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Measuring parametric and semiparametric downside risks of selected agricultural commodities

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Abstract: In this paper, we evaluate the downside risk of six major agricultural commodities – corn, wheat, soybeans, soybean meal, soybean oil and oats. For research purposes, we first use an optimal generalised autoregressive conditional heteroscedasticity (GARCH) model to create residuals, which we later use for measuring downside risks via parametric and semiparametric approaches. Modified value-at-risk (mVaR) and modified conditional value-at-risk (mCVaR) provide more accurate downside risk results than do ordinary value-at-risk (VaR) and conditional value-at-risk (CVaR). We report that soybean oil has the lowest mVaR and mCVaR because it has two very favourable features – skewness around zero and low kurtosis. The second-best commodity is soybeans. The worst-performing downside risk results are in wheat and oats, primarily because of their very high kurtosis values. On the basis of the results, we propose to investors and various agents involved with these agricultural assets that they reduce the risk of loss by combining these assets with other financial or commodity assets that have low risk.

Keywords: Cornish-Fisher expansion; generalised autoregressive conditional heteroscedasticity (GARCH) model; grains

Erratic agricultural price fluctuations are not a novelty among academics and various agricultural professionals, and this fact particularly applies to the last two decades. Various factors have contributed to such volatility. For instance, extreme weather events (floods and droughts), the ever-changing price of oil, weeds, insects and plant diseases, followed by considerable demand deviations and the variability of crop yields, directly translate into the significant volatility of agricultural commodity prices (Huang et al. 2012; Armeanu et al. 2013; Santeramo and Lamonaca 2019). Santeramo et al. (2018) asserted that the prices of the most important cereals, such as wheat and corn, dramatically increased during the period from 2003 to 2008, before tumbling down during the global financial crisis, and the food crisis of 2007 and 2008 produced the largest price changes in agricultural commodity history. All of these price oscillations, at the micro-level, make planning difficult for all market participants, such as consumers, farmers and import-export and commodity traders, while at the macro-level, unstable agricultural prices affect both developed and developing countries. Xouridas (2015) and Lehmijoki and Palokangas (2016) contended that developed countries are concerned about fiscal and economic exposures to commodity price shocks, whereas developing countries are even more vulnerable to agricultural price volatility because they receive significant income from their commodity export revenues.

All of the aforementioned factors impose a significant level of financial risk on all participants in agricultural markets. This situation means that proper quantification of the risk could provide a benefit to individual agricultural investors who are keen to make

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better decisions about how to deal with the risk of price volatility and also to countries that then can design adequate policies that can improve the functioning of the agricultural sector.

Accordingly, in this paper, we try to measure the downside risk for the six major agricultural spot commodities – corn, wheat, soybeans, soybean meal, soybean oil and oats. All of the selected commodities have experienced huge price swings in the last 15 years, meaning that they all have an inherently high risk of price changes, which Figure 1 clearly demonstrates. In the process of risk measurement, we do not rely on ordinary variance, which gives equal weight to positive and negative returns and therefore, could produce biased conclusions about the level of risk; instead, we underline a truly important risk for market participants – downside risk. Simply speaking, the downside risk is the lower extreme quantile of a portfolio or asset return distribution, calculated at a particular confidence level. The most usual way of calculating downside risk is a parametric value-at-risk (VaR) method. VaR measures a left-tail risk, and it is used by many researchers for various purposes (e.g. Ji et al. 2018; Nicolae and Maria-Daciana 2019), but, to our knowledge, very few researchers have applied this method to agricultural commodities. For instance, Xouridas (2015) calculated VaR to measure time-varying extreme event risks in 60 agricultural commodity markets. Morgan et al. (2012) analysed weekly quantile-based risk measures applied to corn and soybean production in the United States. Rehman et al. (2018) researched major crops such as coarse-grain rice, wheat, corn, cotton and

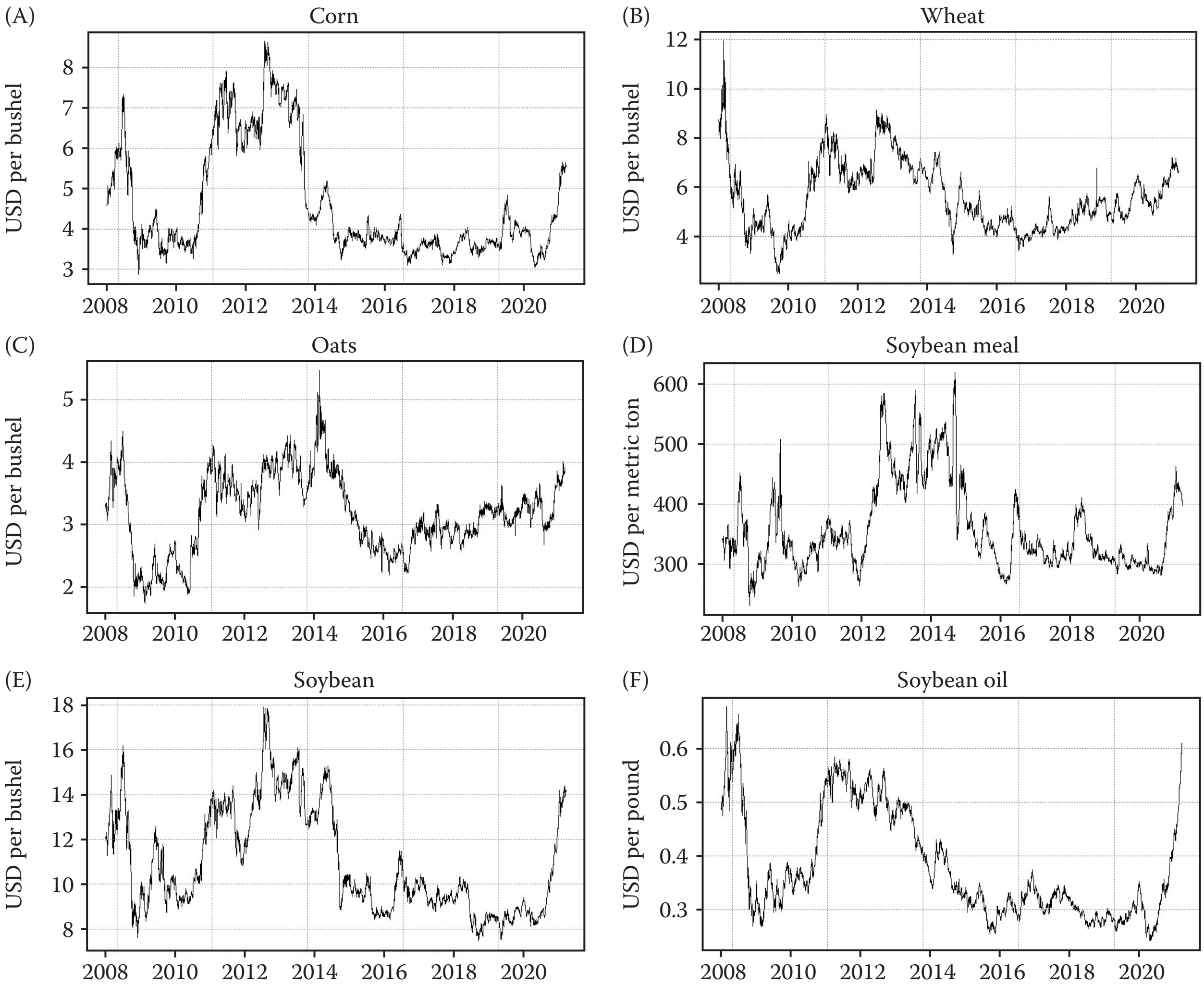

Figure 1. Empirical dynamics of the selected agricultural commodities: (A) corn, (B) wheat, (C) oats, (D) soybean meal, (E) soybean and (F) soybean oil

Source: Authors' own calculations based on data from Stooq (2021)

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soybean in order to determine market risk by using the VaR model.

However, VaR has a number of drawbacks, which have to be addressed if we want to be accurate in the analysis. Therefore, we use several elaborate and sophisticated approaches that improve downside risk measurement. First, it is inappropriate to calculate VaR in empirical time-series because time-series are not independently and identically distributed. Instead, we first fit every agricultural return time-series in the best generalised autoregressive conditional heteroscedasticity (GARCH) model, considering at the same time four different distribution functions – two classical and two innovative fat-tailed distributions. We take this approach because if agricultural time-series are fat tailed and/or skewed, which is a common situation for daily commodity return series, then risk quantification could leave out important information that may be stored in the tails of agricultural time-series. In that regard, we refer to Živkov et al. (2020) and use two traditional distribution functions, normal and student *t*, and two innovative fat-tailed distributions, generalised asymmetric student *t* (GAT) distribution and generalised extreme value (GEV) distribution, in the process of the GARCH estimation.

Second, common VaR does not accurately measure downside risk if the expected loss is greater than or equal to VaR at certain confidence levels. For this reason, besides VaR, we also use a second parametric downside risk measure, known as conditional value-at-risk (CVaR), which provides a more conservative measure of losses relative to that of VaR.

Another issue that needs to be resolved is the fact that parametric risk measures, such as VaR and CVaR, rely on the relatively strict assumption that returns follow a normal distribution, which is not the case for the vast number of financial and commodity time-series. Parametric VaR and CVaR are relatively easy to compute, given that they require only the first two moments, but they cannot recognise features of platykurtic distributions that have negative skewness and heavy tails. In other words, parametric downside risk measures do not account for the third and fourth moments, so these measures eventually may produce misleading results. In this respect, we additionally calculate two semiparametric risk measures based on a Cornish-Fisher expansion: modified VaR (mVaR), introduced by Favre and Galeano (2002), and modified CVaR (mCVaR).

To our knowledge, this is the first paper in which researchers use several sophisticated and complex methodological approaches with the goal of accurately calculating downside risk in agricultural commodities.

MATERIAL AND METHODS

GARCH model. In the measurement of downside risk, the first step is to create residuals free of autocorrelation and heteroscedasticity, which will recognise, in the best possible way, agricultural commodities' empirical features, such as skewness and fat tails. These residuals are used subsequently for the calculation of various VaR metrics. For the creation of white noise residuals, we use the GARCH model in combination with four different distribution functions – normal, student *t*, GAT and GEV. Every agricultural asset is estimated with different GARCH models, and the lowest Akaike information criterion suggests which GARCH model is the best. All GARCH models are estimated with the first autoregressive term in the mean equation, which has enough lag order to deal with an autocorrelation problem successfully in all selected agricultural assets. The variance equation resolves the heteroscedasticity problem. Mathematical specifications of the mean and variance equations in the GARCH process are given in Equations (1) and (2), respectively.

$$y_t = C + \phi y_{t-1} + \varepsilon_t;\ \ \varepsilon_t \sim z_t\sqrt{\sigma_t^2} \tag{1}$$

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

where: C, c – constants in the mean and variance equations; ϕ – autoregressive parameter; y_t – log returns of the particular agricultural commodity; z_t – common white noise; σ_t^2 – conditional variance with the conditions $\alpha \geq 0$ and $\beta \geq 0$; ε_t – error term describes the independent and identically distributed process, whereby we consider four different distributions – normal $\varepsilon \sim N\left(0, \sigma_t^2\right)$, student *t* $\varepsilon \sim St\left(0, \sigma_t^2, \nu\right)$, $\varepsilon \sim GAT\left(0, \sigma_t^2, \tau, \nu_1, \nu_2\right)$ and $\varepsilon \sim GEV\left(0, \sigma_t^2, \nu\right)$; τ and ν – skew and shape parameters, respectively.

We use two unconventional distributions in the GARCH process (GAT and GEV) because we assume that the idiosyncratic properties of the empirical agricultural series are negative skewness and heavy tails. Zhu and Galbraith (2010) introduced GAT, which uses one skewness parameter and two tail parameters. GEV distribution is created to capture extreme tail risk in the probability distribution (McNeil and Frey 2000).

Downside risk measures. As has been said, many investors are eager to know the size of potential negative losses; in that regard, we compute four different downside risk measures, starting with the parametric VaR as a basic measure. VaR gauges a loss that an investor

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might incur in a single day under a certain probability. In practical terms, VaR observes a section or particular quantile and does not go beyond this level, which might be a problem when the actual loss exceeds this level. Parametric VaR is calculated as in Equation (3):

$$VaR_{\alpha} = \hat{\mu} + Z_{\alpha}\hat{\sigma} \tag{3}$$

where: $\hat{\mu}$ and $\hat{\sigma}$ – estimated mean and standard deviation of a particular agricultural asset, respectively, Z_{α} – left quantile of the normal standard distribution.

VaR has a deficiency in that it disregards any loss beyond the VaR level, which might produce erroneous conclusions when VaR is exceeded. Therefore, we also calculate CVaR metrics, which indicate an average expected loss of an asset; CVaR is regarded as a better loss indicator than is VaR. Unlike VaR, which observes a certain section of tail distribution, CVaR considers all losses of tail distribution and calculates an average loss under a certain degree of probability. According to Vo et al. (2019), CVaR is calculated as in Equation (4):

$$CVaR_{\alpha} = -\frac{1}{\alpha}\int_{0}^{\alpha} VaR(x)dx \tag{4}$$

where: $VaR(x)$ – VaR of a particular asset; α – left quantile of the standard normal distribution.

Figure 2 illustrates two downside risk measures.

However, both VaR and CVaR assume the Gaussian distribution of an asset, which is a strong conjecture, particularly when daily financial and commodity data are at stake. In this respect, the downside risk measure might be inaccurate, leading investors to incorrect decisions. This inaccuracy occurs because parametric measures consider only the first two moments of the analysed asset, disregarding the third and fourth moments. To overcome this potentially serious issue, we also calculate the so-called modified or semiparametric VaR and CVaR, which are extensions of traditional parametric downside risk measures. These values are based on a Cornish-Fisher expansion approximation, and they take into account higher moments (i.e. skewness and kurtosis of asset distribution). As a result, they provide more realistic estimates about the downside risk that the investor might incur.

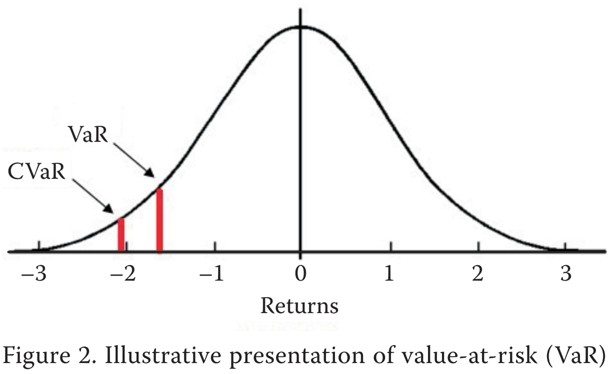

Figure 2. Illustrative presentation of value-at-risk (VaR) and conditional value-at-risk (CVaR)

Source: Authors' illustration

More specifically, skewness indicates the tilt of distribution, whereas kurtosis indicates the presence of heavy tails; this being the case, mVaR (as opposed to conventional parametric VaR) will penalise these unfavourable distribution characteristics and consequently indicate a larger assessment of the loss. However, when the distribution has positive skewness and lower kurtosis, which are favourable characteristics for investors, then mVaR reframes these distribution features, meaning that the calculated mVaR loss will be smaller than that of the traditional VaR. Theoretically speaking, if skewness and kurtosis have Gaussian properties, then mVaR metrics converge to the usual parametric VaR. Accordingly, mVaR is defined as in Equation (5):

$$mVaR_{\alpha} = \hat{\mu} + Z_{CF,\alpha}\hat{\sigma} \tag{5}$$

where: $Z_{CF,\ \alpha}$ – non-normal distribution percentile adjusted for skewness and kurtosis according to the Cornish-Fisher Equation (6):

$$\begin{aligned} Z_{CF,\alpha} = Z_{\alpha} + \frac{1}{6}\left(Z_{\alpha}^{2} - 1\right)S + \\ + \frac{1}{24}\left(Z_{\alpha}^{3} - 3Z_{\alpha}\right)K - \frac{1}{36}\left(2Z_{\alpha}^{3} - 5Z_{\alpha}\right)S^{2} \end{aligned} \tag{6}$$

where: S and K – measures of the skewness and kurtosis of the particular agricultural asset.

Analogously to CVaR, mCVaR is calculated as in Equation (7):

$$mCVaR_{\alpha} = -\frac{1}{\alpha}\int_{0}^{\alpha} mVaR(x)dx \tag{7}$$

Data set and diagnostic tests. We use the daily data of six spot agricultural commodities – corn, wheat, soybeans, soybean meal, soybean oil and oats. Our sample covers the period from January 2008 to February 2021, and all data are collected from the Stooq.com database (Stooq 2021). Our intention is to include the global financial crisis in the sample period because the downside risk results will be more realistic, given that the global

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financial crisis produced higher volatility. As has been said, we calculate the downside risk measures on residuals, not returns, and the residuals are obtained from the optimal GARCH model. Table 1 presents the third and fourth moments of empirical log returns as well as the Ljung-Box test for level and squared log returns.

Table 1. Third, fourth moments and diagnostic tests of the empirical agricultural commodities

	Corn	Wheat	Soybean	Oats	Soybean meal	Soybean oil
Skewness	–0.342	0.122	–0.576	–0.252	–0.206	0.058
Kurtosis	4.831	9.728	5.294	9.945	5.611	2.195
$LB(Q)$	0.001	0.000	0.589	0.026	0.000	0.284
$LB(Q^2)$	0.000	0.000	0.000	0.000	0.000	0.000
DF-GLS	–16.102	–6.325	–8.983	–4.875	–5.812	–14.121

$LB(Q)$ and $LB(Q^2)$ test – P-values of Ljung-Box Q-statistics for level and squared returns for 10 lags; *DF-GLS* – Dickey-Fuller generalised least squares unit root test; 1% and 5% critical values for *DF-GLS* test with 10 lags assuming only constant are –2.566 and –1.941, respectively

Source: Authors' own calculations based on data from Stooq (2021)

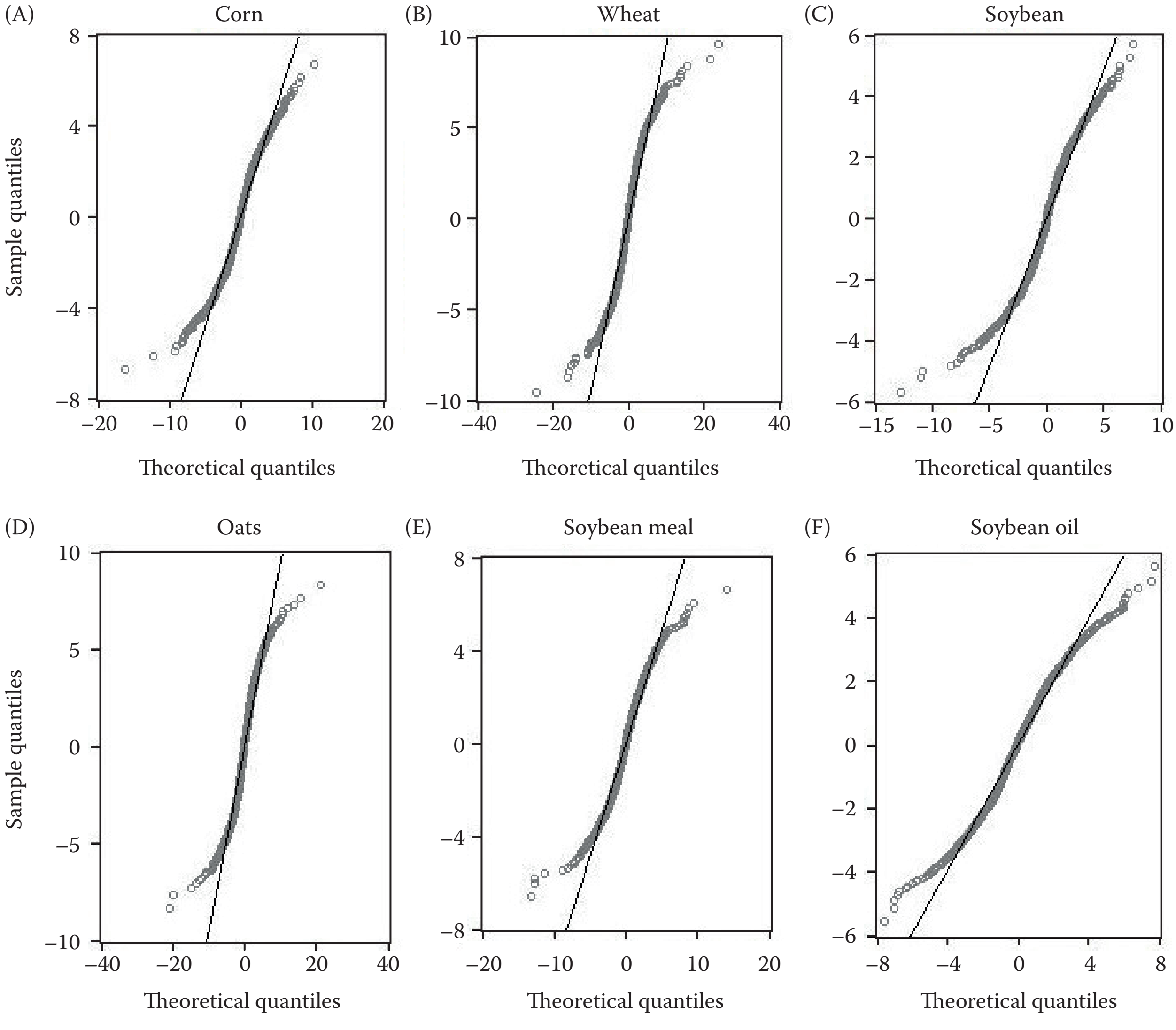

Figure 3. Quantile-to-quantile plots of the selected agricultural commodities: (A) corn, (B) wheat, (C) soybean, (D) oats, (E) soybean meal and (F) soybean oil

Source: Authors' own calculations based on data from Stooq (2021)

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Table 2. Calculated Akaike information criterion (AIC) values for estimated GARCH models

	Corn	Wheat	Soybean	Oats	Soybean meal	Soybean oil
GARCH-*n*	12 850.37	14 925.59	11 622.67	14 482.31	12 539.99	11 674.78
GARCH-*t*	12 575.33	**14 589.93**	11 358.09	13 921.35	12 382.16	11 639.40
GARCH-*gat*	**12 568.34**	14 591.12	**11 342.88**	**13 920.10**	**12 379.34**	**11 635.97**
GARCH-*gev*	13 438.80	15 422.69	12 190.37	15 354.20	12 898.98	11 798.93

GARCH – generalised autoregressive conditional heteroscedasticity; *n*, *t*, *gat*, *gev* – normal, student *t*, generalised asymmetric student *t* and generalised extreme value distribution, respectively; bolded values signal the lowest AIC
Source: Authors' own calculations based on data from Stooq (2021)

As Table 1 shows, four of six asset residuals have negative skewness, and all time-series have excess kurtosis. Also, four of six assets have an autocorrelation problem, and all assets have time-varying volatility. These findings indicate that some form of autoregressive moving average GARCH model could be appropriate to handle these stylised facts. Dickey--Fuller generalised least squares test results suggest that not all time-series have a unit root, which means that they are all suitable for estimation in the GARCH model.

To improve the estimation process, we have to check whether a normal distribution is a good choice in the GARCH model or whether perhaps some other density function is more appropriate. A quantile-quantile plot could provide good information about this issue. According to Figure 3, all empirical returns deviate from a normal distribution (the grey dots are not aligned with the straight line). Also, it is evident that at the beginning and the end of the row, the grey dots are significantly distant from the straight line, which indicates the presence of heavy tails. Table 1 confirms this assertion. Therefore, combining the GARCH model with different heavy-tail distributions is justifiable.

Table 2 contains the Akaike information criterion values calculated for the GARCH model with four different distributions and shows that the innovative GAT function is the best choice in five of six cases. This result means that this function describes the empirical stylised facts of the assets in the best possible way.

RESULTS AND DISCUSSION

GARCH estimates. Table 3 presents the results of the estimated best-fitting GARCH models. All estimated GARCH parameters are highly statistically significant, which indicates the strong presence of an autoregressive conditional heteroscedasticity effect and volatility persistence of the empirical time-series. In addition, Panel B suggests that almost all distribution parameters are highly statistically significant, which confirms a good choice of density functions in GARCH models. In the end, Panel C shows that none of the models has difficulties with serial correlation or heteroscedasticity, which means that none of the results in Table 4 is biased.

Figure 4 presents estimated residuals from the best--fitting GARCH model, which could provide a prelimi-

Table 3. Estimated GARCH parameters for the selected agricultural commodities

	Corn	Wheat	Soybean	Oats	Soybean meal	Soybean oil
Panel A: GARCH parameters						
α	0.070***	0.078***	0.025***	0.094***	0.090***	0.057***
β	0.917***	0.909***	0.932***	0.768***	0.923***	0.955***
Panel B: Distribution parameters						
τ – skew	0.983***	–	0.976***	1.005***	1.051***	1.056***
ν_1 – shape	6.130**	4.719***	10.449	3.056***	4.576***	31.089
ν_1 – shape	1.498***	–	1.359***	1.599***	1.782***	1.652***
Panel C: Diagnostic parameters						
$LB(Q)$	0.241	0.571	0.763	0.082	0.071	0.318
$LB(Q^2)$	0.281	0.440	0.356	0.127	0.624	0.250

***, **Statistical significance at the 1% and 5% level, respectively; GARCH – generalised autoregressive conditional heteroscedasticity; $LB(Q)$ and $LB(Q^2)$ test – P-values of Ljung-Box Q-statistics for level and squared residuals for 10 lags
Source: Authors' own calculations based on data from Stooq (2021)

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Table 4. Results of parametric value-at-risk (VaR) and conditional value-at-risk (CVaR)

	Percentage (%)	Parametric downside risk measures					
		Corn	Wheat	Soybean	Oats	Soybean meal	Soybean oil
VaR	96.0	–3.300	–4.614	–2.826	–4.040	–3.085	–2.591
	97.0	–3.542	–4.959	–3.032	–4.340	–3.323	–2.793
	98.0	–3.864	–5.416	–3.305	–4.740	–3.639	–3.060
	99.0	–4.370	–6.138	–3.736	–5.370	–4.138	–3.482
	99.5	–4.834	–6.798	–4.130	–5.946	–4.594	–3.867
CVaR	96.0	–4.051	–5.683	–3.464	–4.972	–3.823	–3.216
	97.0	–4.262	–5.983	–3.644	–5.235	–4.031	–3.392
	98.0	–4.546	–6.388	–3.885	–5.588	–4.311	–3.628
	99.0	–5.000	–7.034	–4.271	–6.152	–4.757	–4.006
	99.5	–5.421	–7.634	–4.630	–6.676	–5.172	–4.356

Source: Authors' own calculations based on data from Stooq (2021)

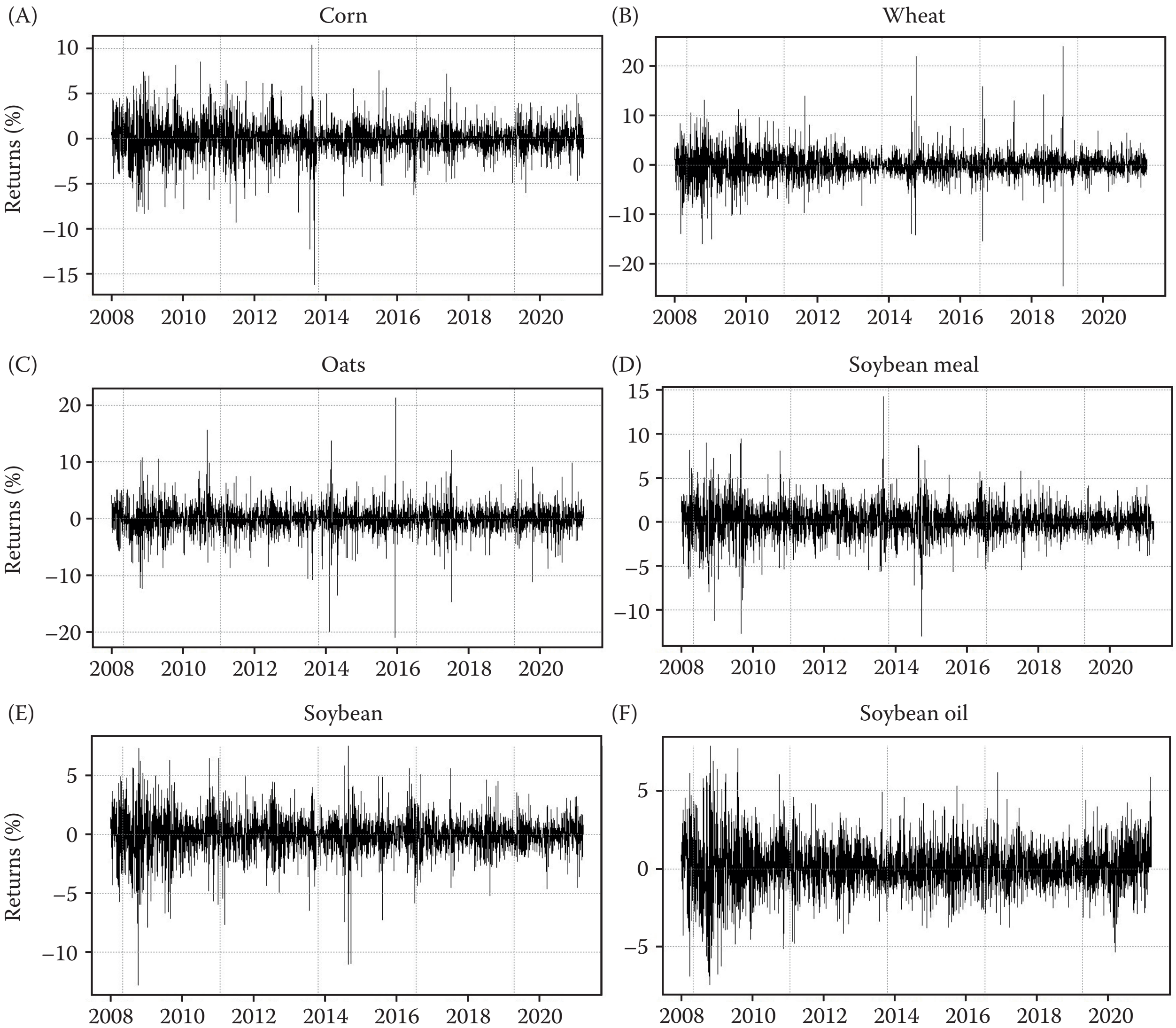

Figure 4. Estimated residuals of the selected agricultural commodities: : (A) corn, (B) wheat, (C) oats, (D) soybean meal, (E) soybean and (F) soybean oil

Source: Authors' own calculations based on data from Stooq (2021)

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nary clue as to which agricultural commodities are most prone to the largest downside risk. According to Figure 4, wheat and oats have the most conspicuous outliers, which is a clear indication that these two assets are the most affected by a large downside risk. However, visual inspection tells us nothing reliable about what the actual size of the downside risk is, nor does it tell us which agricultural commodity has the best (worst) downside risk performances. The next two subsections present these results and remove any doubt.

Parametric downside risk measures of agricultural commodities. This subsection presents the downside risk results of the selected agricultural commodities, calculated via parametric VaR and CVaR. Table 4 contains these results, and Figure 5 illustrates the findings. Having an insight about the actual size of the downside risk, we can compare the results among all the assets and determine which asset bears the highest (lowest) risk of losses. We calculated VaR and CVaR under five different probability levels, ranging from 96% to 99.5%. We did not use these metrics under lower probability because of the assertion of Cavenaile and Lejeune (2012). These authors researched the adequacy of mVaR and contended that mVaR can be used consistently only over a limited interval of confidence levels. They explained that mVaR should never be used under a 95.84% confidence level and that the use of higher confidence levels is limited by the value of skewness. If these restrictions are ignored, then mVaR will yield erroneous results. These rules are not relevant for an ordinary VaR, but we wanted to compare the results between VaR and mVaR, so we also restricted the VaR calculation to the aforementioned lower confidence level.

The parametric VaR indicates the minimum loss that an investor might sustain under a certain probability level. VaR may underestimate potential losses because it does not take into account returns worse than the given VaR level. This potential underestimation is why we also considered CVaR a better approximation of downside risk. CVaR is a stricter risk measure than is VaR, and it indicates what the worst average loss will be under a certain degree of probability.

According to Table 4, wheat has the highest downside risk, followed by oats, taking into account all probability levels. In particular, under a probability of 96%, there is a 4% chance that an investor in wheat will lose 4.61% or more in value in a single day. For oats, the percentage of loss under a 96% probability is 4.04%. These outcomes have been anticipated, as shown in Figure 4, but Figure 4 cannot show the actual size of the loss.

Soybean oil had the best-performing results, followed by soybeans, across all probability levels. Our results diverge from the findings of Morgan et al. (2012), who reported that soybeans have higher VaR and CVaR risks than does corn, but they researched agricultural futures, which might be the reason for the discrepancy. In contradistinction, our results coincide with those of Xouridas (2015), who investigated the level of kurtosis for 60 agricultural commodities and reported that wheat has the highest fourth moment when compared with corn, soybean meal and soybean oil.

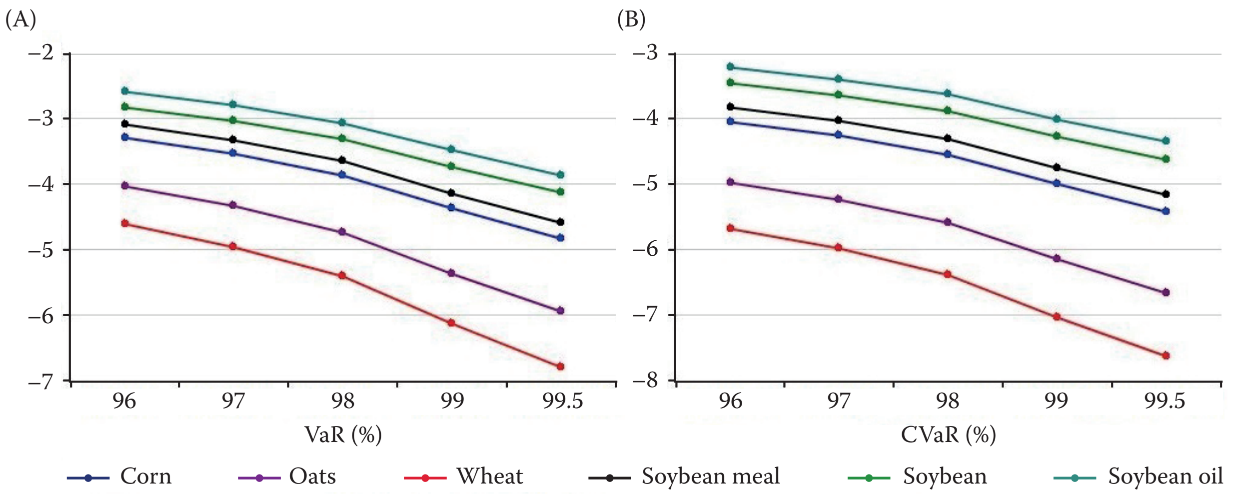

Figure 5. Illustrations of calculated (A) value-at-risk (VaR) and (B) conditional value-at-risk (CVaR)

y-axis in the left plot denotes the minimum loss that an investor might sustain under a certain probability level; *y*-axis in the right plot indicates the worst average loss under a certain degree of probability

Source: Authors' own calculations based on data from Stooq (2021)

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According to Table 4, all CVaR measures are higher than their VaR counterparts, which is expected because CVaR measures the worst average loss. Figure 5 shows that all assets are aligned one under another, without overlapping, and that wheat is far below all other agricultural assets.

Semiparametric downside risk measures of agricultural commodities. The parametric downside risk measures provide reliable results if the analysed asset or portfolio has zero skewness and zero kurtosis. If this is not the case, then parametric risk metrics underestimate the risk values (Favre and Galeano 2002): on these occasions, semiparametric risk measures (mVaR and mCVaR) produce better risk estimates. In other words, modified metrics improve their parametric counterparts by rewarding low kurtosis and positive skewness and penalising high kurtosis and negative skewness, which means that mVaR could be lower than ordinary VaR if the analysed time-series has favourable third and fourth moments. To be sure that the calculated semiparametric risk assessments are accurate, we have to put them in limited confidence intervals.

Table 5. Minimum skewness for modified value-at-risk (mVaR) consistency

	Minimum skewness under certain degree of probability				
Confidence level (%)	96.0	97.5	99.0	99.5	99.9
Minimum skewness	−3.3	−1.62	−0.98	−0.79	−0.59

Source: Cavenaile and Lejeune (2012)

According to Cavenaile and Lejeune (2012), mVaR is consistent only under specific confidence bands (i.e. between a lower level of 95.84% and a higher level that is determined by skewness). Table 5 provides the minimum skewness levels that restrict the upper confidence levels in the mVaR calculation.

On the basis of the information in Table 1, we can make a preliminary estimate as to whether ordinary VaR and CVaR are biased and whether mVaR can produce better downside risk estimates. Table 1 shows very high kurtosis in five of six cases and negative skewness in four of six cases. This finding means that mVaR and mCVaR probably have a higher risk than do basic VaR and CVaR, and Table 6 reveals how much higher. Figure 6 illustrates the results in Table 6.

Under 96% probability, the best-performing soybean oil has lower mVaR than VaR: the mVaR of soybean oil is −2.576, and the VaR is −2.591. Although soybean oil has higher kurtosis than a Gaussian, it has positive skewness that offsets the higher kurtosis and results in lower mVaR. This is the only case in which mVaR is lower than VaR at a particular probability level because all other assets have very high kurtosis and in most cases, pronounced negative skewness. Unlike in Figure 5, Figure 6 shows some overlapping. For instance, corn has higher VaR and CVaR than soybean meal, but for mVaR and mCVaR, soybean meal has slightly higher values than corn. The reason is probably that soybean meal has significantly higher kurtosis than corn does. This higher kurtosis lowers the mVaR and mCVaR more for soybean meal than for corn, which results in soybean meal slightly exceeding corn in negative values. In addition, although wheat still has

Table 6. Results of modified value-at-risk (mVaR) and modified conditional value-at-risk (mCVaR)

	Percentage (%)	Semiparametric downside risk measures					
		Corn	Wheat	Soybean	Oats	Soybean meal	Soybean oil
mVaR	96.0	−3.549	−4.623	−3.150	−4.341	−3.259	−2.576
	97.0	−4.166	−5.901	−3.712	−5.538	−3.906	−2.897
	98.0	−5.098	−7.917	−4.563	−7.418	−4.895	−3.365
	99.0	−6.854	−11.901	−6.164	−11.114	−6.784	−4.207
	99.5	−8.805	−16.510	−7.940	−15.369	−8.904	−5.103
mCVaR	96.0	−6.048	−10.237	−5.426	−9.552	−5.938	−3.787
	97.0	−6.784	−11.909	−6.097	−11.102	−6.729	−4.139
	98.0	−7.879	−14.453	−7.094	−13.455	−7.914	−4.652
	99.0	−9.898	−19.280	−8.931	−17.904	−10.117	−5.571
	99.5	−12.093	−24.668	−10.925	−22.854	−12.529	−6.543

Source: Authors' own calculations based on data from Stooq (2021)

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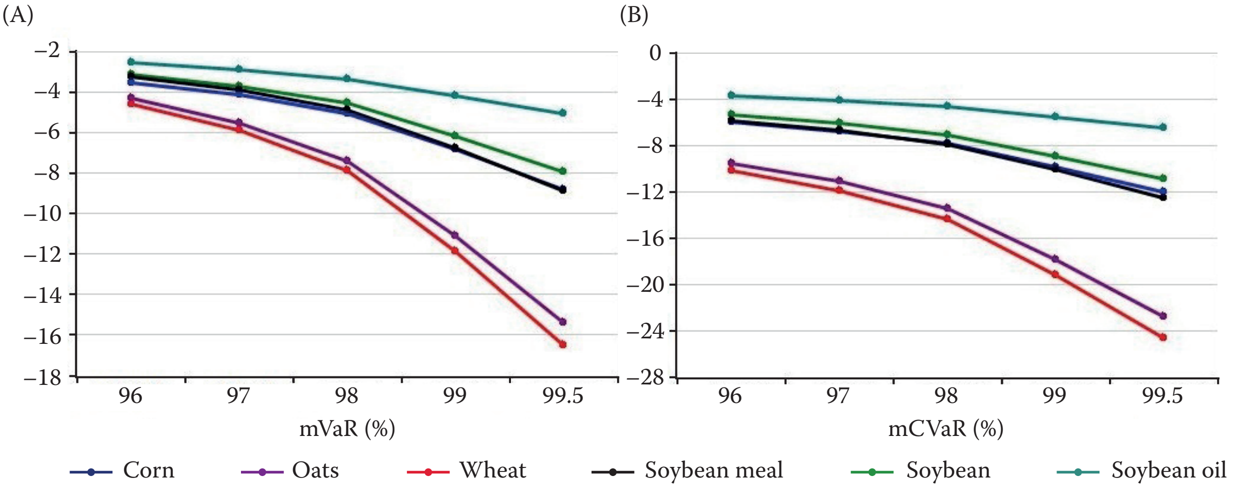

Figure 6. Illustrations of modified value-at-risk (mVaR) and modified conditional value-at-risk (mCVaR)

y-axis in the left plot denotes the minimum loss that an investor might sustain under a certain probability level; *y*-axis in the right plot indicates the worst average loss under a certain degree of probability
Source: Authors' own calculations based on data from Stooq (2021)

the worst performance, the distance between wheat and oats shrinks markedly, as Figure 6 shows. The reason is the same as in the case of soybean meal and corn. In other words, oats have a high negative skewness, which mVaR penalises, whereas wheat has positive skewness, which mVaR rewards. As a consequence, these two agricultural assets almost equalise in mVaR and mCVaR.

CONCLUSION

In this paper, we gauged the downside risk for six spot agricultural commodities, applying several sophisticated techniques in the research process. First, we estimated residuals with the optimal GARCH model, and then we used these residuals to calculate parametric and semiparametric downside risk measures.

mVaR and mCVaR provided more accurate results than did ordinary VaR and CVaR, so it is relevant to comment only on the former findings. We reported that soybean oil had the lowest mVaR and mCVaR because it has two very favourable features – skewness around zero and low kurtosis. The second-best commodity was soybeans. The worst-performing downside risk results were for wheat and oats, primarily because of their very high kurtosis values. Our results agreed very well with those of Fernández-Avilés et al. (2020), who analysed extreme downside risk for 16 commodities and found that wheat had the highest extreme risk when compared with corn and soybeans. On the basis of the results, all agricultural commodities have some level of risk. This finding means that investors who are dealing with the selected assets, particularly wheat and oats, need to reduce the risk of loss with these commodities by combining them with some low-risk financial or commodity assets. For example, Živkov et al. (2021) combined corn with precious metals in a two-asset portfolio and significantly reduced the downside risk of corn.

A logical extension of our research could be a downside risk analysis in a multifrequency framework, which could provide insight into how the level of extreme risk differs when various time horizons are observed. Also, researchers in future studies could investigate how downside risk spills over from one agricultural market to another.

REFERENCES

Armeanu D., Istudor N., Dinica M.C. (2013): The optimal hedging ratio for agricultural market. Economic Computation and Economic Cybernetics Studies and Research, 47: 37–52.

Cavenaile L., Lejeune T. (2012): A note on the use of the modified value-at-risk. Journal of Alternative Investments, 14: 79–83.

Favre L., Galeano J.A. (2002): Mean-modified value-at-risk optimization with hedge funds. Journal of Alternative Investments, 5: 21–25.

Fernández-Avilés G., Montero J-M., Sanchis-Marco L. (2020): Extreme downside risk co-movement in commodity markets during distress periods: A multidimensional scaling approach. European Journal of Finance, 26: 1207–1237.

Huang W., Huang Z., Matei M., Wang T. (2012): Price volatility forecast for agricultural commodity futures: The role of high frequency data. Romanian Journal of Economic Forecasting, 15: 83–10.

https://doi.org/10.17221/148/2021-AGRICECON

Ji Q., Bouri E., Roubaud D., Shahzad S.J.H. (2018): Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. Energy Economics, 75: 14–27.

Lehmijoki U., Palokangas T. (2016): Land reforms and population growth. Portuguese Economic Journal, 15: 1–15.

McNeil A., Frey R. (2000): Estimation of tail-related risk measures for heteroscedastic financial time series: An extreme value approach. Journal of Empirical Finance, 7: 271–300.

Morgan W., Cotter J., Dowd K. (2012): Extreme measures of agricultural financial risk. Journal of Agricultural Economics, 63: 65–82.

Nicolae B., Maria-Daciana R.(C). (2019): Technical analysis in estimating currency risk portfolios: Case study: Commercial banks in Romania. Economic Research – Ekonomska Istraživanja, 32: 622–634.

Rehman A., Jian W., Khan N., Saqib R. (2018): Major crops market risk based on value at risk model in P.R. China. Sarhad Journal of Agriculture, 34: 435–442.

Santeramo F.G., Lamonaca E., Contò F., Nardone G., Stasi A. (2018): Drivers of grain price volatility: A cursory critical review. Agricultural Economics – Zemědělská Ekonomika, 64: 347–356.

Santeramo F.G., Lamonaca E. (2019): On the drivers of global grain price volatility: An empirical investigation. Agricultural Economics – Zemědělská Ekonomika, 65: 31–42.

Stooq (2021): Stooq.com Database. [Dataset]. Available at https://stooq.com/q/d/?s=c.c (accessed Mar, 2021).

Vo D.H., Pham T.N., Pham T.T.V., Truong L.M., Nguyen T.C. (2019): Risk, return and portfolio optimization for various industries in the ASEAN region. Borsa Istanbul Review, 19: 132–138.

Xouridas S. (2015): Agricultural financial risks resulting from extreme events. Journal of Agricultural Economics, 66: 192–220.

Zhu D.M., Galbraith J.W. (2010): A generalized asymmetric student-*t* distribution with application to financial econometrics. Journal of Econometrics, 157: 297–305.

Živkov D., Gajić-Glamočlija M., Kovačević J., Lončar S. (2020): Inflation uncertainty and output growth – Evidence from the Asia-Pacific countries based on the multiscale Bayesian quantile inference. Finance a Úvěr – Czech Journal of Economics and Finance, 70: 461–486.

Živkov D., Balaban P., Kuzman B. (2021): How to combine precious metals with corn in a risk-minimizing two-asset portfolio? Agricultural Economics – Zemědělská Ekonomika, 67: 60–69.

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