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Making a Markowitz portfolio with agricultural commodity futures

Dejan Živkov[1], Suzana Balaban[2], Marijana Joksimović[2]*

[1]Novi Sad School of Business, University of Novi Sad, Novi Sad, Serbia
[2]Faculty of Finances, Banking and Audit, Alfa University, Beograd, Serbia

**Corresponding author: dejanzivkov@gmail.com*

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Abstract: This paper constructs a minimum-variance portfolio of six agricultural futures. We make a full sample analysis as well as a pre-COVID and COVID examination. Using Markowitz portfolio optimisation, we find that soybean futures have the highest share (31%) in the full sample portfolio because it has the lowest variance. Both soybean oil and rice futures have the second highest weight in the full sample portfolio, in an amount of 24%, because soybean oil has the second lowest variance, whereas rice has, by far, the lowest average correlation with other agricultural futures. Soybean oil has the highest share of 35% in the pre-COVID period, whereas rice follows with 27%. On the other hand, in the COVID period, soybean has a very high share in an amount of 47% due to the lowest risk, while rice takes second place with 19%. Based on the results, investors should invest the most in soybean oil and rice in tranquil periods, while the choice should be soybean and rice in crisis periods. Rice is the choice in both sub-periods because rice has a very low correlation with other agricultural commodities, which happens due to the price stabilisation of rice that is often conducted by Asian countries.

Keywords: COVID crisis; efficient frontier line; hedge effectiveness index; minimum-variance portfolio; pre-COVID and COVID subsamples; subsample analysis

The volatility of grain commodities is a well-known fact in academic and professional circles. The causes of these agricultural price instabilities are numerous. For instance, Mensi et al. (2021) listed three major factors. The first factor is the production of biofuels, where the higher price of energy pushes agricultural prices up as the cost of production of agricultural products increases. The second factor is the increasing and more prosperous world population, while the adverse effects of global climate change on agricultural commodities is the third factor. Cong et al. (2014) explained that agricultural production is under risk mainly due to uncontrollable events such as adverse weather, attacks by pests and pathogens, and market uncertainties about future input and output prices. Santeramo and Lamonaca (2019) argued that the level of storage contributes to the price volatility in a sense that building stockpiles reduces price fluctuations, while the lack of stockpiles increases volatility. Sidhoum and Serra (2016) asserted that increased and prolonged food price volatility leads to reduced investments in research and development in this sector, high unemployment, income fluctuations and increased social costs to communities. Also, the low demand and supply elasticity of agricultural products adds to the volatility of these commodities. Addressing high food price volatility is particularly important in developing countries, in which food security can be significantly compromised. Therefore, the ever-increasing volatility of agricultural markets creates a huge challenge for producers, commercial users, traders and investors to adequately hedge themselves against risk exposure.

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According to the above, this paper hypothesises a situation in which an investor constructs a multivariate portfolio of six agricultural futures – corn, wheat, soybean, soybean oil, oats and rice, with an aim to minimise the risk of such a portfolio. These commodities are traded on the Chicago Mercantile Exchange (CME), where they are the six biggest agricultural markets in this futures exchange. According to our best knowledge, this investigation has never been performed before, and this is where our motivation comes from to do this research. We chose futures rather than spot agricultural commodities because futures process new information faster than spot prices, and these markets are highly liquid with low trading costs, which makes futures ideal securities for diversification efforts. Also, You and Daigler (2013) stated that purchasing and selling futures is similar to purchasing and selling stocks, which means that the portfolio theory is also applicable to futures markets. Figure 1 presents the price dynamics of the selected agricultural futures, where the presence of significant price fluctuations over a course of six years can be clearly seen. High price oscillations undoubtedly imply that risk is an intrinsic feature in all the selected agricultural commodities, and the task of this paper is to find a way to mitigate it.

In the process of constructing a multivariate portfolio, we refer to the modern portfolio theory of Markowitz (1952), which is the most popular portfolio optimisa-

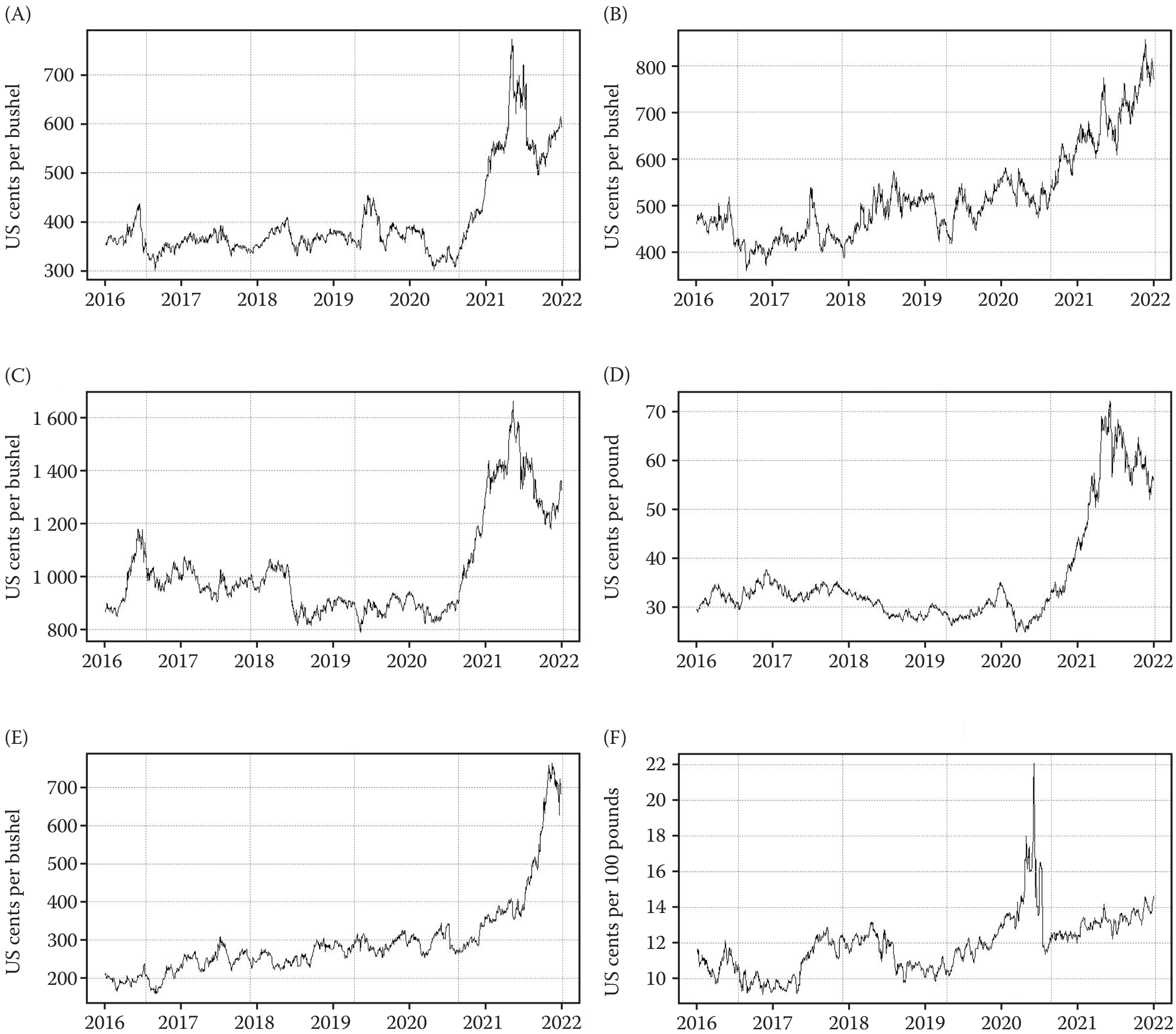

Figure 1. Empirical dynamics of the selected agricultural futures: (A) corn, (B) wheat, (C) soybean, (D) soybean oil, (E) oats, and (F) rice

Source: Authors' own calculations based on data from Investing.com (2022)

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tion framework based on the trade-off between risk and return (Baghdadabad 2013; Jones and O'Steen 2018; Massahi et al. 2020). The primary advantage of this methodology is the efficient diversification, volatility management in a portfolio and joint presentation of every possible asset combination on a graph. On the other hand, the most serious criticism of this approach is that it assesses portfolios based on variance and not the downside risks. Variance can be biased risk measured because it takes both positive and negative returns into account, while the downside risk considers only negative returns. The goal of this study is to determine the optimal structure of six-assets in a multivariate portfolio, which means that this portfolio has the lowest risk compared to all the constituent assets in this portfolio. We observe risk as variance, which is a square deviation from the average returns, and this is the most usual way of measuring risk in agricultural commodities in the literature (Palanska 2020; Tonin et al. 2020). Huang et al. (2012) asserted that measurement and forecasting volatility of agricultural resources is crucial for proper asset allocation, risk management and product pricing. A portfolio with minimum risk is called a minimum variance portfolio (MVP). The spatial position of MVP, vis-à-vis all assets in a portfolio, is presented via an efficient frontier line, which is a visual tool of telling one how much lower risk the MVP has compared to any other asset in the portfolio.

In addition to the full sample analysis, we also address one issue that potentially could have serious repercussions on the portfolio construction, which is the COVID-19 pandemic outbreak. In order to see how the portfolio structure and risk value change when two distinctively different periods are under scrutiny, we partitioned the full sample into pre-COVID and COVID subsamples. It is not unrealistic to assume that the created portfolios in these sub-periods could be quite different because Figure 1 undoubtedly shows that all the agricultural futures recorded a significant price increase since 2020, i.e. after the onset of the pandemic. Similar to the case of the full sample analysis, we created efficient frontier lines for every subsample to help us visualise the risk-return positions of the MVPs and all the agricultural futures.

As for the existing papers on this topic, Hernandez et al. (2021) researched the portfolio allocation and risk contribution characteristics of nine agricultural commodities. They found that sugar cane, followed by wheat and corn, are the largest risk contributors to the total portfolio risk. On the other hand, cocoa, followed by lumber and cotton, are the lowest risk contributors to the total portfolio risk. According to their results, cocoa and lumber are the most desirable for investment. The paper of Rehman et al. (2019) reported important practical implications for portfolio managers in the commodity markets, analysing four precious metals, oil, gas, copper, coal and wheat. They found that crude oil offers more diversification benefits when combined with gold or silver, but minimal diversification benefits can result from combining crude oil with wheat or platinum. Gas futures give more diversification opportunities when combined with copper, wheat, platinum or palladium, while coal provides maximum diversification benefits when combined with gold, silver or wheat. Živkov et al. (2021) investigated which precious metal futures are the best hedging tools for the corn spot commodity, taking three different risk measures into account – variance, value-at-risk, and conditional value-at-risk. Their findings indicated that a portfolio with gold outperforms the other three precious metals (silver, platinum, and palladium) with respect to all three risk metrics. Gold is the best auxiliary asset because gold has the lowest average dynamic correlation with corn, and also, it has the lowest average risk of all the precious metals. Smimou (2010) examined international portfolio diversification by adding foreign agriculture future contracts to the bond and equity portfolio and found results in favour of the international diversification of agricultural commodities. Tóth et al. (2016) used the Markowitz portfolio theory to estimate the risk and profitability of unquoted agricultural farms in Slovakia. They reported that, from the point of view of production orientation, crop farms record higher return and also higher risk in comparison to the animal farms.

MATERIAL AND METHODS

Markowitz portfolio theory. A six-asset portfolio was constructed in this paper, using the portfolio optimisation procedure developed by Markowitz (1952). The goal of this process is to find the optimal weight of all the assets in a portfolio that would have minimum variance. The portfolio optimisation takes the variance of all the assets in a portfolio as well as their pairwise correlations into account. The changing weights of the assets in a portfolio ends when a minimum portfolio risk is achieved (Armeanu and Balu 2008; Cha and Jithendranathan 2009).

The created MVP is placed at the curvature of an efficient frontier line, which means that this portfolio has the smallest risk of all the possible portfolios (Figure 2).

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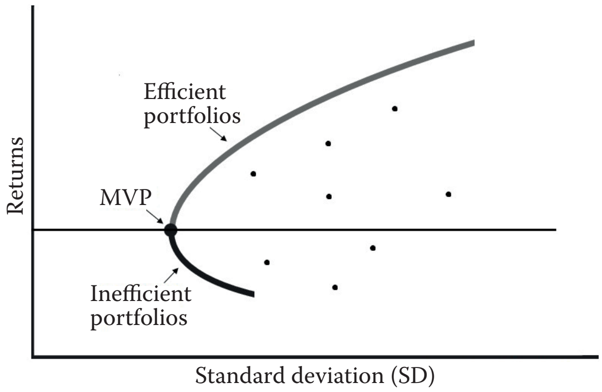

Figure 2. Graphical presentation of an efficient frontier line

MVP – minimum variance portfolio
Source: Authors' illustration

A horizontal line divides all the possible portfolios into a set of efficient portfolios and inefficient portfolios. Efficient portfolios have an increasing risk with increasing returns, which is acceptable from the investor's point of view, while every investor decides about his or her acceptable level of risk. Inefficient portfolios have an increasing risk with decreasing returns, which is a bad choice for every investor. All the dots within the efficient frontier line represent particular assets that have inferior risk-return performances compared to the MVP and the efficient portfolios.

The first task in the portfolio optimisation procedure is to set up an objective function in a form of the minimum portfolio variance (portfolio optimisation is calculated by the 'PortfolioAnalytics' package in 'R'). This is presented in Equation (1).

$$\min \sigma_p^2 = \min \sum_{i=1}^{N} W_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} W_i W_j \sigma_i \sigma_j \rho_{i,j} \tag{1}$$

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

Every MVP has a corresponding rate of return, which is actually the weighted average rate of return (r_p). This can be calculated as per Equation (2).

$$r_p = \sum_{i=1}^{N} W_i r_i \tag{2}$$

where: r_i – particular rate of return of every asset in a portfolio.

A necessary condition is that the sum of all the asset weights in the MVP must be equal to 1.

$$\sum_{i=1}^{N} W_i = 1 \tag{3}$$

On the other hand, the weight of a particular asset in the MVP ranges between zero and one.

$$0 \leq W_i \leq 1 \tag{4}$$

In order to quantitatively estimate how much risk reduction is achieved by the construction of a minimum-variance portfolio compared to all the assets in the portfolio, we calculate the hedge effectiveness index (*HEI*) of the variance in the following way:

$$HEI_{Var} = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{5}$$

where: *Var* – variance; *unhedged* subscript – investment only in a particular agricultural commodity; *hedged* subscript – investment in the portfolio of six assets.

The closer the *HEI* index is to 1, the better the hedging effectiveness is, and *vice versa*.

Dataset. We constructed a multivariate minimum-variance portfolio using six daily agricultural futures time-series – corn, wheat, soybean, soybean oil, oats and rice from the CME market. For the calculations, we considered a time-span of six years, from January 2016 to December 2021. It is clear that our sample includes the COVID-19 pandemic outbreak, which imposed a huge shock and uncertainty to all the financial and commodity markets (Shang et al. 2021). Making a distinction between calm and crisis periods can be useful as a complementary analysis because we can split the full sample into two subsamples and rerun the portfolio optimisation in both the pre-COVID and COVID periods. In this way, we can determine any differences in the calculated weights of the assets and the risk level of both MVPs. All the time-series are collected from the Investing.com website (Investing.com 2022), and all the time-series are synchronised according to the existing observations. Before the portfolio calculation, all the futures time-series are transformed into log-returns ($r_{i,t}$) according to the expression: $r_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, where: P_i – price of a particular asset. Figure 3 presents the plots of the calculated log-returns, and it is obvious that some commodities recorded an increase in volatility after the pandemic outbreak. The descriptive statistics of the selected agricultural commodities, in the form of the first four moments, are given in Table 1.

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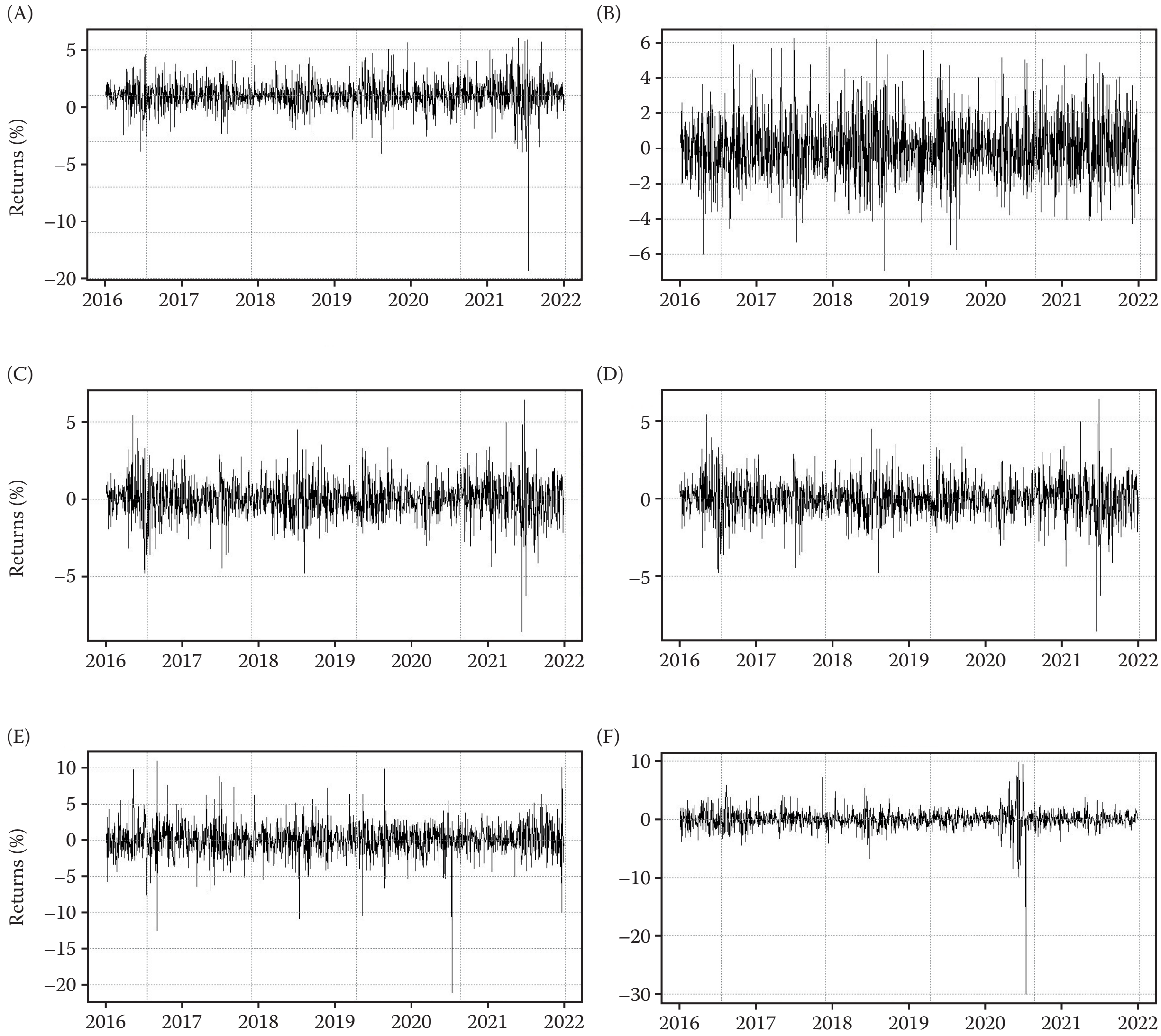

Figure 3. Log-returns of the selected agricultural futures: (A) corn, (B) wheat, (C) soybean, (D) soybean oil, (E) oats, and (F) rice

Source: Authors' own calculations based on data from Investing.com (2022)

According to Table 1, all the assets have a positive mean, which indicates that their prices increase on average in the observed period, whereas oats recorded the highest increase. On the other hand, oats also have the highest risk, while wheat and rice follow. A preliminary insight in the level of risk could suggest that these three assets will probably have a relatively low weight in the full sample MVP. However, this is only a hint because portfolio optimisation also takes the pairwise correlations of all assets in the portfolio into account. Five out of the six assets have negative skewness, which means that majority of the log-return

Table 1. Descriptive statistics of the returns of the selected agricultural commodities

Four moments	Corn	Wheat	Soybean	Soybean oil	Oats	Rice
Mean	0.027	0.030	0.026	0.040	0.071	0.015
SD	1.574	1.736	1.207	1.392	2.113	1.710
Skewness	–1.228	0.256	–0.240	–0.149	–0.750	–3.568
Kurtosis	18.744	3.734	6.832	5.601	12.844	69.314

Source: Authors' own calculations based on data from Investing.com (2022)

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Table 2. Pairwise Pearson correlations in the full sample

Selected assets	Corn	Wheat	Soybean	Soybean oil	Oats	Rice
Corn	1.000	0.543	0.570	0.333	0.260	0.125
Wheat	0.543	1.000	0.405	0.221	0.300	0.101
Soybean	0.570	0.405	1.000	0.566	0.207	0.117
Soybean oil	0.333	0.221	0.566	1.000	0.150	0.067
Oats	0.260	0.300	0.207	0.150	1.000	0.192
Rice	0.125	0.101	0.117	0.067	0.192	1.000
Average ρ	0.366	0.314	0.373	0.267	0.222	0.120

ρ – correlation level

Source: Authors' own calculations based on data from Investing.com (2022)

observations are placed left from the mean. Besides, all the assets have relatively high kurtosis numbers, which indicates the presence of outliers. Figure 3 shows the presence of extreme values in all the plots, except for wheat, and all the extreme values are recorded after the COVID outbreak. This speaks in favour of dividing the full sample into two subsamples.

In order to be thorough in this preliminary analysis, the average values of the pairwise Pearson correlations are presented in Table 2, which are very important inputs in the construction of a portfolio. According to the portfolio theory, assets that have low correlations are more welcomed in a portfolio. Corn and soybean have the highest full sample correlation (0.570), which is not surprising because these commodities are used in biofuel production and they are also close substitutes in animal feed. Also, soybean and soybean oil have a high correlation (0.566), which is expected because soybean oil is a direct extracted from the soybean. As for the average correlations of all the agricultural commodities, rice has, by far, the lowest average correlation with the other agricultural assets (0.120), while oats (0.222) and soybean oil follow (0.267). The next section will indicate which factor has the upper hand in the process of portfolio construction – low variance or low pairwise correlation with the other assets.

RESULTS AND DISCUSSION

Full sample analysis. This section presents and discusses the results of the portfolio construction in the full sample. Table 3 contains the calculated weights of the agricultural assets in the MVP, while Table 4 shows the variances in the MVP and all the assets in the portfolio as well as the *HEI* values. According to Table 3, soybean has the highest share in the full MVP sample (24%), while the lowest share goes to corn (4%). As has been stated, portfolio optimisation takes two factors into account – the level of variance of each asset in a portfolio and the pairwise correlations between the assets. In other words, these two elements have to be considered when the results are explained.

In particular, soybean has the highest share in the MVP probably because this cereal has the lowest vari-

Table 3. Shares of agricultural commodities in the full sample MVP (%)

MVP	Corn	Wheat	Soybean	Soybean oil	Oats	Rice
Share	4	10	31	24	7	24

MVP – minimum variance portfolio

Source: Authors' own calculations based on data from Investing.com (2022)

Table 4. Variances and *HEI* values in the full sample

Risk measures	MVP	Corn	Wheat	Soybean	Soybean oil	Oats	Rice
Variance	0.904	2.477	3.012	1.456	1.935	4.462	2.923
HEI	–	0.635	0.700	0.379	0.533	0.797	0.691

MVP – minimum variance portfolio; *HEI* – hedge effectiveness index

Source: Authors' own calculations based on data from Investing.com (2022)

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ance (1.207). On the other hand, soybean has the highest average correlation with all the other agricultural assets (0.373), but obviously, this does not affect its highest share in the MVP. In other words, in this case, the portfolio optimisation gives more importance to the level of variance than to the pairwise correlations. On the other hand, it is interesting to explain why corn has such a low share, although corn does not have high variance whatsoever. As a matter of fact, corn has the third lowest variance, right after soybean and soybean oil. The most likely reason why corn has the lowest share in the MVP is because soybean has the highest share. In other words, corn and soybean have the highest mutual correlation of 0.570, and this fact is not good for the portfolio construction. Therefore, it can be concluded that soybean has the highest share in the MVP due to the lowest variance, but this directly reflects to the lowest share of corn because these two cereals are closely connected. In addition, corn has a relatively high correlation with the other assets, which is not a favourable characteristic of corn.

Both soybean oil and rice have a relatively high share in the MVP, in an amount of 24%, but the reasons are different. Soybean oil has the second lowest variance and a relatively low average correlation with the other assets. These factors simultaneously contribute to the relatively high share of soybean oil (24%), although soybean oil has a relatively high pairwise correlation with soybean, i.e. the cereal that has the highest share in the MVP. On the other hand, rice has the third highest variance, right after oats and wheat, but rice has, by far, the lowest average correlation with the other agricultural futures, and this factor dominantly determines the high share of rice (24%) in the MVP. Timmer (2014) explained that governments from the Asia and the Pacific regions often conduct aggressive food price stabilisation policies to provide food to the poor in areas where rice is a major food source. This could explain why rice has a very low correlation with other agricultural commodities. Wheat has a relatively low share of 10% because wheat has the second largest variance and the third largest average correlation. The low share of wheat coincides with the paper of Hernandez et al. (2021), who also constructed a multivariate portfolio with the inclusion of agricultural commodities. They contend that wheat is one of the largest risk contributors to the total portfolio risk, which is well in line with our findings. As for oats, we found a very low share of 7%, although oats have the second lowest average correlation. However, oats are the riskiest asset in the MVP, and it is the primary reason why oats have such a low share in the MVP.

Table 4 contains the level of risk of the MVP and all the constituent assets in the portfolio. It can be seen that the MVP has a significantly lower risk (0.904) compared to the lowest risk that some asset has (soybean = 1.456). This clearly indicates that the portfolio optimisation was successful. Besides, we calculated the *HEI* values for every agricultural commodity vis-à--vis MVP. The results show a significant risk reduction when the investment in the MVP is compared to the sole investment in the particular agricultural futures. In other words, the highest risk reduction is achieved when the MVP is compared with the riskiest assets in the portfolio, i.e. oats, which is expected.

Figure 4 depicts the graphical illustration of the efficient frontier line, as well as the spatial positions of the MVP and all the agricultural futures in the portfolio. Figure 4 clearly shows that the MVP is so much better in terms of risk than any other agricultural asset.

Subsample analysis. This section tries to determine whether and how the portfolio performance changes if we observe two distinctively different periods – the relatively tranquil pre-COVID subsample and the relatively turbulent COVID subsample. The pre-COVID period ranges from January 2006 to December 2019, while the latter one covers the period from January 2020 to December 2021. Table 5 contains the calculated shares of the assets of the two portfolios, showing that these shares are significantly different. This justifies our effort to conduct a subsample analysis. In addition, Table 6 presents the pairwise correlations and standard deviations of both sub-periods, and these values help to explain the findings.

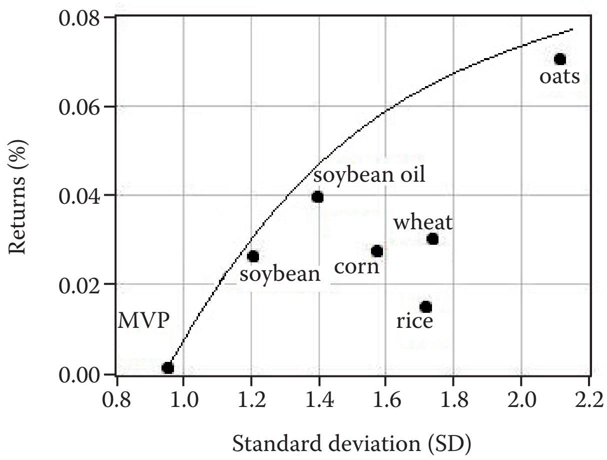

Figure 4. Efficient frontier line of the full sample

MVP – minimum variance portfolio

Source: Authors' own calculations based on data from Investing.com (2022)

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Table 5. Shares of agricultural commodities in the pre-COVID and COVID subsamples (%)

MVP	Corn	Wheat	Soybean	Soybean oil	Oats	Rice
Panel A: pre-COVID sample						
Share	7	4	19	35	8	27
Panel B: COVID sample						
Share	1	18	47	8	7	19

MVP – minimum variance portfolio
Source: Authors' own calculations based on data from Investing.com (2022)

According to Table 5, in the pre-COVID period, soybean oil has the highest share of 35%, whereas rice follows with 27%. Soybean oil reports the highest share because it has the lowest risk (1.111), while rice has a relatively high risk (1.361), but it also has the lowest average correlation with all the other commodities in the portfolio (0.120). Soybean takes third place with a share of 19% although soybean has the second lowest risk. However, soybean has the second highest average correlation (0.347), and this is the reason why soybean holds third place. Oats have the highest standard deviation (2.109), but even the second lowest average correlation with the other assets (0.176) is not enough for oats to have more than 8% in the MVP in the pre-COVID period. Both corn and wheat have a relatively high risk and average correlations, which places these cereals in the last two places with 7% and 4%, respectively.

On the other hand, in the COVID period, situation changes significantly. Soybean now has, by far, the largest share in the MVP in an amount of 47%, while rice and wheat take second and third place with 19% and 18%, respectively. Soybean has the lowest standard deviation in the COVID period (1.324), and this is the main reason why soybean has such a high share, in spite of the highest average correlation with the other assets (0.418). Rice has 19% share due having to the lowest correlation with the other commodities (0.132), although rice has the highest risk (2.247). On the other hand, wheat significantly improves its position, moving from sixth place in the pre-COVID period to third position in the COVID period. In addition, the wheat case is interesting because wheat is the only asset that actually has a lower risk in the COVID period (1.724) than in the pre-COVID period (1.741). However, wheat is not an ideal

Table 6. Pairwise correlations and volatilities in the pre-COVID and COVID subsamples

Selected assets	Corn	Wheat	Soybean	Soybean oil	Oats	Rice
Panel A: pre-COVID sample						
Corn	1.000	0.632	0.555	0.295	0.245	0.157
Wheat	0.632	1.000	0.360	0.159	0.331	0.132
Soybean	0.555	0.360	1.000	0.510	0.160	0.152
Soybean oil	0.295	0.159	0.510	1.000	0.092	0.105
Oats	0.245	0.331	0.160	0.092	1.000	0.055
Rice	0.157	0.132	0.152	0.105	0.055	1.000
Average ρ	0.377	0.323	0.347	0.232	0.176	0.120
SD	1.381	1.741	1.143	1.111	2.109	1.361
Panel B: COVID sample						
Corn	1.000	0.432	0.593	0.367	0.289	0.098
Wheat	0.432	1.000	0.484	0.313	0.237	0.071
Soybean	0.593	0.484	1.000	0.641	0.288	0.085
Soybean oil	0.367	0.313	0.641	1.000	0.229	0.038
Oats	0.289	0.237	0.288	0.229	1.000	0.370
Rice	0.098	0.071	0.085	0.038	0.370	1.000
Average ρ	0.356	0.307	0.418	0.318	0.282	0.132
SD	1.899	1.724	1.324	1.824	2.115	2.247

ρ – correlation level
Source: Authors' own calculations based on data from Investing.com (2022)

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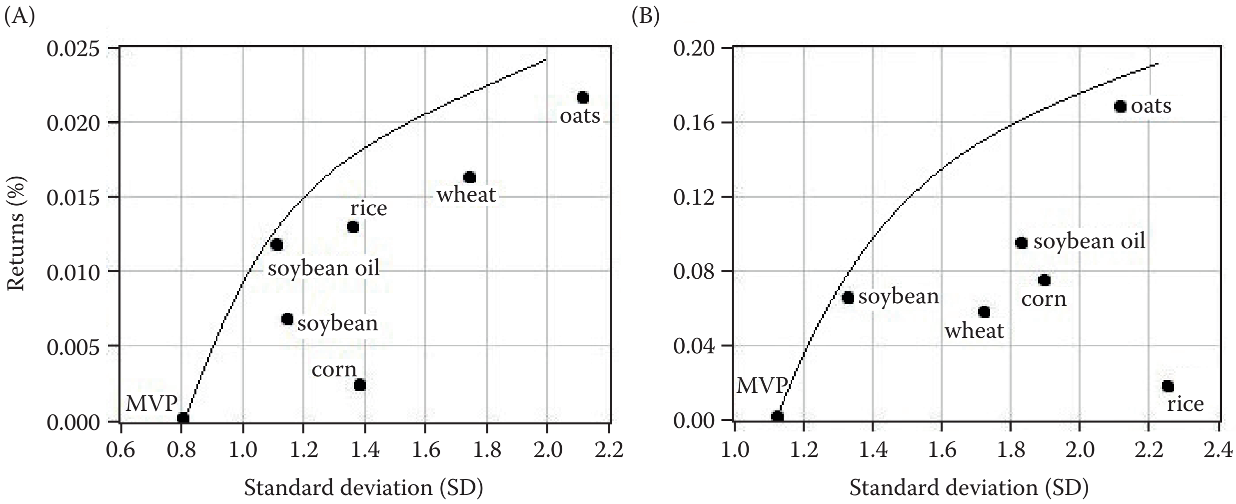

Figure 5. Efficient frontier line in the (A) pre-COVID and (B) COVID subsamples

MVP – minimum variance portfolio
Source: Authors' own calculations based on data from Investing.com (2022)

Table 7. Variances and *HEI* values in the pre-COVID and COVID subsamples

Risk measures	MVP	Corn	Wheat	Soybean	Soybean oil	Oats	Rice
Panel A: pre-COVID sample							
Variance	0.809	1.909	3.031	1.306	1.233	4.449	1.853
HEI	–	0.657	0.784	0.499	0.470	0.853	0.647
Panel B: COVID sample							
Variance	1.266	3.605	2.974	1.754	3.325	4.472	5.051
HEI	–	0.649	0.574	0.278	0.619	0.717	0.749

MVP – minimum variance portfolio; *HEI* – hedge effectiveness index
Source: Authors' own calculations based on data from Investing.com (2022)

instrument for investment in a crisis, because wheat has a relatively high correlation with the other assets (0.307). Soybean oil recorded a dramatic reduction in the share, from 35% to 8%, in spite of the fact that soybean oil has a relatively low risk in the COVID period (1.824) and not such a high correlation with the other assets (0.318). However, soybean oil has a really high correlation with soybean in the COVID period at a value of 0.641, and because soybean has the highest share of 47%, this must spill over to the low share of soybean oil. Oats traditionally have a low share due to the high risk, but the fact that corn falls to only 1% is somewhat surprising. Similar to the case of soybean oil, corn also has a very high correlation with soybean (0.593), and this means that every increase in the share of soybean must negatively transfer to soybean oil and corn, i.e. two assets that have the highest correlation with soybean.

As for the risk performance of the two MVPs, the variance in the pre-COVID portfolio is notably smaller compared to the COVID counterpart, which is expected. However, in both cases, the MVP has a significantly lower risk than any assets in the portfolio, which means that the portfolio construction is efficient in both cases (Table 7).

Figure 5 jointly presents the positions of the MVP and all the assets in the portfolio, regarding both sub-periods. It can be seen that soybean oil, corn and rice recorded a significant increase in the risk in the COVID period and vis-à-vis the pre-COVID period. On the other hand, wheat, soybean and oats have relatively equable levels of risk in both periods. However, it should be said that wheat is the only asset that has a lower risk in the COVID period than in the pre-COVID period.

CONCLUSION

This paper constructed a multivariate portfolio of six agricultural futures with the aim to minimise risk. For this purpose, we used the portfolio optimisation

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procedure of Markowitz (1952). We made a full sample portfolio, but also two portfolios in the relatively calm pre-COVID period and the relatively turbulent COVID period.

Based on the results, we have several noteworthy findings to report. Regarding the full sample analysis, soybean has the highest share in the MVP (31%) because this cereal has the lowest variance. Both soybean oil and rice have the second highest weight in the MVP, in an amount of 24%, because soybean oil has the second lowest variance, whereas rice has, by far, the lowest average correlation with the other agricultural futures.

As for the two subsamples, these results are pretty much different, which justifies the division of the full sample. Soybean oil has the highest share at 35% in the pre-COVID period, whereas rice follows with 27%. Soybean oil has the lowest risk, while rice has the lowest average correlation with all the other commodities in the portfolio, and this is the reason why rice takes second place. Both corn and wheat have a relatively high risk and high average correlations, which puts these cereals in the last two places with 7% and 4%, respectively.

On the other hand, in the COVID period, soybean dominantly has the largest share in the MVP in an amount of 47% due to the lowest risk, while rice takes second place with 19%. Soybean has the lowest standard deviation in the COVID period, and this is the main reason why soybean has such a high share. Rice has the second highest share in the COVID period due to the lowest correlation with the other commodities (0.132).

The results of this paper can be useful for investors who primarily invest in agricultural futures. In order to mitigate risk, an investor should invest the most in soybean oil and rice in tranquil periods, whereas, in crisis periods, the primary choice should be soybean and rice. Future studies can consider multivariate portfolio construction with different goals than our own, i.e. they may focus on the downside risk, considering alternative econometric approaches, such as value-at-risk, conditional value-at-risk or maybe even the modified value-at-risk. This would be a logical extension of our work.

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