

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

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Electronic supplementary material (ESM)

Supplementary Table S1
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Table S1. Statistical tests to determine the data suitability for copula modelling for ARMA (m,n)-GARCH (1,1) standardised residuals

Variable	ADF test P -value	KPSS test P -value	Ljung-Box test P -value	ARCH-LM test P -value
Brent	< 0.01	> 0.10	0.18	0.30
USD	< 0.01	> 0.10	0.27	0.93
SPY	< 0.01	> 0.10	0.97	0.86
Grains	< 0.01	> 0.10	0.96	0.75
Softs	< 0.01	> 0.10	0.85	0.55
Livestock	< 0.01	> 0.10	0.99	0.87

ADF – augmented Dickey–Fuller; ARCH-LM – autoregressive conditional heteroskedasticity Lagrange multiplier test; ARMA-GARCH – autoregressive moving average – generalised autoregressive conditional heteroskedasticity; KPSS – Kwiatkowski–Phillips–Schmidt–Shin; SPY – S&P 500 Stock Index

Source: Own processing

Table S2. The Wang and Wells (2000) goodness-of-fit test results for selected copula models, with the parametric bootstrap for P -values described by Genest et al. (2006) in parentheses

Variable Pair	Family	Cramer-von Mises test statistic
Brent-Grains	Gaussian	0.145 (0.24)
Brent-Softs	Gaussian	0.152 (0.21)
Brent-Livestock	Clayton	0.021 (0.98)
USD-Grains	Frank	0.058 (0.45)
USD-Softs	Gaussian	0.157 (0.29)
USD-Livestock	rotated Joe 270 degrees	1.484 (0.26)
SPY-Grains	survival Joe	2.219 (0.57)
SPY-Softs	survival Gumbel	0.06 (0.52)
SPY-Livestock	survival Gumbel	0.073 (0.43)

SPY – S&P 500 Stock Index

Source: Own processing

Table S3. Results of the MMD two-sample tests (Gretton et al. 2012) applied to pseudo-observations for the pre-COVID (Jan 1, 2017–March 3, 2020), COVID (March 11, 2020–May 5, 2023) and post-COVID (May 5, 2023–Dec 31, 2024) subperiod. The null hypothesis of equal distributions is not rejected at 5% significance levels in any case

Subperiod Comparison	MMD
Pre-COVID vs. COVID	0.002 71 (0.054)
COVID vs. post-COVID	0.002 42 (0.077)
Pre-COVID vs. post-COVID	0.002 68 (0.058)

MMD – Maximum Mean Discrepancy

Source: Own processing

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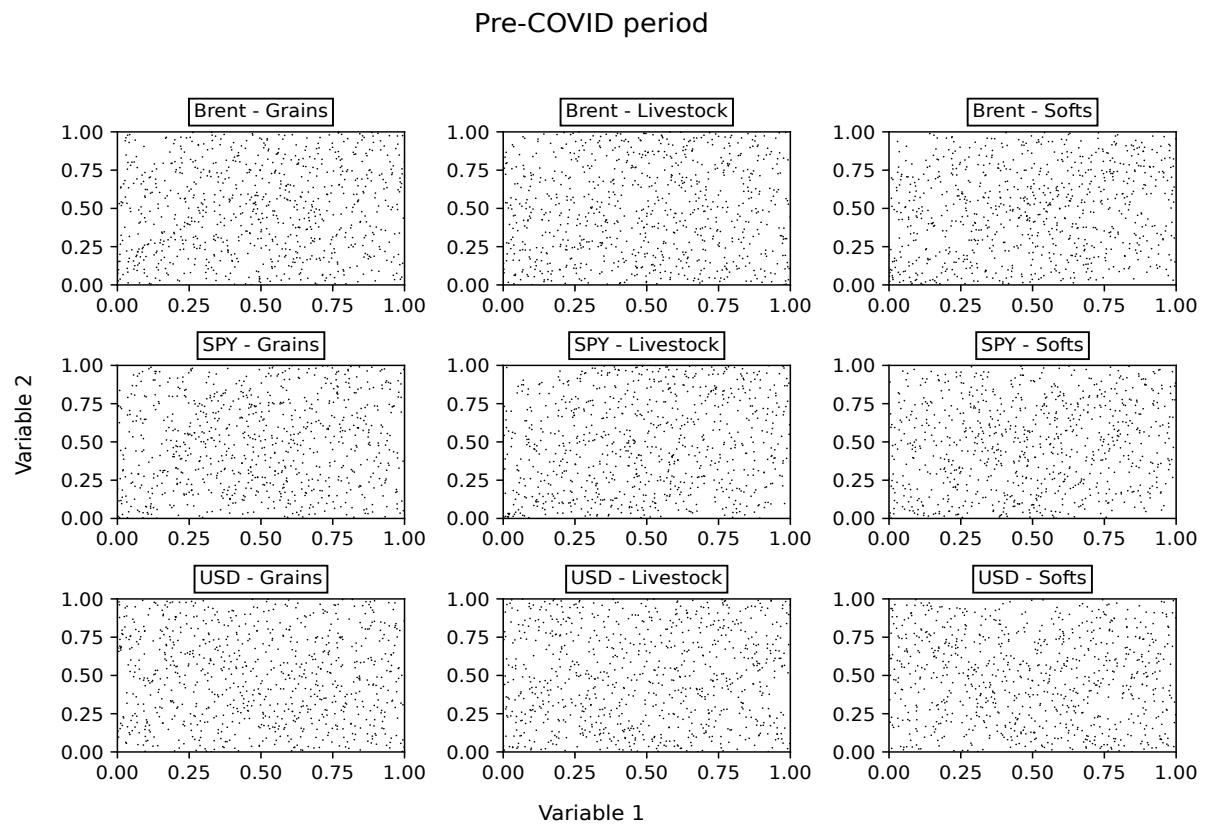


Figure S1. Scatter plots of the pseudo-observations for the pre-COVID subperiod (Jan 1, 2017–March 10, 2020)

SPY – S&P 500 Stock Index

Source: Own processing

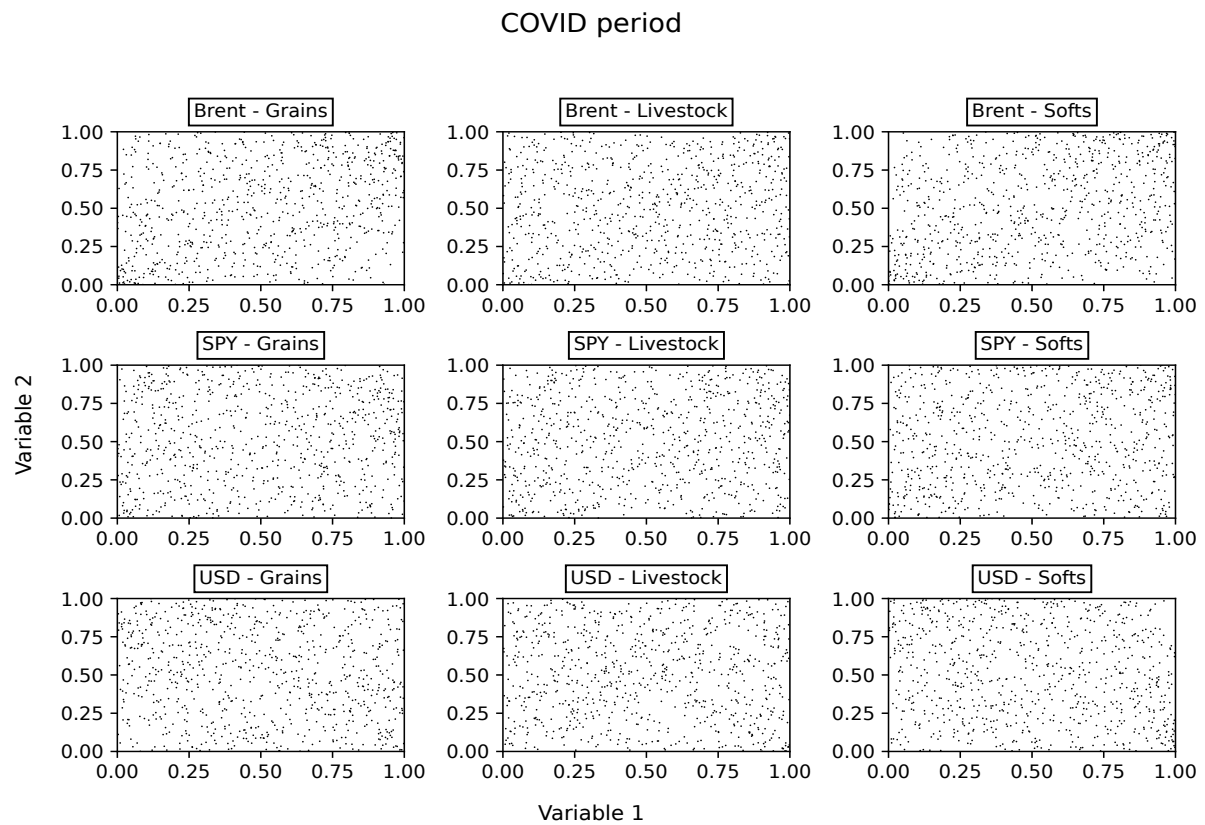


Figure S2. Scatter plots of the pseudo-observations for the COVID (March 11, 2020–May 5 2023) subperiod

SPY – S&P 500 Stock Index

Source: Own processing

<https://doi.org/10.17221/319/2025-AGRICECON>

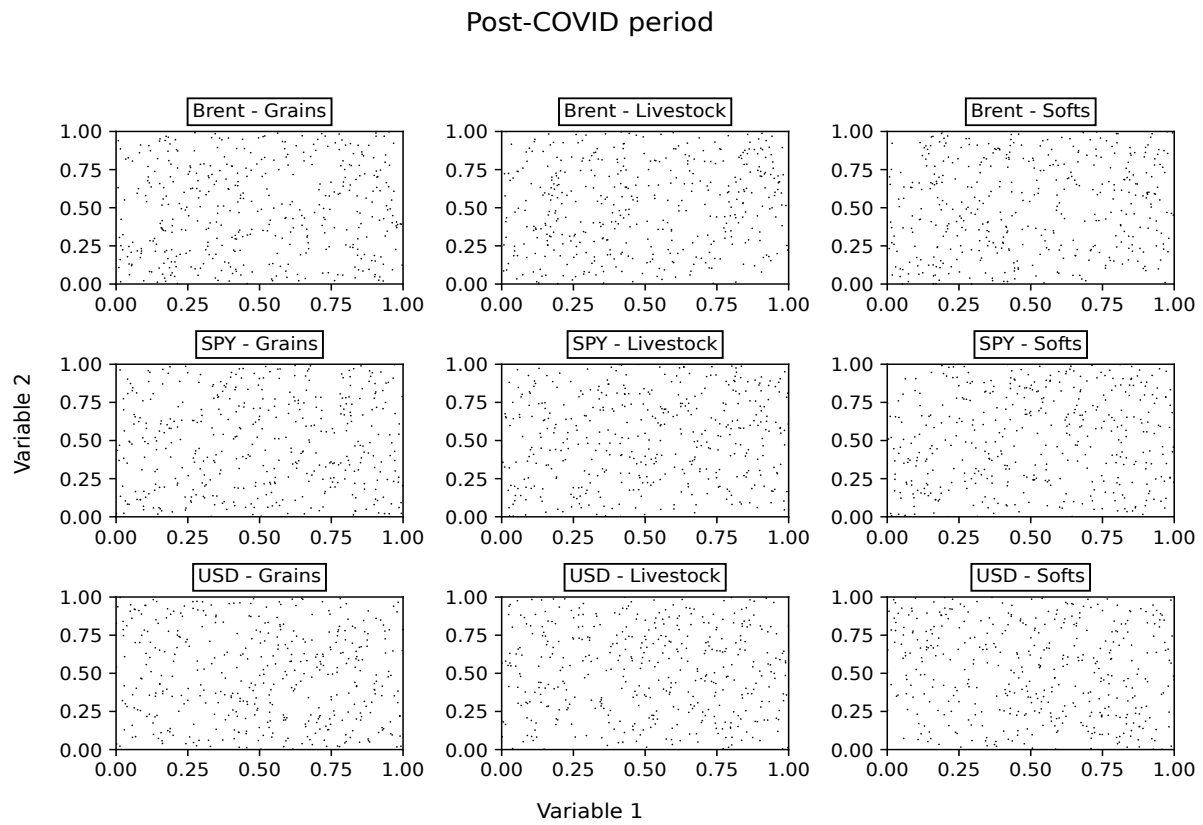
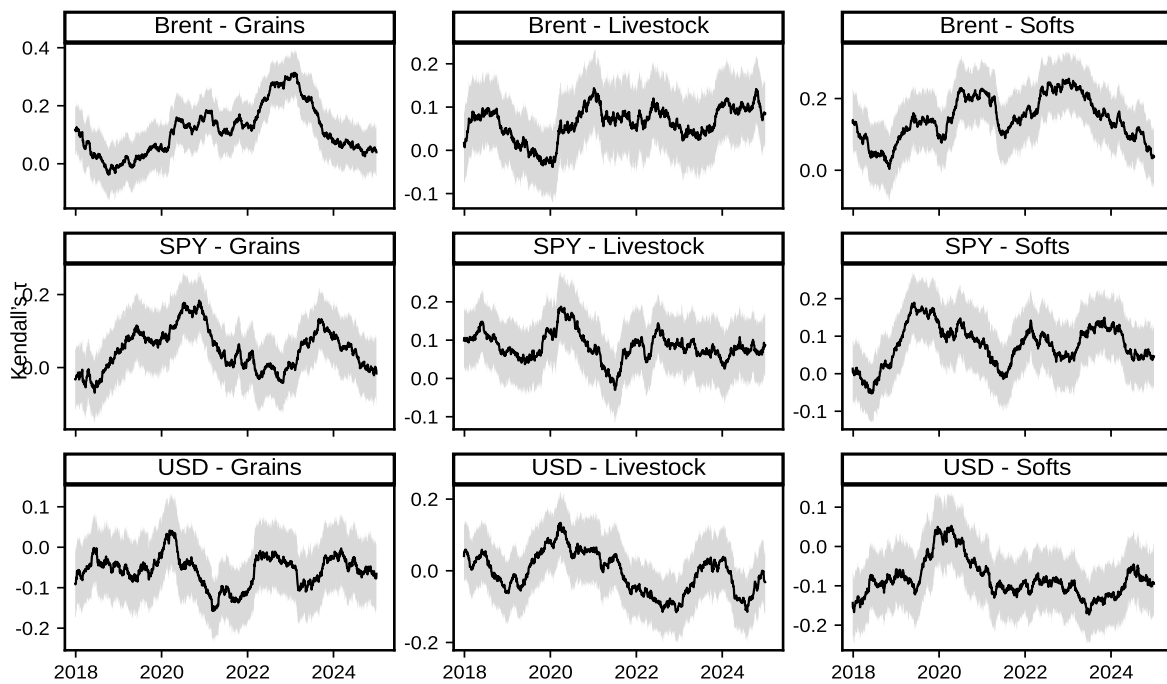


Figure S3. Scatter plots of the pseudo-observations for the post-COVID (May 5, 2023–Dec 31, 2024) subperiod

SPY – S&P 500 Stock Index

Source: Own processing

Rolling Kendall's τ with 95% bootstrap confidence bandsFigure S4. Rolling Kendall's τ with 95% bootstrap confidence bands

SPY – S&P 500 Stock Index

Source: Own processing

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Sensitivity analysis

To assess sensitivity to the choice of rolling-window length, we recomputed time-varying Kendall's τ using alternative window sizes of 200 and 300 trading days for all copula models. The resulting dependence patterns, visualised in Figures S5 and S6, exhibit similar dynamics and levels to those obtained with the 250-day window, indicating that the specific window choice does not drive the main results.

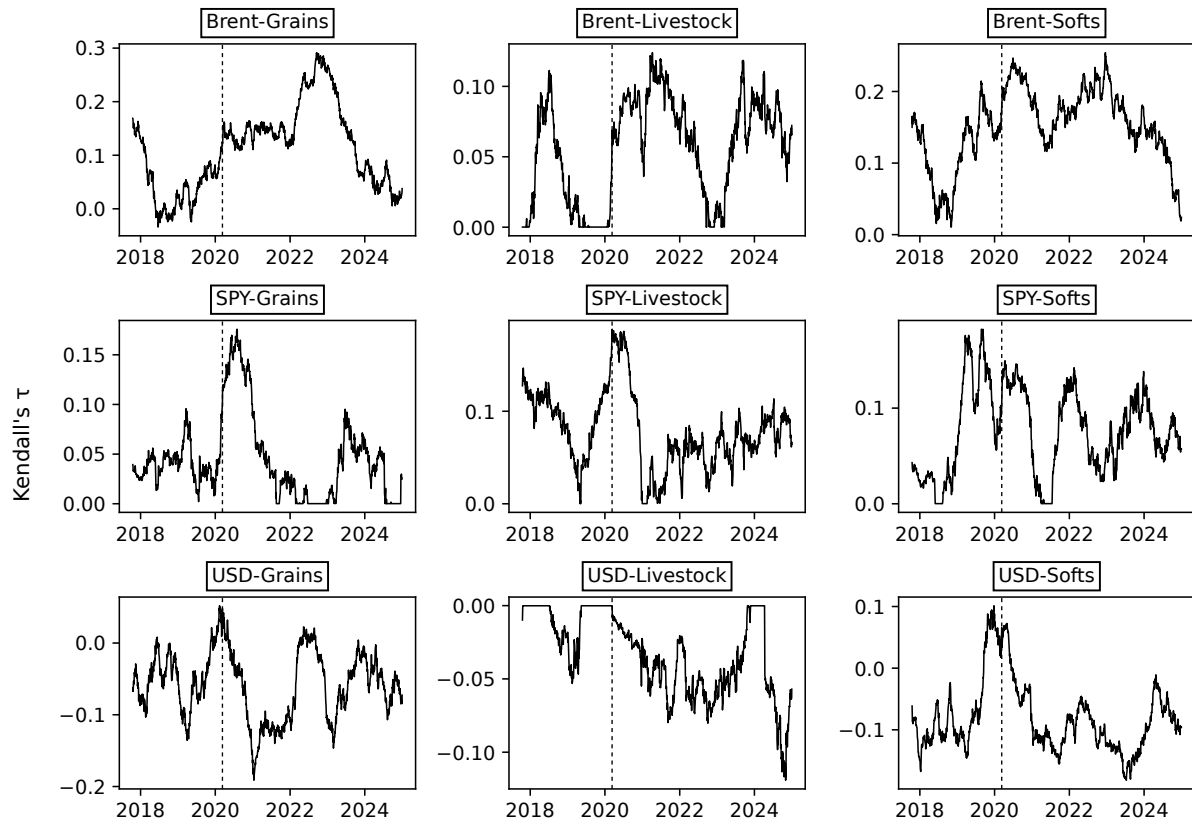


Figure S5. Time-varying Kendall's τ for bivariate pairs with a window size of 200 days

SPY – S&P 500 Stock Index

Source: Own processing

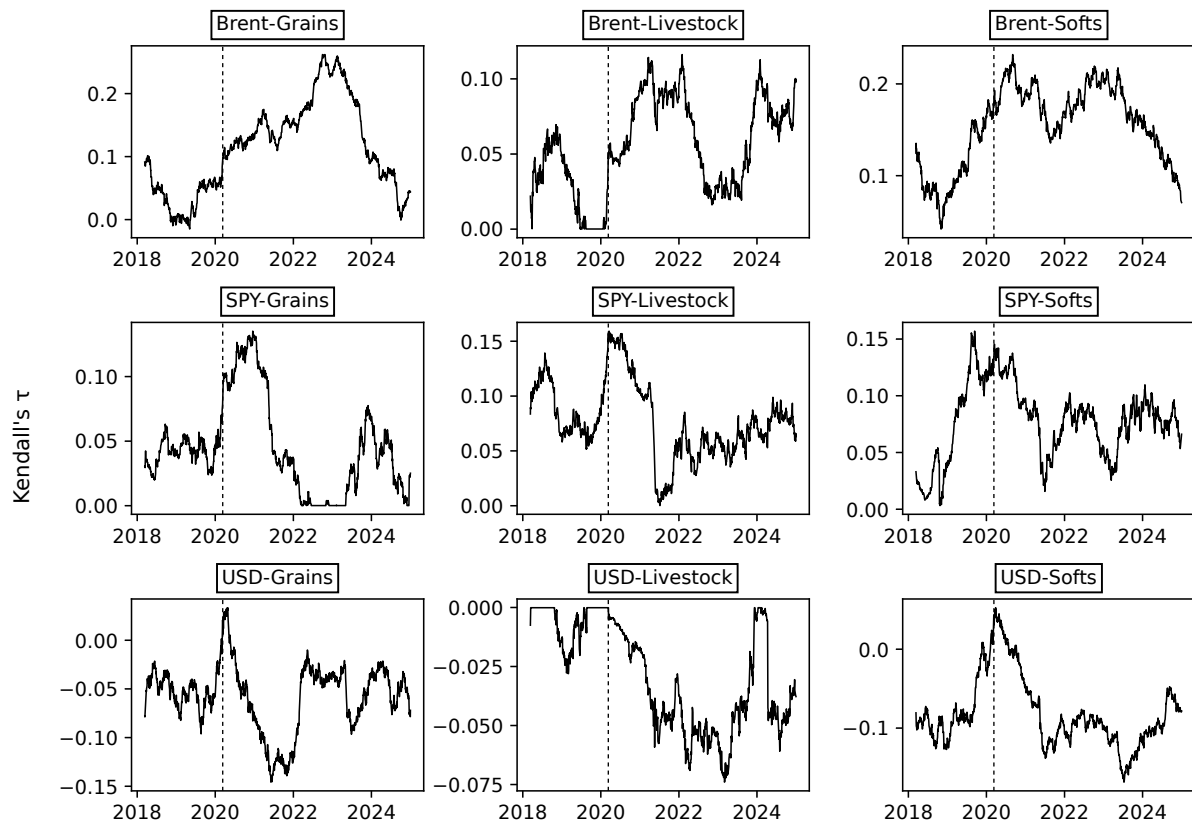


Figure S6. Time-varying Kendall's τ for bivariate pairs with a window size of 300 days

SPY – S&P 500 Stock Index

Source: Own processing

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