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Multifrequency downside risk interconnectedness between soft agricultural commodities

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Abstract: In this article, we explore multiscale extreme risk interdependence between four soft agricultural markets – coffee, cocoa, cotton and orange juice. Wavelet correlation and cross-correlation are used to investigate this interlink, and dynamic conditional Value at Risk is used to measure extreme risk. Wavelet correlation results suggest a very weak connection between the markets in the short-term and midterm horizons, which means that investors who operate in the short term or midterm do not have to apply hedging measures against extreme risk. However, the situation is different in the long term, where relatively high correlations are found on the highest wavelet scale in all pairs, except coffee–cocoa. Complementary cross-correlation analysis indicates a lead–lag relationship between the markets. The results are mostly in line with expectations, as bigger markets lead smaller markets. Only in the cases of cocoa–cotton and cocoa–orange juice does the opposite happen.

Keywords: conditional Value at Risk; extreme risk interdependence; wavelet correlation; wavelet cross-correlation

Investing in commodity futures has become popular in the last decade (Árendáš and Kotlebová 2023; Babar et al. 2023) because investors have paid more attention to alternative assets after the equity market crash in 2008. This type of investment is particularly attractive because a different set of factors affects commodities and traditional assets such as stocks and bonds, which produce low correlation between them (Umar and Olson 2022). This essential prerequisite must be met if investors want to construct a portfolio with good diversification characteristics. However, related to the topic of portfolio construction, volatility transmission remains underexplored in the literature, according to Živkov et al. (2022). Gardebroek et al. (2016) argued that second moment interdependence is very important to address because interlinks in variance could provide a better understanding of dynamic price relationships. This happens because the rise of volatility in one market could generate increased volatility in another market because of demand substitution or the joint underlying causes of volatility. Fernández-Avilés et al. (2020) asserted that close volatility connections between markets might lead to missing arbitrage and hedging opportunities for traders and investors, which is accompanied by huge challenges in balancing their portfolios. In this regard, investigating relationships between agricultural commodity futures has become an imperative in re-

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cent years because more investors consider investing in these instruments (Akyildirim et al. 2022).

Given this situation, we hypothesise in this article the situation of an investor who wants to invest in soft agricultural commodities, with the aim of determining risk interdependence between the markets. This knowledge could be valuable for global investors because if there is an intense risk transfer between markets, then assets from such markets are not good candidates to be in the same portfolio. In particular, the goal of this article is the investigation of time-varying risk interdependence between the four soft agricultural futures commodities (coffee, cocoa, cotton and orange juice) traded on the Chicago Mercantile Exchange. To our knowledge, the authors of very few articles have investigated the risk association between agricultural commodities, and none have researched soft agricultural commodities. This lack of research leaves a lot of room for our contribution, which is where we find a motive for this study. Futures are considered rather than cash prices because futures markets have higher trading volumes that process and incorporate new information into prices more quickly, which makes them more appropriate for the analysis (Palanska 2020). In addition, investigation of risk connections between the markets is particularly important in light of the two recent crises – the COVID-19 pandemic and the war in Ukraine (Boscá et al. 2021) – which have caused significant price oscillations on the global agricultural markets in the last few years, as Figure 1 shows. Huge price movements are fertile ground for extreme risk, and the task of this article is to stipulate whether extreme risk is interconnected between the markets and also to determine which market leads and which one lags in this relationship.

The research contributes in the following ways. In the process of risk evaluation, we do not use common variance because variance is a biased measure of risk that can lead to wrong conclusions, which happens because variance does not distinguish positive and negative returns, and investors are only keen to know the risk of negative returns. In this regard, instead of variance, we observe downside risk that takes into account only negative returns. The most famous measure of downside risk is the parametric value at risk (VaR), introduced by J.P. Morgan bank in 1994. VaR overcomes the problem of positive returns, but it is not an ideal risk measure because it cannot measure the losses beyond the threshold amount of VaR, which might lead to underestimation of the risk of losses (Yu et al. 2018). This issue was addressed by Rockafellar and Uryasev (2002), who proposed parametric conditional VaR (CVaR),

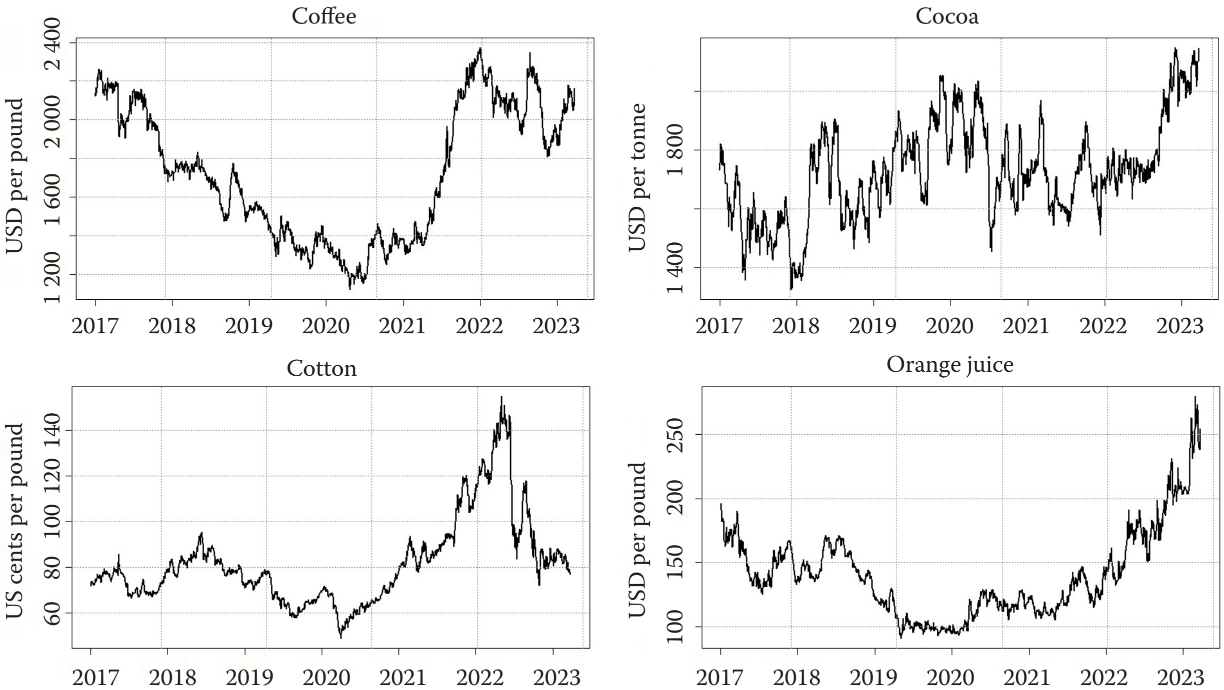

Figure 1. Empirical price dynamics of four soft agricultural commodities

Source: authors' own calculations based on data from investing.com (2023)

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which controls the magnitude of losses beyond VaR. Also, it is relevant to say that calculating VaR is inappropriate in empirical time series because they are not independently and identically distributed (iid). To resolve this problem, we first estimate every agricultural log return time series with the asymmetric Glosten-Jagannathan-Runkle-generalised autoregressive conditional heteroscedastic (GJR-GARCH) model with Student *t*-distribution. In this process, we can generate iid residuals. Because we are researching dynamic risk interdependence, we used created iid residuals for the construction of dynamic CVaR time series of all the selected agricultural commodities.

Another contribution of this article is the use of a multiscale framework in researching the comovement of tail risk between the soft commodities, which has not been done before, to our knowledge. We opted for this approach because different market participants meet their goals in different time horizons, and risk interdependence may vary significantly over frequency domains. Hence, it is important to inspect the strength of risk interdependence in multiple time horizons. This task is performed using two methodologies – wavelet correlation and wavelet cross-correlation. The former method calculates the exact strength of correlation in a multifrequency domain, and the latter shows a multiscale lead-lag relationship between the variables (Almaskati 2022). In particular, created dynamic CVaR time series are embedded in the two wavelet frameworks in a pairwise manner, which produces six pairs of tail-risk interdependencies. Combining these two wavelet methodologies, we can gain a fairly accurate picture of the strength of extreme risk connectedness in multiple horizons among the markets; this method also could indicate from which markets extreme risk transfers and which markets are the recipients of extreme risk. This information can be very valuable for investors in soft commodities because they will avoid combining assets that are highly correlated and assets that are receivers of high risk.

Regarding the existing literature, Fernández-Avilés et al. (2020) studied a number of commodities (including agricultural), showing extreme downside risk comovement maps of these markets during six recent distress periods. They observed no clear risk comovement patterns among the assets. However, they found that financialisation and speculation might have played some role in the dynamics of price and risk only in food commodity markets during the period from 2007 to 2008. Živkov et al. (2022) used VaR to measure a pairwise multiscale extreme risk interdependence between corn, wheat, soybean, rice and oats. They found an absence of high interdependence in the short-term horizons, but at higher wavelet scales, the results indicated stronger connection only in the cases corn–wheat, corn–soybean, wheat–soybean and somewhat corn–rice. Hamadi et al. (2017) examined the level of interdependence across corn, wheat, soybeans and soybean oil in terms of return volatility spillover. They found more significant evidence of bidirectional volatility spillovers, particularly underlining spillovers from soybeans and soybean oil markets to corn and wheat markets, than the inverse. Bonato (2019) investigated the changes in the dynamics of price correlations and spillover effects in the commodity markets, considering the interaction within soft and grain commodities and between these commodities and oil. He reported that soft commodities were segmented before 2008 and became correlated thereafter. However, correlations within grains were significant and positive, and increased only marginally, indicating that this group was affected less by the recent crisis events.

MATERIAL AND METHODS

GJR-GARCH model. To create iid residuals, we estimated all the soft commodities in the GJR-GARCH model with the Student *t*-distribution. In the specification, the first autoregressive term AR(1) is used in the mean equation, which is enough to resolve an autocorrelation problem. The variance equation in the model deals with the problem of heteroscedasticity. Mathematical expressions of the mean and variance equations are presented in Equations (1) and (2), respectively.

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

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}; \quad I_{t-1} = \begin{cases} 1 \text{ if } \varepsilon_{t-1} < 0 \\ 0 \text{ if } \varepsilon_{t-1} > 0 \end{cases} \tag{2}$$

where: C, c – constants in the mean and variance equations, respectively; y_t – log returns of the particular soft commodity; Θ – autoregressive parameter, ε_t – iid residuals; σ^2_t – conditional variance where $\alpha \geq 0$ and $\beta \geq 0$ (α measures the autoregressive conditional heteroscedasticity effect, and β gauges the persistence of volatility); γ – measures asymmetric response of volatility to positive and negative shocks, where the dummy variable (I_{t-1}) activates only if the previous shock (ε_{t-1}) is negative; z_t – independently and identically distributed process.

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If $\gamma > 0$ then negative shocks increase the volatility more than positive shocks do, and the reverse applies if $\gamma < 0$. We estimated all the GJR-GARCH models by using a quasi-maximum likelihood technique.

CVaR. Dynamic extreme risk was measured with the parametric *CVaR*, which indicates an average amount of loss that an investor might experience in a single day at a certain probability. *CVaR* is an integral of *VaR* [Equation (3)], where *VaR* is calculated every single day as $VaR_\alpha = \hat{\mu} + Z_\alpha \hat{\sigma}$, creating a dynamic *CVaR* time series. The variables $\hat{\mu}$ and $\hat{\sigma}$ denote an estimated mean and standard deviation, respectively, of a particular soft commodity, and Z_α is a left quantile of the normal standard distribution.

$$CVaR_\alpha = -\frac{1}{\alpha}\int_0^\alpha VaR(x)\,dx \tag{3}$$

where: $CVaR_\alpha$ – conditional Value-at-Risk; *VaR* – Value-at-Risk.

Wavelet correlation. After creating the dynamic *CVaR* time series, we embedded them in the pairwise wavelet correlation and wavelet cross-correlation frameworks. Wavelet correlation calculates the average value of correlation across wavelet scales, assuming a bivariate stochastic process [$Z = (x_t, y_t)$] of the two time series, *x* and *y*, where each wavelet coefficient is obtained by applying a maximal overlap discrete wavelet transform process of Z_t. In computing wavelet correlation, wavelet variance needs to be calculated for the scale *j* of *x* and *y* time series: $\sigma^2_{x,j,t} = VaR\left(\hat{D}_{x,j,t}\right)$ and $\sigma^2_{y,j,t} = VaR\left(\hat{D}_{y,j,t}\right)$. $D_{j,t} = \left(D_{x,j,t}, D_{y,j,t}\right)$ is a particular wavelet detail at scale *j*. Accordingly, the scale-dependent average wavelet covariance is then $COV\left(\hat{D}_{x,j,t}, \hat{D}_{y,j,t}\right)$. Combining the average wavelet covariance and two wavelet variances in the same equation results in calculating scale-dependent average wavelet correlation coefficients ($\rho_{x,y,j,t}$), as in Equation (4):

$$\rho_{x,y,j,t} = \frac{COV\left(\hat{D}_{x,j,t}, \hat{D}_{y,j,t}\right)}{\left[VaR\left(\hat{D}_{x,j,t}\right)VaR\left(\hat{D}_{y,j,t}\right)\right]^{\frac{1}{2}}} \tag{4}$$

where: *COV* – wavelet covariance.

Wavelet cross-correlation. Wavelet cross-correlation indicates the direction of the spillover effect—that is, it determines which extreme risk leads and which one lags in different time horizons. In this way, researchers can learn from which markets extreme volatility shocks originate and which markets are the recipient of these shocks. Wavelet cross-correlation also couples two time series, as in the case of wavelet correlation, but it calculates a lagged correlation function (ρ_τ) with lag τ. In this way, wavelet cross-correlation has a symmetric lagged correlation function ($\rho_\tau = \rho - \tau$). However, when deviations between ρ_τ and $\rho - \tau$ become significant, this symmetry is interrupted, which creates an asymmetry in the information flow. When asymmetry occurs, the leading asset has predictive power over the lagging asset. The maximal overlap discrete wavelet transform cross-correlation equation for scale *j* and lag τ can be written as follows [Equation (5)]:

$$\rho_{x,y,j,t,\tau} = \frac{COV\left(\hat{D}_{x,j,t}, \hat{D}_{y,j,t+}\right)}{\left[VaR\left(\hat{D}_{x,j,t}\right)VaR\left(\hat{D}_{y,j,t+}\right)\right]^{\frac{1}{2}}} \tag{5}$$

where: *VaR* and *COV* have the same meaning as in Equation (4), and cross-correlation takes the value $-1 \leq \rho_{x,y,j,t} \leq 1$.

Data set and descriptive statistics. In this article, we used the daily near maturity futures prices of four soft agricultural commodities – coffee, cocoa, cotton and orange juice – which are all traded in the Chicago Mercantile Exchange. Sugar is omitted from the sample because the GJR-GARCH model does not fit the returns of sugar, so appropriate dynamic *CVaR* time series cannot be created. The sample covers the period from January 2017 to March 2023, including the COVID-19 pandemic and the war in Ukraine. These two crisis events inevitably created high risk, and the task of this article is to determine the scale-dependent connections between downside risks in these neighbouring markets. All the time series are collected from the investing.com website. Each empirical time series is 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 is the daily price of a particular asset. Also, each time series is synchronised with the other three, making in this way the six pairs of assets.

Table 1 contains descriptive statistics of the selected soft commodities, showing the results of the first four moments, the Jarque-Bera test, the Ljung-Box tests for level and squared log returns and the Dickey-Fuller generalised least squares unit root test. According to the results, orange juice has the highest volatility (0.914), but it has relatively low kurtosis, which means that extreme values are not that frequent in the orange juice market. However, cotton has a relatively high second moment but also very high kurtosis (14.745), which indicates that extreme values are relatively common in this market. Ljung-Box test results showed that the cocoa and orange juice time series have a problem

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Table 1. Descriptive statistics of the selected soft agricultural commodities

Soft commodities	Mean	SD	Skewness	Kurtosis	*JB*	LB(Q)	LB(Q^2)	DF-GLS
Coffee	0.000	0.575	0.188	3.863	58.164	0.818	0.000	–5.817
Cocoa	0.006	0.695	0.317	5.950	598.782	0.024	0.044	–4.014
Cotton	0.002	0.768	–0.677	14.745	9 167.339	0.303	0.000	–4.719
Orange juice	0.007	0.914	–0.206	4.911	249.576	0.005	0.000	–34.860

JB – Jarque-Bera coefficients of normality; LB(Q), LB(Q^2) – P-values of Ljung-Box Q-statistics of level and squared log-returns of 10 lags, 1% and 5% critical values for the Dickey-Fuller generalized least squares test with 5 lags, assuming only constant, are –2.566 and –1.941, respectively; DF-GLS – Dickey-Fuller generalized least squares

Source: Authors' own calculation based on data from investing.com (2023)

with autocorrelation, and all the assets showed heteroscedasticity, which means that the AR(1)-GJR-GARCH model might be appropriate to resolve these issues. All of the time series had no problem with the unit root, as Dickey-Fuller generalised least squares test results suggested, which is a necessary precondition for GARCH modelling.

Table 2 shows the estimated GJR-GARCH parameters, which indicate that past shocks affected conditional variance in the coffee, cotton and orange juice markets and that the persistence of volatility was present in all the markets. An asymmetric effect occurred only in the cocoa market, where the γ parameter was positive, and the orange juice market, where the γ parameter was negative. This finding means that negative shocks have a stronger effect than do positive shocks on the conditional variance of the cocoa market, whereas in the orange juice market, the reverse applies. All ν parameters were highly statistically significant, meaning that empirical distribution was recognised well by the Student *t*-distribution. Autocorrelation and heteroscedasticity problems were resolved in the models according to the diagnostic test results, which means that all models created reliable residuals and that this is a good basis for the creation of dynamic *CVaR* time series.

Figure 2 plots the estimated residuals of the soft commodities and the two dynamic extreme downside risks (*VaR* and *CVaR*) calculated at 95% probability. Cotton had the highest downside risk in 2022, which is likely due to high price growth and a steep decline in 2022 (Figure 1). However, the pandemic did not have a significant effect on the soft commodity markets, except to some extent for orange juice. To inspect extreme risk interdependencies between the markets, we used lower blue lines and embedded them in the wavelet correlation and cross-correlation methodologies. Multiscale interdependence occurred across six wavelet scales, where the scales represent the following time horizons: scale 1 (2–4 days), scale 2 (4–8 days), scale 3 (8–16 days), scale 4 (16–32 days), scale 5 (32–64 days) and scale 6 (64–128 days). The first four scales cor-

Table 2. Estimated GJR-GARCH parameters

Estimated parameters	Coffee	Cocoa	Cotton	Orange juice
Panel A: GARCH parameters				
α	0.044**	0.001	0.048***	0.080***
β	0.852***	0.831***	0.932***	0.951***
γ	0.033	0.133***	0.009	–0.082***
Panel B: Distribution parameter				
ν	11.049***	5.621***	4.743***	8.852***
Panel C: Diagnostic tests				
LB(Q)	0.785	0.898	0.325	0.192
LB(Q^2)	0.404	0.972	0.974	0.275

**, ***statistical significance at the 5% and 1% level, respectively; LB(Q), LB(Q^2) – P-values; GJR-GARCH – Glosten-Jagannathan-Runkle-generalised autoregressive conditional heteroscedastic model; α measures the autoregressive conditional heteroscedasticity effect; β measures the persistence of volatility; γ measures asymmetric response of volatility to positive and negative shocks; ν – shape parameter of Student t-distribution

Source: Authors' own calculation based on data from investing.com (2023)

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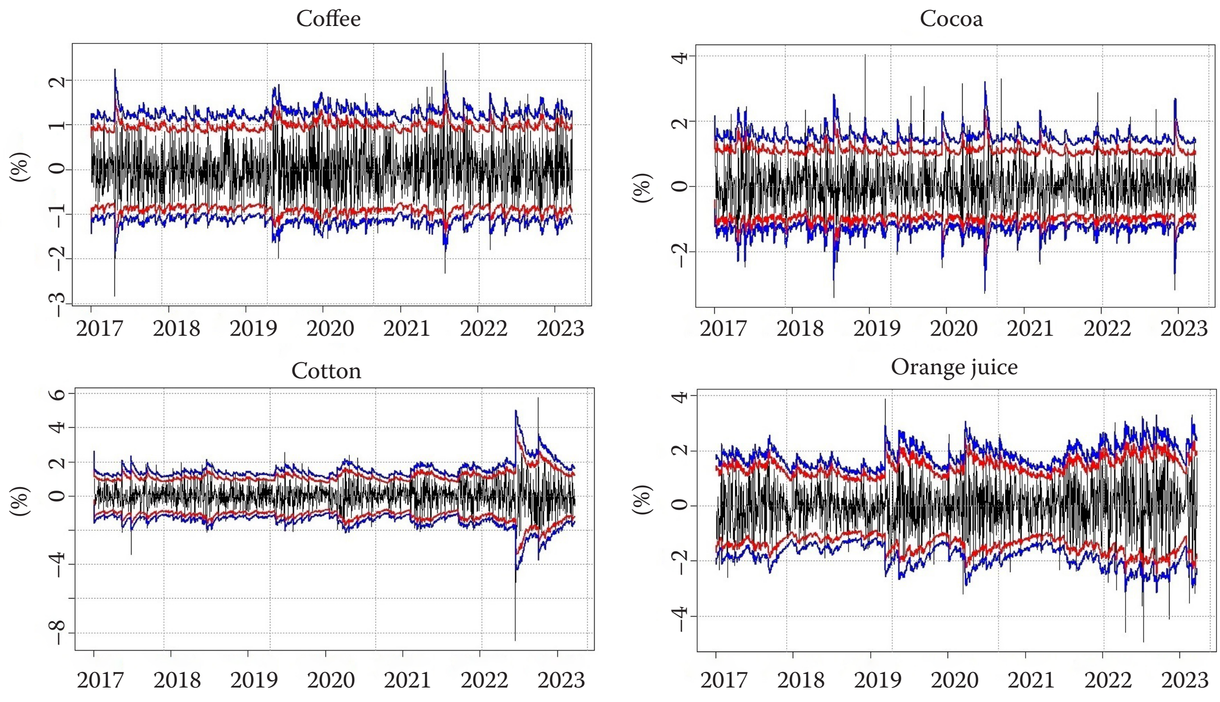

Figure 2. Created dynamic downside risk time-series of the soft commodities

Blue (red) lines denote upper and lower dynamic *VaR* (*CVaR*) time-series; *VaR* – Value-at-Risk; *CVaR* – condtional *VaR*
Source: authors' own calculation based on data from Investing (2023)

respond to the short-term horizon, and the fifth and sixth scales are regarded as midterm and long term, respectively. Frequency scales can also be called wavelet details, and the label of wavelet details is the capital letter D.

RESULTS AND DISCUSSION

Wavelet correlation findings. This section presents the results of pairwise wavelet correlations, where Figure 3 contains the plots and Table 3 shows the exact values of scale-dependent correlations. According to the results, wavelet correlations were very low up to the fifth scale, which means that soft agricultural markets were mostly segmented in the short-term and midterm horizons. These results are in line with those of Živkov et al. (2022) who researched multiscale interdependence between five cereal markets and found lower wavelet correlations in short time horizons, particularly between smaller markets. These authors also asserted that in the cases when one asset is the largest market (corn), higher correlations can be found even at lower wavelet scales. Our results coincide with these findings because very low or even negative correlations were found between smaller markets (cocoa, cotton and orange juice), whereas in the cases when one asset in the combination was the largest market (coffee), higher correlations were found at lower wavelet scales. Table 4 shows the average daily trading volumes in the four markets, where coffee is the largest market, according to this parameter.

For example, in the coffee–cocoa combination, a relatively high correlation exists in the D4 scale (0.142); in the coffee–cotton pair, the higher correlation is in the D3 scale (0.123); and in the coffee–orange juice pair, the higher correlation is in the D4 scale (0.246). These results could indicate that smaller markets follow the largest market to some extent, but these correlations are still relatively small. The smaller markets do not have higher correlations whatsoever at lower wavelet scales. These results indicate that strong connections between high risks do not exist among soft agricultural markets in the short term and midterm, which is good news for market participants who operate in these time horizons. In other words, investors do not have to worry too much that high risk from another market will have an effect on their market in the short term and midterm.

However, the situation is totally different in the long-run, in the sense that five out of six pairs have high corre-

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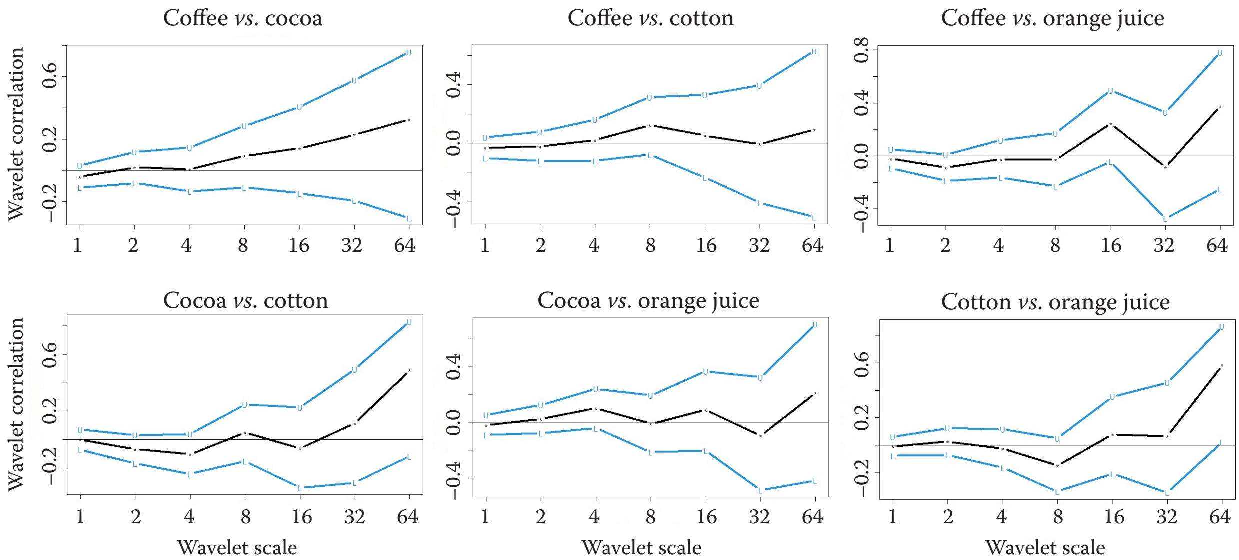

Figure 3. Pairwise wavelet correlations between the selected soft agricultural commodities

Source: Authors' own calculation based on data from Investing (2023)

lation in the long-term horizon (D6 scale). These results are not unusual in commodity markets (Tiwari et al. 2023) and probably occur because time series lose idiosyncratic features in the long-run while being affected by the same external factors. As a result, high correlation occurs even between smaller markets, meaning that market participants have to consider some type of protection against extreme risk from another market in the long-run.

Wavelet cross-correlation findings. This section describes complementary cross-correlation findings, which show from which market extreme risk originates and which market is the recipient of extreme risk. Table 5 presents the results, and Figures 4 and 5 show plots of wavelet cross-correlations. This methodology indicates whether any pulling effect exists between the soft agricultural markets at contrasting time lags.

Table 3. Pairwise wavelet correlations

Frequency scales	Coffee *vs.* cocoa	Coffee *vs.* cotton	Coffee *vs.* orange juice	Cocoa *vs.* cotton	Cocoa *vs.* orange juice	Cotton *vs.* orange juice
Raw	–0.040	–0.033	–0.021	–0.001	–0.016	–0.009
D1	0.020	–0.023	–0.089	–0.068	0.027	0.026
D2	0.007	0.020	–0.023	–0.104	0.103	–0.026
D3	0.093	0.123	–0.029	0.049	–0.007	–0.150
D4	0.142	0.051	0.246	–0.061	0.091	0.078
D5	0.229	–0.007	–0.085	0.115	–0.092	0.065
D6	0.327	0.093	0.378	0.489	0.213	0.588

D1–6 – wavelet details (scales)
Source: Authors' own calculation based on data from Investing (2023)

Table 4. Average daily trading volumes of the selected soft agricultural commodities in 2019

Observed category	Coffee	Cocoa	Cotton	Orange juice
Volume	57 652	46 816	31 579	1 698

Average trading volumes, i.e. number of contracts, are observed in 2019 in order to avoid possible biasedness that can be caused by the pandemic and the war in Ukraine in the years 2020–2022
Source: Authors' own calculation based on data from Stooq (2023)

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Table 5. Wavelet cross-correlation results at D6 wavelet scale

Cross-correlation	Wavelet scale	Negative lagged correlations				Positive lagged correlations			
		–20	–15	–10	–5	5	10	15	20
Coffee *vs.* cocoa	D6	0.073	0.135	0.190	0.225	0.185	0.110	0.015	–0.084
Coffee *vs.* cotton	D6	0.001	–0.023	–0.040	–0.045	–0.045	–0.041	–0.038	–0.042
Coffee *vs.* orange juice	D6	0.219	0.182	0.129	0.065	–0.055	–0.101	–0.128	–0.127
Cocoa *vs.* cotton	D6	–0.031	–0.011	0.016	0.049	0.106	0.124	0.132	0.123
Cocoa *vs.* orange juice	D6	0.065	0.072	0.050	–0.003	–0.161	–0.230	–0.266	–0.252
Cotton *vs.* orange juice	D6	–0.003	0.038	0.069	0.083	0.068	0.054	0.048	0.058

Source: Authors' own calculation based on data from Investing (2023)

The names of the pairs in Table 5 suggest which variable enters the computational process first and which comes second. This order is important because negative lag correlations are connected with the first vari-

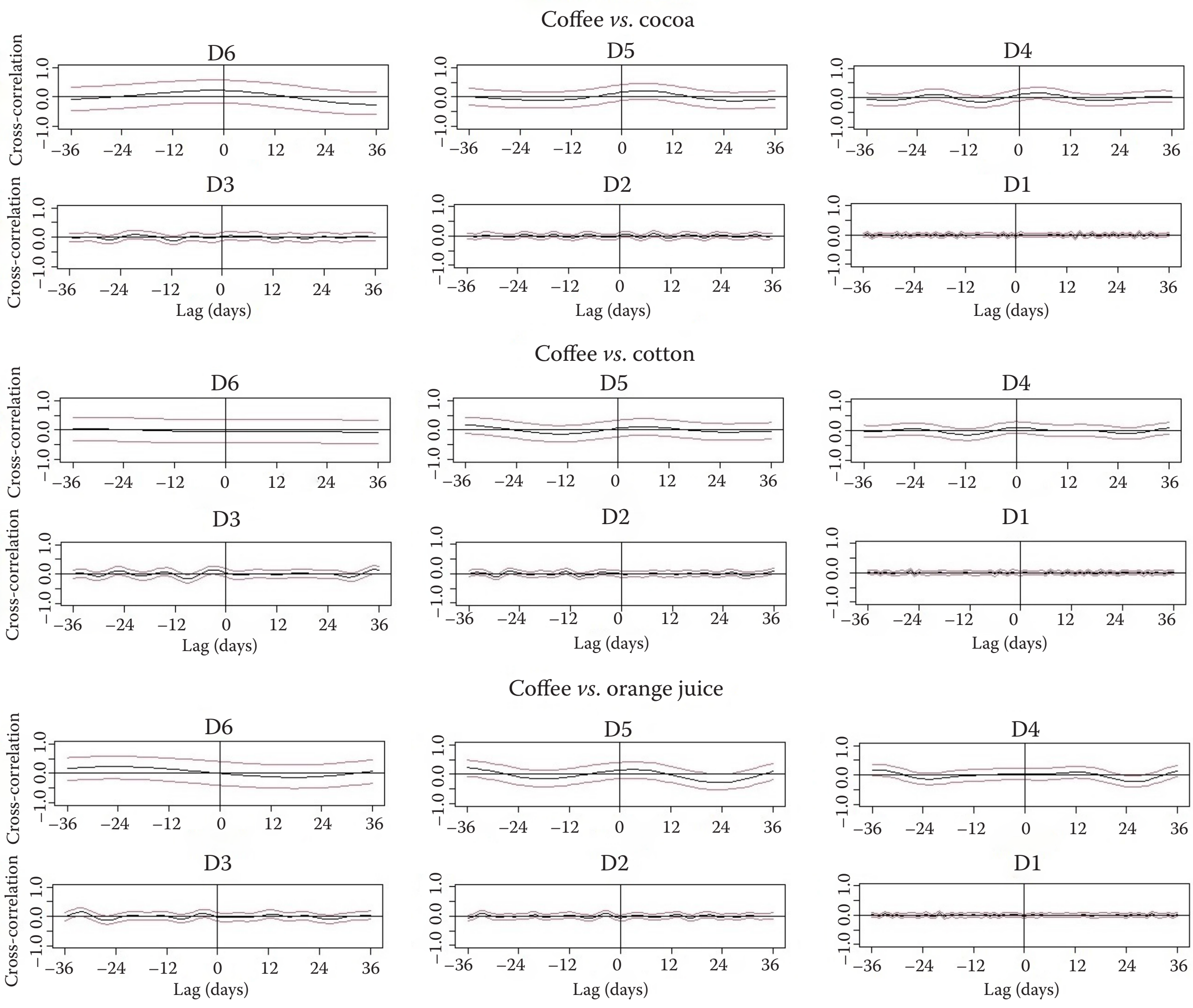

Figure 4. Cross-correlation between the selected soft agricultural commodities

D1–6 – wavelet details (scales)

Source: Authors' own calculation based on data from Investing (2023)

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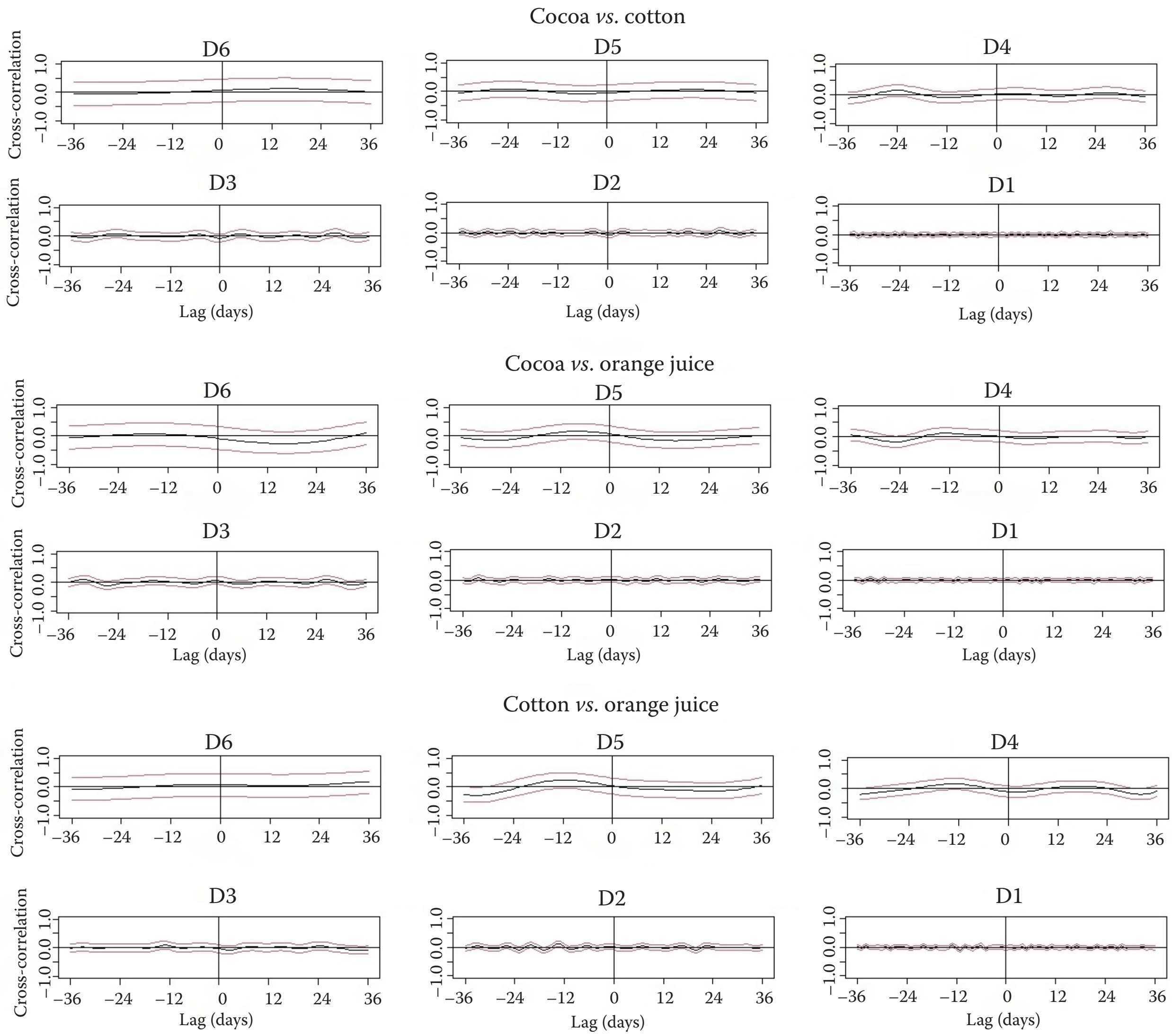

Figure 5. Cross-correlation between the selected soft agricultural commodities

D1–6 – wavelet details (scales)

Source: Authors' own calculation based on data from Investing (2023)

able, and positive lag correlations are connected with the second variable. The lead-lag interlink is determined via skewness of the cross-correlation curve, meaning that the curve being skewed significantly on the left side of the graph implies that the first time series leads the second and vice versa. A significant lead-lag relationship exists only if the correlation between variables is relatively strong, which means that only cross-correlation on the D6 scale is worthy of note because only at the long-term horizon does the strongest interdependence exist. Only cross-correlations at lag 5 are compared and commented.

According to the results, coffee as the largest market leads cocoa and orange juice, which is expected because larger markets usually process new information faster, and smaller markets then follow the developments on the larger market. The situation between coffee and cotton is inconclusive because the cross-correlations are equal. Even if there would be a pulling effect between the two markets, the result would be questionable because these assets have very low correlation on the D6 scale (0.093). Cotton leads orange juice, which also makes sense because cotton is a bigger market. However, in the

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cases of cocoa–cotton and cocoa–orange juice, the larger market does not lead the smaller market, contrary to common knowledge. This finding means that further research needs to be done by using different methodologies to confirm or refute our results between these markets.

CONCLUSION

In this article, we investigated the nature of extreme risk interdependence between four soft agricultural futures markets. We performed the analysis by using a multiscale framework and two wavelet methodologies—wavelet correlation and wavelet cross-correlation. Extreme risk was measured via *CVaR*, and the dynamic *CVaR* time series were computed using the asymmetric GJR-GARCH model.

Wavelet correlation results indicated that a very weak connection exists between the markets in the short-term and midterm horizons. Only in the cases when coffee was an element in the combination did somewhat higher wavelet correlations occur on some short-term and midterm wavelet scales. These results favour investors who run their businesses in the short term or midterm because they do not have to apply hedging measures to protect themselves against extreme risk. However, the situation is significantly different in the long-run, where relatively high correlations were found on the D6 scale in all the pairs, except coffee–cocoa. This finding means that some hedging measures should be implemented if investors operate in the long-term horizon.

Additional cross-correlation analysis results revealed lead-lag relationships between the markets. The results were mostly in line with expectations, meaning that bigger markets led smaller markets, but only in the cases of cocoa–cotton and cocoa–orange juice did the opposite happen. From this point of view, further research is needed to verify or reject the results for cocoa–cotton and cocoa–orange juice.

These findings could be useful for investors in soft commodities to gain knowledge about extreme risk interdependence between these markets. Short-term market participants can freely invest in soft commodities or construct a portfolio with them without worrying that extreme risk from a neighbouring market will spill over. In the long-term horizon, the situation is somewhat different in the sense that some risk protection is needed because higher correlation exists in this timescale. Besides, long-term cross-correlation results can be useful to indicate to investors in lagging markets how to behave if extreme price swings occur in leading markets.

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