



An Investigation of Symmetric Risk Spillovers between Carbon Trading and Commodity Markets

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ABSTRACT

Systemic risk spreads through interconnections between markets in the financial system. This study investigated symmetric upside and downside risk spillovers between carbon assets trading markets and commodity markets, including energy, base metals, and agricultural commodities. To measure systemic risk and symmetric upside and downside risk spillovers between carbon emission allowance (CEA) and commodity markets, daily returns time series of the data utilized in modeling upside and downside risk spillovers were filtered through the ARMA-APGARCH process, and marginal distributions of each variable were estimated based on residuals following data collection and continuous calculation of daily data returns. Then, symmetric upside and downside risk spillovers between the studied groups were tested using methodology and the bootstrapped Kolmogorov-Smirnov (KS) test statistic. The research results confirmed the null hypothesis of symmetric upside and downside risk spillovers between commodity and carbon emission trading markets under investigation at a confidence level of 99%. In addition, based on the one-sided KS test, upside risk spillovers occur with greater intensity than downside risk spillovers (their downside counterparts) between the studied commodity and carbon emission trading markets.

Keywords: Systemic risk, Upside and downside risks, Symmetric risk spillovers, Carbon emission trading market.



1. Introduction

Most major international treaties, including the Kyoto Protocol (1995) and the Paris Agreement (2015), are now centered on finding a way to lower the costs associated with greenhouse gas (GHG) emissions and global warming. EU Emissions Trading System (EU ETS) was introduced in 2005 by the European Commission (EC) as part of international initiatives to lower pollutant volume and combat global warming. This cap-and-trade system is currently the largest GHG emissions permit trading market and carbon pricing mechanism throughout the European Union (EU). This trading mechanism allows pollutant emitters to select the least expensive way to lower their pollution levels by allocating a certain volume of pollutant emission permits (PEPs) to the markets and distributing the permits available for trading to market participants through trades. In this mechanism, the most cost-effective way for industries and businesses that produce pollution is to weigh their options. These include lowering production levels to reduce pollution, investing in technological innovations that lower pollution levels, or obtaining more emission permits from the market (Venmans, 2012).

The EU-ETS program is currently regarded as the largest international carbon trading market to reduce GHG emissions since the conclusion of the Kyoto Protocol on February 16, 2005. By implementing the aforementioned program, environmental costs resulting from pollutant emissions are no longer seen as a side effect of industrial activities because the carbon trading pilot is designed to internalize environmental costs for companies and industries that consume fossil fuels. Only in the event of favorable economic conditions will industries incur additional production and GHG emissions costs. In this case, companies will have to purchase additional emission permits. Emission permit prices will rise as a result of the growing demand for emission permits, given the constant total volume of marketable permits (Brink, Vollebergh, & van der Werff, 2016).

The last few decades have seen a number of developments that have contributed to the study of the mechanisms by which financial market components affect or are affected by one another. These include the extraordinary diversification of markets, instruments, and financial institutions; the growth and increasing influence of financial markets in societies; the facilitation of transactions in financial markets; the

financialization of the economy and the transfer of resources from the real to the financial sectors of economies; and the movement of many world economies toward this financialization of the economy and key economic variables. A distinct financial institution or market that still functions independently of other financial institutions and markets is uncommon in today's financial systems. Financial institutions' capabilities and opportunities are heavily overshadowed by news, information, and shocks arising from other financial institutions and the financial system (Silva, Kimura, & Sobreiro, 2017).

Risk spillover in this study refers to the extreme states on the left and right sides of the studied time series return distribution that alter the size and intensity of those on the left and right sides of the return distribution of other studied variables. This concept of risk spillover was first proposed in the literature on systemic risk by Adrian & Brunnermeier (2011), which is used to depict extreme risk spillover (Sun, Liu, Wang, & Li, 2020).

The first rational step in monitoring financial market performance and directing investment portfolios in the predetermined and expected direction is to understand the dependence structure of financial markets and instruments, as well as the quality of contagion and the mechanisms of spread of systemic events between financial system components and identify institutions that can overshadow the entire financial system with their upside (positive?) and downside (negative?) events. The soundness of the financial system cannot be ensured without such understanding, even when devising investment strategies or managing the risk of investment portfolios independently of one another. On the other hand, there is a pressing need for emerging economies to expand the perceptions of market participants, financial institutions, and regulatory bodies regarding the mechanisms underlying the emergence, spread, and intensification of financial crises. This need will be especially important because of the indisputable need to invest the proceeds from exporting commodities and natural resources, such as oil, as well as the cumulative earnings from these exports in a particular class of investment institutions called sovereign wealth funds in oil-rich nations like Iran, where the export of various commodities (e.g., oil, gas, petrochemicals, metals, and metallic minerals) accounts for a significant portion of export earnings (73–87% in

various years) (Financial Tribune, 2019). Along these lines, researchers and financial and economic activists can benefit from the experience of developed economies on the one hand and can add more complexity to widely used available models thanks to the development of econometric, mathematical, and computational power models at their disposal on the other.

The current research aims to investigate the symmetric upside and downside risk spillovers between carbon assets trading markets and commodity markets, including energy, base metals, and agricultural commodities, to further the existing understanding of financial markets based on carbon pollutants and financial instruments designed based on carbon dioxide (CO₂) emission allowances.

Research Background

From a theoretical perspective, carbon prices can be linked to other markets through two transmission mechanisms: first, the correlated information channel known as returns spillover, through which relationships are established during the price discovery process. Second, the relationship between the carbon market and other markets, the risk premium channel known as volatility spillovers, through which a shock in one market affects the participants' willingness to maintain risk in another market (Tang et al., 2020). A harmful relationship between the elevated systemic risk in the financial and commodity markets is becoming more pronounced, as evidenced by the growing trends of globalization and carbon financing as well as the strengthening feedback effects between the carbon markets and other markets. The findings of the most significant research on the contagion and symmetry of upside and downside risk spillovers between carbon assets trading markets and commodity markets, including energy, base metals, and agricultural commodities will be discussed below. Studies that share a theme with the topic of the current study are chosen and briefly outlined.

Bredin & Muckley (2011) explored the correlation between crude oil and carbon emission allowances (CEA) prices in the EU using Johansen's multivariate cointegration likelihood ratio and found a long-term relationship between them. Reboredo (2013) examined the relationship between oil and CEA prices using static copula functions. They found an independent extreme symmetry between the two markets, which is

consistent with the lack of financial contagion effect between them. Zhenjin Wu (2015) argued that there is a bidirectional nonlinear Granger causality between European CEA and oil markets based on empirical findings. Maramoto & Suri (2015) investigated the dependence between fluctuations in the price of CO₂ pollutants and those in one of their major sources, namely the price of fossil energy carriers. They surveyed the dependence between the returns of the two markets above using a special class of copula functions called stochastic autoregressive copulas, time-varying copula functions introduced by Hafner & Manner (2012). The results indicated changes over time in the dynamics of the dependence between CO₂ pollutants' price fluctuations and volatility of energy returns, including crude oil, coal, and natural gas. While this change is negligible during periods of stability, it increases dramatically during periods of crisis. Maramoto & Suri (2015) found a time-varying and non-linear correlation between carbon and oil markets as well as a significant difference in the correlation coefficient between the two markets before and after the European debt crisis. In a study, Xiaoqin et al. (2017) investigated whether energy commodities are an active asset class to help investors reduce their carbon risk. They analyzed the relationship between the EU CEA and the four abovementioned energy commodities and their effects on the diversification of carbon risk using the methodology of static and dynamic copulas. The experimental results of this research indicated a symmetric tail dependence between carbon and energy commodity markets. Salah Uddin et al. (2018) modeled the multivariate dependence structure and spillover effect between energy commodities, including crude oil, natural gas, ethanol, fuel oil, coal, and diesel using canonical vine (C-vine) copula and Conditional Value-at-Risk (CoVaR). Based on the findings, carbon assets create diversification benefits for investing in energy commodities. In a paper, Chang & Zhang (2018) examined the comovement and dependence structure between China's emissions allowances and wholesale diesel market using a hybrid model of GARCH-copula and generalized error distribution (GED). In this research, the price of China's emission allowances exhibited an extreme comovement with the wholesale diesel price using GARCH and TARARCH models. The empirical evidence also indicated a divergence in the asymmetric tail structure of dependence between

diesel and emissions allowances markets in different markets, except the Hebei market. Du and Feng (2019) explored the relationship between European [emissions] allowances and Brent oil markets using various copula functions. The findings suggested a significant effect of oil price on emissions allowances price and oil market volatility on CEA price fluctuations. They underlined the necessity of considering the role of other markets on the carbon market and CEA price. Yuana & Yang (2020) explored the asymmetric risk spillover between uncertainties in financial and carbon markets using the generalized autoregressive score (GAS)-dynamic conditional score (DCS) model. They discovered a significant asymmetric risk spillover from uncertainties in financial markets to the carbon market. Ma & Wang (2021) investigated the dynamic price spillover and dependence between iron ore, scrap steel, seaborne transportation, China's steel stock, and CEA using price spillover and copula models in the 2011-2020 period. According to the results, among the three iron ore price indices, including Platts, Metal Bulletin Iron Ore Index (MBOI), and Chinese Iron Ore spot prices (CIOPI) [China's iron ore price index], Platts is the main risk spillover factor to other markets. CEA shows a slight price spillover to China Steel Corporation (CISXF) with moderate dependence on the stocks of Chinese companies. Zhou (2021) measured China's energy market uncertainty using the conditional volatility of Daqing crude oil returns based on the GAS-driving model. By combining the copula and GARCH approaches, this research revealed the asymmetric volatility spillover from uncertainties in global and domestic Chinese oil markets to Hubei and Shenzhen CEA trading markets. While both global and domestic energy markets impose a significant risk spillover effect on CEA prices, the effect varies in size and intensity.

Methodology

To measure and quantify systemic risk and model the effect of upside and downside risk spillovers between CEA and commodity markets, daily returns time series data used in modeling upside and downside risk spillovers are filtered using the ARMA-APGARCH process following data collection and continuous calculation of daily data returns. Also, the marginal distributions of each variable are estimated based on residuals. After estimating the parameters of the

ARMA-APGARCH and fitted distribution functions for each standardized random value, the variables including standardized residual data will be arranged to construct specific pair copulas and determine the appropriate structure for dependence modeling between the investigated variables. Afterward, the appropriate copula functions are selected for modeling the dependence between the variables of dual joint distributions or conditional distributions determined, and the parameters of optimal copula functions are computed. Next, upon determining pair and conditional distributions and copulas, the CoVaR measure is calculated as the VaR of variable i under a specific event in variable j using the resulting conditional distributions in two cases, i.e., median event and q th quantile event in the distribution of variable j based on Reboredo & Ugolini's (2015) methodology. This measure is employed to measure upside and downside risk spillovers between each of the studied subindices.

Furthermore, the role and contribution of each financial system component in the formation and escalation of systemic risk in other components is measured by calculating the Δ CoVaR measure between the financial subindices of the Tehran Stock Exchange (TSE) as a representative of the national financial system components after selecting a suitable copula function to describe the dependence structure between each financial institution and the financial system. The risk spillover effect between financial system components is analyzed using the bootstrapped KS test introduced by Abadie (2002) by considering significant differences between CoVaR and VaR distributions. The asymmetric effect of extreme upward and downward movements between different financial system components will also be tested.

Standard normal distribution (aka Gaussian distribution) is often deemed unsuitable for modeling the behavior of distributed random variables in many cases, especially in financial econometrics. The behavior of financial random variables should be described by appropriate distributions sufficiently flexible to demonstrate the skewness and tail fatness of distributions (skewed and fat-tailed distributions). Skewed distributions (skewness of distribution) allow asymmetric modeling of the right and left sides of the distribution. Extremely good or bad events are asymmetrically distributed in many cases. Fat-tailed distributions allow the modeling of extreme events

with a higher probability than what the normal distribution predicts. In this research, the returns of each studied variable (each financial subindex, e.g., banks, insurance and pensions, investments, and other financial institutions) consist of two components: predictable and random. The predictable component in returns is estimated by the ARMA (p, q) model, while the random component is described by the variable ϵ_t . As mentioned earlier, the marginal return distribution of each financial institution under study is a function of a standardized random component distribution such as z_t indicated by D_{θ} .

Student's t -distribution function is a shape of distribution, which allows modeling of fat-tailed distributions of financial variables. The student's t -distribution density can be expressed as follows:

$$f(z_t|\Omega_{t-1}, \eta) = \frac{\Gamma(\frac{\eta+1}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})} \left(1 + \frac{z_t^2}{\eta-2}\right)^{-\frac{\eta+1}{2}}$$

The t -distribution function allows modeling a variety of statistical distributions with different positions, scales, and distribution tail fatness. The degree of freedom (DOF) parameter η can take values between 2 and ∞ ($2 < \eta < \infty$). Fig. 2 illustrates the t -distribution for different η values along with a standard normal distribution. As can be seen, the shape of the distribution tends towards a standard normal distribution by increasing the η value. Also, the t -distribution will have a truly heavy tail when η tends to 2 ($\eta \rightarrow 2$).

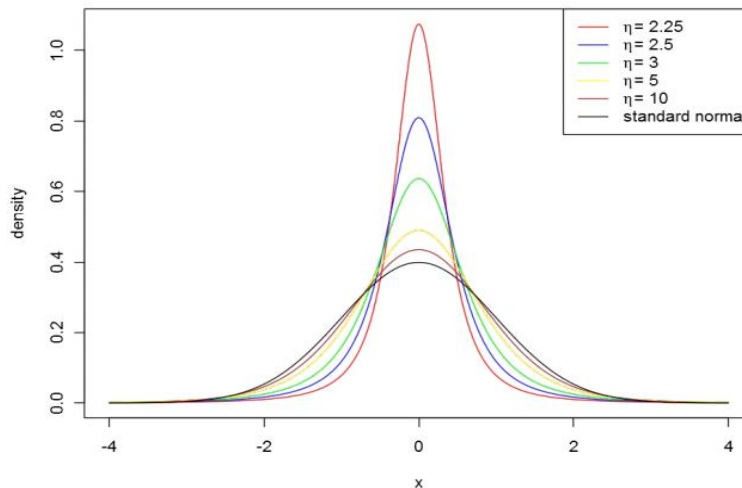


Fig. 3-1: A comparison between normal distribution and t -distribution with different DoFs

As mentioned above, the symmetric distribution assumption should be abandoned in many cases. This can be achieved by modifying the above equation so that the student's t -distribution becomes skewed. Hansen (1994) presented the autoregressive conditional Fréchet (AcF) model as a tool to combine fat-tailed behavior and skewed conditional distributions. In this sense, He presented skewed student's t -distribution, a special form of skewed generalized student's t -distribution, as follows:

$$f(z_t|\Omega_{t-1}, \eta, \lambda) = bc \left(\frac{1}{(\eta-2)} + \left(\frac{bz_t + a}{(1-\lambda)} \right)^2 \right)^{-\frac{\eta+1}{2}} \quad z_t < -\frac{a}{b}$$

$$f(z_t|\Omega_{t-1}, \eta, \lambda) = bc \left(\frac{1}{(\eta-2)} + \left(\frac{bz_t + a}{(1+\lambda)} \right)^2 \right)^{-\frac{\eta+1}{2}} \quad z_t \geq -\frac{a}{b}$$

where $a = 4 \lambda c \left(\frac{\eta-2}{\eta-1} \right)$, $b^2 = 1 + 3\lambda^2 - a^2$, and $c = \frac{\Gamma(\frac{\eta+1}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})}$.

The parameter λ , which controls skewed distributions, can take values between -1 and +1 ($-1 < \lambda < +1$). If $\lambda=0$, our distribution becomes a normal student's t -

distribution with a DoF of η . Fig. 3 depicts a skewed student's t -distribution density function vs student's t and standard normal distributions. As shown, different shapes of distributions can be obtained by changing the λ values (Ruppert & Matteson, 2015).

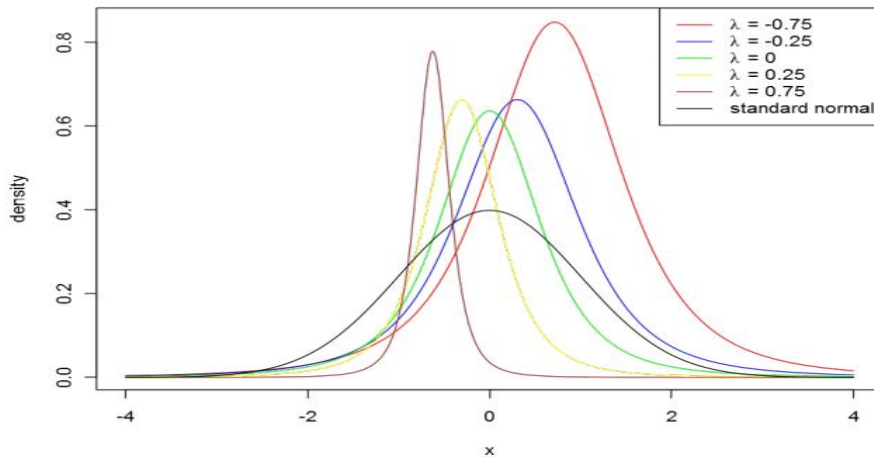


Fig. 2-3: Skewed student's t -distribution with different degrees of skewness vs student's t and standard normal distributions

Copula functions

The term "copula" was first applied in a statistical and mathematical sense by Sklar (1959) in the form of Sklar's theorem.

Copulas can be defined as follows: if X and Y are continuous random variables with distribution functions $F(x) = P(X \leq x)$ and $G(y) = P(Y \leq y)$ and joint distribution function $H(x,y) = P(X \leq x, Y \leq y)$, there is a point in space I^3 ($I = [0,1]$) with coordinates $(F(x), G(y), H(x,y))$ for each pair (x, y) in space $[-\infty, \infty]^2$. A copula can be defined as a mapping tool from space I^2 to space I (Nelsen, 2006).

In other words, a copula is a function with domain I^2 and range I ($C: I^2 \rightarrow I$) such that $x \in I$ for all values:

- 1) $C(0, x) = c(x, 0) = 0$
- 2) $C(1, x) = c(x, 1) = x$
- 3) For the values of $a, b, c, d \in I$, where $a \leq b, c \leq d$, the following relation holds:

$$V_C([a, b] \times [c, d]) = C(b, d) - C(a, d) - C(b, c) + C(a, c) \geq 0$$

where the function V_C is defined as the volume of the rectangle $[a, b] \times [c, d]$ under the C function (Nelsen, 2006).

Indeed, copulas are functions that join or "couple" multivariate distribution functions to their one-dimensional marginal distribution functions. Each copula assigns a probability measure to the points located on the rectangle $[0, u] \times [0, v]$ in the space I^2 as follows:

$$V_C([0, u] \times [0, v]) = C(u, v)$$

In multivariate mode, copula functions (multivariate copula functions) integrate the dependence structure data between $n > 1$ random variables X_1, X_2, \dots, X_n . Each random variable X_i has a probability density function and probability distributions $f(X_i)$ and $F(X_i)$. Assuming continuous functions $F(X_i)$, the relationship between the random variable U_i and the uniform probability distribution defined in the interval $(0, 1)$ and the probability distribution function of the random variable X_i can be described as follows (Nelsen, 2006):

$$U_i \equiv F(X_i) \text{ or } X_i = F_i^{-1}(U_i)$$

According to the above equation, the joint multivariate distribution of random variables X_1, X_2, \dots, X_n can be written as follows:

$$P(X_1 \leq x_1, \dots, X_n \leq x_n) = P(F_1(X_1) \leq F_1(x_1), \dots, F_n(X_n) \leq F_n(x_n)) \equiv C(F_1(x_1), \dots, F_n(x_n))$$

According to the above equations, there is a one-to-one correspondence between the copula function C and the distribution $X = (X_1, X_2, \dots, X_n)$, which can be expressed as Sklar's theorem (Kurowicka & Joe, 2011).

As Fischer (1997) states in the Encyclopedia of Statistical Sciences, copulas have become popular for two reasons: first, they are scale-free measures to evaluate the dependence and relationship between random variables; second, they are considered as a starting point for forming a family of double and multiple distributions (Fischer, Schluter, & Weigert, 2009).

The capacity of copula functions as a tool for modeling cross-sectional dependence structures between random variables originates from their potential to separate marginal distributions from the mutual dependence of variables. Since marginal models do not necessarily have to belong to the same family or have the same characteristics in using copula functions, copula modeling provides great flexibility in describing data and defining multivariate distributions. Therefore, a valid multivariate is obtained by combining any copula function with any set of marginal distributions. The characteristics of copula functions contrast with those of multivariate models, which do not allow the customization of marginal and dependence characteristics. Next, the parameters of the selected copula functions are estimated.

Gruber (2014) compared different dependence modeling options in terms of accuracy and time required for calculations by reviewing the dependence modeling literature using certain vine copulas. He determined that it would take two hours to estimate the optimal vine structure and copula function parameters used in this structure for six variables and 500 observations of each variable. However, a step-by-step method in conjunction with the maximum likelihood estimation (MLE) method provides the solution in a matter of seconds. Accordingly, it becomes increasingly crucial to consider the time needed to find the optimal solution, particularly when backtesting the

resulting model, since it might be implemented and estimated multiple times consecutively. In addition, the copula density can be calculated after a given vine structure specification. Copula density can be defined as the product of all selected bivariate copulas for certain vine branches. In general, a given vine density is uniquely defined as follows:

$$c(F_1(x_1), \dots, F_d(x_d)) = \prod_{i=1}^{d-1} \prod_{e \in E_i} c_j(e), k(e) | D(e) (F(x_j(e) | x_D(e)), F(x_k(e) | x_D(e)))$$

where $e = j(e), k(e) | D(e)$ is the E_i branches, $j(e), k(e)$ is the conditioned nodes, $D(e)$ is the conditioning set, and $c_j(e), k(e) | D(e)$ is the bivariate copula density function.

CoVaR

Considering the return series of a financial institution, an investment portfolio, or a specific component of the financial system R_t^i , assuming a confidence level of q , the VaR of the return time series of the financial institution or investment portfolio is defined and shown as the q th quantile of the return distribution as follows:

$$\Pr(R_t^i \leq VaR_{q,t}^i) = q$$

For example, if $q=0.05$, $VaR_{0.05,t}^i$ is defined as the fifth quantile of the return distribution. Adrian & Brunnermeier (2011) defined the CoVaR measure for any financial institution or investment portfolio as their VaR under the occurrence of an event such as value in another financial institution or investment portfolio. As defined by Adrian & Brunnermeier (2011), a conditioning event refers to the occurrence of VaR in the conditioning variable. Girardi & Ergün (2014) modified their definition such that the calculation of VaR in the return distribution of financial institution 1 was conditioned on the precise occurrence of the VaR state in the return distribution of variable 2 to the maximum state of VaR in the return distribution of variable 2. Conditioning the return distribution of variable 2 to the state $R_t^2 \leq VaR_{q,t}^2$ is considered a more general case of a crisis event for financial institution 2, making it possible for larger losses to occur. Girardi & Ergün (2012) listed another reason for redefining (revising) the definition

provided by Adrian & Brunnermeier, namely to facilitate CoVaR backtesting. Through the redefinition of CoVaR stated above, it can be tested as an estimate of VaR using widely used tests such as Kopik (1995) and Kristoffersen (1998) for periods where $R_t^j \leq VaR_{q,t}^j$. Also, Mainik and Schaanning (2012) concluded that this redefinition of financial crisis made CoVaR a consistent measure in terms of dependence. Girardi and Ergün defined CoVaR as an ascending function of the dependence between two financial institutions i and j after adjusting the definition of financial crisis. However, Adrian and Brunnermeier's definition of CoVaR lacks the mentioned feature. By adjusting the definition of CoVaR as described above, if X_t^1 and X_t^2 respectively indicate the return time series of financial institutions 1 and 2, the CoVaR for financial institution 1 at the confidence level of $1-\beta$ at time t can be defined as the β -quantile of the conditional distribution X_t^1 (Girardi & Ergun, 2013).

$$\Pr (X_t^1 \leq CoVaR_{\beta,t}^{1|2} | X_t^2 \leq VaR_{\alpha,t}^2) = \beta$$

In the above equation, the occurrence of crisis in financial institution 2 is defined as $X_t^2 \leq VaR_{\alpha,t}^2$ (Girardi & Ergun, 2013).

In the above equation, $VaR_{\alpha,t}^2$ is the VaR of financial institution 2, i.e., the maximum potential loss experienced by financial institution 2 at the significance level of $1-\alpha$ in a certain time period t . Besides, $VaR_{\alpha,t}^2$ indicates the α -quantile in the distribution return of financial institution 2. Statistically, the calculation of CoVaR involves determining the quantiles of conditional distributions, and $CoVaR_{\beta,t}^{1|2}$ is implicitly defined as the β -quantile of a conditional distribution. Calculating conditional distribution quantiles requires identifying a bivariate dependence between X_t^1 and X_t^2 as well as a multivariate dependence between all financial institutions in the financial system. This is because, apart from the direct effect of Financial Institution 2 on Financial Institution 1, the effect of Financial Institution 2 on Financial Institution 1 emerges through the existing dependence between Financial Institution 2 on other financial institutions and also the dependence between other financial institutions and financial institution 1. By considering a multivariate dependence structure and assuming four financial

institutions in the financial system, the CoVaR can be defined as follows:

$$\Pr (X_t^1 \leq CoVaR_{\beta,t}^{1|2} | X_t^2 \leq VaR_{\alpha,t}^2, X_t^3, X_t^4) = \beta$$

In calculating the CoVaR using the above equation, conditional distribution quantiles are determined by considering the financial conditions and interdependence of other financial institutions and financial institutions 1 and 2. The CoVaR can be calculated using this equation when a crisis occurs in more than one financial institution.

$\Delta CoVaR$

Herein, like Adrian & Brunnermeier (2011) and Girardi & Ergün (2012), $CoVaR^{(1|2)}$ is calculated to estimate the contribution of each financial institution and the financial system subsector in the escalation of systemic risk in other financial institutions. In calculating $CoVaR^{(1|2)}$, the VaR in a financial system component is conditioned on the occurrence of a financial crisis in financial institution j . The contribution of each financial institution forming the financial system in systemic risk can be defined as follows:

$$\Delta CoVaR_{q,t}^{(1|2)} = 100 \times (CoVaR_{q,t}^{(1|2)} - CoVaR_{q,t}^{(1|b^2)}) / CoVaR_{q,t}^{(1|b^2)}$$

The above equation measures the percentage difference in the VaR of Financial Institution 1 conditioned on the critical conditions of Financial Institution 2 compared to the VaR of the financial system while Financial Institution 2 is operating under normal conditions. There are several options to determine the standard normal mode. Adrian and Brunnermeier defined the base and standard mode using the median return distribution of financial institution j , while Girardi & Ergün (2012) used a standard deviation around the median event.

$$\mu_t^j - \sigma_t^j \leq R_t^j \leq \mu_t^j + \sigma_t^j$$

The effect of a crisis in any financial institution on the occurrence of a crisis in other financial institutions and the financial system, in general, can be evaluated by a

[certain] measure to evaluate and quantify risk spillover from one financial institution to the other (Reboredo & Ugolini, 2015).

Calculation of CoVaR using copula functions

Adrian & Brunnermeier (2011) calculated and estimated $VaR_{\beta,t}^2$ and $CoVaR_{\beta,t}^{1|2}$ using quantile regression. They calculated $CoVaR_{\beta,t}^{1|2}$ using β -quantile regression of time series R_t^1 for R_t^2 and a set of variables describing lagged conditions. They obtained an equation $CoVaR_{\beta,t}^{1|2} = c + dVaR_{\beta,t}^2 + eM_{t-1}$ after implementing the abovementioned regression. In this equation, M_{t-1} represents a vector of variables describing the conditions, and the values $a, b, c, d,$ and e are the coefficients of the quantile regression function. Also, the VaR effect of variable 2 on $CoVaR_{\beta,t}^{1|2}$, measured with coefficient d , remains constant even despite the time-varying correlation coefficient between variables 1 and 2. However, $CoVaR_{\beta,t}^{1|2}$ should also vary over time due to the variation in correlation coefficients between the two variables.

This study aimed to calculate and display the CoVaR using vine copula structures. The process of calculating the CoVaR as vine copula structures was first expressed by Reboredo (2015) and evolved by Reboredo & Ugolini (2015).

According to Sklar's theorem (1954), β can be rewritten as:

$$\frac{F_{x_{1t},x_{2t}|x_{3t},x_{4t}}(CoVaR_{\beta,t}^1, VaR_{\alpha,t}^2)}{F_{x_{2t}|x_{3t},x_{4t}}} = \beta$$

According to the previously discussed expression of probability distribution functions based on copula functions, the above equation can be rewritten as follows:

$$C_{x_{1t},x_{2t}|x_{3t},x_{4t}}(F_{x_{1t}|x_{3t},x_{4t}}(CoVaR_{\beta,t}^1), F_{x_{2t}|x_{3t},x_{4t}}(VaR_{\alpha,t}^2)) = \alpha\beta$$

The CoVaR values can be derived from the selected optimal vine copula structure using the following three-step process:

- 1) X can be solved to obtain $F_{x_{1t}|x_{3t},x_{4t}}(CoVaR_{\beta,t}^1)$ values by considering the significance level selected for the VaR and CoVaR (α and β , respectively) and the copula family selected for each tree branch of the vine structure and its parameters.
- 2) $F_{x_{1t}}(CoVaR_{\beta,t}^1) = u_1$ data is extracted using the values obtained in the previous step and the conditional copula model.
- 3) The CoVaR value can be obtained as follows as a quantile of return distribution x_l with cumulative probability u_1 by inverting the marginal distribution function using the resulting u_1 value (Reboredo & Ugolini 2015):

$$CoVaR_{\beta,t}^1 = F_1^{-1}(u_1)$$

Bootstrapped KS test

The cumulative distribution of CoVaR and VaR indices were analyzed and compared using the bootstrapped KS test to perform a significance test of risk spillover among the investigated institutions. This test was introduced by Abadie (2002) and utilized by Bernal, Gnabo, & Guilmin (2014) to compare the CoVaR values. It measures the difference between two cumulative quantile functions by relying on an empirical distribution function without considering any basic distribution function. This test can be defined as follows:

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_x |F_m(x) - G_n(x)|$$

where $F_m(x)$ and $G_n(x)$ are cumulative distribution functions of CoVaR and VaR, respectively. Besides, n and m are the sample sizes of each of the two distributions. This statistic can be used to test the assumption of the lack of a systemic effect between two financial institutions or symmetric risk spillovers between financial institutions (Reboredo & Ugolini, 2015).

$$H_0: CoVaR_{\beta,t}^1 = VaR_{\beta,t}^1$$

Data analysis

This study employed the daily return time series values of Brent crude oil, Grade A copper, edible soybean, and European CEA markets as a representative of the energy, base metals, agricultural commodities, and

carbon emissions markets of banks between April 23, 2017 and April 1, 2022. An analysis of the indices utilized herein indicated that CEA prices have gone through an upward trend in almost the entire study period. On the other hand, the oil and copper markets have experienced a downward trend and then a

medium-term upward rally. The soybean market has also gone through a phase of stability (with no ups and downs) and has seen slower (lagged) price growth than the copper and oil markets. Daily returns of each commodity group were calculated according to the daily data collected from the studied markets.

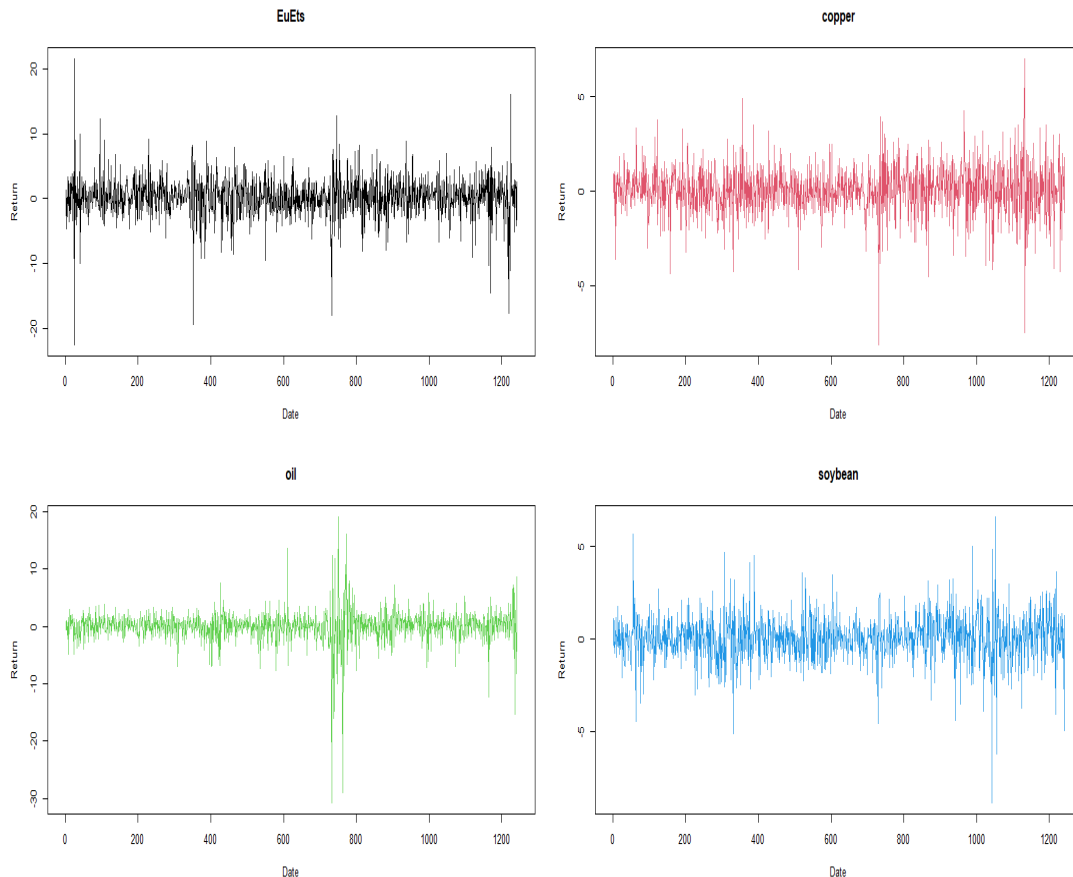


Fig. 4-1: Daily returns of crude oil, copper, soybean, and CEA markets

Fig. 4-1 illustrates the daily returns of crude oil, copper, soybean, and CEA markets, as well as the return time series dynamics of the studied indices during the research period. Fig. 2 depicts the clustering in return time series volatility. Table 1 lists the descriptive statistics and the results of some tests on the return time series characteristics of the studied commodities to better understand the return time series behavior of the commodities used herein.

As can be seen in Table 4-3, the return time series of commodity and carbon markets, which is comprised

of 1242 observations on average, is positive for all indices during the research period. EU CEA and soybean [markets] obtained the highest and lowest average returns in this time period, respectively. Unconditional volatility was roughly the same for copper and soybean time series, on the one hand, and CEA and Brent oil markets, on the other. However, the EU CEA and soybean return time series had the highest and lowest volatility, respectively. Examining the parameters describing the shape of distribution, including kurtosis and skewness, indicated the

different shapes of return distributions from symmetrical distributions such as normal distributions. All time series showed negative skewness and excess kurtosis. The null hypothesis regarding the normality of the time series distribution under study was rejected at a significance level of 1% based on the results of the Jarque-Bera and Shapiro-Wilk test statistics, which were used to test the distribution normality. Available evidence did not support the time series independence assumption based on the Ljung-Box autocorrelation test with 20 lags. That is, past time series values (data) contained useful information to explain their current values and predict their future values. Also, evidence of the ARCH effect was found in all time series

according to the Lagrange coefficient test, which was used to determine whether conditional heteroskedasticity existed.

Table 4-4 shows the unconditional correlation matrix of the studied time series.

Significant positive values of unconditional correlation between the studied time series confirmed the positive time series dependence relationship around the median of unconditional marginal distributions. The highest and lowest correlation coefficients were observed between the return time series of CEA/Brent crude oil and soybean/copper pair groups, respectively.

Table 4-3: Descriptive statistics of the return time series of commodity markets

	EuEts	Copper	oil	Soybean
nbr.val	1242	1242	1242	1242
nbr.na	0	0	0	0
min	-22.5314	-8.09937	-30.7458	-8.88594
max	21.56329	6.977071	19.0774	6.613093
range	44.09465	15.07644	49.82323	15.49904
sum	284.1272	60.76298	72.81717	54.27606
median	0.253845	0.055236	0.240391	0.057737
Mean (%)	0.228766	0.048923	0.058629	0.043701
SE.mean	0.090601	0.037063	0.080427	0.035444
var	10.19498	1.706096	8.033949	1.560308
std.dev	3.192958	1.306176	2.834422	1.249123
skewness	-0.56004	-0.3436	-1.74138	-0.26707
kurtosis	7.362763	3.225527	25.96141	4.44812

Table 4-4: Unconditional correlation matrix of the studied time series

	EuEts	copper	Oil	Soybean
EuEts	1	0.39055	0.48561	0.1333
copper	0.39055	1	0.42866	0.0069
oil	0.48561	0.42866	1	0.01517
soybean	0.1333	0.0069	0.01517	1

Marginal distribution modeling

This research employed the ARMA-APGARCH model to model the return time series of the marginal distributions of CEA, crude oil, copper, and soybean variables assuming that the random component of the residuals follows Hansen's (1996) skewed student's *t*-distribution. Different lag combinations of ARMA and GARCH components (p, q, r, m) are compared between the lower limit (0) and upper limit (1) according to Bayesian Information Criterion (BIC) to choose the best fit of ARMA-APARCH on the studied

time series. The model with the lowest BIC value was considered as the optimal specification.

Table 4-5 lists the estimation results of marginal distributions for the studied time series. According to a comparison between different combinations of ARMA and APGARCH components for each time series, the best models in terms of BIC were ARMA (1,1)-APGARCH (1,1) with skewed student's *t* random values for EU CEA returns, ARMA (0,1)-APGARCH (1,1) for copper returns, and ARMA (0,0)-APGARCH

(1,1) with skewed student's t random values for crude oil and soybean returns.

As can be seen, the moving average (MA) and autoregression (AR) components were significant at a confidence level of 1% to describe the median of the CEA return time series. The significance of the AR component in this time series indicated how quickly historical data appeared in the current returns of this group. The significance of the ARCH coefficient at a significance level of 1% in all studied time series indicated the effect of the square of shocks in the previous period on the conditional volatility in the current period. Besides, the significance of the GARCH component in the marginal models of all time series at a significance level of 1% indicated highly stable volatility in all time series.

According to the table above, the significance of the leverage effect (γ) at a significance level of 1% for

all the studied time series suggested that the studied indices reacted asymmetrically to negative and positive shocks. Engle & Ng's (1996) sign bias test (SBT) is usually adopted to test the adequacy of asymmetric GARCH family models in comparison with their symmetric counterparts. This research also applied the aforementioned test to measure the adequacy of the APGARCH model to describe the variance equation of the studied time series. This confirmed the absence of positive and negative biases in the residual components of the estimated ARMA-APGARCH model for the studied time series.

The significance of the estimated value for δ or the power component of the APGARCH equation ($\neq 1$ or 2 for all the studied time series at a confidence level of 99%) indicated that the standard GARCH family models, where the value of δ is set to 2 by default, cannot provide the best fit for the studied time series.

Table 4-5: Estimation of marginal distributions

	EuEts	Copper	oil	Soybean
Mean equation				
AR (1)	-0.673862 (0.000941)	-	-	-
MA (1)	0.603246 (0.000016)	-0.065971 (0.017241)	-	-
Variance Equation				
ARCH (1)	0.099234 (0.004086)	0.027513 (0.0000)	0.107535 (0.0000)	0.055332 (0.0000)
GARCH (1)	0.795741 (0.0.00000)	0.974213 (0.0000)	0.892387 (0.0000)	0.945066 (0.0000)
APGARCH (gamma)	0.162092 (0.0232)	0.080920 (0.0293)	0.540380 (0.000520)	0.18758 (0.0.00504)
APGARCH(Delta)	1.803415 (0.000508)	1.274831 (0.0000)	0.823716 (0.0000)	0.73665 (0.0000)
Asymmetry	0.977165 (0.0000)	0.977820 (0.0000)	0.853596 (0.0000)	0.975204 (0.0000)
Shape	4.635091 (0.0000)	5.621488 (0.0000)	4.143647 (0.0000)	5.464483 (0.0000)
Diagnostic test				
BIC	4.9691	3.2911	4.2223	3.1578
Adjusted Pearson Goodness-of-Fit Test	52.352 (0.3452)	31.3 (0.8052)	32.91 (0.3927)	27.41 (0.095404)
Sign Bias	0.4737 (0.6358)	1.229 (0.2192319)	0.03486 (0.97220)	1.2035 (0.2290)
Q2(20)	4.36998 (0.6026)	4.466 (0.1605)	3.913 (0.6036)	9.94192 (0.05162)
ARCH (7)	0.514187 (0.9771)	3.5710 (0.4127)	2.1689 (0.6816)	8.658 (0.3737)

Tests for autocorrelation and ARCH effect in the residuals of the model with 20 lags did not reject the lack of autocorrelation and heteroskedasticity effect in

the residual components of the ARMA-APGARCH model.

The adjusted Pearson goodness-of-fit test was utilized to check the fitness of the empirical residual distribution for each ARMA-APGARCH model estimated with a skewed student's *t*-distribution assumed for the residuals. This test, which was designed to evaluate how well random variables' behavior matched the claimed theoretical behavior, validated the assumption that the residual random component follows the skewed student's *t*-distribution for all time series. As mentioned earlier, the evidence indicated the adequacy of the asymmetric model used in time series volatility modeling at a confidence level of 5%, according to Engle & Ng's (1996) SBT results. Moreover, the estimation of DoF and skewness parameters in Hansen's (1996) skewed student's *t*-distribution supports the claim of tail fatness in the return distribution of all investigated indices.

Accordingly, the return time series of the examined indices show evidence of tail dependencies.

Estimation of marginal cumulative distributions

Marginal models were first estimated, and time series were obtained for the residuals from the estimation of ARMA-APGARCH models for EU CEA, copper, crude oil, and soybean returns based on the estimated parameters for DoF and skewed student's *t*-distributions. Then, marginal skewed student's *t*-distribution values were calculated for each time series. Table 4-6 lists marginal distribution parameters. Fig. 4-3 displays a general overview of cumulative distributions of residual random components.

Table 4-6: Marginal distribution parameters

	EuEts	Copper	Oil	Soybean
Skewness	0.977165 (0.0000)	0.977820 (0.0000)	0.853596 (0.0000)	0.975204 (0.0000)
Degree of freedom	4.635091 (0.0000)	5.621488 (0.0000)	4.143647 (0.0000)	5.464483 (0.0000)

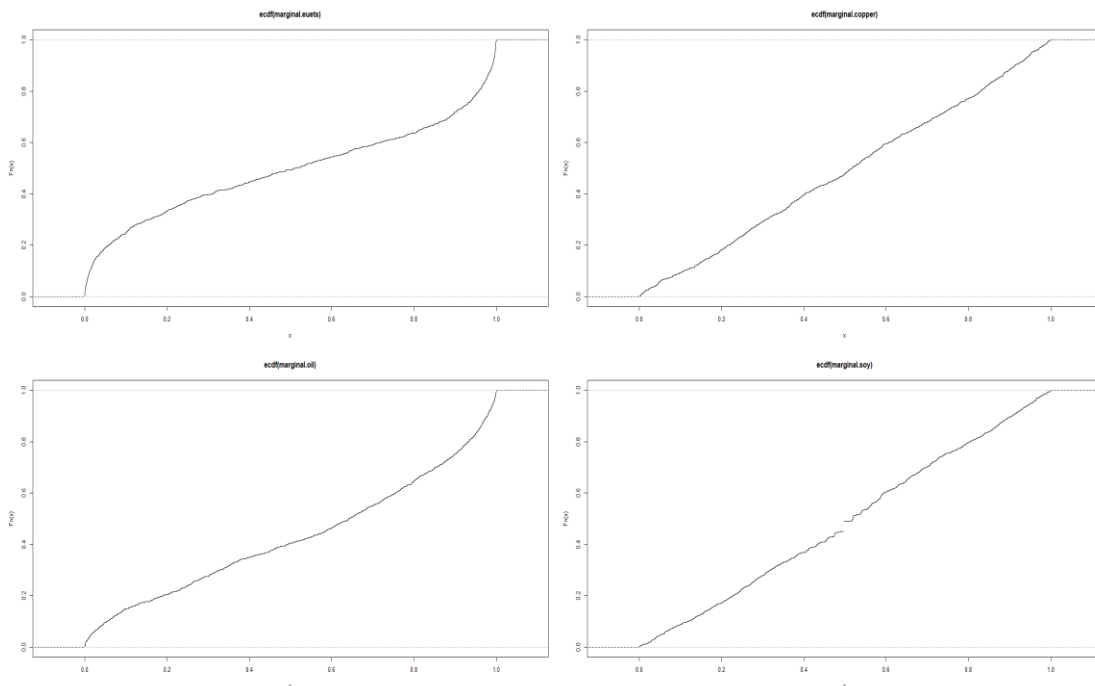


Fig. 4-3: Cumulative skewed student's *t*-distributions for each residual of ARMA-APGARCH models

Upside and downside risk spillovers between commodity and carbon markets:

This section presents the estimation results of the copula structures consisting of CEA, copper, crude oil, and soybean time series and also identifies the optimal copula functions, and estimates the parameters of pair copula functions to describe pair joint distribution functions among the abovementioned markets.

For this purpose, the CoVaR values were calculated for each market contingent on the presence of the VaR state in other markets by estimating the pair copula functions selected to model the joint distribution functions of these markets. Then, the research hypotheses were tested by measuring the degree to which the calculated CoVaR values overlap with the VaR values calculated under unconditional and asymmetric upside and downside [risk] spillovers between the markets under study.

Estimation of pair copula functions:

The parameters of the marginal distributions of the random return time series values of commodity and carbon markets were initially estimated. Afterward, pair copula functions corresponding to each pair of commodity and carbon markets were selected, and their parameters were estimated. Table 4 presents the estimation results of pair copula functions. The Adjusted Akaike Information Criterion (AIC) was used to estimate copula functions for small sample sizes to select the optimal copula function. To this aim, the coefficients and specification parameters of various copula functions, including Gaussian copula, Student's

t, Gumbel, Clayton, Frank, and Joe functions were first computed. Next, the function with the lowest AIC value was selected as the optimal copula function using the copula structure MLE method and comparing the obtained functions in terms of AIC. Table 4 reports the specifications used for the 44 copula structures and the standard deviation (SD) values for each coefficient in square brackets along with the tail dependence measures between the aforementioned pairs.

All parameters of copula functions listed in the above table are estimated using the MLE method.

As can be seen, the CEA-copper joint distribution was described by the Gumbel copula survival function, which is mostly characterized by its asymmetry and lower tail dependence. The CEA-oil joint distribution function was modeled by the student's *t* copula function, a symmetric function appropriate for describing and modeling tail dependencies on the right and left sides of symmetric distributions. The CEA-soybean and copper-soybean joint distributions were described by Joe's inverse copula function, an asymmetric copula that models lower tail dependence. Besides, the copper-oil joint distribution was described by Clayton's inverse copula function, which is mostly characterized by the tail dependencies on its left side. The oil-soybean pair was described by Frank's copula function, which is mostly characterized by the lack of tail dependencies on its left and right sides, as discussed in detail in the third chapter. The important point in the above table is the presence of tail dependencies in all the investigated pairs except the oil-soybean pair.

Table 4-7: Estimation of pair copulas

	EuEts, Copper	EuEts, Oil	EuEts, Soybean	Copper, Oil	Copper, Soybean	Oil, Soybean
Copula	Survival Gumbel	T student	Survival Joe	Survival Clayton	Survival Joe	Frank
Parameter 1	1.01	-0.002387	1.01	0.04	1.02	0.32
Parameter 2	0.00	8.4102	0.00	0.00	0.00	0
Upper Tail dependency	-	0.01258	-	0.0016	-	-
Lower tail dependency	0.01	0.01258	0.01	-	0.02	-

Calculation of CoVaR and downside risk spillover:

Downside risk spillover refers to the effect of extreme events on the left side of the return distribution of one market or financial instrument on another. That is,

knowledge of a crisis occurring in one market can alter the VaR estimate in another.

The VaR and CoVaR values were calculated at a confidence level of 95% ($\beta=0.05$) using univariate

marginal distributions estimated for each index and the best pair copula function selected for each pair. Fig. 13 depicts a general and comparative view of the VaR and CoVaR size and dynamics during the research period, where the colored and black curves represent the CoVaR and VaR time series of the indices under study, respectively. As can be seen, a comparison between the location of the CoVaR and VaR time series in all studied indices confirmed the

distance and difference between VaR and CoVaR. In all cases, while the CoVaR values are situated at the bottom of the VaR curve, the intensity of the difference between the two curves varied among the studied markets. In other words, although commodity and carbon markets differ in systemic importance, appropriate statistical tools and econometrics must be used to thoroughly investigate this matter.

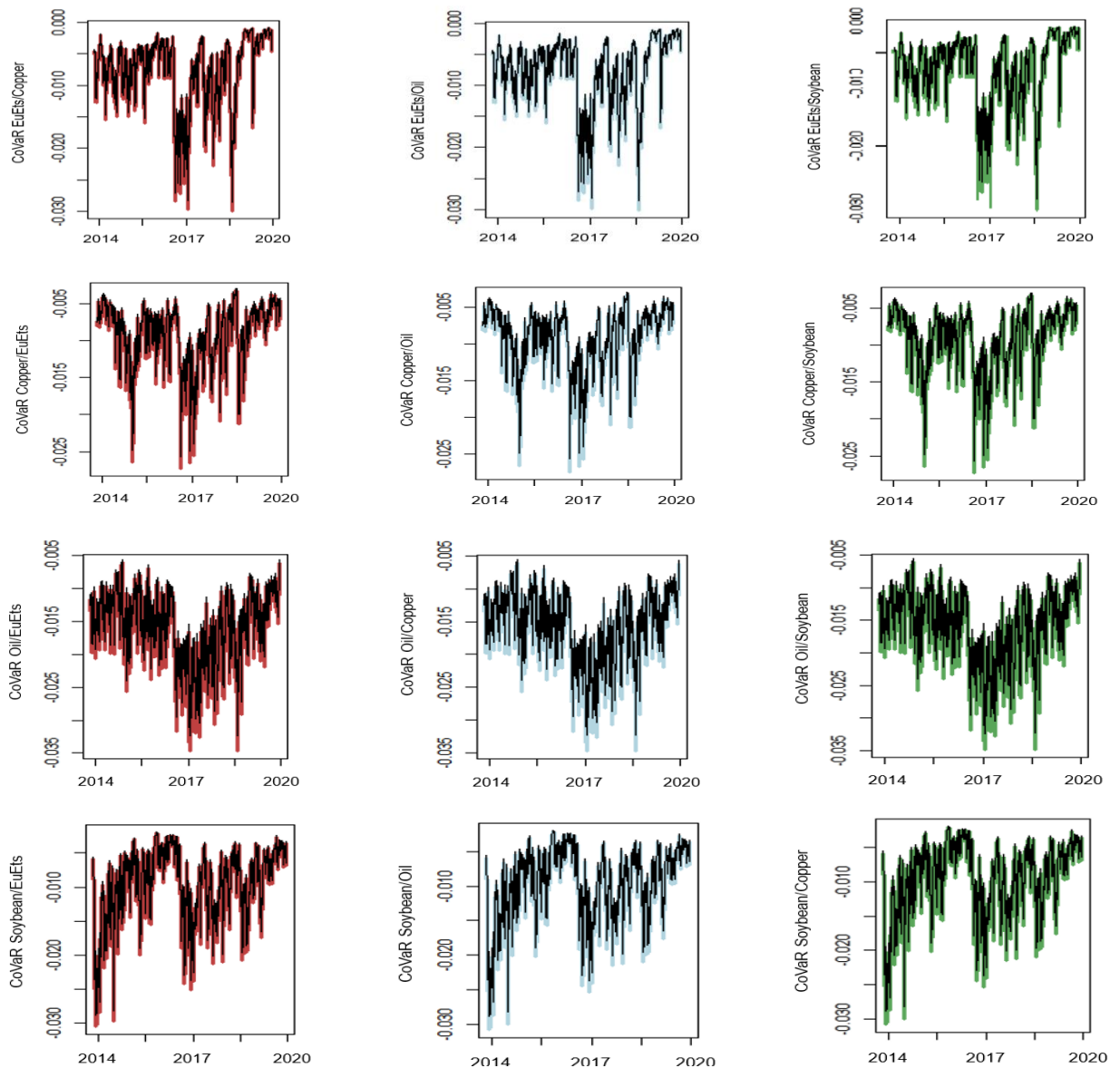
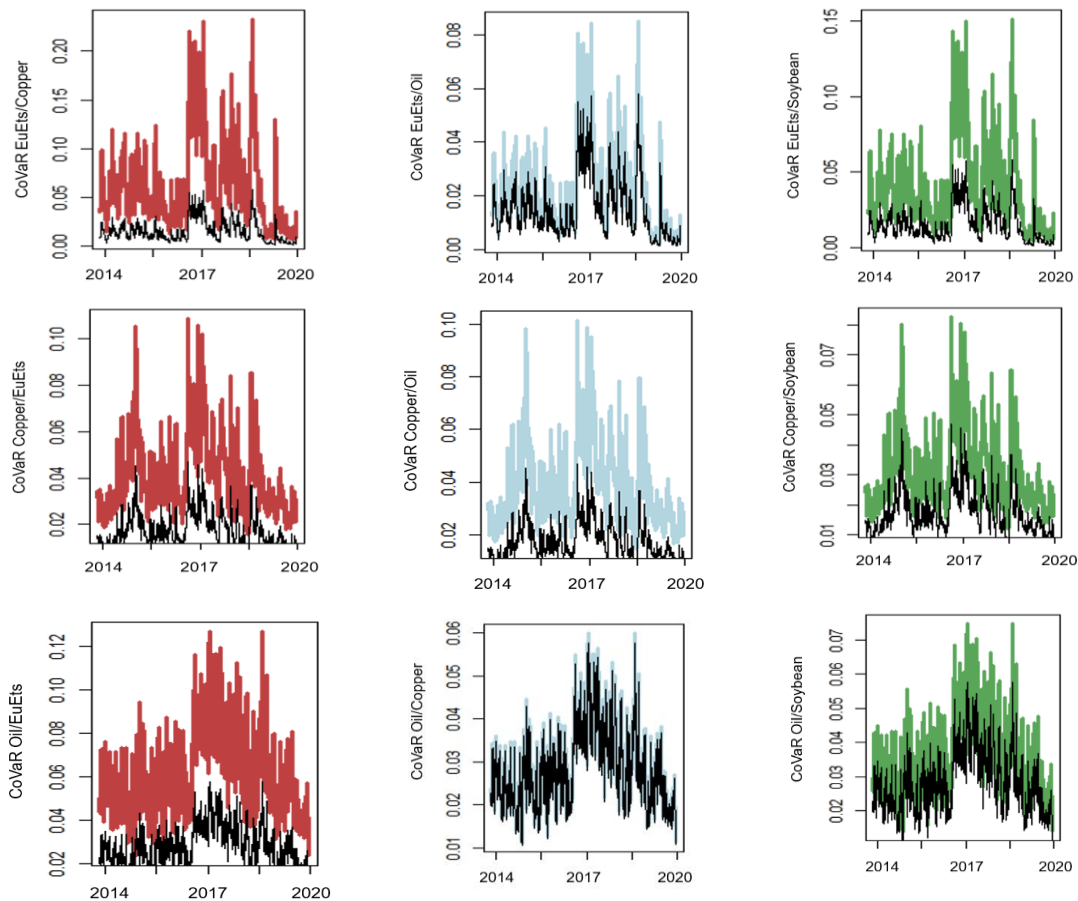


Fig. 4-4: A general comparison of downside VaR and CoVaR between commodity and carbon markets

Calculation of CoVaR and upside risk spillover:

The upside VaR and CoVaR values were calculated at a confidence level of 95% ($\alpha=0.05$ and $\beta=0.05$) using univariate marginal distributions estimated for each index and the best pair copula function selected for each pair. Upside VaR refers to extreme conditions on the right side of the distribution function of the investigated indices, a value that will not be exceeded by investment portfolio returns with a probability of 95%. Obviously, according to the above definition, upside CoVaR refers to the returns that will not be exceeded by the returns of the target markets with a probability of 95%, contingent on the returns higher than the extreme determined by VaR or upside extreme events in other commodity markets.

Fig. 14 shows the upside risk spillover between financial institutions in comparison with the upside VaR of each market under study, calculated by applying the unconditional marginal distribution of that financial institution. A visual examination of this diagram indicates a difference in the upside VaR and CoVaR size and dynamics during the research period. As shown, a comparison between the location of the CoVaR and VaR time series in all studied indices confirmed the distance and difference between VaR and CoVaR. In some cases, the intensity of the upside risk spillover can exceed that of the downside risk spillover. An assertion in this sense depends on testing asymmetric upside and downside risk spillovers between commodity and carbon markets in the next sections of this chapter.



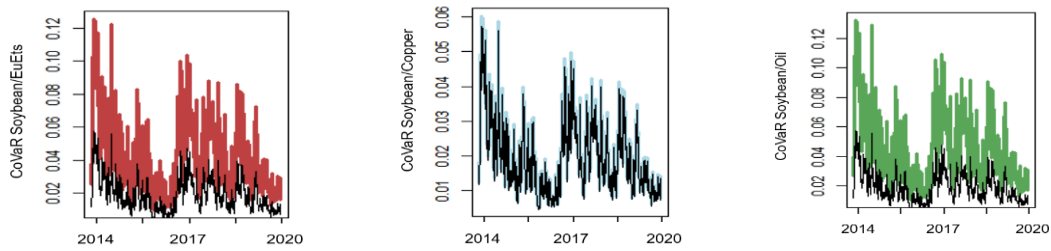
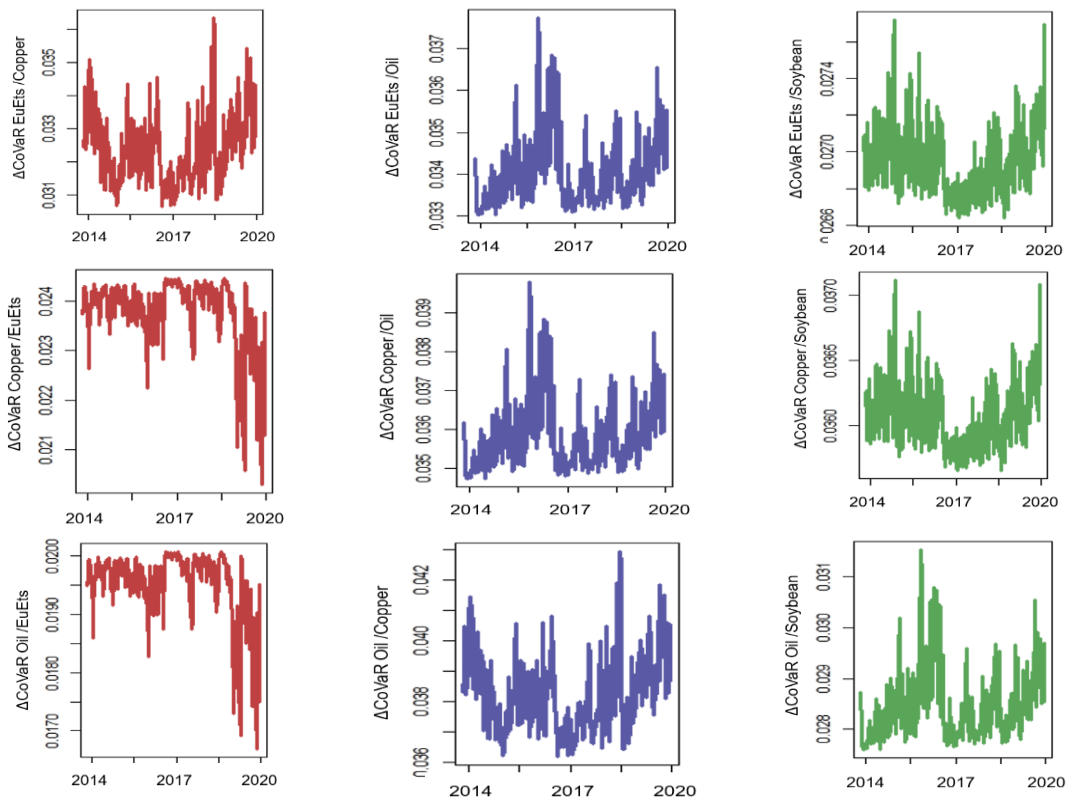


Fig. 4-5: A general comparison of upside VaR and CoVaR between commodity and carbon markets

Δ CoVaR and how commodity and carbon markets are affected by each other's upside and downside risks:

Adrian & Brunnermeier (2011) introduced Δ CoVaR after analyzing a systemic risk measurement method called CoVaR. They defined financial institutions' contribution to systemic risk as the difference between CoVaR, when the institution in question is under emergency circumstances, and CoVaR when it is

under normal conditions (Δ CoVaR). They concluded that there is a strong relationship between the VaR of individual (independent) institutions and their differential CoVaR (Δ CoVaR) in the time series dimension. In what follows, Figs. 15 and 16 depict the systemic role of commodity and carbon markets examined herein as upside and downside Δ CoVaR criteria.



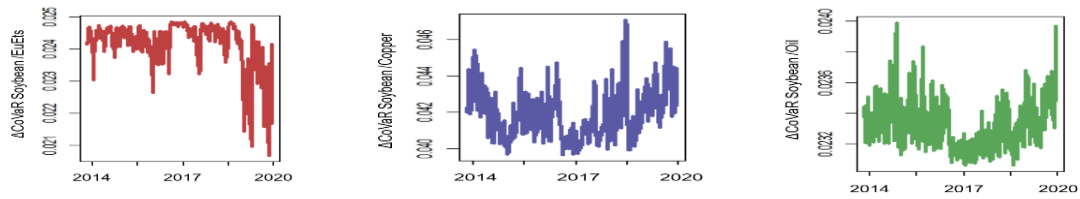


Fig. 4-6: The systemic role of each commodity and carbon market in downside risk spillover based on the ΔCoVaR measure

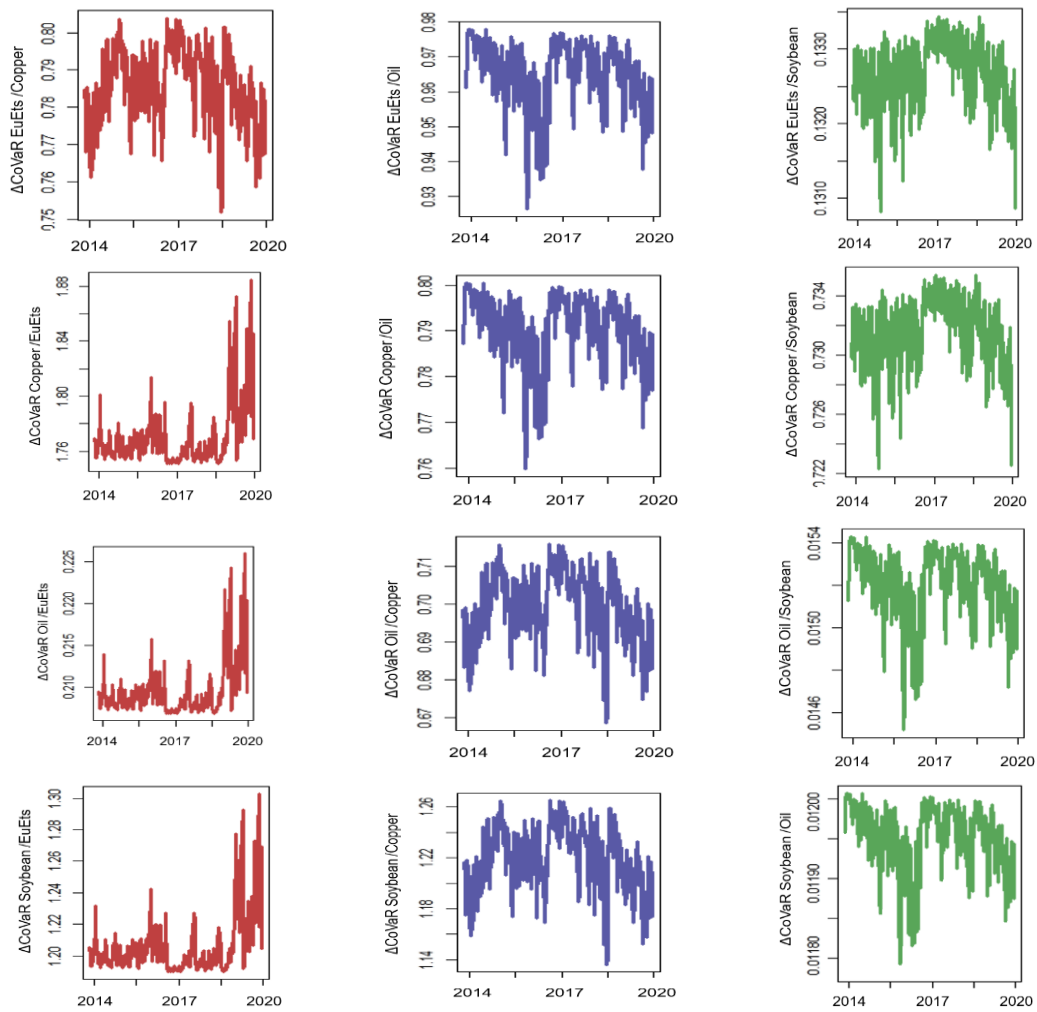


Fig. 4-7: The systemic role of each commodity and carbon market in upside risk spillover based on the ΔCoVaR measure

Asymmetric upside and downside [risk] spillovers test

This research draws on Mensi et al.'s methodology (2017) to test symmetric upside and downside risk spillovers between the studied groups. This methodology adopts the bootstrapped KS test statistic to test asymmetric upside and downside risk spillovers by measuring the significance of the difference

between normalized downside CoVaR based on downside VaR and normalized upside CoVaR based on upside VaR.

The null hypothesis based on symmetric upside and downside [risk] spillovers can be rejected at a confidence level of 95% according to the research findings (listed in the above table) and the bootstrapped KS test statistic.

$EuEts \quad H_0: \frac{CoVaR(Downside)}{VaR(Downside)} = \frac{CoVaR(Upside)}{VaR(Upside)}$ $H_a: \frac{CoVaR(Downside)}{VaR(Downside)} \leq \frac{CoVaR(Upside)}{VaR(Upside)}$		
(EuEts Copper)	(EuEts Oil)	(EuEts Soybean)
1.000 [0.000]	1.000 [0.000]	1.000 [0.000]
$Copper \quad H_0: \frac{CoVaR(Downside)}{VaR(Downside)} = \frac{CoVaR(Upside)}{VaR(Upside)}$ $H_a: \frac{CoVaR(Downside)}{VaR(Downside)} \leq \frac{CoVaR(Upside)}{VaR(Upside)}$		
(Copper EuEts)		
1.000 [0.000]		
$Oil \quad H_0: \frac{CoVaR(Downside)}{VaR(Downside)} = \frac{CoVaR(Upside)}{VaR(Upside)}$ $H_a: \frac{CoVaR(Downside)}{VaR(Downside)} \leq \frac{CoVaR(Upside)}{VaR(Upside)}$		
(Oil EuEts)		
1.000 [0.000]		
$Soybean \quad H_0: \frac{CoVaR(Downside)}{VaR(Downside)} = \frac{CoVaR(Upside)}{VaR(Upside)}$ $H_a: \frac{CoVaR(Downside)}{VaR(Downside)} \leq \frac{CoVaR(Upside)}{VaR(Upside)}$		
(Soybean EuEts)		
1.000 [0.000]		

Discussion

The results obtained in this research can be discussed in two general dimensions:

- 1) Upside and downside risk spillovers between commodity and CEA markets;
- 2) Asymmetric downside and upside risk spillovers between the studied markets

Upside and downside risk spillovers between commodity and CEA markets:

A literature review of systemic risk suggested that systemic risk is spread through the risk-taking capability of the components of a system, including the system consisting of commodity markets, due to

interconnections between markets in the financial system, including commodity and CEA markets. Therefore, it is crucial to explore the interdependencies and gauge how well the system components are affected by endogenous shocks within the system or negative exogenous shocks in the environment to understand the nature of the emergence, spread, and intensification of financial crises and measure systemic risk in the financial system consisting of commodity markets.

As mentioned earlier, the main problem of this research was to analyze the dependence structure and risk spillover between CEA and commodity markets from a systemic risk perspective. Modeling upside and downside risk spillovers between financial markets

and calculating the contribution of each financial instrument and market to the systemic risk in financial systems requires modeling the multivariate dependence structure between these markets and the marginal behavior of each time series of changes and its ups and downs. To measure [and quantify] systemic risk and model the effect of upside and downside risk spillovers between CEA and commodity markets, the daily return time series of the data used in modeling upside and downside risk spillovers were filtered during the ARMA-APGARARCH process, and marginal distributions of each variable were estimated based on residuals, following data collection and continuous calculation of daily data returns. Then, after determining the pair and conditional distributions and copulas, the CoVaR measure was calculated as the VaR of variable i under the condition that a specific event occurs in variable j using the resulting conditional distributions in two cases, i.e., the median event and the q th quantile event, in the distribution of variable j . This measure was employed to measure upside and downside risk spillovers between each of the studied markets. The role and contribution of systemic risk in the formation and intensification of systemic risk in the financial system were also measured, and the ΔCoVaR measure was calculated once an appropriate copula function was selected to characterize the dependence structure of each market in the financial system.

The effect of risk spillover between the financial system components was analyzed using the bootstrapped KS test, given the significant differences between CoVaR and VaR distributions. Furthermore, the asymmetric effect of extreme upside and downside movements between various financial system components was tested. This study examined the spread of upside and downside risks between carbon assets trading markets and commodity markets, including energy, base metals, and agricultural commodities, as well as the effect of each component on systemic risk in a system consisting of commodity markets.

The most important conclusions drawn from this research are as follows:

- 1) Upside risk spillovers or extreme events on the right side of the return distribution of the studied commodity markets significantly affected similar events in the carbon emission trading market for all the studied markets at a

confidence level of 99%. In this context, the null hypothesis of uniform individual marginal unconditional VaR distributions with VaR distributions conditioned on the occurrence of extreme upside events in the carbon emission trading market for oil, base metals, and agricultural commodities markets was rejected at a significance level of 1%.

- 2) From investors' viewpoint, the upside events occurring respectively in the oil and base metals markets have a stronger effect on those in the carbon emission trading market.
- 3) According to the upside ΔCoVaR measure, the carbon emission trading market experiences an increase in upside events of 123%, 102%, and 87%, respectively, when upside extreme events occur in the oil, base metals, and agricultural commodities markets as opposed to when they are under normal circumstances.
- 4) Downside events in the base metals market have no spillover effect on those in the carbon emission trading market. In this sense, it is reasonable to assume that the prospect of downside events or crises in the base metals market will not affect the likelihood of critical events occurring in the carbon emission trading market, as represented by the events in the VaR area and to its left. Since there is no tail dependence between the base metals market and the carbon emission trading market, it is reasonable to assume that the former does not, either directly or indirectly, intensify the downside events occurring on the left side of the distribution of the latter.
- 5) The lack of a systemic effect of downside events in the agricultural commodities market on the carbon emission trading market cannot be rejected at a significance level of 5%. However, crises in the former have no systemic effect on those in the latter with increasing the confidence level from 95% to 99%.
- 6) Based on the downside ΔCoVaR measure, extreme events in the base metals, agricultural commodities, and oil markets, intensified downside events and crises in the carbon emission trading market by 2.9%, 3.7%, and 4.1% as compared to their normal conditions. In this respect, the oil market had a more

systemic effect on the downside events in the carbon emission trading market.

- 7) A comparison between upside and downside event spillovers between the studied markets indicated that upside events spread more intensely and significantly among the studied commodity and carbon emission trading markets. In this context, upside events can be seen as playing a more systemic role than downside events.

Asymmetric downside and upside risk spillover, contagion, and intensification

Among other things discussed herein were symmetric or asymmetric upside and downside events between commodity and carbon emission trading markets. In other words, this research aimed to answer the question: "Are upside and downside extreme events in the studied commodity markets identically affected by similar events in the carbon emission trading market?" This study adopted an innovative measure introduced by Mensi et al. (2017) to answer the question raised above and evaluate whether upside and downside risk spillovers between the studied commodity and carbon emission trading markets are symmetric or asymmetric. This innovative method relied on normalizing the estimated CoVaR values at the right and left tails of the distribution using the VaR values at the left and right sides of the return distribution and comparing the obtained statistics using the bootstrapped KS test. According to the test results, the null hypothesis of symmetric upside and downside risk spillovers between the studied commodity and carbon

emission trading markets can be confirmed at a confidence level of 99%. Besides, upside risk spillovers occur more intensely than downside risk spillovers between the studied commodity and carbon emission trading markets, according to the one-sided KS test.

Therefore, the commodity and carbon emission trading markets examined herein can be considered to have a stronger systemic effect in upside extreme modes than in downside extreme modes. From an investment perspective, these markets appear to have greater potential to benefit from upside events therein. Some commodity markets, e.g., the base metals market, are not significantly affected by the events occurring in other system components in case of upside or downside events.

Conclusions

This section tests research hypotheses regarding upside and downside risk spillovers between carbon asset and commodity markets using the bootstrapped KS test, where the test statistic and its critical values are extracted by conducting 2000 bootstraps. As previously mentioned, this test is predicated on the comparison between VaR and CoVaR empirical distributions. It is adopted to measure the significance of the difference emphasized visually in the diagrams illustrated in the previous sections.

Table 4-10 summarizes the test results of testing the research hypotheses regarding upside risk spillover.

Table 4-11 summarizes the test results of testing the research hypotheses regarding downside risk spillover.

Table 4-10: Bootstrapped KS test results

	VaR Upside (average)	CoVaR Upside (average)	$H_0: VaR = CoVaR$ $H_a: VaR > CoVaR$
(EuEts Oil)		0.06627	0.63742 [0.000]
(Oil EuEts)		0.1606	0.85603 [0.000]
(EuEts copper)		0.0399	0.72564 [0.000]
(copper EuEts)		0.1634	0.7757 [0.000]
(EuEts soybean)		0.1111	0.5182 [0.000]
(soybean EuEts)		0.0448	0.7266 [0.000]

Table 4-11: Bootstrapped KS test results

	VaR Downside (average)	CoVaR Downside (average)	$H_0: VaR = CoVaR$ $H_a: VaR > CoVaR$
(EuEts Oil)		-0.0081	0.033931 [0.093]
(Oil EuEts)		-0.0081	0.038778 [0.0454]
(EuEts copper)		-0.0094	0.07367 [0.000]
(copper EuEts)		-0.0095	0.074164 [0.000]
(EuEts soybean)		-0.0097	0.04508 [0.01511]
(soybean EuEts)		-0.0098	0.051866 [0.0039]

As can be seen, among the hypotheses regarding downside risk spillover, the ninth hypothesis regarding downside risk spillover from the CEA market to the base metals market can be rejected at a confidence level of 95% based on the statistics and significance level of the bootstrapped KS test. Evidence indicated no significant difference between the empirical distributions of VaR and CoVaR statistics of the CEA market contingent on the occurrence of extreme events on the left side of the return distribution of the base metals market.

Regarding other hypotheses about downside risk spillover between the studied groups, the null hypothesis regarding identical empirical distributions of unconditional and conditional VaRs to extreme events on the left side of the distribution in the agricultural commodities market can be rejected according to the available evidence at a significance level of 5%.

Regarding the hypotheses regarding upside risk spillover between studied commodity and carbon markets, the assumption of the uniform distributions of unconditional and conditional VaRs to extreme events on the right side of the return distribution of the agricultural commodities market can be rejected at a confidence level of 95% for all indices in these markets. In other words, the upside event spillover on the right side of the distribution of all investigated markets can play a systemic role in intensifying similar events in the agricultural commodities market.

References

Aatola, P, Ollikainen, M, Toppinen (2013). A“ .Price determination in the EU ETS market: Theory and econometric analysis with market

fundamentals”.*Energy Economics* 38 (3): 390

- Batten, Jonathan A, Grace E Maddo و ,Martin R Young .(2020).“Does weather, or energy prices, affect carbon prices ”?*Energy Economics*. 96
- Bonenti, Francesca,(2013).Giorgia Oggioni, Elisabetta Allevi و ,Giacomo Marangoni“ .Evaluating the EU ETS impacts on profits, investments and prices of the Italian electricity market ”.*Energy Policy*. 206-222
- Chen, J, S Cheng و ,M Song .(2018).“Changes in energy-related carbon dioxide emissions of the agricultural sector in China from 2000 to 2013”*Renewable and Sustainable Energy Reviews* 94 : 961-978
- Daeyoung, K و ,et-al .(2013)“Mixture of d-vine copulas for modelling dependence ”. *Computational Statistics & Data Analysis* 74 : 99-111
- Ding, Z, C Granjer و ,R Engle“ .A long memory property of stock market returns and a new model ”.*Journal of Empirical Finance* : 993 , 106-123
- Dutta, A(2018)“ .Modeling and forecasting the volatility of carbon emission trading market: The role of outliers, time-varying jumps and oil price risk ”.*Journal of Cleaner Production* 172: 2781-2793
- Fernandez-Diaz, Jose و ,Bruce Morley .(2018).“ Title: Interdependence among agricultural commodity markets, macroeconomic factors, crude oil and commodity index ”.*Research in International Business and Finance*-174 : (17) 194

- Flues, Florens , Kurt VanDender (2020). *Carbon pricing design: Effectiveness, efficiency and feasibility: An investment perspective* . Working Paper, OECD.
- Frank, Stefan, Petr Havlík, Hugo Valin, Eva Wollenberg (2017) , Tomoko Hasegawa . *Carbon prices, climate change mitigation & food security: How to avoid trade-offs ?* research program on climate change, agriculture and food security,
- Girardi, G , T Ergun .(2013)“ Systemic risk measurement: Multivariate GARCH estimation of CoVaR ”.*Journal of Banking & Finance* 37, 3169-3180.
- Gou, J“ .(2018).Co-movement of international copper prices, China's economic activity, and stock returns: Structural breaks and volatility dynamics ”.*Global Finance Journal* 36 : 77-92
- Gubler, Matthias, Matthias Hertweck .(2013). “Commodity price shocks and the business cycle: Structural evidence for the U.S ”. *Journal of International Money* 37 : 202-224
- Hintermann, Beat“ .(2010)Allowance price drivers in the first phase of the EU ETS ”.*Journal of Environmental Economics and Management* 69: 56-83
- Ji, Chang Jing, Yu Jie Hu , Bao Jun Tang .(2018). “Research on carbon market price mechanism and influencing factors: a literature review ”. *Natural Hazards* 92 : 782-791
- Ji, Q, D Zhang, j bo Geng .(2018).“ Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets ”.*Cleaner Production* 198 : 978-992
- Ji, Qiang, Elie Bouri, David Roubaud, Syed Jawad Hussain Shahzad .(2018).“ Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model ”.*Energy Economics* 70 : 27-44
- Jiao, L , Liao, Y , Zhou, (2018).Q“ .Predicting carbon market risk using information from macroeconomic fundamentals ”.*pertain*.
- Khan, H, Metaxoglou, K, R. Knittel, C, Papineau, M . “(2019).Carbon emissions and business cycles ”.*Macroeconomics*. 19-1 : (70)
- Koch, Nicolas“ .(2014).Causes of the EU ETS price drop: Recession, CDM, renewable policies or a bit of everything—?New evidence ”.*Energy Policy* 73 : 780-796 ;
- Koleini, A .(2011).“ Portfolio Diversification; Benefits of Investing in Carbon Markets ”.*dissertation submitted*.33
- Kumar, S, S Managi , A Matsuda (2012).“ .Stocks prices of clean energy firms, oil and carbon ”. *Energy Economics*. 226-230 : 34
- Lin, J .(2013). *Development of the Carbon Market* . Shanghai: Shanghai Jiao Tong University Press,.
- Patton, Andrew (2012)“ .A review of copula models for economic time series ”.*Journal of Multivariate Analysis* 110 : 18-42
- Pradhana, Shrestha Bijay, Nguyen Ram, Matsuoka Hoac , Yuzuru .(2017).“Carbon prices and greenhouse gases abatement from agriculture, forestry and land use in Nepal ”.*Global Environmental Change* 43 : 26-26
- Qi, C, Y Ye, X Ma, D Yang , J Hong .(2017).“ Life cycle assessment of the hydrometallurgical zinc production chain in China ”.*Journal of Cleaner Production* 106 : 408-409
- Reboredo, Juan C , Andrea Ugolini .(2015)“ A vine copula conditional value at risk approach to systemic sovereign debt risk for the financial sector ”.*North American Journal of Economics and Finance*,
- Ruppert, David , David Matteson (2015) .*Statistics and Data Analysis for Financial Engineering* . New York: Springer,
- Sadorsky, Perry .(2014)“ Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat ”. *Energy Economics*. 11-22 : 43
- Salah Uddin, Gaz, Jose Areola Hernandez, (2018). Syed Jawad Hussain Shahzad , Axel Hedström“ .Multivariate dependence and spillover effects across energy commodities and diversification potentials of carbon assets ”. *Energy Economics* 71 : 46-50 ;
- Yao, Shujie, Shuai Zhang , Xingmin Zhang . (2019).“Renewable energy, carbon emission and economic growth: A revised environmental Kuznets Curve perspective ”. *Journal of Cleaner Production* 230 :- 1338 . 1302
- Yinpeng, Zhang, Liu Zhixin , Yu Xueying .(2017). “The Diversification Benefits of Including Carbon Assets in Financial Portfolios ”. *sustainability*. 9

- Yu, Lean, Jingjing Li, Ling Tang , WangT Shuai .
(2015)“ Linear and nonlinear Granger
causality investigation between carbon market
and crude oil market: A multi-scale approach ”.
Energy Economics 51 :.311-300
- Yuan, Nannan , Lu Yang .(2020).“Asymmetric risk
spillover between financial market uncertainty
and the carbon market: A GAsECSecopula
approach ”.*Journal of Cleaner Production*
209..
- Zhou, Kaile , Yiwen Li .(2019)“ Carbon finance and
carbon market in China: Progress and
challenges ”.*Journal of Cleaner Production*
214:.049-036