https://doi.org/10.17221/371/2022-AGRICECON

How to reduce the extreme risk of losses in corn and soybean markets? Construction of a portfolio with European stock indices

Dejan Živkov, Biljana Stankov, Nataša Papić-Blagojević, Jelena Damnjanović, Željko Račić*

Department of Economics, Novi Sad School of Business, University of Novi Sad, Novi Sad, Serbia

**Corresponding author: dejanzivkov@gmail.com*

Citation: Živkov D., Stankov B., Papić-Blagojević N., Damnjanović J., Račić Ž. (2023): How to reduce the extreme risk of losses in corn and soybean markets? Construction of a portfolio with European stock indices. Agric. Econ. – Czech., 69: 109–118.

Abstract: Because of the COVID-19 pandemic and the war in Ukraine, agricultural commodities had significant price increases, which inevitably implies high risk. In this article, we try to mitigate the extreme risk of corn and soybeans by constructing multivariate portfolios with developed and emerging European stock indices. We measured extreme risk via conditional value at risk. To address different goals that investors might prefer, we produced portfolios with the lowest risk and highest return-to-risk ratio. According to the results, corn and soybeans had relatively high portfolio shares. However, they are the riskiest assets because they have a very low pairwise correlation with the stock indices. Portfolios with emerging European indices had better risk-reducing results, considering both agricultural commodities because these indices are less risky than developed indices. In particular, the risk reductions of corn were 38% and 50% in the portfolios with developed and emerging stock indices, respectively, whereas, for soybeans, the results were 28% and 41%, respectively. In optimal portfolios, emerging European stock indices had the upper hand in most cases.

Keywords: agricultural commodities; portfolio optimisation; risk-minimising optimal portfolios

The production of agricultural commodities depends on various factors—natural, socioeconomic and geopolitical – which makes these markets very susceptible to global turbulence (Moncarz and Barone 2020; Palanska 2020; Chenarides et al. 2021). Recent years have been particularly stressful for the global economy because of the COVID-19 pandemic and the Russian invasion of Ukraine, which significantly increased agricultural commodities' volatility; corn and soybeans are no exception. In particular, the unexpected effects of the pandemic and measures imposed against the pandemic have overwhelmed all markets around the globe, causing supply chain disruptions and high transportation costs, which have contributed to the increase in agricultural prices (Minondo 2021). However, the pandemic has not yet ended, and the world has been struck by another major crisis – the war in Ukraine. This crisis has imposed a different pressure on agricultural markets than the pandemic, but the effect is equal to or even more intensive. First, Ukraine has very rich soil, making it the fourth-world producer and exporter of corn (Saâdaoui et al. 2022). However, agricultural land and infrastructure devastation have put Ukrainian corn production and export at risk. In addition,

Supported by the Erasmus+ Jean Monnet project The European Union Trade and Investment Module (Project No. 101085405 – EU TRaIN), funded and supported by the Erasmus+ programme of the European Union.

https://doi.org/10.17221/371/2022-AGRICECON

as a consequence of Western sanctions on Russia, energy prices have surged, driving fertiliser and shipping costs higher, which inevitably spills over into higher agricultural prices. According to the FAO (2022), global food prices have increased by 65% since the start of the pandemic and additionally by 12% since the beginning of the Russian invasion of Ukraine. All of these factors have caused much instability in the agricultural markets, which could result in non-optimal production and investment and hedging decisions if neglected, as Wu et al. (2011) have asserted.

According to these facts, in this article, we tried to reduce the extreme risk of corn and soybeans by combining each of these commodities separately with European stock indices in a five-asset portfolio. We chose corn and soybean commodities because they are among the most significant agricultural markets, and corn and soybeans are complementary in many ways (Alexakis et al. 2017). Figure 1 indicates that the price dynamics of these two agricultural products are very aligned, which confirms the complementary nature of corn and soybeans. Also, it is evident that both commodities had significant price increases in 2021 because of the pandemic, and the prices peaked in 2022. All of these adverse developments caused many daily oscillations in these markets (Figure 1), which produced massive risk for all agents working with corn and soybeans.

Generally speaking, hedging is a strategy for reducing the risk of adverse price movements and can be achieved by taking an offsetting position in an asset or investment that reduces the price risk of an existing position. Another approach, which we use in this article, involves constructing a portfolio in which risk reduction can be realised through diversification. In the process of portfolio construction, we considered the stock indices of the largest economies in the European Union as auxiliary assets. In particular, we chose four Western European countries (WECs) – Germany, France, Italy and Spain – and four Central and Eastern European countries (CEECs) – Poland, Czech Republic, Hungary and Romania. We intentionally considered the two intrinsically different groups of indices to inspect their hedging performances. In other words, developed stock markets are more integrated and have higher trading volumes, increasing volatility, whereas emerging European stock markets are less integrated and have lower trading volumes. This difference is important because these two factors are crucial in the portfolio optimisation procedure in determining the share of a particular asset in a portfolio.

To target extreme risk in portfolios, we observed the downside risk. We chose this approach because variance equalises positive and negative returns, which biases the measure of risk. However, downside risk in-

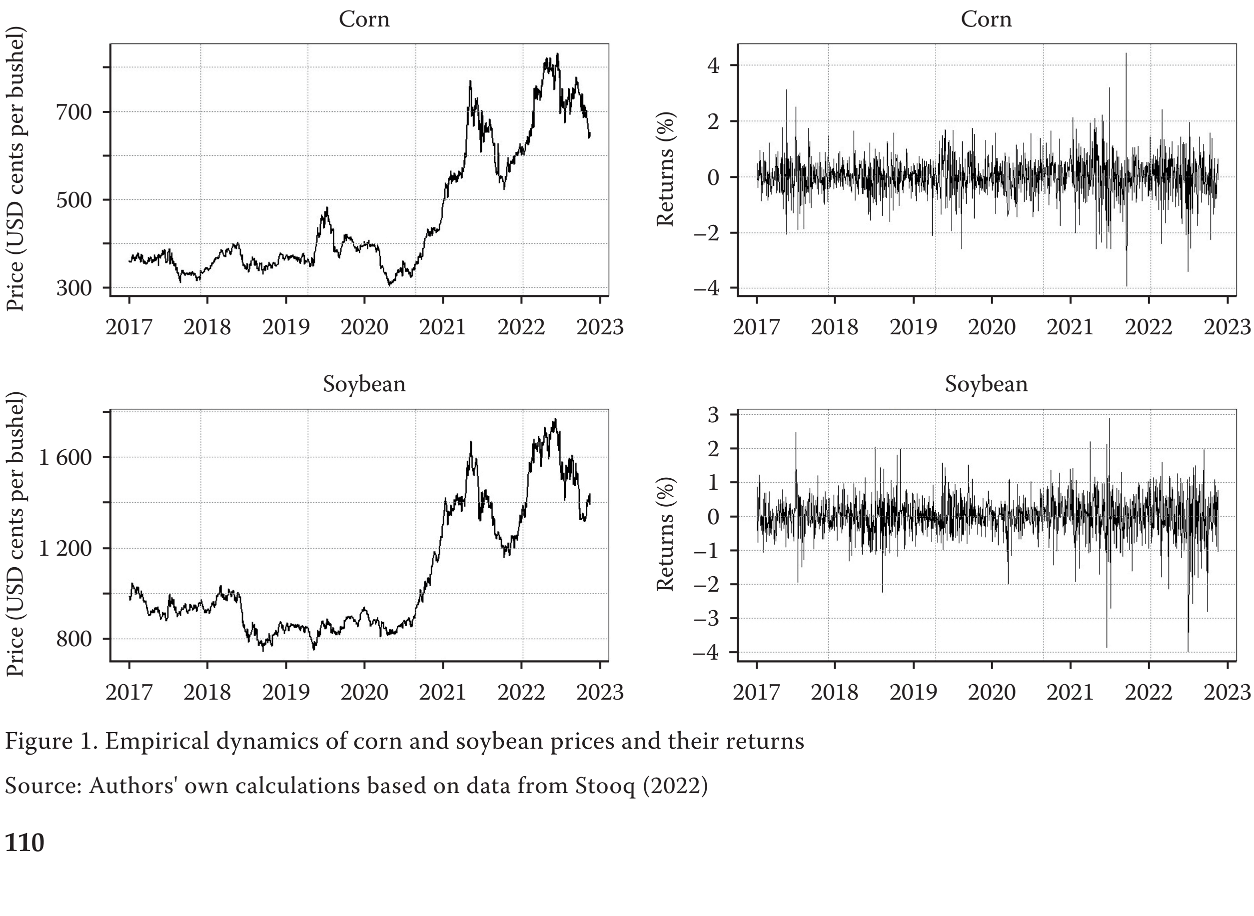

Figure 1. Empirical dynamics of corn and soybean prices and their returns

Source: Authors' own calculations based on data from Stooq (2022)

https://doi.org/10.17221/371/2022-AGRICECON

dicates only negative returns, which is more important for investors because downside risk indicates potential losses that might occur. In this regard, parametric value at risk (VaR) is a standard measure of downside risk (Altun et al. 2017; Zhu and Feng 2017), and it measures the maximum loss that a portfolio might endure, taking into account a specified timeframe with a certain probability level. However, VaR is not an ideal risk measure because it has several undesirable theoretical properties, such as the lack of subadditivity and non-convexity, which can create multiple local optima and unstable VaR rankings (Li et al. 2012). However, an even more unfavourable feature of VaR is the inability to measure the losses beyond the threshold amount of VaR (Sajjad et al. 2008), which could result in misleading investment decisions. This very serious issue of VaR was addressed by Rockafellar and Uryasev (2002), who proposed parametric conditional VaR (CVaR), which controls the magnitude of losses beyond VaR. We wanted to target the extreme risk of losses, so we optimised portfolios under the 99% probability level. In a CVaR portfolio, this level is interpreted as an average loss of the worst 1% of returns, and this risk is placed at the left tail of the distribution. Finding an optimal portfolio with minimum CVaR is a very complex task, and the authors of very few articles have used this methodology (Vo et al. 2019; Luan et al. 2022), and none of the authors of these articles examined CVaR portfolio optimisation with corn and soybeans, which is where we found the motivation for this research.

To address the fact that various market participants have different investment objectives, we designed two types of portfolios. The first is the minimum CVaR portfolio (MCVaRP), and the other is a portfolio with the best return-to-CVaR ratio. In constructing the latter portfolio, we referred to Martin et al. (2003) and optimised the portfolio with the stable tail-adjusted return ratio (STARR), which puts CVaR in the denominator. The portfolio with the highest STARR is called an 'optimal CVaR portfolio' (OCVaRP), giving the highest excess returns over the unit of downside risk.

There is very little literature in the field of corn and soybean hedging, which is particularly true for complex multi-asset portfolio construction. Therefore, with this article, we tried to fill that gap. For instance, Naeem et al. (2022) examined the safe haven and hedging potential of oil and gold against industrial metals and agricultural commodities by using a novel approach of quantile-on-quantile regression. Based on the time-varying correlation results, they reported that oil and gold had a lower correlation with metals and agriculture before the global financial crisis than after it. As for the hedging results, they concluded that oil was a haven for metals and agricultural commodities before the global financial crisis but lost that ability after the global financial crisis. Elliott et al. (2020) quantified the risk reduction and price received when agricultural producers adopted new-generation grain contracts to hedge corn and soybean production. They found that the Price Plus contracts performed best overall during the period from 2008 to 2017, obtaining the highest bushel price and the highest average Sharpe ratio for both corn and soybeans. They concluded that the price-plus contracts offered corn and soybean producers the best risk-adjusted return to hedge production from 2008 to 2017. Wu et al. (2011) investigated the magnitude and changing nature of volatility spillover effects from crude oil markets to corn markets. They found that volatility spillovers from crude oil prices were significant and had a similar impact on corn cash and futures prices. They suggested that corn market participants may consider pursuing a cross hedge with crude oil, which performs slightly better than traditional hedging strategies. Živkov et al. (2021) constructed a two-asset portfolio with precious metals and corn. Their findings indicated that a portfolio with gold outperformed the three other precious metals (silver, platinum and palladium). They explained that gold has the lowest average dynamic correlation with corn, and gold has the lowest average risk compared with all precious metals.

MATERIAL AND METHODS

Research methodology. In this article, we designed five-asset portfolios, combining corn and soybeans with two groups of European stock indices. The goal was to find the best combination of assets to reduce the extreme risk of these agricultural commodities. In this process, we used the portfolio optimisation method of Markowitz (1952), but we applied it to a multivariate CVaR portfolio. This theory distinguishes between efficient portfolios and inefficient portfolios. Efficient portfolios imply increasing risk with increasing returns, which is acceptable from the investors' point of view, where every investor decides on an acceptable level of risk (Massahi et al. 2020). However, inefficient portfolios have increased risk with decreasing returns, which is a wrong choice for every investor. Both groups of portfolios are graphically presented on an efficient

https://doi.org/10.17221/371/2022-AGRICECON

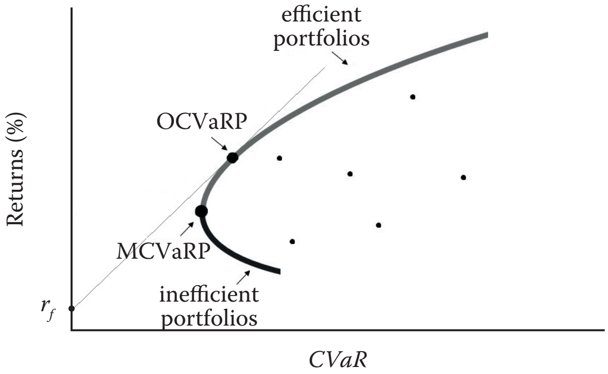

Figure 2. Graphical illustration of *CVaR* efficient frontier line

CVaR – conditional Value-at-Risk; MCVaRP – minimum *CVaR* portfolio; OCVaRP – optimal *CVaR* portfolio; r_f – risk free rate
Source: Authors' own elaboration

frontier line in Figure 2, where efficient portfolios are placed on the upper half of the efficient frontier line, and inefficient portfolios are on the bottom half. The portfolio with the lowest risk is set at the curvature of the efficient frontier line, and no other portfolio has a lower downside risk. In our case, this portfolio is labelled MCVaRP. However, the portfolio with the highest return-to-risk ratio is placed at the tangent point of the efficient frontier line and marked OCVaRP. All dots within the efficient frontier line represent particular assets with inferior risk performances compared to those of the MCVaRP or efficient portfolios.

The first step in constructing the MCVaRP is finding a portfolio with the lowest variance [Equation (1)].

$$\min \sigma_p^2 = \min \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{i,j} \qquad (1)$$

where: σ_p^2 – portfolio variance; σ_i^2 – variance of a particular asset i; w_i – calculated weight of an asset i in a portfolio; $\rho_{i,j}$ – correlation coefficient between the particular pair of assets (i and j).

A necessary precondition in every portfolio optimisation process requires that the sum of all asset weights in a portfolio is equal to one while all asset weights are between zero and one [Equation (2)].

$$\sum_{i=1}^{N} w_i = 1;\ \ 0 \le w_i \le 1 \qquad (2)$$

Every portfolio with minimum variance has a corresponding mean value, the weighted average portfolio return (r_p), which can be calculated as in the following Equation (3).

$$r_p = \sum_{i=1}^{n} w_i r_i \qquad (3)$$

where: r_i – average return of asset i in a portfolio.

To minimise the *CVaR* of a portfolio, first, we needed to calculate *VaR*; for this task, we used calculated first and second moments in Equations (3) and (1), respectively. The *VaR* was calculated as follows:

$$VaR_p = r_p + Z_\alpha \sigma_p \qquad (4)$$

where: Z_α – left quantile of the standard distribution; α – probability level, which in this case is 99%. After the calculation of the *VaR*, *CVaR* is an integral of *VaR* [Equation (5)].

$$CVaR_\alpha = -\frac{1}{\alpha} \int_0^\alpha VaR(x)\mathrm{d}x \qquad (5)$$

where: x – particular variable.

The MCVaRP can be optimised as in Equation (6).

$$\min CVaR_p(w), \sum_{i=1}^{n} w_i r_i \qquad (6)$$

where: min$CVaR_p$ – minimum conditional Value-at-Risk portfolio.

Equation (7) shows how the *STARR* is calculated. We used yields of US 3 Month Treasury Bills for the risk-free rate.

$$STARR = \frac{r_p - r_f}{|CVaR|} \qquad (7)$$

where: r_p – average daily return of a portfolio; r_f – risk-free rate.

An optimal portfolio can be constructed by solving Equation (8).

$$\max \left\{ \frac{w^T r - r_f}{CVaR(w)} \right\} \qquad (8)$$

where: w^T – weights of individual assets in the portfolio; T – the number of returns.

https://doi.org/10.17221/371/2022-AGRICECON

The last task involved calculating how much the downside risks of corn and soybeans would be reduced in the portfolios with the stock indices. We calculated this using a *CVaR* hedge effectiveness index (HEI_{CVaR}). The *HEI* cannot be higher than one, and hedging is better if *HEI* is closer to one [Equation (9)].

$$HEI_{CVaR} = \frac{CVaR_{plant} - CVaR_{portfolio}}{CVaR_{plant}} \tag{9}$$

where: $CVaR_{plant}$ – downside risk of unhedged agricultural commodities (corn and soybeans); $CVaR_{portfolio}$ – downside risk of the created portfolios.

Data set and descriptive statistics. In this article, we used daily spot prices of corn and soybeans, as well as Western and Eastern European stock indices – DAX (Germany), CAC (France), FTSE MIB (Italy), IBEX 35 (Spain), WIG (Poland), PX (Czech Republic), BUX (Hungary) and BET (Romania). The sample was from Jan 1, 2017, to Nov 18, 2022, and we obtained all the selected time series from the Stooq. We transformed all the time series into log returns ($r_{i,t}$) according to the expression [Equation (10)]:

$$r_{i,t} = 100 \times \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{10}$$

where: P_i – daily price of a particular asset.

Both corn and soybean log returns were synchronised separately with the WEC and CEEC indices. Table 1 shows the classical statistical properties of the selected assets—the values of the first four moments and the Jarque-Bera test of normality; corn was the riskiest asset, followed by soybeans. Most stock indices had a lower risk than the agricultural commodities, indicating they could serve well as auxiliary instruments in the portfolios. All the assets had negative skewness, which means they were left inclined relative to the mean, and all the assets had high kurtosis values. High values of the third and fourth moments imply non-normal distribution of all the assets. However, skewness and kurtosis do not have a role in constructing portfolios because *CVaR* is determined only by the first and second moments.

In constructing the MCVaRPs and OCVaRPs, the portfolio optimisation involved considering the individual values of *CVaR* and *STARR*, which are also presented in Table 1. These values will help in explaining the structure of the optimised portfolios.

The second factor that is important in designing a portfolio is a mutual correlation between the portfolio assets. In this regard, Table 2 shows pairwise Pearson correlations between the assets. Both corn and soybeans had relatively low correlation vis-à-vis stock indices, which is another argument favouring using stock indices as auxiliary instruments. Also, the pairwise correlations between the WEC stock markets were higher than those in the CEEC counterparts. Therefore, based on the preliminary findings of risk and pairwise correlations, we could hypothesise that portfolios with the CEEC indices might have lower *CVaR* than those with the WEC indices. In other

Table 1. Descriptive statistics of the agricultural commodities and stock indices

Selected assets		Mean	SD	Skewness	Kurtosis	*JB*	*CVaR*	*STARR*
Agricultural commodities	corn	0.018	0.691	–0.122	6.938	927.5	–1.823	0.010
	soybean	0.012	0.577	–0.559	8.003	1 569.0	–1.525	0.008
WEC indices	DAX	0.007	0.555	–0.674	17.063	11 891.1	–1.472	0.005
	CAC	0.009	0.537	–1.019	18.019	13 687.5	–1.423	0.006
	FTSE-MIB	0.006	0.606	–2.225	30.392	45 884.6	–1.609	0.004
	IBEX 35	–0.005	0.546	–1.348	22.903	24 034.8	–1.461	–0.004
CEEC indices	WIG	0.000	0.559	–1.366	18.924	14 465.5	–1.482	0.001
	PX	0.010	0.436	–1.044	15.919	9 490.7	–1.144	0.009
	BUX	0.011	0.593	–1.570	16.522	10 679.2	–1.560	0.008
	BET	0.008	0.474	–2.051	25.174	28 179.7	–1.247	0.006

JB – Jarque-Bera test of normality; *CVaR* – conditional Value-at-Risk; *STARR* – stable tail adjusted return ratio; WEC – Western European countries; CEEC – Central and Eastern European countries
Source: Authors' own calculations based on data from Stooq (2022)

https://doi.org/10.17221/371/2022-AGRICECON

Table 2. Pairwise Pearson correlations between the assets in the portfolios

Portfolios with WEC indices						Portfolios with CEEC indices					
Assets	corn	DAX	CAC	FT–mib	IBEX	assets	corn	WIG	PX	BUX	BET
Corn	1	0.038	0.041	0.041	0.042	corn	1	0.024	0.073	–0.008	0.045
DAX	0.038	1	0.938	0.880	0.847	WIG	0.024	1	0.545	0.588	0.429
CAC	0.041	0.938	1	0.886	0.879	PX	0.073	0.545	1	0.559	0.507
FT-mib	0.041	0.880	0.886	1	0.871	BUX	–0.008	0.588	0.559	1	0.402
IBEX	0.042	0.847	0.879	0.871	1	BET	0.045	0.429	0.507	0.402	1
Assets	soybean	DAX	CAC	FT–mib	IBEX	assets	soybean	WIG	PX	BUX	BET
Soybean	1	0.138	0.138	0.137	0.135	soybean	1	0.117	0.134	0.037	0.104
DAX	0.138	1	0.938	0.880	0.847	WIG	0.117	1	0.545	0.588	0.428
CAC	0.138	0.938	1	0.886	0.879	PX	0.134	0.545	1	0.559	0.507
FT-mib	0.137	0.880	0.886	1	0.871	BUX	0.037	0.588	0.559	1	0.402
IBEX	0.135	0.847	0.879	0.871	1	BET	0.104	0.429	0.507	0.402	1

FT-mib – FTSE-MIB index; WEC – Western European countries; CEEC – Central and Eastern European countries
Source: Authors' own calculations based on data from Stooq (2022)

words, the CEEC indices could serve as a better hedge for corn and soybeans. The following section addresses this question.

RESULTS AND DISCUSSION

Table 3 contains calculated shares of assets of the four optimised portfolios.

For the portfolios with the WEC indices, both agricultural commodities had the highest share in the MCVaRPs, although they had the highest risk, according to Table 1. In other words, corn had the highest downside risk (–1.823) but a relatively high share of 36%, whereas soybeans had a somewhat lower *CVaR* (–1.525) and a significantly higher share of 45%. The likely reason is that corn and soybeans had a very low correlation with the indices, which means that the covariance matrix played a very important role in portfolio optimisation. Soybeans had a higher share than corn, probably because soybeans had a lower risk than corn (Table 1). As for the indices, the CAC had 28% and 25% in the corn and soybean portfolios, respectively, because CAC had the lowest *CVaR* (–1.423). The Spanish IBEX 35 followed with 26% and 23%, respectively, because it had a higher *CVaR* (–1.461) than CAC. The DAX had a relatively high *CVaR* (–1.472), which gave the German index relatively low shares of 10% and 7%, respectively, whereas the Italian index, with the highest risk (–1.609), had no share in both portfolios.

Table 3. Calculated shares of assets (%) in the portfolios

Portfolios with WEC indices					Portfolios with CEEC indices				
Assets	corn		soybean		assets	corn		soybean	
	MCVaRP	OCVaRP	MCVaRP	OCVaRP		MCVaRP	OCVaRP	MCVaRP	OCVaRP
Plant	36	100	45	100	plant	23	23	29	29
DAX	10	0	7	0	WIG	9	9	6	6
CAC	28	0	25	0	PX	34	34	32	32
FTSE-mib	0	0	0	0	BUX	6	6	7	7
IBEX 35	26	0	23	0	BET	28	28	26	26
Σ	100	100	100	100	Σ	100	100	100	100

MCVaRP – minimum *CVaR* portfolio; OCVaRP – optimal *CVaR* portfolio; WEC – Western European countries; CEEC – Central and Eastern European countries
Source: Authors' own calculations based on data from Stooq (2022)

https://doi.org/10.17221/371/2022-AGRICECON

In the optimal portfolios, corn and soybeans had 100% shares, meaning both assets had the best return-to-risk ratio of all the WEC indices. This information is confirmed in Table 1, where the *STARR*s of corn and soybeans are 0.010 and 0.008, respectively, and all the WEC indices had significantly lower *STARR*s.

However, in MCVaRPs of the CEEC, corn and soybeans did not have the largest share, but it was the Czech PX index with 34% and 32%, respectively. The PX had by far the lowest *CVaR* (–1.144), which puts the PX index at the top. The Romanian BET index had the second largest share of 28% in the portfolio with corn and the third largest share of 26% with soybeans because BET had the second lowest *CVaR* with –1.247. Corn had the third-highest share of 23%, and soybeans had the second-highest share of 29%, primarily because of their low pairwise correlations with the CEEC indices. The WIG and BUX indices are in the last two positions in the two *CVaR* portfolios because they had the highest *CVaR* risks (Table 1).

For the optimal portfolios, both OCVaRPs had the same structure as the MCVaRPs, which means that the MCVaRPs also had the best return-to-risk ratio. In other words, investors who combined corn and soybeans with the CEEC indices could achieve two gains with one stroke.

After portfolio construction, we compared and discussed the performances of the portfolios. To this end, we present the results of the three indicators – *CVaR*, *HEI* and *STARR* – in Table 4. According to Table 4, portfolios with the CEEC indices had lower extreme risk. This finding aligns with the previous hypothesis that the portfolio with the CEEC indices might have better results because of the lower risk of these indices and lower pairwise correlations. In particular, the level of risk was –1.127 *versus* –1.098 for corn, whereas the relation was –1.098 *versus* –0.892 for soybeans. However, the absolute level of *CVaR* did not show how much downside risk in the portfolios was reduced relative to the unhedged asset – the sole investment in corn and soybeans. This difference is caused by different groups of indices bearing different levels of risk, which makes the *CVaR* comparison incoherent. Therefore, we calculated *HEI*s as a better indicator than the raw *CVaR* values. From this viewpoint, the WEC indices reduced the downside risk of corn by 38%, and the CEEC indices reduced the level of risk by 50%. For soybeans, risk reductions were 28% and 41%, respectively. Therefore, the risk reduction of corn was higher in both portfolios than in the portfolios with soybeans, probably because corn had a higher risk than soybeans (Table 1).

For the return-to-risk ratio, the portfolio with the WEC indices had a slightly higher *STARR* than with the CEEC indices for corn (0.0098 *versus* 0.0092). However, the soybean portfolio with the CEEC indices had a significantly higher *STARR* than the portfolio with the WEC indices (0.0101 *versus* 0.0076). This finding means that the soybean portfolio with the CEEC indices produced better results in both downside risk reduction and *STARR* than WEC counterparts. WEC indices had only a slight upper hand in the *STARR* in the corn portfolio.

Figure 3 shows a graphical presentation of the constructed portfolios via *CVaR* efficient frontier lines. The positions of the dots indicate that OCVaRP was equal with the agricultural commodities in the WEC portfolio, which means that investors who wanted to pursue OCVaRP with WEC indices did not need to combine corn and soybeans with these indices. However, MCVaRPs and OCVaRPs were equal in the CEEC portfolios, which indicates that investors who combined the agricultural assets with the CEEC indices could achieve two goals with one shot. Also, according to the distance between dots one and three in all of the plots, all portfolios significantly reduced the extreme risk of corn and soybeans, meaning that both groups of European indices were excellent hedgers of these commodities. However, the CEEC indices were better than the WEC counterparts in this task.

Table 4. Calculated values of *CVaR*, *HEI* and *STARR* of the constructed portfolios

Indicators	Portfolios with WEC indices		Portfolios with CEEC indices	
	corn	soybean	corn	soybean
CVaR	–1.127	–1.098	–0.914	–0.892
HEI	0.38	0.28	0.50	0.41
STARR	0.0098	0.0076	0.0092	0.0101

CVaR – conditional Value–at-Risk; *HEI* – hedge effectiveness index; *STARR* – stable tail adjusted return ratio; WEC – Western European countries; CEEC – Central and Eastern European countries

Source: Authors' own calculations based on data from Stooq (2022)

https://doi.org/10.17221/371/2022-AGRICECON

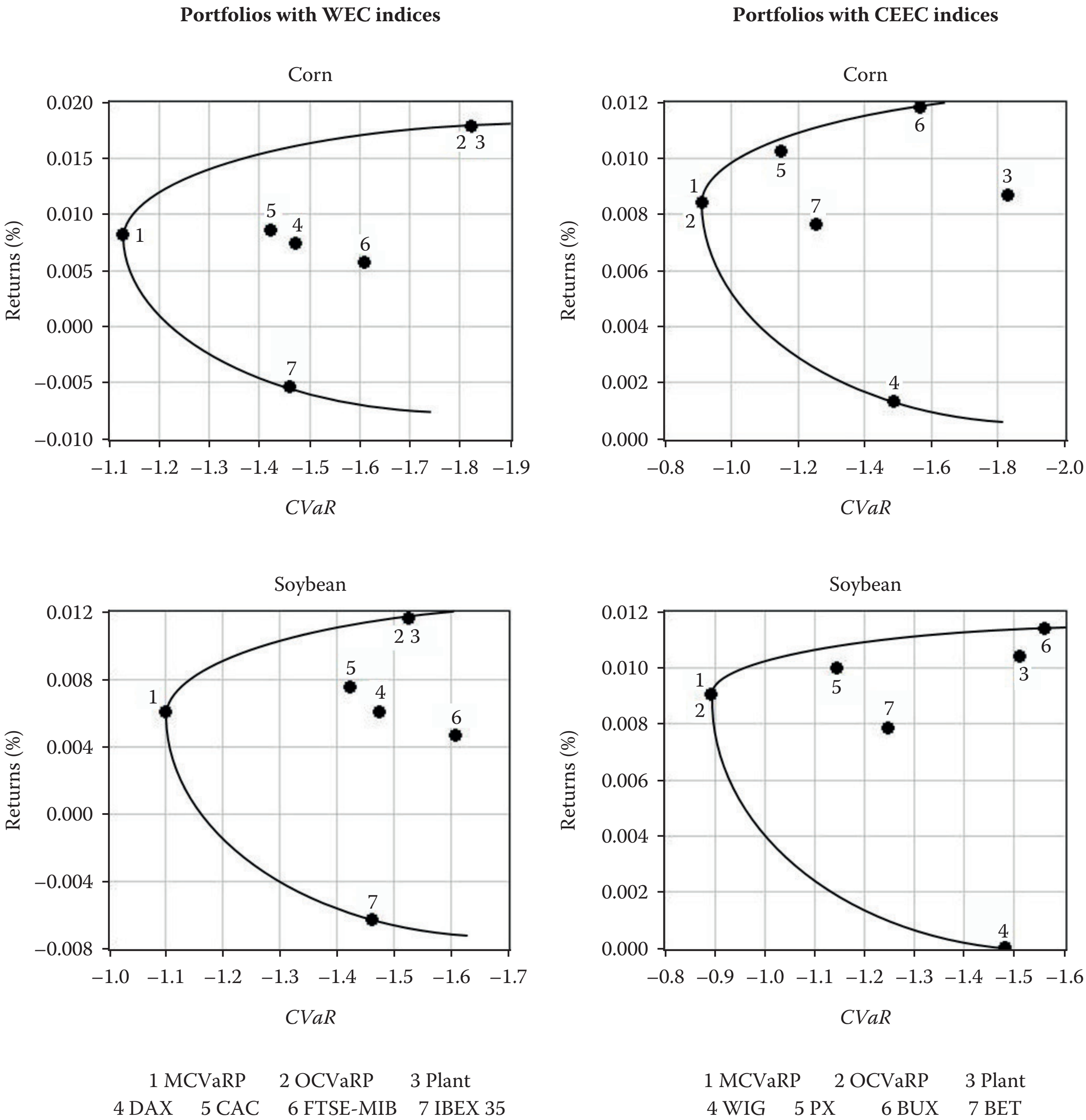

Figure 3. Conditional Value-at-Risk efficient frontier lines of the constructed portfolios for corn and soybean

CVaR – conditional Value-at-Risk; MCVaRP – minimum *CVaR* portfolio; OCVaRP – optimal *CVaR* portfolio; WEC – Western European countries; CEEC – Central and Eastern European countries

Source: Authors' own calculations based on data from Stooq (2022)

CONCLUSION

In this article, we investigated the downside risk reduction of corn and soybeans by making CVaR portfolios with the developed and emerging European stock indices. To show the difference between goals investors might prefer, we constructed two types of portfolios – MCVaRP and OCVaRP. All portfolios were constructed via the portfolio optimisation process.

On the basis of the results, we have several noteworthy findings to report. Both agricultural commodities had relatively high risk and relatively high share in the portfolios, which can be attributed to very low pair-

https://doi.org/10.17221/371/2022-AGRICECON

wise correlation with the stock indices. Corn and soybeans had the highest share in the MCVaRP with the WEC indices, whereas in the CEEC portfolio, they were in second and third places, respectively. The WEC indices were riskier than the CEEC indices, which is why portfolio optimisation gives a higher share to agricultural assets. In the OCVaRP with the WEC indices, corn and soybeans had the best return-to-CVaR ratio, but in the CEEC portfolios, the MCVaRPs were also optimal portfolios.

As for the comparative performances between the portfolios with different stock indices, the CEEC portfolio had better risk-reducing results, considering both commodities, because the CEEC indices were less risky than the WEC indices. In other words, the downside risk reduction of corn was 38% and 50% in the portfolios with WEC and CEEC, respectively, whereas, for soybeans, the results were 28% and 41%, respectively. Risk reduction was higher in the portfolios with corn than in the portfolios with soybeans because corn was a riskier asset. The WEC portfolio had a higher STARR only for corn for the optimal portfolios. In contrast, the CEEC indices had the upper hand in all other cases.

This article proposes to investors how to reduce the extreme risk of these two agricultural commodities when market participants want to mitigate extreme risk with the European stock indices. In summary, the emerging stock markets produced better results in the MCVaRPs and the optimal portfolio when combined with soybeans.

Future researchers can investigate the hedging abilities of different auxiliary assets, such as energy commodities, precious and industrial metals, bonds and other indices. Investigators in future articles also might pursue different risk measures, such as semiparametric CVaR or historical CVaR, in portfolio construction.

REFERENCES

Alexakis C., Bagnarosa G., Dowling M. (2017): Do cointegrated commodities bubble together? The case of hog, corn, and soybean. Finance Research Letters, 23: 96–102.

Altun E., Alizadeh M., Ozel G., Tatlidil H., Maksayi N. (2017): Forecasting Value-at-Risk with two-step method: GARCH-exponentiated odd log-logistic normal model. Romanian Journal of Economic Forecasting, 20: 97–115.

Chenarides L., Grebitus C., Lusk J.L., Printezis I. (2021): Food consumption behavior during the COVID-19 pandemic. Agribusiness, 37: 44–81.

Elliott L., Elliott M., Slaa C.T., Wang Z. (2020): New generation grain contracts in corn and soybean commodity markets. Journal of Commodity Markets, 20: 100113.

FAO (2022). Food and Agriculture Organisation of the United Nations. Available at https://www.fao.org/home/en (accessed Nov 1, 2022).

Li J., Huang H., Xiao X. (2012): The sovereign property of foreign reserve investment in China: A CVaR approach. Economic Modelling, 29: 1524–1536.

Luan F., Zhang W., Liu Y. (2022): Robust international portfolio optimisation with worst-case mean-CVaR. European Journal of Operational Research, 303: 877–890.

Markowitz H (1952): Portfolio selection. Journal of Finance, 7: 77–91.

Martin D., Rachev S.T., Siboulet F. (2003): Phi-Alpha optimal portfolios and extreme risk management. Wilmott, 6: 70–83.

Massahi M., Mahootchi M., Khamseh A.A. (2020): Development of an efficient cluster-based portfolio optimisation model under realistic market conditions. Empirical Economics, 59: 2423–2442.

Minondo A. (2021): Impact of COVID-19 on the trade of goods and services in Spain. Applied Economic Analysis, 29: 58–76.

Moncarz P.E., Barone S.V. (2020): Rising commodity prices and welfare in Brazil: A simulation of medium-term effects using a SAM price model. International Journal of Emerging Markets, 15: 1029–1060.

Naeem M.A., Hasan M., Arif M., Suleman M.T., Kang S.H. (2022): Oil and gold as a hedge and safe-haven for metals and agricultural commodities with portfolio implications. Energy Economics, 105: 105758

Palanska T. (2020): Measurement of volatility spillovers and asymmetric connectedness on commodity and equity markets. Czech Journal of Economics and Finance, 70: 42–69.

Rockafellar R.T., Uryasev S. (2002): Conditional Value-at-Risk for general loss distributions. Journal of Banking and Finance, 26: 1443–1471.

Saâdaoui F., Jabeur S.B., Goodell J.W. (2022): Causality of geopolitical risk on food prices: Considering the Russo-Ukrainian conflict. Finance Research Letters, 49: 103103.

Sajjad R., Coakley J., Nankervis J.C. (2008): Markov-Switching GARCH modelling of Value-at-Risk. Studies in Nonlinear Dynamics and Econometrics, 12: 1–31.

Stooq (2022): Stooq. [Dataset]. Available at https://stooq.com/q/?s=zc.c (accessed Nov 1, 2022).

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

https://doi.org/10.17221/371/2022-AGRICECON

Wu F., Guan Z., Myers R. (2011): Volatility spillover effects and cross hedging in corn and crude oil futures. Journal of Futures Markets, 31: 1052–1075.

Zhu N.J., Feng Y.L. (2017): Optimal change-loss reinsurance contract design under tail risk measures for catastrophe insurance. Economic Computation and Economic Cybernetics Studies and Research, 51: 225–242.

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

Received: December 5, 2022
Accepted: February 6, 2023
Published online: March 10, 2023