

Agricultural commodity markets during the COVID-19 pandemic and the energy crisis: A time-varying copula approach

PETER ÁRENDÁŠ^{*}, BARBARA ČERYOVÁ, JANA KOTLEBOVÁ

*Department of Banking and International Finance, Faculty of Economics and Finance, Bratislava
University of Economics and Business, Bratislava, Slovakia*

**Corresponding author: peter.arendas@euba.sk*

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Abstract: Agricultural commodity markets are highly important not only for investors but also for consumers. Given their importance, closer attention should be paid to agricultural commodity prices and their interactions with other segments of the financial market. In this paper, we apply time-varying copula analysis to investigate the development of the dependence structure between three main groups of agricultural commodities (Bloomberg Grains TR Index, Bloomberg Softs TR Index, and Bloomberg Livestock TR Index) and other segments of the financial market (Brent crude oil, the US Dollar Index, and the broader stock market represented by the S&P 500 stock market index). We use daily data from 2017 to 2024, covering the relatively calm pre-COVID-19 period and the turbulent COVID-19 and subsequent energy crisis periods. The results show that, despite increases in both overall and lower-tail dependence during the pandemic, the relationships remained relatively weak even at their peak. This indicates that the ability of agricultural commodities to provide risk diversification remained intact, even during the two extreme global events. However, the observed time variation indicates that hedging strategies should include dynamic risk monitoring and stress testing.

Keywords: grains, softs, livestock, stock markets, dollar index, risk spillovers

Agricultural commodities are highly important, not only as the source of food for the human population but also as underlying assets for a broad range of financial instruments. Therefore, steep price changes may have significant socio-economic impacts, and understanding the relationships between agricultural commodity markets and other segments of the broader financial market is of high importance.

The aim of this paper is to evaluate the development of the dependence structure between three main groups of agricultural commodities (grains, softs, livestock), and other segments of the financial market (Brent crude

oil, the US Dollar index, and the broader stock market represented by the S&P 500 stock market index) during the COVID-19 pandemic and the energy crisis.

As agricultural commodity derivatives are traded on commodity exchanges, agricultural commodity prices are affected not only by physical supply and demand but also by the overall sentiment and developments in other segments of financial markets. The growing financialisation of commodity markets has been documented by several studies, including Adams et al. (2020) or Kim (2020). According to Jana and Ghosh (2023), geopolitical uncertainty is another

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important factor affecting agricultural commodity prices. However, other market factors are also at play. In this paper, we examine the relationships among agricultural commodity prices, oil prices, the S&P 500 stock index, and the US Dollar Index, as these factors are widely recognised to significantly affect agricultural commodity prices, as indicated by numerous studies.

The dependence between agricultural commodity prices and oil prices is based on several practical aspects. Oil is an important input for agricultural production, as the vast majority of vehicles used in agriculture are still equipped with traditional combustion engines. Moreover, oil and natural gas are important for the production of fertilisers and pesticides. This means that higher oil prices push the production costs of agricultural commodities higher. On the other hand, when oil prices are higher, it is more profitable to produce biofuels. Higher production of biofuels pushes demand for commodities such as corn, sugar, soybeans, and rapeseed higher.

The existence of a relationship between oil and agricultural commodity prices, due to the production of ethanol and consumption of oil-based products in agriculture, is confirmed by Harri et al. (2009). On the other hand, Cabrera and Schulz (2016) conclude that biofuel production doesn't have a major impact on the volatility of agricultural commodity prices. Su et al. (2019) found time-varying positive bidirectional causality between oil and agricultural commodity prices; however, this effect was observed only in some periods. Based on findings of Zilberman et al. (2013), the impacts of biofuels on agricultural commodity prices vary across crops and regions. According to Nazlioglu and Soytaş (2012), panel cointegration and causality analyses confirm the impact of oil prices on agricultural commodity prices. They even found a causal relationship running from agricultural commodity prices to oil prices and to the value of the USD, attributing this unexpected finding to investors' portfolio diversification strategies. The existence of relationships between oil prices and agricultural commodity markets is also confirmed by Miljkovic and Vatsa (2023) and Wang et al. (2014).

A study by Rezitis (2015) confirms that oil prices, as well as the USD exchange rates, affect agricultural commodity prices. The results indicate a bidirectional panel causality. Lerkeithamrong et al. (2019) identify a long-term relationship between global stock market volatility, the USD exchange rate, and agricultural commodity prices. They conclude that stock market volatility has a positive impact on agricultural commodity

prices, while the strengthening of the USD exchange rate has a negative impact.

Zapata et al. (2012) examine the long-term relations between the stock and commodity markets, including agricultural commodities, over a 140-year period. They find that the two markets tend to switch price leadership in 29–32-year cycles. Baldi et al. (2016) and Babar et al. (2024) confirm spill-over effects between stock and agricultural commodity markets during crisis periods.

Borgards et al. (2021) investigate the intraday price behaviour of 20 commodities (including wheat, corn, soybeans, soybean oil, cocoa, coffee, sugar, and cotton) during the COVID-19 pandemic. They discover price overreaction in all 20 cases; however, according to their findings, the overreaction is strongest in energy commodities and much weaker in soft commodities (agricultural commodities included).

The main currency used for trading in the global agricultural markets remains the USD, as shown also by Rees (2023). Therefore, we also include the US Dollar Index in our analysis.

The application of copula models on agricultural commodity markets is not a new idea. Several studies examine this issue (Fousekis and Grigoriadis 2017; Albulescu et al. 2020; Tansuchat and Rakpho 2022); however, they usually focus on the dependence structure within the agricultural commodity market segment.

Although the relationships among agricultural commodity prices, oil prices, the value of the USD, and broader stock market performance have been investigated by earlier studies, there remain gaps to be filled. In this paper, we apply the time-varying copulas to analyse the evolution of the relationships over time. This paper focuses on the evolution of dependence structure during the COVID-19 pandemic and the energy crisis. The impacts of the COVID-19 pandemic on agricultural commodity markets are also investigated in a study by Palason et al. (2022); however, they focus on the dependence among individual agricultural commodities. Moreover, their study uses a period ending in July 2021, in the middle of the pandemic. Umar et al. (2021), who use wavelet analysis to assess the impact of COVID-19, focus on the period ending in July 2020. And the time period investigated by Hung (2021) ends as early as May 2020.

Our paper fills this gap by capturing not only the whole pandemic period but also the subsequent energy crisis period. These are two of the most important events to have affected the global economy in recent decades. Moreover, we use time-varying copulas, which enable us to better capture the evolution of the relationships over time.

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Table 1. Bloomberg indices components and weights

Bloomberg grains TR	Bloomberg softs TR	Bloomberg livestock TR
soybeans (25.55%)	coffee (40.99%)	live cattle (65.56%)
corn (24.35%)	sugar (36.66%)	lean hogs (34.44%)
soybean meal (15.59%)	cotton (22.35%)	
soybean oil (14.42%)		
wheat (12.34%)		
HRW wheat (7.75%)		

HRW – Hard Red Winter

Source: Own processing, using data from Bloomberg

MATERIAL AND METHODS

Our investigation focuses on the 2017–2024 period. The first cases of COVID-19 were reported in December 2019 in China; however, the disease started spreading globally only in January 2020. In February, the first measures to contain the disease were adopted by individual countries. The WHO declared the COVID-19 pandemic on March 11 (Cucinotta and Vanelli 2020). It means that the investigated period covers approximately three pre-COVID-19 years, the COVID-19 period, the energy crisis period (approximately June 2021–January 2023), and two post-energy-crisis years.

The analysed daily data are retrieved from Investing.com databases. Three indices represent the agricultural commodity market: the Bloomberg Grains TR Index (Grains Index), the Bloomberg Softs TR Index (Softs Index), and the Bloomberg Livestock TR Index (Livestock Index). The 2023 target weights attributed to individual commodities are presented in Table 1. Although the weights change every year, the changes are relatively small. Therefore, the numbers presented in Table 1 are relevant for the entire investigated period.

We examine the relationships of the abovementioned three indices with the stock market (represented by the S&P 500 stock index), the oil prices (Brent), and the US Dollar Index. We expect that due to the interconnectedness of global financial markets, developments in major stock markets, especially during volatile periods, should have an impact on agricultural commodity markets. At the same time, we also anticipate an influence from the oil market, as oil is used for the production of fuels and nitrogen fertilisers. Another important transmission channel lies in biofuels. Their production is more attractive when oil prices are high, which also helps push up the prices of commodities such as sugar, corn, wheat, and soybeans.

Conforming to the common practice in studies focusing on volatility and dependence structures, all six data series used for analysis are transformed to log returns, as they exhibit desirable statistical properties, including approximate stationarity and additivity over time, making them suitable for ARMA-GARCH (autoregressive moving average – generalised autoregressive conditional heteroskedasticity) filtering and copula-based dependence modelling (Patton 2012). Their summary statistics are presented in Table 2.

Table 2. Summary statistics of univariate log returns ($n = 2\,011$)

Variable	Mean	SD	Min	25th Percentile	75th Percentile	Max
Brent	0.000 1	0.025	–0.28	–0.01	0.013	0.191
USD	0.000 03	0.004	–0.021	–0.002	0.002	0.016
SPY	0.000 5	0.012	–0.128	–0.004	0.006	0.09
Grains	0.000 02	0.013	–0.064	–0.007	0.007	0.062
Softs	0.000 2	0.013	–0.052	–0.008	0.008	0.049
Livestock	0.000 01	0.011	–0.063	–0.006	0.006	0.056

SPY – S&P 500 Stock Index; SD – Standard Deviation

Source: Own processing

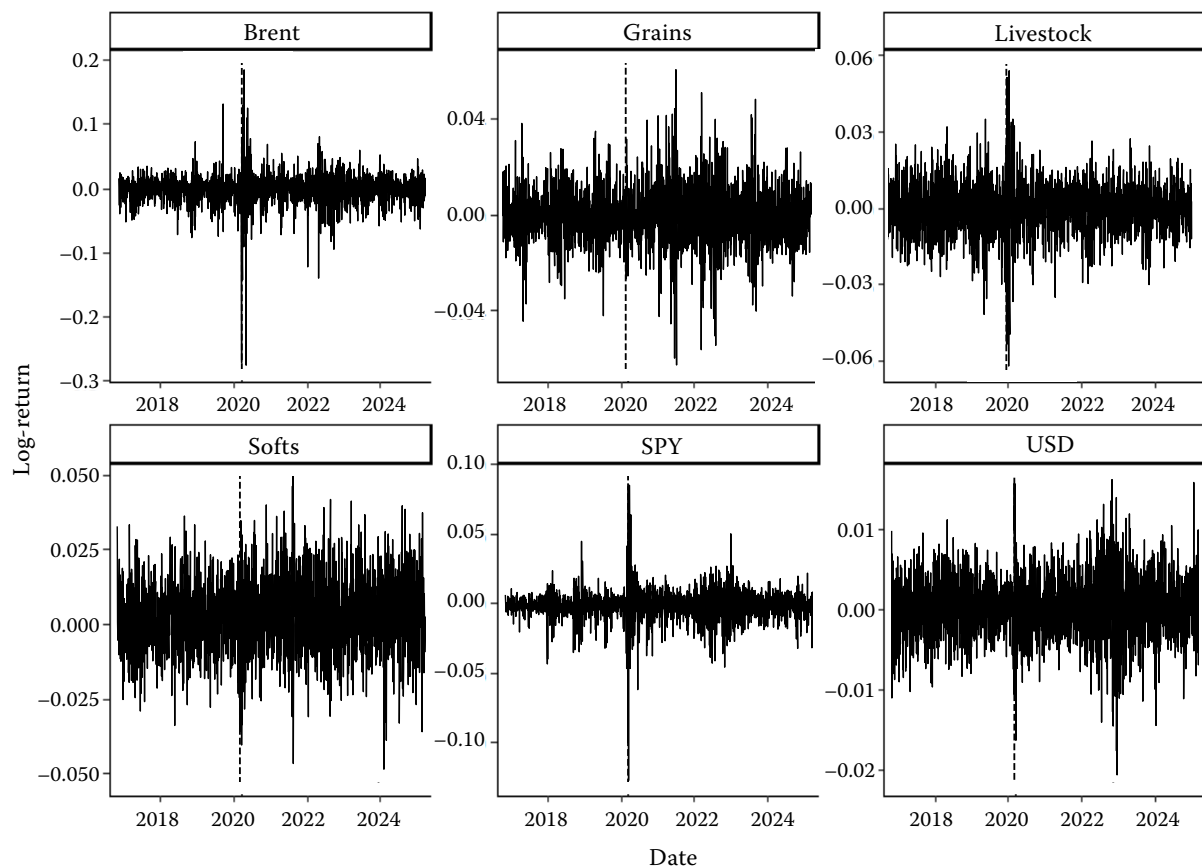


Figure 1. Log returns line chart for univariate time series

SPY – S&P 500 Stock Index

Source: Own processing

The log returns of the analysed time series are also visualised in Figure 1, highlighting the sudden jumps around the dashed vertical line marking the official declaration of the COVID-19 pandemic by the WHO.

We implement time-varying copula models to monitor the evolution of all nine bivariate relationships formed from combinations of the analysed time series. The approach originally applied by Gregoire et al. (2008)

and Aloui et al. (2013) is loosely followed. As copula modelling requires the data to be stationary and serially independent, several statistical tests are performed. Results of the ADF (augmented Dickey–Fuller) and KPSS (Kwiatkowski–Phillips–Schmidt–Shin) test, portrayed in Table 3, jointly confirm the stationarity of all log-differenced variables. However, based on the results of the Ljung–Box test in Table 3, the presence of serial

Table 3. Statistical tests to determine the data suitability for copula modelling

Variable	ADF test <i>P</i> -value	KPSS test <i>P</i> -value	Ljung–Box test <i>P</i> -value
Brent	< 0.01	> 0.10	0.00
USD	< 0.01	> 0.10	0.00
SPY	< 0.01	> 0.10	0.00
Grains	< 0.01	> 0.10	0.00
Softs	< 0.01	0.04	0.00
Livestock	< 0.01	> 0.10	0.00

ADF – augmented Dickey–Fuller; KPSS – Kwiatkowski–Phillips–Schmidt–Shin; SPY – S&P 500 Stock Index

Source: Own processing

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autocorrelation is indicated. Therefore, data filtration through an ARMA-GARCH process is necessary to obtain serially independent standardised residuals, which is performed over the full sample period (2017–2024). GARCH (1,1) is estimated via the maximum likelihood method and is used in all the cases, as it provides accurate volatility estimates despite its simplicity, as suggested by Bollerslev et al. (1992), validated by Hansen and Lunde (2001), Rašiová and Árendáš (2023), and Čeryová and Árendáš (2025) in copula modelling. To discover the optimal lag length for the ARMA(m,n) process, different specifications are estimated, and the final lag structure is chosen to balance goodness of fit and parsimony using AIC (Akaike information criterion) and BIC (Bayesian information criterion) model selection criteria. Although both criteria balance model fit and complexity, they differ in the degree to which additional parameters are penalised. AIC favours models with better in-sample fit, whereas BIC imposes a stronger penalty on model complexity. Using both of them allows for a balanced assessment of alternative specifications and helps avoid overfitting. Considering a time series of Y_t , an ARMA(m,n)-GARCH(1,1) model can be specified as:

$$Y_t = \mu + \sum_{i=1}^m \alpha_i Y_{t-i} + \sum_{j=1}^n \beta_j \varepsilon_{t-j}$$

$$\varepsilon_t = \sigma_t Z_t \quad (1)$$

$$\sigma_t^2 = \omega_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

where: coefficients $\omega_0 > 0$, $\alpha \geq 0$, $\beta \geq 0$; μ – a constant term; $Z_t = \varepsilon_t / \sigma_t$ – the standardised residuals, which are independent and identically distributed, following a standard normal distribution; σ_t – the conditional variance of the time series at time t ; ε_t – the innovation term at time t .

The selected lag lengths are presented in Table 4. They are relatively low-order, which is consistent with the weak dependence typically observed in financial and commodity return series. Additionally, the selected ARMA (m,n)-GARCH (1,1) models are validated through post-estimation diagnostics, confirming that the serial dependence is removed from the standardised residuals. Their stationarity and serial independence are verified to meet the requirements for copula modelling, as reported in [Table S1 \(Electronic Supplementary Material – ESM\)](#). As a last step of data preparation, standardised residuals undergo probability integral transformation based on the standard normal distribution, since the copula is a function of uniform margins, and the so-called pseudo-observations enter the modelling phase.

Time-varying copula models. Traditional multivariate models such as GARCH, vector error correction and conditional heteroskedasticity (VECH) model, or the Baba, Engle, Kraft, and Kroner (BEKK) model are typically estimated under the assumption of multivariate normality or a combination of elliptical distributions (Brutti et al. 2012). However, this assumption proves unrealistic, as financial asset returns tend to exhibit skewness, leptokurtosis, and asymmetric dependencies. Copulas provide a solution to these challenges by decomposing the joint probability density function into the marginal distributions of variables and the cross-correlation structure, constructing a model as a product of these components. Consequently, they demonstrate greater flexibility in accommodating measurement variations, outperforming popular models, including dynamic conditional correlation (DCC)-GARCH (Han et al. 2023).

Introduced by Sklar (1959), copulas serve as mathematical functions that facilitate the modelling of a wide range of dependency patterns by connecting multivariate distributions to their individual univariate

Table 4. ARMA (autoregressive moving average) lag lengths chosen by AIC (Akaike information criterion) and BIC (Bayesian information criterion) used for univariate time series to obtain standardised residuals for copula modelling

Variable	AR coefficient	MA coefficient
Brent	2	2
USD	2	2
SPY	4	4
Grains	0	1
Softs	2	0
Livestock	2	2

AR – Autoregressive; MA – Moving Average; SPY – S&P 500 Stock Index

Source: Own processing

components. In the realm of finance, copulas have been gaining attention since the early 2000s, especially in fields such as risk management, portfolio management, and modelling asset returns. This paper focuses on three categories of copula models: elliptical copulas (such as Gaussian and Student- t), Archimedean copulas (including Clayton, Frank, Gumbel, and Joe), and extreme-value copulas (specifically Gumbel).

The various copula models examined in this paper encompass a broad spectrum of dependency structures, ranging from complete independence to extreme interdependence. The Gaussian copula, for instance, is symmetric and lacks tail dependence, whereas the Student- t copula captures symmetric tail dependence between variables. Among the Archimedean copulas, the Frank copula exhibits symmetric dependence, making the other Archimedean copulas more suited for capturing asymmetric dependencies compared to elliptical copulas. Specifically, the Clayton copula demonstrates stronger dependence in the lower tail, while the Gumbel and Joe copulas exhibit stronger dependence in the upper tail. Within the extreme-value copula category, the Gumbel copula provides an appropriate model for representing the dependence structure between extreme events associated with unexpected, abnormal, or extreme outcomes.

Additionally, rotated versions of Archimedean and extreme-value copulas are considered to portray negative dependence. Particularly, the distribution functions C_{90} and C_{270} of a copula C rotated by 90 and 270 degrees. In addition, the survival copula, which can be viewed as the mirror image of the density of the respective copula, is obtained by a 180-degree rotation, C_{180} , and is implemented.

With $u_1, u_2 \in [0, 1]$ representing univariate margins, rotated copulas are defined in Brechmann and Schepmeier (2013) as:

$$\begin{aligned} C_{90}(u_1, u_2) &= u_2 - C(1 - u_1, u_2) \\ C_{180}(u_1, u_2) &= u_1 + u_2 - 1 + C(1 - u_1, 1 - u_2) \\ C_{270}(u_1, u_2) &= u_1 - C(u_1, 1 - u_2) \end{aligned} \quad (2)$$

After the selected copula models and their rotated versions are fitted to the variable pairs, we use the AIC criterion to select the most appropriate specification for each case and to describe the bivariate dependence

over the full sample period. We also use the goodness-of-fit (GOF) test of Wang and Wells (2000), with parametric-bootstrap P -values described by Genest et al. (2006), to ensure that the chosen model specifications fit the data.

However, empirical evidence indicates that correlations among asset returns exhibit temporal variability (Engle 2002). While copulas offer flexibility in capturing various dependence structures, it appears unrealistic to maintain the assumption of constant dependence, considering the established evidence of time-varying correlations. Additionally, given that the observed period includes the COVID-19 pandemic, as well as the energy crisis, we aim to examine how dependence evolved during this turbulent era. To achieve this objective, we employ time-varying copulas. Within the selected copula parametrisation, we utilise a 250-day window, corresponding to approximately one year, to estimate the rolling copula dependence parameter θ , Kendall's τ rank correlation, and tail dependence coefficients where the underlying model allows it, as further specified in Gregoire et al. (2008) and Aloui et al. (2013). The rolling window is selected to balance the trade-off between capturing time variation and ensuring sufficient observations for reliable estimation. To quantify estimation uncertainty, 95% bootstrap confidence bands for Kendall's τ were constructed using 250-day rolling windows; the results are reported in Figure S4 (ESM). As a sensitivity check, the analysis was also repeated using 200- and 300-day rolling windows; the resulting dependence patterns are presented in Figures S5 and S6 (ESM).

RESULTS AND DISCUSSION

The best-fitting bivariate copula models for each variable pair, based on the AIC and BIC criteria, are presented in Table 5. Their suitability is further confirmed by the GOF test of Wang and Wells (2000), with parametric bootstrap for P -values described by Genest et al. (2006), presented in Table S2. The Gaussian copula, selected for three variable pairs (Brent-Grains, Brent-Softs, and USD-Softs), is the prevailing specification. Their bivariate dependence is therefore symmetrical and does not increase in times of highest and lowest returns due to the absence of tail dependence. For Brent-Livestock, the Clayton copula is selected, featuring an asymmetric dependence structure with only lower tail dependence and greater dispersion in higher quartiles. However, tail dependence amounts to 0, likely as a consequence of a weak overall dependence.

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Table 5. The best-fitting bivariate copula models (based on AIC and BIC criteria). *P*-values for tail dependence are not reported, as they are deterministic functions of the estimated copula parameters

Variable Pair	Family	Copula parameter	Kendall's tau	Upper tail dependence	Lower tail dependence	Log-likelihood	AIC	BIC
Brent-Grains	Gaussian	0.179	0.114	0	0	32.268	−62.535	−56.929
Brent-Softs	Gaussian	0.23	0.148	0	0	54.088	−106.176	−100.569
Brent-Live-stock	Clayton	0.108	0.051	0	0.002	9.616	−17.233	−11.627
USD-Grains	Frank	−0.553	−0.061	0	0	8.439	−14.879	−9.272
USD-Softs	Gaussian	−0.131	−0.083	0	0	17.112	−32.225	−26.618
USD-Live-stock	rotated Joe 270 degrees	−1.047	−0.027	0	0	5.975	−9.95	−4.344
SPY-Grains	survival Joe	1.072	0.04	0	0.091	9.08	−16.159	−10.553
SPY-Softs	survival Gumbel	1.08	0.074	0	0.101	18.831	−35.662	−30.055
SPY-Live-stock	survival Gumbel	1.087	0.08	0	0.108	22.043	−42.086	−36.48

AIC – Akaike information criterion; BIC – Bayesian information criterion; SPY – S&P 500 Stock Index

Source: Own processing

For USD-Grains, a Frank copula is picked. It is typical for symmetrical dependence with no tail dependence. A rotated Joe 270-degree copula is selected for the USD-Livestock pair. It is an Archimedean copula with negative low-tail dependence, which is 0 in our case. For SPY(S&P 500 Stock Index)-Grains, SPY-Softs, and SPY-Livestock, Survival Joe and Survival Gumbel copulas are selected. Both of them picture positive dependence with a pronounced lower tail; however, in the case of Joe, higher dispersion of values in the higher quartiles can be observed.

As expected, the results show a negative dependence between the US Dollar Index and the three agricultural commodity indices. This means that strengthening the USD is associated with weaker agricultural commodity prices, and *vice versa*. Another important finding is the low lower-tail dependence between the S&P 500 and the agricultural commodity indices. In this case, the relationship is positive, indicating the existence of a contagion effect during periods of market turbulence. This may be attributed to investors' tendency to liquidate positions and prefer liquidity during periods of sudden market turbulence (Coval and Stafford 2007; Brunnermeier and Pedersen 2009). However, the values are not high, indicating that contagion effects are limited.

To investigate the time variance of the observed dependencies, we apply time-varying copula analysis (Figure 2). For each analysed pair, the copula family

presented in Table 5 is fitted in 250-day (approximately 1-year) moving windows. The dependence parameters θ and Kendall's τ are used to track the evolution of the dependence. The dependence parameter is central to copula modelling; however, it doesn't enable a reliable comparison of results across different copula families because of differing parameter ranges. Kendall's τ solves this problem, as its value always belongs to the interval $(-1;1)$, regardless of the copula family (Figure 3).

Interestingly, in the case of the Brent-Grains and Brent-Softs pairs, dependence started rising in late 2018/early 2019, long before the first cases of COVID-19 appeared. However, the growth trend continued after the pandemic was declared. Dependence between Brent and Grains peaked in late 2022 and early 2023, during the energy crisis. As the energy crisis eased, the relationship began to weaken considerably. The same applies to the Brent-Softs pair. A completely different situation can be observed in the case of Brent-Livestock, where an almost non-existent dependence started rising rapidly around the time of the pandemic declaration. However, in early 2022, it started declining steeply, returning to values close to zero in late 2022/early 2023. It subsequently increased again.

It is also possible to see that the dependence between oil and grains and oil and softs tends to be stronger than the dependence between oil and livestock. The largest difference is observed during the energy crisis, with τ

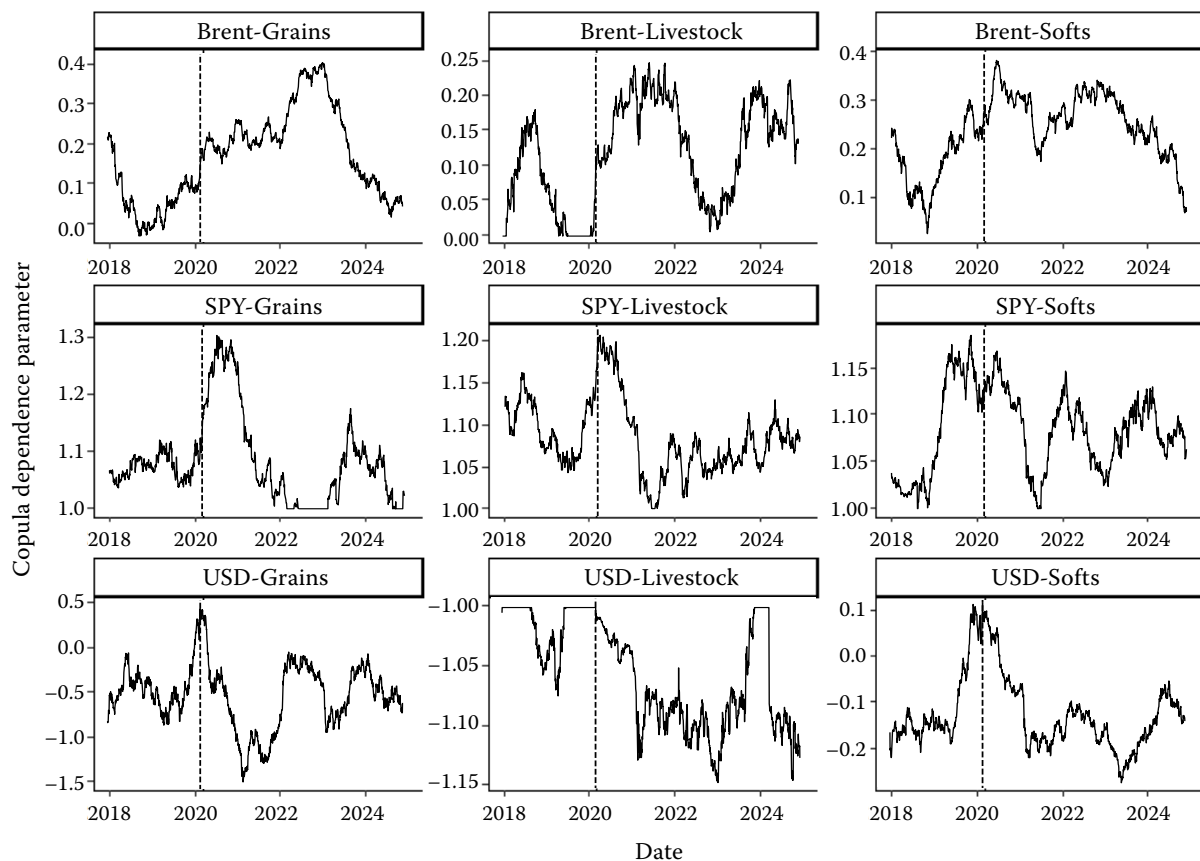


Figure 2. Time-varying dependence parameters for bivariate pairs

SPY – S&P 500 Stock Index

Source: Own processing

values around 0.2 for grains and softs, and close to 0 for livestock. This can be attributed to higher fuel and fertiliser costs, which affect crop production much more strongly than livestock production, as well as to higher demand for biofuel production, which pushes soybean (grains), corn (grains), and sugar (softs) prices higher.

A different picture emerges in pairs containing SPY or USD. Kendall's τ reaches negative values, which is in line with the theory. The stronger the USD, the lower the USD-denominated prices of agricultural commodities. This is also confirmed by the findings of Lerkeithamrong et al. (2019). In all three cases, meaningful changes in the dependence were observed. For USD-Grains, a near-zero dependence declined to negative levels shortly after the WHO declared the pandemic. A very similar picture could also be seen at USD-Livestock. But an interesting pattern appears for USD-Softs. In late 2019, the negative τ values turned positive, only to return to the original levels. At SPY-Livestock, USD-Grains, USD-Livestock, and USD-Softs, the decline began almost immediately,

whereas for SPY-Grains and SPY-Softs, there was a delay of several weeks.

Although τ -values remained low for SPY-Grains and SPY-Livestock during the energy crisis, SPY-Softs showed a recovery. Also, the behaviour of the USD pairs is interesting. While for USD-Livestock and USD-Softs, the τ -values did not change significantly during the energy crisis, at USD-Grains, they increased from negative values to 0 in 2022.

It is important to note that although the strength and, in some cases, the direction of the relationships evolved, τ values remained relatively low, in the $(-0.15 - 0.20)$ range. This means that the contagion effects were only limited.

Figure 4 captures the evolution of the lower tail dependence coefficient λ_l for bivariate pairs for which it is defined, namely Brent-Livestock, SPY-Grains, SPY-Livestock, and SPY-Softs. As can be seen, in all four cases, the evolution of the low tail dependence mirrors the evolution of the copula parameter θ and Kendall's τ . In the case of Brent-Livestock and SPY-Grains pairs, a notable increase occurred during the

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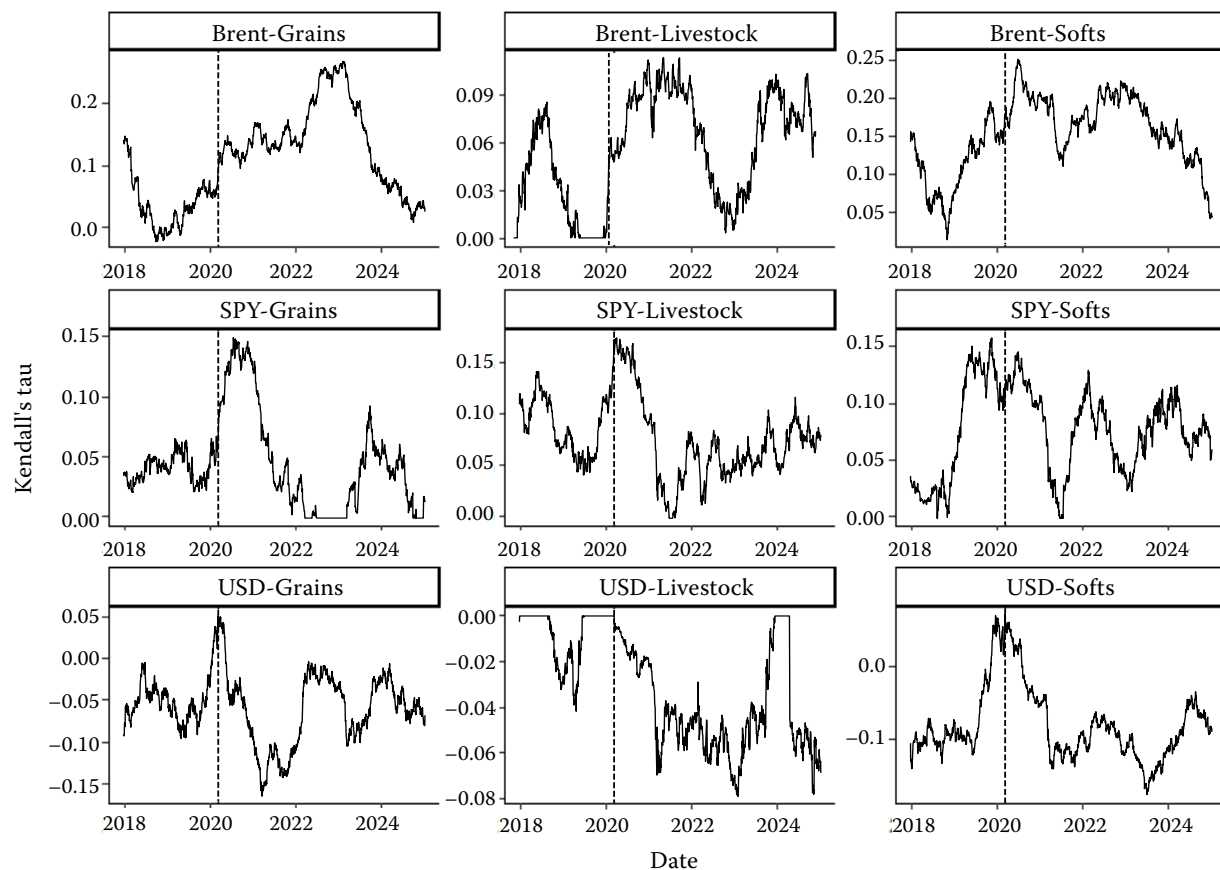


Figure 3. Time-varying Kendall's τ for bivariate pairs

SPY – S&P 500 Stock Index

Source: Own processing

COVID-19 outbreak, and some increase also occurred at SPY-Softs. This is in line with the findings of Babar et al. (2024), who conclude that the spill-over effects between agricultural commodity markets and stock markets increase during crisis periods. On the contrary, at SPY-Livestock, the lower tail dependence started to decline. Subsequently, in 2021, during the steep stock market recovery, lower-tail dependence declined rapidly for all three pairs containing SPY. Except for SPY-Softs, lower-tail dependence declined and then stagnated during the energy crisis. For SPY-Softs, dependence rebounded.

Despite the increase shortly after the COVID-19 pandemic outbreak, the low tail dependence remained relatively low for all the investigated pairs. It is possible to assume that dependence remained relatively low also during the crisis periods, especially due to the specific nature of agricultural commodity markets. Demand for them is relatively stable and inelastic, and their supply is heavily dependent on weather conditions, inventories, crop outlook, and related factors

(Taskin et al. 2021; Letta et al. 2022). Another important role may be played by government policies, such as the management of strategic food reserves or export restrictions (Giordani et al. 2016; Dorosh et al. 2025). These factors may be a major limiting factor on the dependence between agricultural commodities and broader financial markets.

The low level of dependence further indicates the potential of agricultural commodities to provide diversification to investment portfolios. This finding is in line with the study by Umar et al. (2021), which uses wavelet analysis to examine how the COVID-19 pandemic influenced the volatility of various commodity classes. They outline the potential of commodities to be used in cross-asset hedge strategies.

As an additional robustness check, multivariate two-sample tests were applied to assess the stability of the joint distributions across the pre-COVID, COVID, and post-COVID periods, with their start dates defined by Cucinotta and Vanelli (2020) and Sarker et al. (2023). The results are reported in Table S3.

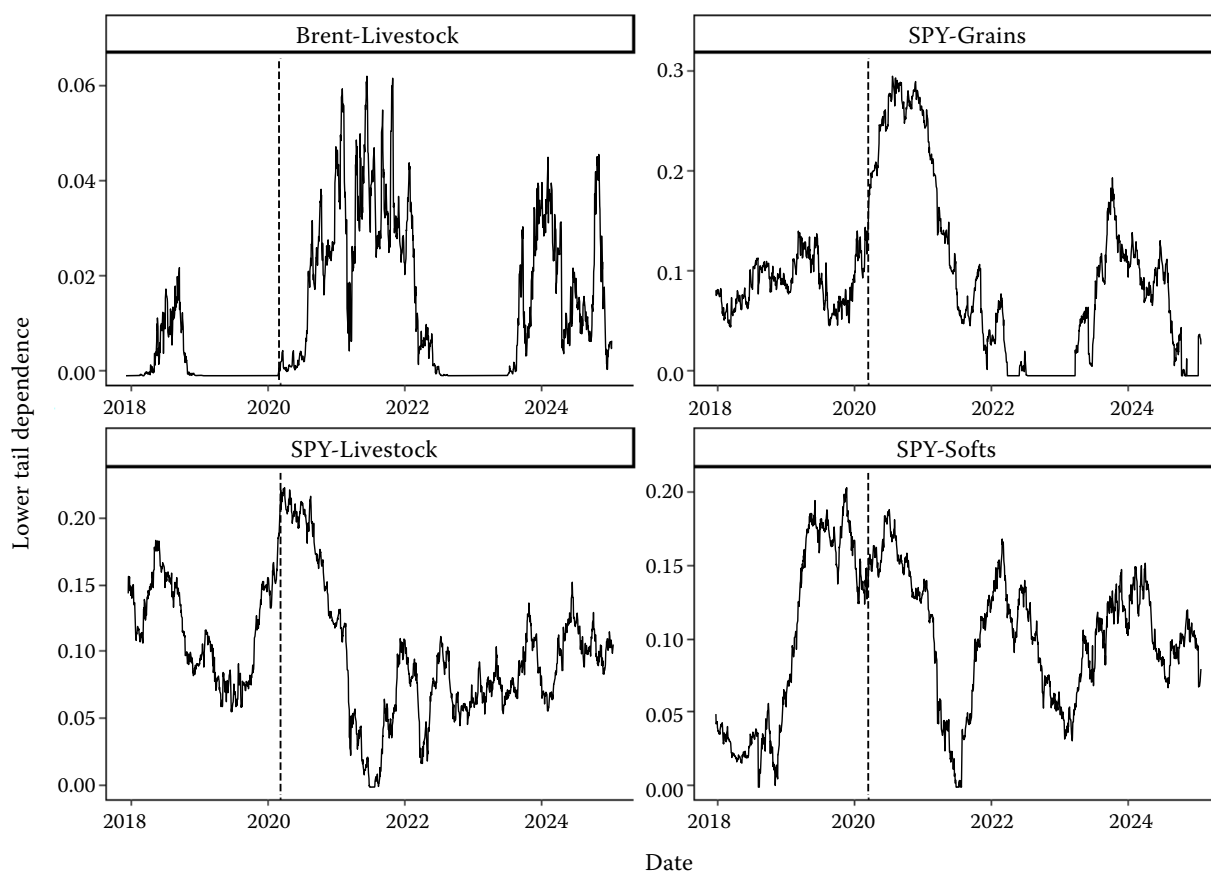


Figure 4. Time-varying lower tail dependence coefficient λ_l for bivariate pairs where it is defined.

SPY – S&P 500 Stock Index

Source: Own processing

The corresponding scatter plots of the pseudo-observations for the pre-COVID, COVID, and post-COVID periods are presented in [Figures S1–S3 \(ESM\)](#).

The time variation (although limited) in copula parameters and τ values indicates that dependence is state-dependent, and models and hedging strategies calibrated for calm periods may underestimate downside risks. Therefore, hedging strategies should be supplemented by dynamic dependence monitoring and stress tests based on data from previous crisis periods. Moreover, one-year rolling windows smooth the dependence estimates, which means that while the agricultural commodities may provide a positive diversification effect in the mid-to-long term, they may be less efficient over shorter time horizons.

CONCLUSION

In this paper, we analyse the evolution of the dependence structure between three main groups of agricultural

commodities (grains, softs, livestock) and three important non-agricultural markets (Brent oil, the US Dollar index, and the S&P 500) during the 2017–2024 period. The implementation of time-varying copula analysis enables a closer look at the dynamics of relationships during the COVID-19 pandemic and the energy crisis, which is a major advantage over other commonly used methods.

The results show several findings. The dependence between agricultural commodities and the US Dollar Index is predominantly negative, due to pricing mechanisms and purchasing power effects. Moreover, the dependence between grains and softs and Brent oil prices tends to increase during the energy crisis period, pointing to an important role of biofuel and input-cost channels. However, the most important finding, especially from a practical perspective, is the weak dependence between agricultural commodity markets and the S&P 500. On the other hand, although the relationship is relatively weak, it grows slightly during crisis periods. While the weak relationship is a positive finding

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in terms of portfolio diversification, its growth during the crisis periods may mean that hedging strategies calibrated on calm-period data can underestimate downside risks during crisis periods. The employment of dynamic dependence monitoring and stress tests based on data from previous crisis periods could help to mitigate this issue.

An important finding for policymakers is that although agricultural commodity markets tend to react to broader financial market turbulence, the reaction is limited in both extent and duration. This means that no special measures to deal with dependence between financial and agricultural commodity markets are necessary. Policymakers should focus on sector-specific factors, such as weather and climate shocks and supply chain disruptions.

However, we are aware of several limitations to our study that may be addressed in future research. We use only benchmark index values. Using price series of individual agricultural commodities could provide a deeper picture of the dependency structures. Investigating country-level price series could provide an additional level of information. From a methodological standpoint, the use of regime-switching copulas could help better capture dependence structures during periods of abrupt market shocks.

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