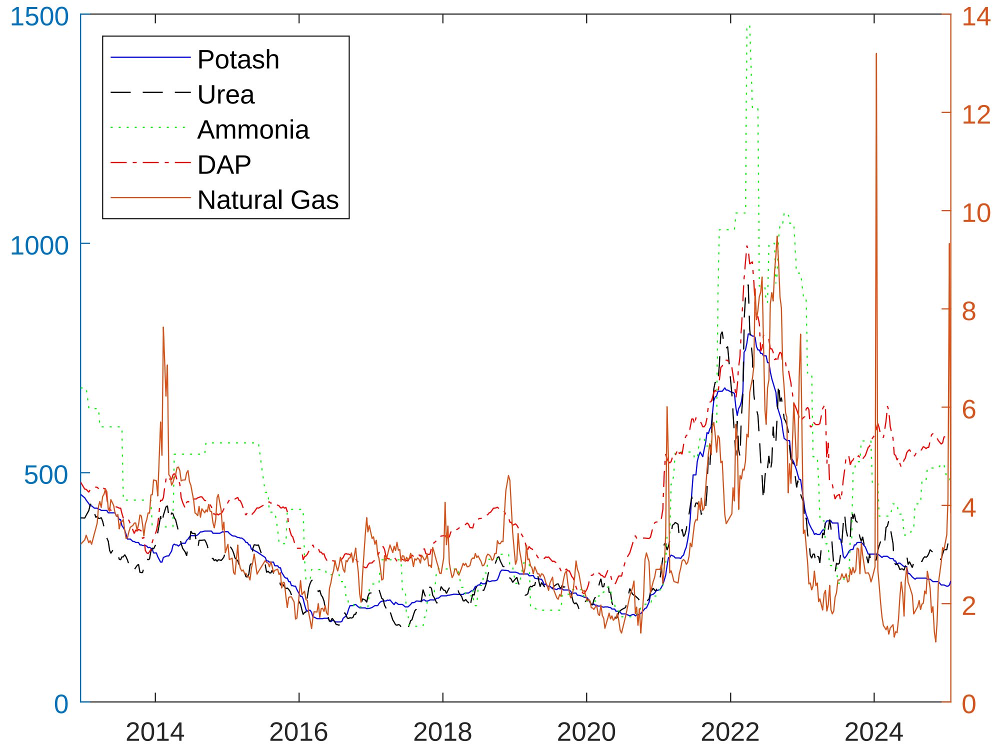
The remainder of the note is organized as follows. In Section 2, we describe the fertilizer price series and returns. In Section 3, we briefly review the methodology used in the early warning system and discuss the adaptation needed for the fertilizer series, proposing an alternative estimation method. Section 4 presents the predictive performance of the existing estimators used in the early warning system and compares it to that of the newly proposed estimator. Section 5 concludes.

2 Fertilizer prices and returns

The weekly fertilizer price data used for the analysis are spot prices obtained from Bloomberg. The specific price series are: Potash US Gulf NOLA (618 observations from December 17, 2012 to January 24, 2025), Urea US Gulf NOLA (granular) (1025 observations from January 3, 2005 to January 24, 2025), Ammonia US Gulf NOLA (621 observations from October 29, 2012 to January 24, 2025), and DAP US Gulf Nola (625 observations from October 29, 2012 to January 24, 2025).

Figure 1 plots the four weekly fertilizer prices, together with daily natural gas (Henry Hub) prices, to compare the dynamics of fertilizer prices relative to energy prices. The left vertical axis measures fertilizer prices (in US dollars per short ton, USD/ST, for potash, urea, and ammonia, and US dollars per metric tonne, USD/MT, for DAP) and the right vertical axis measures natural gas prices (in US dollars per Million British Thermal Units, USD/MMBtu). We restrict the plot to the shortest overlapping period, ensuring continuity across all series. We observe that all five price series exhibit a somewhat similar variation over time, with natural gas prices displaying slightly more frequent ups and downs (given their higher frequency). This analogous behavior is not surprising given that natural gas is an important input for several fertilizers. We also note that potash and urea prices are generally lower while ammonia prices tend to vary less frequently (with the series exhibiting a step function shape). Overall, this preliminary overview supports the application of a common modeling framework for both fertilizer and energy prices.

Figure 1: Weekly price series for potash, urea, ammonia, and DAP together with natural gas



For the analysis below, we work with the price return, which is defined as $y_t = ln(p_t/p_{t-1})$, where p_t is the corresponding price of potash, urea, ammonia and DAP observed at week t. This logarithm transformation is generally applied in empirical finance and is a standard measure for the rate of return in a market, which in this case approximates the weekly percentage change in each fertilizer price. Figures 2-5 depict the weekly price returns (multiplied by 100) for the four fertilizers over the period available for each series (indicated above). We observe notably high fluctuations in price returns for urea during the 2007-2008 food price crisis and across all fertilizer series during the COVID-19 period.

Table 1 provides descriptive and test statistics for the four weekly price return series. The means of all returns are close to zero, while ammonia exhibits the greatest variability, as indicated by its widest range and highest standard deviation. Most series seem to be negatively skewed (except potash) and all returns exhibit a leptokurtic distribution with a sample kurtosis greater than three. Based on the Jarque-Bera test statistics, the null hypothesis of normally distributed returns is strongly rejected in all cases. We typically observe statistically significant sample auto correlations (AC) at lags one and two, and large Ljung-Box statistics for up to 5 and 10 lags for the returns and squared returns, with the exception of ammonia for squared returns. These patterns support the strong dependence of returns and squared returns on lagged returns for most series, empirically motivating the use of an autoregressive model for fertilizer price returns that we discuss below. Lastly, the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests generally confirm the stationarity of all return series.

Figure 2: Weekly price returns for potash

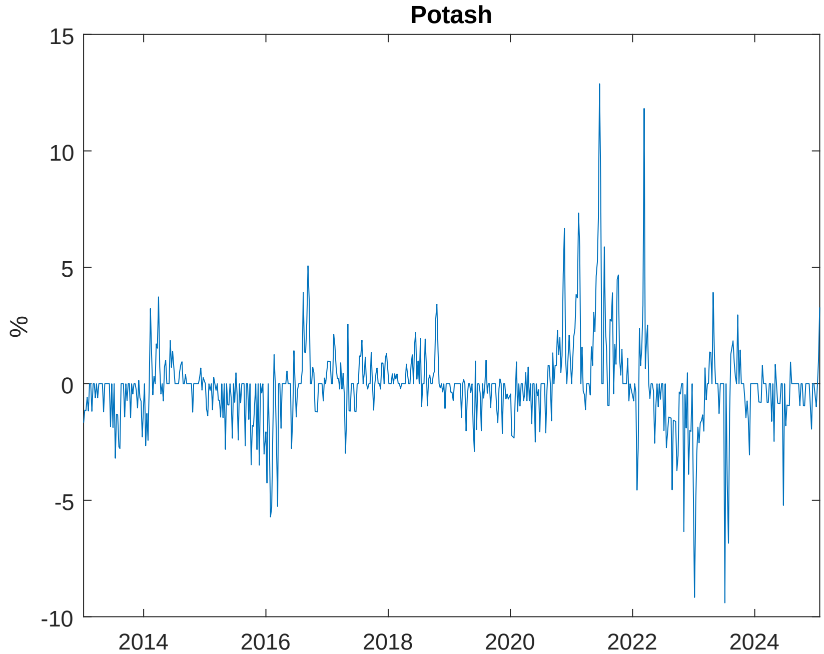


Figure 3: Weekly price returns for urea

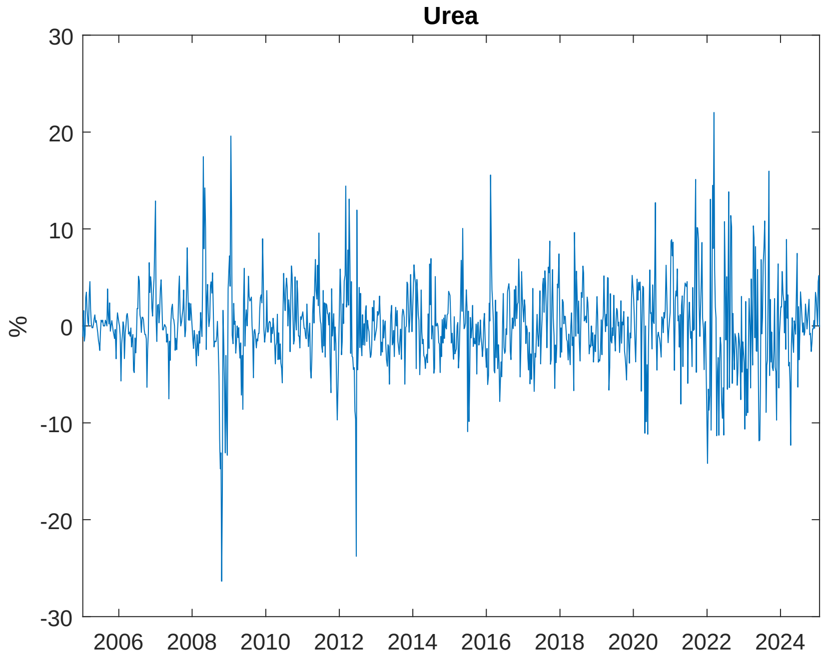


Figure 4: Weekly price returns for ammonia

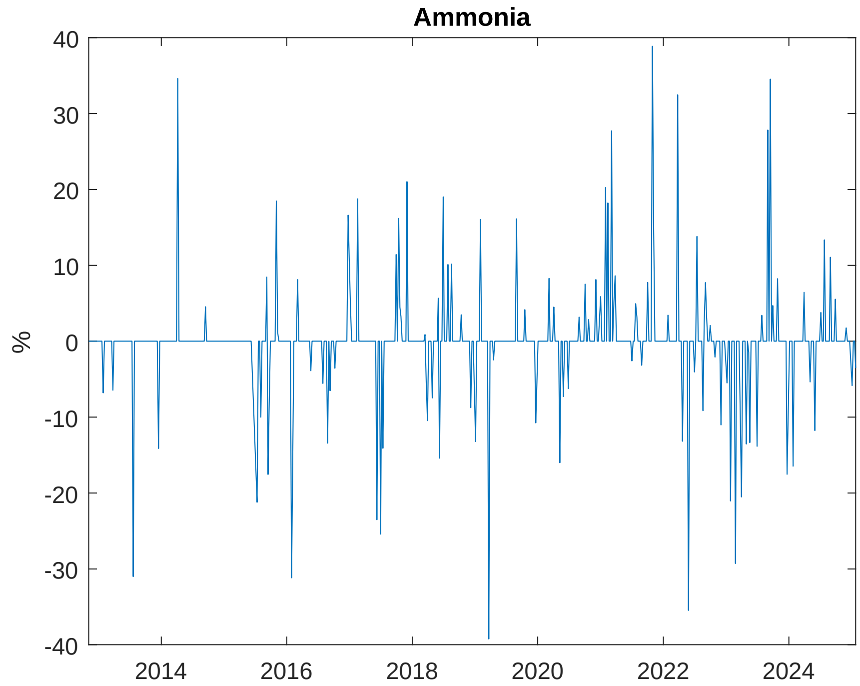


Figure 5: Weekly price returns for DAP

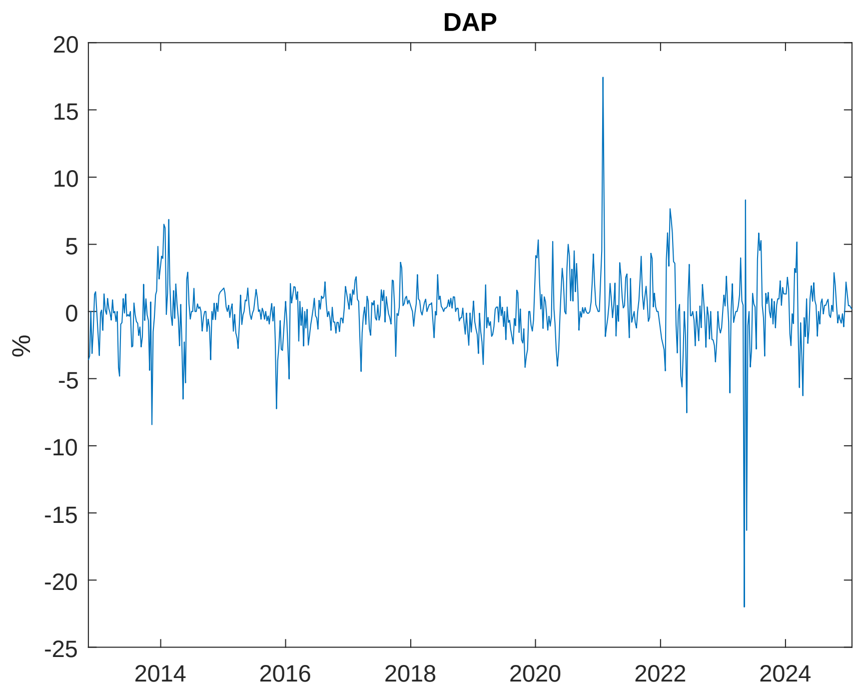


Table 1: Summary Statistics

Statistics	Fertilizer price return			
	Potash	Urea	Ammonia	DAP
Mean	-0.088	0.048	-0.060	0.018
Median	0	0	0	0
Minimum	-9.403	-26.342	-39.237	-22.006
Maximum	12.883	22.015	38.874	17.435
Standard Deviation	1.835	4.383	6.287	2.423
Skewness	0.959	-0.009	-0.017	-0.974
Kurtosis	13.828	7.307	18.081	21.448
Jarque-Bera	3108.9	791.405	5875.1	8946.9
p-value	0.001	0.001	0.001	0.001
Returns correlations				
AC(lag=1)	0.495*	0.373*	0.061	0.289*
AC(lag=2)	0.362*	0.214*	0.087*	0.277*
Ljung-Box(5)	421.399*	234.113*	20.919*	111.479*
Ljung-Box(10)	485.847*	245.109	23.246*	117.817*
Squared returns correlations				
AC(lag=1)	0.328*	0.327*	-0.020	0.177*
AC(lag=2)	0.123*	0.233	0.020	0.301*
Ljung-Box(5)	96.383*	221.531*	0.642	76.926*
Ljung-Box(10)	98.421*	270.182*	8.383	77.364*
Test for stationarity				
ADF(lag=5)	-6.556*	-11.131*	-8.071*	-8.562*
KPSS (lag=5)	0.272*	0.031	0.064	0.0871
# Observations	618	1025	621	625

Note: * Denotes statistical significance at 5% level.

3 Methodology

Consider a fully nonparametric location-scale model defined as

$$r_t = m(r_{t-1}) + h^{1/2}(r_{t-1})\epsilon_t. \quad (1)$$

where r_t is the price return of a given fertilizer (potash, urea, ammonia, and DAP) at week t. Based on the statistical features of the returns described above, we model the conditional mean $m(\cdot)$ and conditional variance $h(\cdot)$ of the price returns as a function of past returns (r_{t-1}), and ϵ_t is an independent and identically distributed (IID) innovation term with a marginal distribution $F_\epsilon(\cdot)$, $E(\epsilon_t) = 0$, and $V(\epsilon_t) = 1$.

The specification in Equation (1) can be considered as a nonparametric generalization of an autoregressive conditional heteroskedasticity (ARCH) model. We could incorporate more explanatory variables in $m(\cdot)$ and $h(\cdot)$, but we refrain from doing so for two reasons. First, fertilizer price data series are weekly based, which results in a much smaller sample size relative to, for example, agricultural and energy commodity prices that are available daily. As $m(\cdot)$ and $h(\cdot)$ are modeled as nonparametric functions, their estimation is subject to the “curse of dimensionality" such that univariate nonparametric modeling is more suitable in this situation. Second, Geng et al. (2021) include exogenous covariates (input, macroeconomic, and financial factors) when modeling $m(\cdot)$ and $h(\cdot)$ following a similar two-step estimation for agricultural commodity price returns. The authors do not find clear evidence regarding the usefulness of including exogenous covariates, particularly for the estimation of the high order quantile, as we do below, for predictability purposes. We thus adopt the location-scale mode as in Equation (1).

Define the α-order conditional value-at-risk, α-CVaR(x), as the α-quantile $q_{r_t|r_{t-1}=x}(\alpha)$ for $F_{r_t|r_{t-1}=x}$, the conditional distribution of r_t given $r_{t-1} = x$. Similarly, define the α-order conditional expected shortfall, α-CES(x), as the conditional expectation of r_t given that r_t exceeds α-CVaR(x). Given the stochastic structure in Equation (1), with $q(\alpha)$ denoting the α-qunatile for $F_\epsilon(\cdot)$, we have

$$\alpha - CVaR(x) \equiv q_{r_t|r_{t-1}=x}(\alpha) = m(x) + h^{\frac{1}{2}}(x)q(\alpha), \quad (2)$$

$$\alpha - CES(x) \equiv E(r_t|r_t > q_{r_t|r_{t-1}=x}(\alpha)) = m(x) + h^{\frac{1}{2}}(x)E(\epsilon_t|\epsilon_t > q(\alpha)). \quad (3)$$

Equations (2) and (3) represent popular measures of market risk in empirical finance. Following Geng et al. (2021), we only consider the α-CVAR(x) measure to save space. α-CVAR(x) is a risk measure, as it gives the value of return r_t that is exceeded with probability $1 - \alpha$, given the one period lagged return r_{t-1}. Certainly, we could consider α-CVAR(x) with either a small α (loss) or large α (gain). As we are mainly interested on abnormally high price behaviors that can affect fertilizer access, we focus on a large and positive α. In this case, the threshold α-CVAR(x) is expected to be exceeded with a small probability $1 - \alpha$. A large and positive return implies a substantial upward change in fertilizer prices from one week to another, which can indeed be detrimental to vulnerable farmers in developing regions.

3.1 Two-step approach

A popular approach to estimate α-CVAR(x) is the two-step estimation proposed by Martins-Filho et al. (2018). First, the conditional mean $m(\cdot)$ and conditional variance $h(\cdot)$ functions are estimated relying on nonparametric local linear estimation. These estimations produce a sequence of standardized residuals. Second, a likelihood-based procedure is applied to estimate $q(\alpha)$. Plugging these back to Equation (2) produces the α-CVaR(x) estimate. We work with the 95%-CVaR(x), calculated for each week using a rolling window containing previous 270 weekly observations. Based on the smallest sample size in our working sample, we use approximately half of the observations for estimation purposes.

To evaluate the performance of estimation in capturing α-CVAR(x) for a specific return, we perform a backtesting during a period of m consecutive weeks. For each of the m weeks (with M denoting the set of time indices for these m weeks), we estimate α-CVAR(r_{t-1}) using the previous 270 returns, and define a violation occurring when $I_t = I(r_t > \alpha - CVAR(r_{t-1})) = 1$, where $I(\cdot)$ is an indicator function. Under the null hypothesis that return dynamics on r_t are correctly specified, $I_t \sim Bernoulli(1-\alpha)$. Consequently, $D = \sum_{t \in M} I_t$ will follow a Binomial $(m, 1-\alpha)$ distribution. We perform an one-sided test with the alternative hypothesis that α-CVAR(x) is not correctly specified with too many violations. Naturally, a two-sided test, with the alternative hypothesis being α-CVAR(x) is not correctly specified with too many or too few violations, can also be used. However, we are interested in identifying periods with excessive price hikes, thus, rejection with the one-sided test can be more informative.

With $\alpha = 0.95$, we report the number of violation weeks (k), the percentage of violations in m weeks (k/m), together with the p-value that $P(D > k)$. If the p-value is greater than 5%, we fail to reject the null hypothesis that the number of violations is consistent with the expectation from the model (i.e., the dynamics is correctly captured), and we characterize this week as belonging to a period of low volatility; if the p-value is between 2.5% and 5%, we mark it as a period of moderate volatility; and if the p-value is below 2.5%, we consider it a period of high or excessive volatility. When comparing the relative predictive performance of different estimators during backtesting, the interest is in identifying weeks that effectively exhibit unusual volatility and use p-values. Alternatively, we can simply assess the proportion of days when the fertilizer price returns exceed the estimated 95%-CVaR from different estimators, and check which estimator leads to a proportion of k/m closer to 5%.

3.2 An alternative approach

In this section, we propose an alternative approach to estimate the high order α quantile $q(\alpha)$ for ϵ. If the distribution of ϵ is assumed to have Pareto right tail, for $x > 0$,

$$P(\epsilon \geq x) = L(x)x^{-a},$$

where $L(x)$ is slowly varying at infinity and a is the tail index. If $x > 0$ and $x_0 > 0$, then

$$\frac{P(\epsilon \geq x)}{P(\epsilon \geq x_0)} = \frac{L(x)}{L(x_0)} (\frac{x}{x_0})^{-a}.$$

Now suppose that $x = q(\alpha)$ and $x_0 = q(\alpha_0)$ for $1 > \alpha > \alpha_0 > 0$ and α_0 close to 1 (to estimate the high-order α quantile). Then, there is

$$\frac{1-\alpha}{1-\alpha_0} = \frac{P(\epsilon \geq q(\alpha))}{P(\epsilon \geq q(\alpha_0))} = \frac{L(q(\alpha))}{L(q(\alpha_0))}(\frac{q(\alpha)}{q(\alpha_0)})^{-a}.$$

Since $L(\cdot)$ is slowly varying at infinity, $q(\alpha)$ and $q(\alpha_0)$ are assumed to be reasonably large, and we have

$$\frac{L(q(\alpha))}{L(q(\alpha_0))} \approx 1.$$

From the above

$$\frac{q(\alpha)}{q(\alpha_0)} = (\frac{1-\alpha_0}{1-\alpha})^{1/a}.$$

So we can estimate

$$q(\alpha) = q(\alpha_0)(\frac{1-\alpha_0}{1-\alpha})^{1/a}.$$

We use the Hill estimator (Hill (1975)) for a defined as

$$\hat{a}(c) = \frac{n(c)}{\sum_{\epsilon_i \geq c} ln(\epsilon_i/c)},$$

where $n(c)$ is the number of ϵ_i greater than c. The challenge lies in choosing c or $n(c)$. A common procedure is to use the Hill plot of $\hat{a}(c)$ against $n(c)$, expecting that the Hill plot will exhibit certain stability for $n(c)$ not too small (small sample size, variability could be large) or not too large (using most data, could suffer from bias). We can then use a value of $n(c)$ in the stability region. However, this approach is not always helpful because the stability region may not reveal itself in the plot, i.e., a Pareto tail does not imply that the tail is exactly like that of a Pareto (Danielsson and De Vries, 1997).

The advantage of a carefully chosen c along the suggestion of Danielsson and De Vries (1997) could also be explored. In this case, we simply use $\hat{q}_{a_0}$ for a simple comparison with the two-step approach, where $\hat{q}_{a_0}$ refers to the threshold to determine exceedance in the two-step approach, and we use it to determine c and the associated $n(c)$. Relying on the local linear estimation of $m(\cdot)$ and $h(\cdot)$, together with $\hat{q}(\alpha)$ based on the Hill estimator, we use Equation (2) to produce an alternative estimator for α-CVaR(x), which we denote below as the Hill-based α-CVaR(x) estimator.

4 Predictive performance and comparison across methods

We now turn to our estimation results. We first present the realized returns and estimated $95\% - CVaR(x)$ based on the two methods described above, the two-step α-CVaR(x) and Hill-based α-CVaR(x) estimator; for completeness, we also report the two-step 95%-CES(x). We drop ammonia from the analysis, as the price for this fertilizer commodity does not exhibit much variation, leading to too many zeros in their modeled returns as shown in Figure 4. We consider a rolling window of 270 observations to perform the estimation of $95\% - CVaR(x)$, such that the time periods shown focus on more recent periods and are shorter than what is presented in Figures 2, 3, and 5. We additionally plot the estimates for the conditional mean (m) and variance (h) of the price returns, as we learn from Table 1 that both depend on the past return. Figures 6-8 correspond to potash, Figures 9-11 to urea, and Figures 12-14 to DAP.

We observe several interesting patterns. First, across the three fertilizer returns, there is a significant degree of nonlinearity in the estimates of the conditional mean (m) and variance (h). While m is increasing in r_t for potash and urea, the effect of r on m is U-shaped in the case of DAP. Second, we find both ups and downs in h estimates, with the effect of r on h resembling an inverted U-shape. This illustrates the importance of allowing a nonparametric specification for both $m(\cdot)$ and $h(\cdot)$ in Equation (1). Third, as expected, the 95%-CVaR(x) estimates sit mostly above the returns, with the 95%-CES(x) estimate being even larger. Yet, when comparing the two-step versus the Hill measure, the two-step 95%-CVaR(x) tends to be smaller than the Hill-based 95%-CVaR(x). This difference is more evident for urea that has a larger sample for comparison than potash and DAP.

We are also interested in assessing which estimation method offers a better predictive performance in terms of identifying periods of abnormal price fluctuations. We accordingly compare the proportion of weeks where price returns effectively exceed the estimated 95%-CVaR(x) following the two-step and Hill-based estimators. The preferred model is the one in which the proportion of such weeks is closer to the 5% target, which is the pre-determined expected percentage of exceedance. Specifically, for m weeks with an estimated 95%-CVaR(x) (using a rolling window containing the preceding 270 weekly observations to estimate the threshold value), we identify the number of weeks k_i where the return exceeds the estimated threshold value based on the $i\text{-}th$ method, $i = 1$ for the two-step method and $i = 2$ for the Hill-based method. If k_1/m is closer to 5%, then method 1 performs better, and the opposite otherwise.[4] We adopt the bias-corrected two-step method in Martins-Filho et al. (2018), which correctly centers the asymptotic distribution to account for the bias present in the estimator based on Extreme Value Theory. This method generally yields more reliable statistical inference than the bias-uncorrected procedure.

[4] As discussed before, we additionally report the one-sided p-value of Binomially distributed D with mean $m * 5\%$ and variance of $m * 5\% * 95\%$. Following this criterion, the preferred method is the one with a larger p-value, which is indicative that the method better captures the return dynamics.

Figure 6: Potash returns, $95\% - CVaR(x)$ estimates

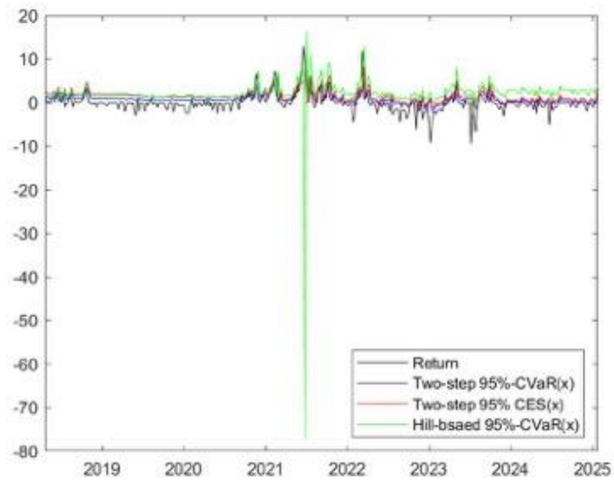


Figure 7: Conditional mean estimates for potash returns

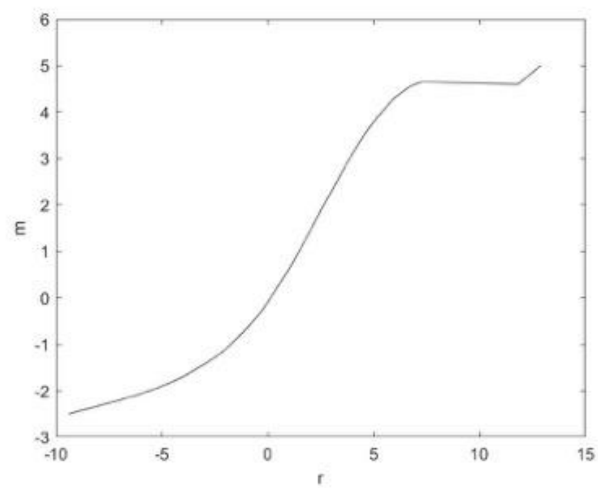


Figure 8: Conditional variance estimates for potash returns

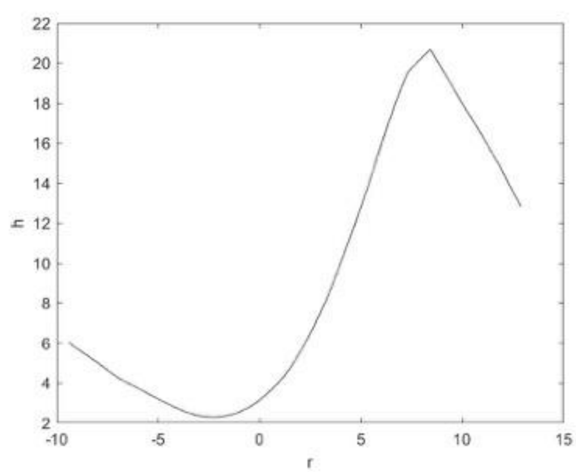


Figure 9: Urea returns, $95\% - CVaR(x)$ estimates

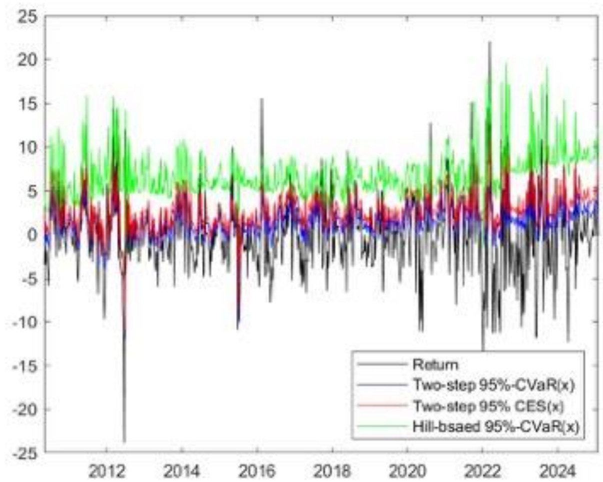


Figure 10: Conditional mean estimates for urea returns

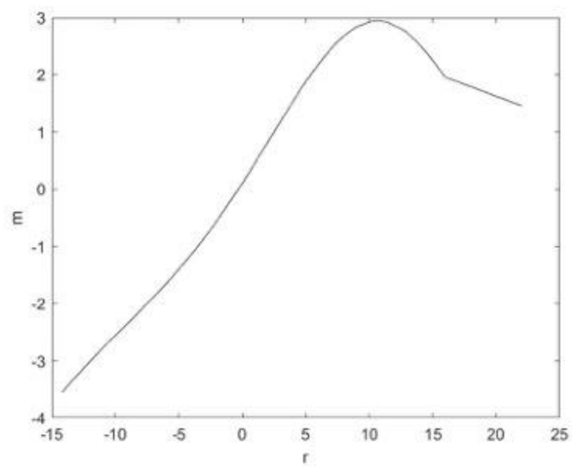


Figure 11: Conditional variance estimates for urea returns

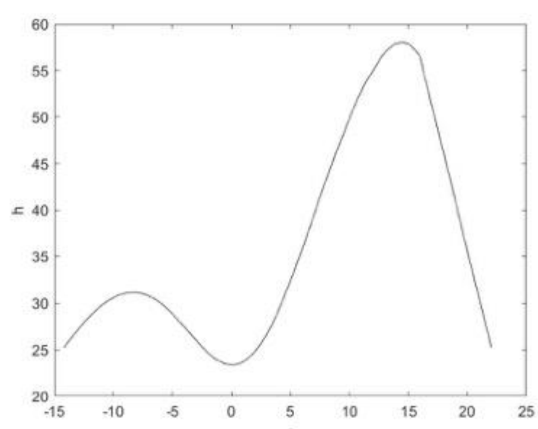


Figure 12: DAP returns, $95\% - CVaR(x)$ estimates

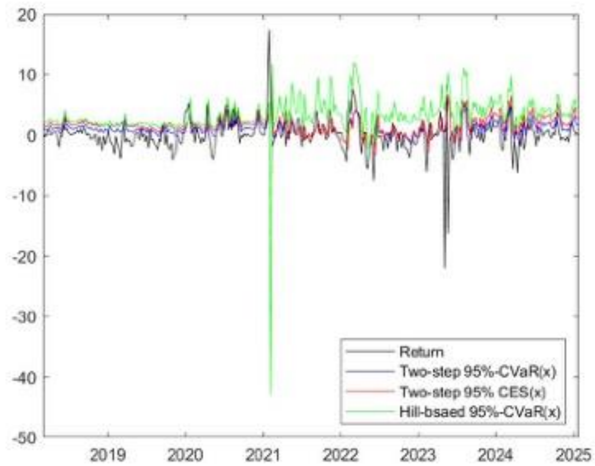


Figure 13: Conditional mean estimates for DAP returns

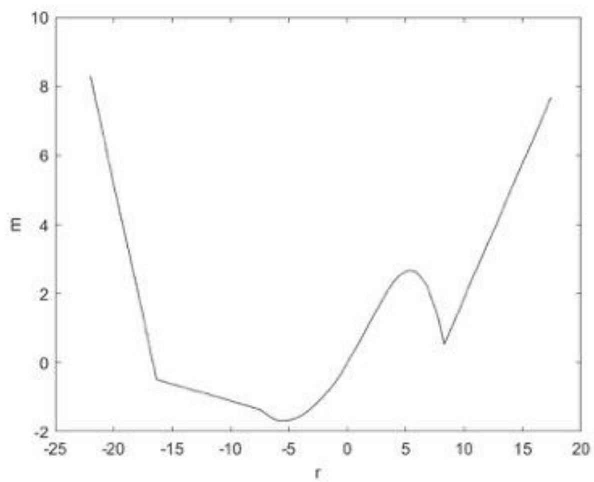


Figure 14: Conditional variance estimates for DAP returns

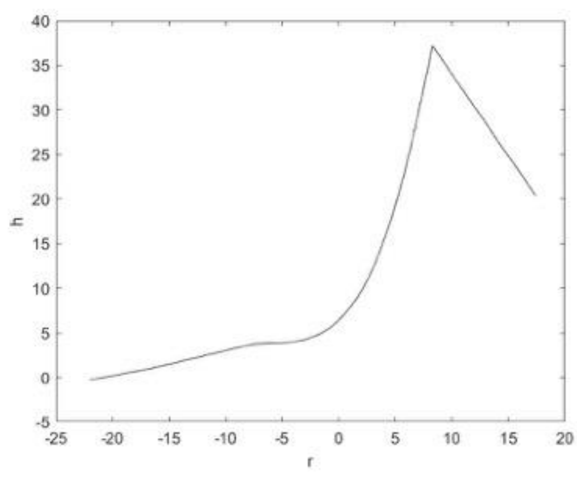


Table 2 presents the out-of-sample performance for the two estimators of 95%-CVaR(x) for the three fertilizer series. In line with the graphical analysis, the two-step method presents a 95%-CVaR(x) that is smaller than the Hill-based method. The former method leads to a larger number of weeks in which the return exceeds the 95%-CVaR(x) compared to the Hill-based method. Furthermore, using 5% as the expected percentage of weeks in which the return should exceed the 95%-CVaR(x), we observe that the Hill-based method exhibits a percentage that is substantially closer to the target of 5%, thus, being the preferred method across all three fertilizer series considered.[5]

Table 2: Out-of-sample performance of the two methods

Commodity	**Two-step method**			**Hill-based method**			**Preferred method**
	$\boldsymbol{k}$	$\boldsymbol{k/m}$	**p-value**	$\boldsymbol{k}$	$\boldsymbol{k/m}$	**p-value**	
Potash ($m = 346$)	79	0.228	0.000	23	0.066	0.080	Hill-based
Urea ($m = 753$)	228	0.303	0.000	33	0.044	0.782	Hill-based
DAP ($m = 353$)	98	0.278	0.000	28	0.079	0.006	Hill-based

Note: m: total # of weeks; k: # of weeks return $> 95\%$-CVaR(x); k/m: % of weeks return $> 95\%$-CVaR(x); p-value for the null hypothesis that the number of violations is consistent with the expectation of the model.

5 Conclusion

This note formally models the behavior of fertilizer prices to identify periods of abnormal price fluctuations that can be detrimental for vulnerable smallholders global wide. The ultimate goal is to incorporate these fertilizer series into the Early Warning System, maintained by IFPRI's Food Security Portal, to facilitate effective and timely responses on input and agricultural markets.

We work with weekly fertilizer price data, resulting in significantly smaller sample sizes compared to those for agricultural and energy prices already monitored in the Early Warning System on a daily basis. We continue to model the price return series following a conditional location-scale approach, but restrict the conditional mean and variance to depend solely on the one-period lag of the return. We similarly implement the bias-corrected two-step estimator, proposed by Martins-Filho et al. (2018), to model the 95%-level conditional Value-at-risk for fertilizer price returns (two-step 95%-CVaR(x)), as in the case of agricultural and energy commodity prices monitored in the Early Warning System, and further propose the Hill-based 95%-CVaR(x) estimator as an alternative approach.

[5] Although not reported, we additionally examined the performance of the bias-uncorrected two-step 95%-CVaR(x) estimate. We observe that the out-of-sample performance of this estimator is not as good as the Hill estimate, but better than the bias-corrected two-step 95%-CVaR(x) estimate for the three fertilizer price returns, which we believe may stem from the reduced sample size of these series.

The estimation results are encouraging regarding the out-of-sample performance for the Hill-based estimator for all three fertilizer price returns analyzed, including potash, urea, and DAP. We conjecture that the much smaller sample size for fertilizer prices (relative to agricultural and energy prices) might be an important factor explaining the results obtained, as the bias-corrected two-step estimator requires estimating second order parameters, which is more appropriate for relatively larger sample sizes. Overall, the Hill-based estimator, being simple to construct and exhibiting a more robust out-of-sample performance, can serve as a promising tool for expanding the Early Warning System to monitor fertilizer price returns, at least for the three series modeled.

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