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Tail-risk Dependence Networks in the US Commodity Sectors. Has Covid-19 Made A Thing?

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Abstract: The objective of this paper is to examine the tail-risk dependence networks in the US commodity sectors: agriculture, livestock, energy, industrial and precious metals before and during COVID-19. Applying penalised quantile regression models extended with the dummy variable for the COVID-19 period in daily commodity returns and in the time horizon 3/1/2012 to 31/5/2022, *CoVaR* estimations are provided. The main empirical results are that (i) COVID has affected the tail-risk connectedness between commodities in the case of their extreme good events (ii) energy sector has remained a risk receiver in the risk-network of commodities independently of their conditions (welfare, burst) and (iii) the risk transmission linkages between commodity sectors are mostly positive. As a result, all commodity markets counterparts (farmers, investors, policymakers, governments) should not ignore pandemic uncertainties, as well that shocks in the other commodities sectors can control the booms and bursts of the energy sector. Finally, commodity markets seem to attract more speculators than hedgers. To the best of author(s) knowledge this is the first research paper that examines formally potential difference in the pattern of the tail risk dependence of the 5 US commodity sectors with respect to COVID's existence and defines new connectedness measures for the detection of the tail-risk net transmitters and receivers of the US commodity sectors' network.

Keywords: Commodity sectors, Tail- risk network, COVID-19

JEL Classification: C5, D8, Q02

1. INTRODUCTION

The objective of this paper is to examine the tail-risk dependence networks in the US commodity sectors: agriculture, livestock, energy, industrial and precious metals before and during COVID-19.

In general, the dependence of commodities (agriculture, livestock, energy, industrial and precious metals) is an issue of substantial importance for farmers, investors, policymakers and countries. This is not accidental.

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A potential relation of agricultural commodities with another sector may in turn raise the farmers risk premium. Hernandez (2015), Liu *et al.* (2017) and Kumar *et al.* (2019) supported the importance of investigating the dependence of commodities for both policymakers and investors to have practical implications for their portfolio risk management, i.e., absence of diversification opportunities. The dependence structure of commodities is also important as it directly influences the developing countries who act either as importers or exporters of them. Moreover, the examination of the dependence of commodities with respect to the presence of COVID is a highly topical issue for both economic researchers and investors. Particularly, for the first it gives implications for the behaviour of the counterparts of the commodity markets while for the latter it gives implications for a potential change of trading strategies and thus may assist in the prediction of the tail-risk transmission.

As dependence of the commodity sectors (inter-dependence) in the present empirical analysis is considered the definition of their price linkages network, a link between energy and agricultural commodities is rational due to the oil- dependent production costs of the latter (i.e., fertilizers, machinery, and transportation). In addition, these sectors of commodities are nowadays related through the development of bio fuels (ethanol, biodiesel) and thus the need of agricultural products for their production (corn, maize, soybean). A link between agriculture and industrial metals can be justified as the former is used as an input factor for the latter (machinery). Furthermore, a link between energy and metals is rational as oil is an important input factor for the production of metals. Last but not least, it is crucial to be mentioned that after the 2000s the inter-dependence of commodities has increased through the fundamental process of commodity markets known as financialisation (Tang and Xiong, 2012). This process was introduced to describe the transformation of commodities to financial assets with the introduction of commodity indexes and the increasing role of institutional investors in these markets. In this way, commodities are no longer solely determined on their supply-demand, but from the risk appetite for financial assets (Adhikari & Putnam, 2020).

The majority of previous empirical studies examined the dependence between commodities applying either copula models (Ji *et al.*, 2018; Mokni & Joussef, 2020; Kumar *et al.*, 2020; Albulescu *et al.*, 2020) or volatility spillovers (Diebold *et al.*, 2017; Kang *et al.*, 2017; Caporin *et al.*, 2021; Bouri *et al.*, 2021). The findings are mixed with Diebold *et al.* (2017), Ji *et al.* (2018) and Bouri *et al.* (2021) suggesting that the energy sector is the main driver (crude oil), while Kang *et al.* (2017) supported th-at this position belongs to the precious metals. Diebold *et al.* (2017) and Caporin *et al.* (2021) proposed distinct group clustering of commodities while the latter also found low inter-group connectedness and the dictation of bad volatility connectedness compared to the good one. Mokni and Joussef (2020), and Albulescu *et al.* (2020) found extreme co-movements between energy and agriculture markets with the latter to attribute these results in the complementarity between agriculture and metal markets and in the substitution effect between the energy and the metals markets. On the other hand, Kumar *et al.* (2020) concluded that the interdependence of the three commodity groups- agriculture, energy and precious metals, is changing in a complicated manner and spanning during the financial conditions. As the results of the above empirical works are conflicting, further research on this subject is substantial. In addition, the mathematical tools employed appear to have limitations in their estimation in cases of multidimensional variables and demand distributional assumptions.

Against this background, the objective of the present work is to examine the tail-risk dependence of the five US commodity sectors agriculture, livestock, energy, precious and industrial metals. To this end, tail-risk connectedness relies on the estimation of conditional-value-at-risk (*CoVaR*). First proposed by Adrian and Brunnermeier (2016), this risk-measure is well-known for quantifying the exposure of any asset to tail-risk of a second asset. In this context, for each sector we first define its tail-risk commodity transmissions and then represent these in a tail-risk network. The econometric approach is based on the penalised quantile regression *SCAD*. The Smoothly Clipped Absolute Deviation technique (Fan & Li, 2001) identifies only the relevant tail transmitters in a data-driven way, reducing the complexity of the estimated model and ensuring robust results. It is noteworthy that although *CoVaR* has been already employed in the empirical studies of Hautsch *et al.* (2015), Algieri and Leccadito (2017), Borri (2019) and Nguyen *et al.* (2020) for detecting tail events in the financial, commodities and crypto currencies sectors, its estimation is based on either the simple quantile regression or the Least Absolute Shrinkage and Selection Operator (*LASSO*). While the first is not consistent in the case of models with large numbers of regressors, small numbers of observations, and more importantly when only some of the regressors in the model have non zero impacts on the dependent variable; the second approach lacks the three desirable properties of a good penalty function: unbiasedness, sparsity, and continuity (Fan & Li, 2001). Moreover, earlier empirical studies have examined the tail dependence across commodity markets with the use of *CoVaR* employing copula models (Ji *et al.*, 2018; Shahzad *et al.*, 2018). Apart from the potential spurious estimations through the copulas' "curse" of dimensionality, these works investigated the interconnections of energy and agriculture commodities ignoring the metal sector.

The empirical analysis here emphasises whether the tail- risk dependence pattern of the 5 US commodity markets changes due to the pandemic crisis of COVID-19. Thus, in the initial step the tail-risk dependence is estimated and compared at both before and during COVID season and at lower (5%, 10%, 20%, 40%) and upper tail risk thresholds (95%, 90%, 80%, 60%). This division is made in order to capture the potential asymmetry in the connectedness of commodities in both bad and good extreme states. Afterwards, from the two tail-risk network representations with or without COVID-19, respectively, and according to the type and extent of interconnectedness the major tail-risk transmitters and receivers are identified.

As far as we know, there have been no earlier empirical studies that investigated the difference of the tail price risk spillovers in the 5 US commodity sectors with respect to COVID-19's existence using the penalised quantile regression *SCAD*. Earlier studies which examined potential difference in the connectedness pattern of financial markets due to COVID-19 applied volatility spillover models between crypto currencies or stock markets (Ajmi *et al.*, 2021; Polat & Günay, 2021). In what follows, section 2 presents the analytical framework and section 3 the data, the empirical models, and the results. Section 4 offers conclusions and suggestions for future research.

ANALYTICAL FRAMEWORK

The SCAD model

The most common measure for quantifying the tail-risk exposure of a commodity market is the calculation of its return's Value-at-Risk (*VaR*). Depending on whether the risk exposure examined is on the lower (*L*) or the upper (*U*), tail is determined as lower and upper tail *VaR* and is defined as

$$q = \begin{cases} \Pr(r_{it} \leq VaR_{it}^{q,L}) \\ \Pr(r_{it} \geq VaR_{it}^{1-q,\mathrm{U}}) \end{cases} = \begin{cases} \Pr(r_{it} \leq VaR_{it}^{q,L}) \\ \Pr(-r_{it} \leq -VaR_{it}^{q,\mathrm{L}}) \end{cases} \tag{1}$$

where r_{it} is the return of the commodity market *i* and $VaR_{it}^{q,\mathrm{L}}$ ($VaR_{it}^{1-q,\mathrm{U}}$) is the maximum (minimum) return of commodity market *i* at a confidence interval *1-q*, $0<q\leq 0.5$. In other words, *VaR* as a lower or an upper threshold of a commodity market's r_{it} distribution expresses the maximum or the

minimum return of commodity market *i* in its extreme conditions (crashes or booms, respectively).

Consequently, the tail-risk dependence between two commodities sectors can be defined with the calculation of the Conditional Value-at Risk (*CoVaR*) measure (e.g., Adrian & Brunnermeier, 2016; Borri, 2019). Particularly, lower or upper tail conditional value at risk for commodity market *i* given that *j* is in a bad or a good state of the world ($CoVaR_{it/jt}^{q,L}$) is defined as

$$q = \begin{cases} \Pr(r_{it} \le VaR_{it}^{q,L} / r_{jt} \le VaR_{jt}^{q,L}) \\ \Pr(r_{it} \ge VaR_{it}^{1-q,\mathrm{U}} / r_{jt} \ge VaR_{jt}^{1-q,\mathrm{U}}) \end{cases} = \begin{cases} \Pr(r_{it} \le VaR_{it}^{q,L} / r_{jt} \le VaR_{jt}^{q,L}) \\ \Pr(-r_{it} \le -VaR_{it}^{q,L} / -r_{jt} \le -VaR_{jt}^{q,L}) \end{cases}. \quad (2)$$

The estimation of *CoVaR* can be accomplished with the use of quantile regressions (Koenker & Basset, 1978). Specifically, the *VaR* for each commodity sector *i*, depending on whether it is employed on a lower or an upper tail threshold, is modeled as

$$VaR_{it}^{q,L} = a_{0i}^{q,L} + a_{ij}^{q,L} E_{jt}^{q,L} + b_i^{q,L} P_{it}^{'} + (a_{0i}^{q,L}{}' + a_{ij}^{q,L}{}' E_{jt}^{q,L} + b_i^{q,L}{}' P_{it}^{'}) D_{it} + e_{it}^{\ L} \quad (3)$$

$$VaR_{it}^{1-q,\mathrm{U}} = a_{0i}^{1-q,\mathrm{U}} + a_{ij}^{1-q,\mathrm{U}} E_{jt}^{1-q,\mathrm{U}} + b_i^{1-q,\mathrm{U}} P_{it}^{'} + (a_{0i}^{1-q,\mathrm{U}}{}' + a_{ij}^{1-q,\mathrm{U}}{}' E_{jt}^{1-q,\mathrm{U}} + b_i^{1-q,\mathrm{U}}{}' P_{it}^{'}) D_{it} + e_{it}^{\ U} \quad (4)$$

where $a_{0i}^{q,L}$, $a_{0i}^{1-q,\mathrm{U}}$ are the individual lower and upper risk levels of commodity market *i*, $E_{jt}^{q,L}$ is the loss exceedance on a lower tail threshold in r_{jt} and is defined as $E_{jt}^{q,L} = 0 \ (r_{jt})$ for $r_{jt} > (\le)$ $VaR_{jt}^{q,L}$, $E_{jt}^{q,\mathrm{U}}$ is the loss exceedance on an upper tail threshold in r_{jt} and is defined as $E_{jt}^{q,\mathrm{U}} = r_{jt}\ (0)$ for $r_{jt} > (\le)$ $VaR_{jt}^{q,U}$, $P_{it}^{'}$ is a vector of other relevant right hand side variables, D_{it} is a dummy variable for COVID-19, and equals to 0 (1) when time horizon is before 2020 (otherwise) and $e_{it}^{\ L}, e_{it}^{\ U}$ are the error terms (Hautsch *et al.*, 2015; Nguyen *et al.*, 2020; Fousekis & Tzaferi, 2022; Fouseks, 2022). Thus, the coefficients $a_{ij}^{q,L}$ and $a_{ij}^{1-q,\mathrm{U}}$ quantify the lower and upper tail-risk spillover from commodity sector *j* to commodity sector *i*. In that way, a positive value of $a_{ij}^{q,L}$ implies that a distress of commodity market *j* flows to commodity market *i*, while a non-positive one implies whether the absence of a lower tail-risk spillover from commodity market *j* to commodity market *i* ($a_{ij}^{q,L} = 0$), or that a distress of commodity market *j* influences positively commodity market *i* ($a_{ij}^{q,L} < 0$). Likewise, when

$a_{ij}^{1-q,U} > 0$ the good state of commodity sector *j* influences positively the commodity sector *i*, when $a_{ij}^{1-q,U} = 0$ the good state of commodity sector *j* does not have an impact on commodity sector *i* and when $a_{ij}^{1-q,U} < 0$ the good state of commodity sector *j* influences negatively the commodity sector *i*. Finally, it is clarified that the coefficients $a_{0i}^{q,L}{}'$, $a_{ij}^{q,L}{}'$, $b_{i}^{q,L}{}'$, $a_{0i}^{1-q,U}{}'$, $a_{ij}^{1-q,U}{}'$, $b_{i}^{1-q,U}{}'$ do quantify the potential difference of the coefficients $a_{0i}^{q,L}$, $a_{ij}^{q,L}$, $b_{i}^{q,L}$, $a_{0i}^{1-q,U}$, $a_{ij}^{1-q,U}$, $b_{i}^{1-q,U}$ under the presence of the pandemic COVID time horizon. From a microeconomics point of view, positive (negative) values of coefficients $a_{ij}^{q,L}$, $a_{ij}^{1-q,U}$ indicate that commodity sectors *i* and *j* in extreme market conditions do behave like substitute (complementary) goods and zero values suggest the existence of independent goods. As a substitute (complementary) good is defined a good which displays a positive (negative) cross elasticity of demand, meaning that an increase of another's good price constitutes to the increase (decrease) of its demand and consequently an increase (decrease) of its price. An independent good has a zero-cross elasticity of demand and thus changes in the price of one good will have no effect on its demand and moreover on its price. From, a game theory approach, a positive (negative) value of coefficients corresponds to the existence of commodity sectors which are strategic complements (substitutes). Strategic complements (substitutes) are called when a player's action induces the rival to take the same (opposite) action, i.e the prices (quantities) in Bertrand (Cournot) duopoly model. From a finance point of view, positive (negative) coefficients indicate that commodity sector *j* is a speculative (hedging-safe haven) asset for commodity sector *i* while a zero coefficient implements that commodity market *j* diversifies commodity market *i*. It is clarified that hedge (diversifier) is an asset which has a negative (weak positive) correlation with another asset. As a result, its existence in a portfolio serves the limitation in risk exposure. Moreover, a hedge asset is defined as safe haven when the market is under extreme pressure, while speculative asset is defined as the opposite of a hedge asset.

Though quantile regression is a popular and widely accepted technique to estimate *VaR*, in cases of models with large numbers of regressors, small numbers of observations, and more importantly when only some of the regressors in the model have non zero impacts on the dependent variable, is not consistent (Belloni & Chernozhukov, 2011; Nguyen *et al.*, 2020). In such circumstances penalised quantile regression is the most appropriate approach, as by excluding from the final model the regressors with insignificant explanatory power on the dependent variable, it avoids the decrease of the model's predictive ability. The exclusion of the irrelevant drivers from a *VaR* model is accomplished with the choice of a good penalty function. A good penalty function guarantees that the estimators satisfy simultaneously the three properties of unbiasedness, sparsity and continuity. Such a penalty function is the smoothly clipped absolute deviation (*SCAD*) (Fan & Li, 2001). In that sense, the estimated coefficients $\xi_{ij}^{q,L}$ and $\xi_{ij}^{1-q,U}$ for the lower and the upper tail thresholds respectively, are obtained from the minimisation of

$$\frac{\sum_{i=1}^{T} \rho_q (VaR_{it}^{q,L} - W_{it}^{L'} \xi_{ij}^{q,L})}{T} + \sum_{k_L=1}^{K_L} p_{\lambda_i}(|\xi_{ik_L}^{q,L}|) \tag{5}$$

$$\frac{\sum_{i=1}^{T} \rho_{1-q} (VaR_{it}^{1-q,U} - W_{it}^{U'} \xi_{ij}^{1-q,U})}{T} + \sum_{k_U=1}^{K_U} p_{\lambda_i}(|\xi_{ik_U}^{1-q,U}|) \tag{6}$$

where $\xi_{ij}^{q,L} = (\alpha_{0i}^{q,L}, \alpha_{ij}^{q,L}, b_i^{q,L})$, $\xi_{ij}^{1-q,U} = (\alpha_{0i}^{1-q,U}, \alpha_{ij}^{1-q,U}, b_i^{1-q,U})$, $W_{it}^{L'} = (1, E_{jt}^{q,L}, P_{it}^{'})$, $W_{it}^{U'} = (1, E_{jt}^{1-q,U}, P_{it}^{'})$, $\rho_q(u) = (q - I(u<0))$ a piecewise linear check (loss) function and the quadratic spline function with knots at λ_i and $c_i\ \lambda_i$, $c_i > 2$ $p_{\lambda_i}(|\xi_{ik}|) = \lambda_i |\xi_{ik}| I(0 \le |\xi_{ik}| < \lambda_i) + \frac{c_i \lambda_i |\xi_{ik}| - (\xi_{ik}^{2} + \lambda_i^{2})/2}{c_i - 1}$ $I(\lambda_i \le |\xi_{ik}| \le c_i\lambda_i) + \frac{(c_i+1)\lambda_i^2}{2} I(|\xi_{ik}| > c_i \lambda_i)$ is the *SCAD*-penalty function for the *VaR* model of commodity *i* (Sherwood & Maidman, 2020). The optimum penalty parameter λ_i estimated with cross validation determines which regressors have their shrunken coefficients $\xi_{ij}^{q,L}$ ($\xi_{ij}^{1-q,U}$) sufficiently close to zero and that's why they should be removed from the final model of commodity *i*. Afterwards, the validity of the above results is checked with the estimation of the unrestricted models

$$\frac{\sum_{i=1}^{T} \rho_q (VaR_{it}^{q,L} - W_{it}^{L'} \xi_{ij}^{q,L})}{T} \tag{7}$$

$$\frac{\sum_{i=1}^{T} \rho_{1-q} (VaR_{it}^{1-q,U} - W_{it}^{U'} \xi_{ij}^{1-q,U})}{T} \tag{8}$$

taking into account only the selected relevant regressors W_{it}^{L} and W_{it}^{U}. These post-*SCAD* quantile regressions explain the *VaR* of the commodity sector *i* at the lower and upper tail thresholds and their estimated coefficients are the $a_{ij}^{q,L}$ and $a_{ij}^{1-q,U}$ from equations (3) and (4), respectively.

Network Representation

A weighted tail-risk network is constructed for both lower and upper tail thresholds without or with the presence of COVID-19 with nodes all the commodity sectors and weights the estimated coefficients $a_{ij}^{q,L}$, $a_{ij}^{1-q,U}$ and $a_{ij}^{q,L} + a_{ij}^{q,L}{}'$, $a_{ij}^{1-q,U} + a_{ij}^{1-q,U}{}'$, respectively. In that way, an edge from commodity sector *j* to commodity sector *i* is drawn if the loss exceedance $E_{jt}^{q,L}$ has been selected from the *SCAD* model as a relevant driver of the *VaR* of commodity market *i*. If $E_{jt}^{q,L}$ has not been selected from the *SCAD* model there will be no arrow from commodity market *j* to *i*. Moreover, the characterisation of commodities as tail-risk recipients or transmitters (drivers) is obtained with the calculation of their to- and from- spillovers in the network. The to- spillover of commodity sector *i* is defined as the sum of the non-zero entries of the *i*th row of the tail-risk connectedness matrix $a_{ij}^{q,L}$ at the lower tail threshold ($a_{ij}^{1-q,U}$ at the upper tail threshold) divided with the sum of the elements of the matrix $a_{ij}^{q,L}$ ($a_{ij}^{1-q,U}$ at the upper tail threshold). Likewise, the from spillover of commodity market *i* is defined as the sum of the non-zero entries of the *i*th column of the tail-risk connectedness matrix $a_{ij}^{q,L}$ at the lower tail threshold ($a_{ij}^{1-q,U}$ at the upper tail threshold) divided with the sum of the elements of the matrix $a_{ij}^{q,L}$ ($a_{ij}^{1-q,U}$ at the upper tail threshold). Finally, the tail-risk net-degree is calculated as the difference between the from- and the to- spillovers. It is specified that positive (negative) value of net spillover corresponds that the commodity sector is a transmitter (receiver) of risk. In the case of COVID-19, the above measures are calculated with the coefficients $a_{ij}^{q,L} + a_{ij}^{q,L}{}'$, $a_{ij}^{1-q,U} + a_{ij}^{1-q,U}{}'$, respectively.

DATA, EMPIRICAL MODELS AND THE RESULTS

The data and the empirical models

The empirical data consists of the daily returns of the SP & GSCI indices agriculture, livestock, energy, precious and industrial metals. The data refers to the period from 3/1/2012 to 31/5/2022 and they have been obtained from the website https://www.spglobal.com/. Figure A1 presents the evolution of the natural logarithm of the prices of the five indexes. It is observed that there are some periods where the commodity sectors tend to move together and either boom or burst. In the COVID-19 season (2020-) all commodities seem to follow an upward trend. Table AI in the Appendix presents the descriptive statistics and tests on the distribution of the data. All time series are leptokurtic with the majority of them to have negative skewness (only agriculture has positive skewness). Finally, the normal fit in all variables is rejected in any statistical significance level.

In the initial model, as in Nguyen *et al.* (2020), the *P* vector in (3) and (4) includes the lagged values of the relevant dependent variable. The optimal number of lags is determined with the Bayesian Information Criterion (BIC) and is set equal to 5. Moreover, because the aim of this study is the simultaneous tail connectedness across commodity markets, in the estimation the loss exceedances ($E_{jt}^{q,L}$, $E_{jt}^{1-q,\mathrm{U}}$) are in the same time with the dependent variable. The potential case of simultaneity bias is erased as according to Hautsch *et al.* (2015) the relationship between a specific quantile and the conditional distribution of exceedances, given a fixed threshold, is not known. The lower (burst events) and the upper (boom events) tail dependence of 5 commodity sectors is estimated with the use of rqPen R-package at the lower thresholds 5%, 10%, 20% and 40% and at the upper thresholds 95%, 90%, 80% and 60%, respectively. The validity of the estimated coefficients $a_{ij}^{q,L}$ and $a_{ij}^{1-q,\mathrm{U}}$ is ensured with 2500 bootstrap in the post- *SCAD* models. The 5% statistically significant coefficients in the Tables I-IV are in bold, while the out-directional negative vertices of the networks in the Figures 1-4 are colored with red. Finally, the width of the arrows and the size of the edges depend on the strength of the estimated coefficients $a_{ij}^{q,L}$ ($a_{ij}^{q,L} + a_{ij}^{q,L}$ ') and $a_{ij}^{1-q,\mathrm{U}}$ ($a_{ij}^{1-q,\mathrm{U}}$ + $a_{ij}^{1-q,\mathrm{U}}$ ') (absolute values) and the layout of the networks is circular.

The empirical results

Table I shows the estimated coefficients $a_{ij}^{q,L}$ and $a_{ij}^{1-q,\mathrm{U}}$ as well the $a_{ij}^{q,L}$ ' and $a_{ij}^{1-q,\mathrm{U}}$ ' at 5% and 95% tail thresholds, respectively. Particularly in the

5% tail dependence before the COVID arise, the livestock market affects the energy one, while the energy market both affects the livestock and the industrial metals markets. In addition, the precious metals affect the industrial metals, while the industrial metals affect both the markets of agriculture and precious metals. During the COVID presence the only difference in the tail risk transmission is the decrease of the impact of industrial metals risk to the precious metals sector. In the meanwhile, in the 95% tail risk dependence and before the COVID season, the agriculture market seems to drive the energy sector, the energy sector does affect the metals' markets, the precious metals affect both the markets of the livestock and the industrial metals and finally the industrial metals affect the energy and the precious metals sectors, respectively. During the COVID season new tail risk linkages were created; the livestock's risk boom has affected both the sectors of energy and precious metals while the energy sector has affected the livestock market. What is striking is that the COVID's existence has changed the type of the 95% tail risk transmission from the precious metals to the livestock market. Specifically, before (during) the COVID this linkage has been negative (positive) corresponding that the precious metals and the livestock markets are either complementary (substitutes) goods, or strategic substitutes (complements) or hedging (speculative) assets.

Table II shows the estimated coefficients $a_{ij}^{q,L}$ and $a_{ij}^{1-q,U}$ as well the $a_{ij}^{q,L}{}'$ and $a_{ij}^{1-q,U}{}'$ at the 10% and 90% tail thresholds, respectively. Specifically in the 10% tail dependence level independently of the COVID presence, the agriculture and the energy (industrial metals) markets do affect all the commodity sectors apart from the precious metals (livestock), while the livestock (precious metals) market has affected only the agriculture (industrial metals) sector. In the 90% tail risk dependence level and before the COVID season the livestock market drives the precious metals, while the energy sector has affected the metals. Moreover, the precious metals have affected the risk evolution of the markets of agriculture, livestock and industrial metals. Finally, the industrial metals have affected both the energy and the precious metals sectors. During the COVID season the new tail risk linkages which had been created were those from the agriculture domain to the livestock and the industrial metals, from the livestock market to the sectors of agriculture and precious metals, from the energy market to both the agriculture and livestock domains and finally from the precious metals to the livestock market. Again, just like in the 95% tail threshold the presence of COVID had changed the type of the upper tail risk transmission from the precious metals sector to the livestock market. Specifically, before (during) the COVID this linkage has been negative (positive) corresponding that the precious metals and the livestock are either complementary (substitutes) goods, or strategic substitutes (complements) or hedging (speculative) assets. This finding has been also observed, here, in the opposite direction of risk transmission, meaning from the livestock sector to the precious metals. Moreover, negative linkages in the booms of the commodity markets have been created during the COVID season between the agriculture and the livestock sectors in both directions.

Table III shows the estimated coefficients $a_{ij}^{q,L}$ and $a_{ij}^{1-q,U}$ as well the $a_{ij}^{q,L}$' and $a_{ij}^{1-q,U}$' at the 20% and 80% tail thresholds, respectively. Particularly, in the 20% tail risk dependence irrelevantly of the COVID's presence the agriculture market has affected the metals (both precious and industrial), the energy and the industrial metals sectors (the livestock) have affected all the commodity sectors apart from the livestock one (precious metals), while the precious metals market has affected both the energy and the industrial metals. In the 80% tail risk dependence level and before the COVID season the energy and the precious metals (the agriculture) have (has) driven all the commodities sectors (apart from the precious metals), the livestock market has affected the precious metals and finally the industrial metals have affected both the energy and the precious metals sectors. During the COVID season the new tail risk linkages which have been created are those from the livestock market to the energy sector and from the industrial metals to the sector of agriculture. Moreover, in contrast to the 95% and the 90% tail thresholds the COVID has not changed the type of the upper tail risk transmission (negative) from the precious metals to the livestock market and vice versa.

Table IV shows the estimated coefficients $a_{ij}^{q,L}$ and $a_{ij}^{1-q,U}$ as well the $a_{ij}^{q,L}$' and $a_{ij}^{1-q,U}$' at the 40% and the 60% tail thresholds, respectively. Particularly, in the 40% tail dependence irrelevantly of the COVID's presence the sectors of agriculture and industrial metals have affected all the other commodity sectors, while the livestock and the energy (precious metals) markets have affected all the commodity sectors apart from the metals (livestock), respectively. It is clarified that the linkage from the livestock market to the precious metals is negative and thus the two commodity markets can be defined as complementary goods, or strategic substitutes or that livestock is a safe haven asset for precious metals. In the meanwhile, in the 60% tail risk dependence level and before the COVID season the energy market has driven all the commodities sectors, the agriculture and the industrial metals have affected all the commodity sectors apart from the livestock one, the livestock sector has affected the agriculture market and finally the precious metals have affected both the agriculture and the industrial metals sectors. During the COVID season, the tail risk linkage from the industrial metals to the agriculture market has been empowered.

The tail-risk connectedness representations are synopsised in the Figures 1-4 with the (a) panel referring to the lower tail threshold (5%, 10%, 20%, 40%) and the (b) panel to the upper tail threshold (95%, 90%, 80%, 60%), respectively. Moreover, it's panel is divided in two plots the left one, (a1) and (b1) similarly, represents the tail-risk dependence network before the COVID, while the right one, (a2) and (b2), during the COVID. As mentioned earlier in the 3a. section, the red (black) arrows of the networks correspond to the out-directional negative (positive) vertices and thus their transmitting nodes-commodities can be defined as complementary (substitutes) goods, or strategic substitutes (complements) or hedging-safe haven (speculative) assets. Consequently, the precious metals for the livestock market at the 95%, 90%, 80% tail thresholds before the COVID and at the 80% tail threshold during the COVID, the livestock market for the precious metals at the 90% tail threshold before the COVID and at the 80% and 40% tail thresholds before and during the COVID, the livestock sector for the agriculture market and vice versa at the 90% tail threshold during the COVID season can be characterised as complementary goods, or strategic substitutes or hedging-safe haven assets. It is rational that in extreme bad events (in the lower tail thresholds, meaning at 5%, 10%, 20% and 40% tail risk thresholds, the existence of hedging commodities is desirable in a portfolio. On the other hand, if the extreme events are good (in the upper tail thresholds, meaning at 95%, 90%, 80% and 60% tail risk thresholds), then hedging commodities have the adverse results and thus investors should exclude them from their portfolio. In the case of positive estimated coefficients, which are the most in our analysis, the suggested trading strategies are the adverse from that of the hedging commodities. For instance, when two commodities are strategic complements and the one is in a good state, this drives positively the other and thus their co-existence in a portfolio should be aimed at. In the opposite condition where a commodity is in a bad state and is strategic complement with another commodity, the first worsens the evolution of the other and thus their co-existence should be avoided. In addition, Figures 1-4 do confirm the results of the Tables 1-4 with the majority of the changes in the commodity network tail connectedness before and during the COVID season becoming in the upper tail thresholds (95%, 90%, 80%, 60%), meaning in the booms of commodity markets. Equivalently, it seems that COVID have not made a thing in the dependence structure of the commodity markets when they (the commodities) are in distress and thus, they might constitute substantial financial investment tools during other arising pandemic crises.

In order to better quantify the tail risk transmission in the network of commodities connectedness measures are provided at the Tables V-VIII. Specifically, Table V summarises the tail-risk connectedness measures of the five commodity sectors: agriculture, livestock, energy, precious and industrial metals with or without the COVID-19's presence at both the 5% and the 95% tail thresholds. At the lower tail threshold 5%, or equivalently when the commodities are in distress conditions, and before the COVID's presence the tail risk network drivers (positive net-degree) have been the livestock market and the industrial metals, while the tail risk receivers (negative net-degree) have been the rest commodity sectors. During the COVID the 5% tail risk connectedness pattern has changed for the metals both the industrial and the precious with the first to be risk receiver and the latter risk driver. On the other hand, before the COVID and at the 95% tail threshold, or equivalently when commodities are in euphoria, the price risk transmitters appeared to be the agriculture market and the metals (industrial and precious), while the risk receivers seem to be the energy and the livestock sectors. In the case of COVID's presence the tail risk transmission's pattern has basically changed for the livestock and the precious metals markets. It is noteworthy that independently of the tail threshold (5% or 95%) and the time horizon (before or during COVID) selected the energy sector has remained a tail risk receiver of the commodities network. This means that any extreme changes (good or bad) of the other commodity markets do influence similarly the energy sector. As a result, a substantial tool for the estimation of the risk evolution on the energy markets is the estimation of the risk of the other commodities. As for potential asymmetry in the tail risk dependence of the 5 commodity sectors depending on the type of the tail risk threshold (lower, upper) this is justified for example with the type of connectedness of the agriculture market. Specifically, in the bursts (5% tail threshold) of commodity markets agriculture seems to be a tail risk network receiver, while in the booms (95% tail threshold) does behave as a tail risk network driver.

Table VI summarises the tail-risk connectedness measures of the five commodity sectors with or without the COVID-19's existence at both the 10% and the 90% tail thresholds. At the lower tail threshold of 10%, or equivalently when the commodities are in distress conditions, the connectedness before and during the COVID are the same with the risk network drivers to be the agriculture and the industrial metals sectors, and the risk receivers are the rest commodity sectors. On the other hand, at the 90% tail threshold before and during the COVID time period, the price tail risk connectedness differs with the livestock market in the first place to behave as a risk network transmitter and in the second one as a weak risk receiver. The tail risk transmission pattern of the other commodities is the same (meaning that the industrial metals are tail risk transmitters, while the agriculture and the energy sectors are receivers) but is debilitated with the presence of COVID. Moreover, it is observed that independently of the tail risk threshold (10% or 90%) and the time horizon (before or during the COVID period) the energy sector and the metals retain their tail risk type of connectedness (the energy and the precious metals as receivers and the industrial metals as risk drivers). As for potential asymmetry in the tail risk dependence of the 5 commodity sectors depending on the type of the tail threshold (lower, upper) this is justified again with the connectedness of the agriculture market. Specifically, in the bursts (at 10% tail threshold) of commodity markets the agriculture domain is a tail risk network transmitter while in the booms (at 90% tail threshold) is a tail risk network receiver.

Likewise, Table VII summarises the tail-risk connectedness measures of the five commodity sectors with or without the COVID-19's presence at the 20% and at the 80% tail thresholds, respectively. At the lower tail threshold of 20% the connectedness before and during the COVID is the same with the tail risk network drivers to be the livestock and the industrial metals markets, and the risk receivers to be the rest commodity sectors. On the other hand, at the 80% tail threshold before and during the COVID, the price tail risk connectedness differs with the agriculture sector (livestock) in the first place to act as a transmitter (receiver) and in the second one as a risk receiver (transmitter) in the commodities network. The tail risk transmission's pattern of the other commodities remains the same (meaning that the metals are tail risk transmitters, while the energy market is receiver). Moreover, it is observed that independently of the tail threshold (20% or 80%) and the time horizon (before or during the COVID) the energy sector and the industrial metals retain their tail risk type of connectedness (energy market as receiver and industrial metals as risk drivers). As for potential asymmetry in the tail risk dependence of the 5 commodity sectors depending on the type of the tail threshold (lower, upper) this is justified with the connectedness of the precious metals sector. In the bursts (at 20% tail threshold) of commodity markets is a tail risk network receiver while in the booms (80% tail threshold) is a tail risk network transmitter.

Finally, Table VIII summarises the tail-risk connectedness measures of the five commodity sectors with or without the COVID-19's presence at the 40% and 60% tail thresholds, respectively. At the lower tail threshold of 40% the connectedness before and during the COVID is the same with the risk network receiver to be the energy commodity market, and the risk receivers the rest commodity sectors. On the other hand, at 60% tail threshold before and during COVID, the price risk connectedness differs with the agriculture sector in the first place to be a transmitter whiles in the second one a risk receiver. The risk transmission pattern of the other commodities is the same with that at the 40% tail threshold. Thus, independently of the tail threshold (40% or 60%) and the time horizon (before or during COVID) all the commodity sectors apart from the agriculture one do retain their tail risk type of connectedness. As for potential asymmetry in the tail risk dependence pattern of the 5 commodity sectors depending on the type of tail threshold (lower, upper) is justified again only in the connectedness of the agriculture market and during the COVID season. In the bursts (at 40% tail threshold) of commodity markets agriculture is a tail risk network transmitter while in the booms (at 60% tail threshold) is a tail risk network receiver.

CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

The purpose of this empirical study is the investigation of the tail-risk dependence of the 5 US commodity sectors: agriculture, livestock, energy, precious and industrial metals commodity markets in both extreme good and bad conditions before and during the COVID-19 season. In that way, it is examined whether commodity markets are influenced from this pandemic crisis and consequently whether they constitute substantial financial investment tools in highly volatile periods. Particularly, this investigation is important, as it can reveal unexpected tail-risk transmissions, potential size and sign asymmetries and thus it can provide useful insights for farmers, investors and governments. For example, from an investing point of view the tail-risk dependence across commodity markets can reveal opportunities for speculators, hedgers, diversifiers. At the same time, from a macroeconomics point of view extreme price dependence between commodities may raise concerns for developing countries that import/export these products. In this context, *CoVaR* estimated functions have been employed through the mathematical tool of penalised *SCAD* quantile regression. The prevalence of this technique is its ability to identify only the relevant tail transmitters in a data-driven way.

The empirical results of our analysis are summarised in the following:

(a) The weights of the tail-risk spillovers are mostly positive indicating that the commodities appear similar in behaviour under extreme events and thus can be defined as substitute goods, either strategic complements processes or speculating assets. In that way, these networks may seem unattractive for passive investors who seek diversification benefits and attractive for speculators. On the other side, negative weights are observed mainly in the upper tail-risk

Table I: Tail risk spillovers

	Tail dependence										
	(Intercept)	Agriculture	Livestock	Energy	Precious Metals	Industrial Metals	(1lag)	(2lags)	(3lags)	(4lags)	(5lags)
Commodities	(Lower) 5%										
Agriculture	-0.016 (<0.01)	-	0.129 (0.11)	0.058 (0.09)	0.055 (0.35)	**0.183 (0.01)**	0.045 (0.34)	-	-	-	-
Livestock	**-0.016 (<0.01)**	0.103 (0.36)	-	**0.091 (0.01)**	-0.072 (0.47)	0.243 (0.08)	**0.118 (0.01)**	0.043 (0.41)	-	**0.099 (0.03)**	0.078 (0.13)
Energy	**-0.028 (<0.01)**	-	**0.846 (0.01)**	-	-	0.615 (0.26)	-	-	-	-	-
Precious Metals	-0.015 (<0.01)	0.199 (0.52)	-0.079 (0.49)	-0.095 (0.21)	-	**0.785 (<0.01)**	-	0.010 (0.87)	0.045 (0.42)	0.077 (0.25)	-
Industrial Metals	**-0.016 (<0.01)**	-	-	**0.164 (<0.01)**	**0.349 (<0.01)**	-	-	-	-	-	-
Commodities	**(Upper) 95%**										
Agriculture	**-0.016 (<0.01)**	-	-	0.156 (0.05)	-	-	0.035 (0.49)	**0.111 (0.03)**	-	-	-
Livestock	**-0.016 (<0.01)**	-0.074 (0.36)	-	-	**-0.168 (0.04)**	0.118 (0.26)	-	-0.075 (0.18)	-0.063 (0.20)	-	-
Energy	**-0.024 (<0.01)**	**0.497 (0.02)**	-	-	0.389 (0.22)	**0.861 (<0.01)**	-	-	-	-	-
Precious Metals	-0.014 (<0.01)	-	-	**0.086 (0.04)**	-	**0.303 (<0.01)**	-0.061 (0.15)	-0.061 (0.11)	-	-	-
Industrial Metals	**-0.016 (<0.01)**	-	-	**0.195 (<0.01)**	**0.343 (<0.01)**	-	-	-	-	-	-

Table I: Tail risk spillovers (continue)

	Tail dependence										
Differences of COVID presence	*(Intercept)*	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*	*(1lag)*	*(2lags)*	*(3lags)*	*(4lags)*	*(5lags)*
Commodities	**(Lower) 5%**										
Agriculture	-	-	-	-	0.379 (0.21)	-	-	-	-	-	-
Livestock	-	0.188 (0.60)	-	0.063 (0.54)	0.163 (0.46)	-	0.168 (0.23)	-0.025 (0.82)	-0.233 (0.11)	0.138 (0.34)	-0.019 (0.90)
Energy	-	1.001 (0.40)	0.575 (0.81)	-	-	2.036 (0.51)	-	-	-	-	-
Precious Metals	-0.005 (0.03)	0.023 (0.95)	0.688 (0.06)	0.092 (0.41)	-	**-0.671** **(0.04)**	-	-	-0.073 (0.49)	**-0.327** **(0.04)**	-0.165 (0.05)
Industrial Metals	-	-	-	-	-	-	-	-	-	-	-
Commodities	**(Upper) 95%**										
Agriculture	-0.002 (0.12)	-	-	-	-	-	-	-	-	-	-
Livestock	-	-0.106 (0.45)	-	**0.223** **(<0.01)**	**0.610** **(0.01)**	-0.230 (0.58)	-	-0.133 (0.33)	-	0.056 (0.58)	-
Energy	**-0.009** **(<0.01)**	0.928 (0.14)	**2.010** **(<0.01)**	-	-	-	-	-0.143 (0.06)	-	-	-
Precious Metals	-0.002 (0.03)	-	**0.826** **(0.04)**	-	-	-	-	0.118 (0.31)	-	-0.178 (0.05)	-
Industrial Metals	-	-	-	-	-	-	-	-	-	-	-

Table II: Tail risk spillovers

	Tail dependence										
	(Intercept)	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*	*(1lag)*	*(2lags)*	*(3lags)*	*(4lags)*	*(5lags)*
Commodities	(Lower) 10%										
Agriculture	-0.011 (<0.01)	-	**0.127 (<0.01)**	**0.122 (<0.01)**	-	**0.197 (<0.01)**	-	-	-	-	-
Livestock	**-0.011 (<0.01)**	**0.257 (<0.01)**	-	**0.105 (0.01)**	-0.073 (0.13)	0.031 (0.68)	0.112 (0.05)	0.043 (0.28)	0.060 (0.21)	**0.105 (0.02)**	-
Energy	**-0.017 (<0.01)**	**0.418 (0.03)**	0.357 (0.13)	-	-	**0.630 (<0.01)**	-	-	-	-	-
Precious Metals	-0.010 (<0.01)	-	-	-	-	**0.488 (<0.01)**	-	-	-	-	-
Industrial Metals	**-0.010 (<0.01)**	**0.248 (<0.01)**	-	**0.155 (<0.01)**	**0.344 (<0.01)**	-	**-0.075 (0.04)**	-	-	-	-
Commodities	**(Upper) 90%**										
Agriculture	**-0.011 (<0.01)**	-	-	-	**0.180 (0.01)**	0.111 (0.17)	-	**0.094 (0.03)**	-	-	-
Livestock	**-0.012 (<0.01)**	-	-	0.037 (0.28)	**-0.097 (0.03)**	-	-	**-0.097 (0.01)**	-	-	-
Energy	**-0.016 (<0.01)**	0.095 (0.34)	0.189 (0.22)	-	0.123 (0.49)	**0.807 (<0.01)**	-0.047 (0.34)	-	-	0.078 (0.05)	0.035 (0.41)
Precious Metals	-0.010 (<0.01)	0.082 (0.09)	**-0.194 (<0.01)**	**0.083 (0.03)**	-	**0.390 (<0.01)**	-0.063 (0.05)	-	-	-	-
Industrial Metals	**-0.011 (<0.01)**	-	-	**0.207 (<0.01)**	**0.362 (<0.01)**	-	-	-	-	-	-

Table II: Tail risk spillovers (continue)

	Tail dependence										
Differences of COVID presence	*(Intercept)*	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*	*(1lag)*	*(2lags)*	*(3lags)*	*(4lags)*	*(5lags)*
Commodities	*(Lower) 10%*										
Agriculture	-	-	-	-	-	-	-	-	-	-	-
Livestock	-	-	-	0.065 (0.45)	0.045 (0.83)	0.129 (0.46)	0.167 (0.17)	-0.055 (0.52)	-0.097 (0.46)	0.072 (0.49)	0.169 (0.09)
Energy	-	0.613 (0.24)	-	-	0.480 (0.42)	1.466 (0.06)	-	-	-	-	-
Precious Metals	-	0.228 (0.08)	0.274 (0.25)	-	-	-	-	-	-	-	-
Industrial Metals	-0.001 (0.37)	-	-	-	-	-	0.123 (0.17)	-0.111 (0.16)	0.050 (0.30)	0.081 (0.26)	-
Commodities	**(Upper) 90%**										
Agriculture	**-0.004 (<0.01)**	-	**-0.269 (<0.01)**	**0.137 (<0.01)**	-	-	-	-	-	-	-
Livestock	-	**-0.180 (<0.01)**	-	**0.185 (0.01)**	**0.490 (0.02)**	-	-	-	-0.092 (0.19)	0.109 (0.11)	-
Energy	**-0.007 (<0.01)**	0.308 (0.33)	0.861 (0.15)	-	0.551 (0.33)	-	-0.010 (0.92)	-0.098 (0.18)	-0.043 (0.64)	-0.113 (0.23)	**-0.235 (0.03)**
Precious Metals	-0.001 (0.24)	-	**0.681 (0.02)**	0.036 (0.57)	-	-	-	-	-	**-0.232 (<0.01)**	-
Industrial Metals	-	**0.259 (0.02)**	-	-	-	-	-	-	-	-	-

Table III: Tail risk spillovers

	Tail dependence										
	(Intercept)	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*	*(1lag)*	*(2lags)*	*(3lags)*	*(4lags)*	*(5lags)*
Commodities	(Lower) 20%										
Agriculture	-0.006 (<0.01)	-	**0.174 (<0.01)**	**0.092 (<0.01)**	-	**0.209 (<0.01)**	-	-	-	-	-
Livestock	**-0.007 (<0.01)**	0.103 (0.10)	-	0.044 (0.27)	-0.021 (0.70)	0.072 (0.23)	**0.091 (0.02)**	0.073 (0.05)	**0.073 (0.03)**	0.069 (0.09)	-
Energy	**-0.008 (<0.01)**	0.184 (0.05)	**0.263 (0.02)**	-	**0.156 (0.02)**	**0.617 (<0.01)**	-	0.041 (0.17)	-	-	0.049 (0.09)
Precious Metals	-0.005 (<0.01)	**0.119 (0.04)**	-	**0.062 (0.01)**	-	**0.357 (<0.01)**	**-0.065 (0.01)**	-	-	-	-
Industrial Metals	**-0.005 (<0.01)**	**0.173 (<0.01)**	**0.090 (0.03)**	**0.185 (<0.01)**	**0.307 (<0.01)**	-	**-0.071 (<0.01)**	-	-	**-0.064 (<0.01)**	-
Commodities	**(Upper) 80%**										
Agriculture	**-0.006 (<0.01)**	-	-	**0.100 (<0.01)**	**0.137 (<0.01)**	0.101 (0.07)	-	-	-	-	-
Livestock	**-0.001 (<0.01)**	**0.108 (0.01)**	-	**0.042 (0.03)**	**-0.085 (0.04)**	-	0.033 (0.33)	-	-	-	-0.056 (0.08)
Energy	**-0.008 (<0.01)**	**0.281 (<0.01)**	-	-	**0.216 (0.03)**	**0.466 (<0.01)**	**-0.064 (0.03)**	-	-	-	-
Precious Metals	-0.005 (<0.01)	0.086 (0.09)	**-0.107 (<0.01)**	**0.061 (0.02)**	-	**0.301 (<0.01)**	**-0.079 (<0.01)**	-	-0.003 (0.91)	0.032 (0.36)	-0.042 (0.19)
Industrial Metals	**-0.005 (<0.01)**	**0.116 (0.01)**	0.074 (0.13)	**0.242 (<0.01)**	**0.381 (<0.01)**	-	-0.059 (0.05)	0.062 (0.11)	0.024 (0.41)	**-0.055 (0.04)**	-0.050 (0.11)

Table III: Tail risk spillovers (continue)

	Tail dependence										
Differences of COVID presence	*(Intercept)*	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*	*(1lag)*	*(2lags)*	*(3lags)*	*(4lags)*	*(5lags)*
Commodities	**(Lower) 20%**										
Agriculture	-	-	-	-	-	-	-	-	-	-	-
Livestock	0.001 (0.35)	0.158 (0.21)	-	0.123 (0.09)	0.058 (0.63)	0.050 (0.66)	0.125 (0.14)	-0.112 (0.20)	-	0.050 (0.60)	**0.159 (0.03)**
Energy	-	0.352 (0.30)	0.322 (0.22)	-	-	0.551 (0.15)	-	-	-	-	-
Precious Metals	-	-	0.122 (0.30)	-	-	-	-	-	-	-	-
Industrial Metals	-	-	-	-	-	-	-	-	-	0.109 (0.16)	-
Commodities	**(Upper) 80%**										
Agriculture	-	-	-	-	-	**0.282 (<0.01)**	-	-	-	-	-
Livestock	0.000 (0.64)	-0.108 (0.23)	-	0.114 (0.07)	-	-	-	-	-0.045 (0.47)	-0.085 (0.18)	0.061 (0.38)
Energy	**-0.004 (<0.01)**	0.271 (0.19)	**0.643 (0.02)**	-	-	-0.009 (0.97)	-	**-0.129 (0.03)**	-	-	-0.112 (0.13)
Precious Metals	-0.001 (0.34)	0.079 (0.39)	0.048 (0.71)	-	-	-	0.046 (0.35)	-0.020 (0.68)	-0.015 (0.77)	**-0.195 (<0.01)**	0.060 (0.25)
Industrial Metals	**-0.002 (<0.01)**	0.130 (0.25)	-0.088 (0.49)	-0.143 (0.05)	-0.214 (0.06)	-	0.110 (0.06)	-0.005 (0.95)	-	**0.134 (0.02)**	0.131 (0.05)

Table IV: Tail risk spillovers

	Tail dependence										
	(Intercept)	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*	*(1lag)*	*(2lags)*	*(3lags)*	*(4lags)*	*(5lags)*
Commodities	**(Lower) 40%**										
Agriculture	**-0.001 (0.03)**	-	**0.098 (0.01)**	**0.096 (<0.01)**	**0.141 (<0.01)**	**0.192 (<0.01)**	0.021 (0.43)	-	-	**-0.062 (0.01)**	-
Livestock	**-0.001 (0.04)**	**0.130 (<0.01)**	-	**0.051 (0.03)**	-	**0.105 (<0.01)**	-	0.036 (0.15)	-	-	-
Energy	**0.001 (0.01)**	**0.201 (<0.01)**	**0.191 (0.01)**	-	**0.138 (<0.01)**	**0.654 (<0.01)**	-	-	-	-	-
Precious Metals	-0.001 (0.04)	**0.122 (<0.01)**	**-0.063 (0.04)**	-	-	**0.297 (<0.01)**	**-0.066 (<0.01)**	-	-	-	-
Industrial Metals	**0.001 (<0.01)**	**0.200 (<0.01)**	0.080 (0.06)	**0.184 (<0.01)**	**0.321 (<0.01)**	-	**-0.074 (<0.01)**	-	-	-	-
Commodities	**(Upper) 60%**										
Agriculture	0.000 (0.53)	-	**0.115 (<0.01)**	**0.098 (<0.01)**	**0.159 (<0.01)**	**0.148 (<0.01)**	-	-	-	-0.027 (0.30)	-
Livestock	**-0.002 (<0.01)**	0.068 (0.06)	-	**0.071 (<0.01)**	-	-	-	-	-	-	-
Energy	0.000 (0.80)	**0.283 (<0.01)**	0.102 (0.05)	-	-	**0.549 (<0.01)**	-0.041 (0.17)	-	-	0.029 (0.17)	-
Precious Metals	0.000 (0.73)	0.104 (<0.01)	-0.021 (0.56)	**0.068 (<0.01)**	-	**0.299 (<0.01)**	**-0.094 (<0.01)**	0.017 (0.37)	0.030 (0.17)	0.044 (0.08)	-
Industrial Metals	**0.001 (0.02)**	**0.137 (<0.01)**	0.065 (0.15)	**0.190 (<0.01)**	**0.365 (<0.01)**	-	-0.033 (0.16)	0.039 (0.05)	-	-0.046 (0.07)	-

Table IV: Tail risk spillovers (continue)

	Tail dependence										
Differences of COVID presence	*(Intercept)*	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*	*(1lag)*	*(2lags)*	*(3lags)*	*(4lags)*	*(5lags)*
Commodities	**(Lower) 40%**										
Agriculture	**0.002 (<0.01)**	-	-	-	-	-	-	-	-	-	-
Livestock	-	-	-	-	-	-	**0.154 (0.02)**	-	-	-	-
Energy	**0.003 (0.01)**	0.361 (0.07)	-	-	-	-	-	-	-	-	-
Precious Metals	-	-	-	-	-	-	-	-	-	-	-
Industrial Metals	**0.002 (0.01)**	-	-	-	-0.153 (0.12)	-	-	-	-	-	-
Commodities	**(Upper) 60%**										
Agriculture	-	-	-	-	-	**0.171 (0.01)**	-	**0.108 (0.02)**	-	-	-
Livestock	-	-	-	-	-	-	-	-	-	-	-
Energy	-	0.190 (0.16)	0.291 (0.11)	-	-	0.117 (0.37)	-	-0.065 (0.22)	-	-	-
Precious Metals	-0.001 (0.05)	-	-	-0.041 (0.22)	-	-	0.090 (0.06)	-0.090 (0.09)	-	**-0.118 (0.01)**	0.056 (0.19)
Industrial Metals	**-0.002 (0.02)**	-	-	-0.104 (0.08)	-0.066 (0.52)	-	0.025 (0.61)	-	-	0.108 (0.04)	0.009 (0.78)

Table V: The tail risk connectedness at 5% and 95% thresholds

	Lower tail dependence (5%)					
	Pro			*Covid*		
Commodities	***To***	*From*	*Net*	*To*	***From***	Net
Agriculture	7.56	0.00	-7.56	10.46	0.00	-10.46
Livestock	3.77	35.00	31.23	5.22	48.45	43.23
Energy	35.00	10.55	-24.45	48.45	14.61	-33.84
Precious Metals	32.46	14.43	-18.03	6.52	19.97	13.45
Industrial Metals	21.21	40.02	18.81	29.36	16.98	-12.38
	Upper tail dependence (95%)					
	Pro			*Covid*		
Commodities	*To*	*From*	*Net*	*To*	*From*	*Net*
Agriculture	0.00	20.26	20.26	0.00	8.59	8.59
Livestock	6.84	0.00	-6.84	11.49	49.02	37.53
Energy	55.37	11.46	-43.91	58.21	8.71	-49.50
Precious Metals	15.85	20.82	4.97	21.01	13.56	-7.45
Industrial Metals	21.93	47.46	25.53	9.30	20.12	10.82

Table VI: The tail risk connectedness at 10% and 90% thresholds

	Lower tail dependence (10%)					
	Pro			*Covid*		
Commodities	*To*	*From*	*Net*	*To*	*From*	*Net*
Agriculture	14.40	29.84	15.44	14.40	29.84	15.44
Livestock	11.70	4.10	-7.60	11.70	4.10	-7.60
Energy	33.91	12.36	-21.55	33.91	12.36	-21.55
Precious Metals	15.81	11.14	-4.67	15.81	11.14	-4.67
Industrial Metals	24.18	42.55	18.37	24.18	42.55	18.37
	Upper tail dependence (90%)					
	Pro			*Covid*		
Commodities	*To*	*From*	*Net*	*To*	*From*	*Net*
Agriculture	7.77	0.00	-7.77	14.88	11.15	-3.73
Livestock	4.19	8.35	4.16	19.23	19.21	-0.02
Energy	34.80	12.49	-22.31	20.50	15.52	-4.98
Precious Metals	28.72	27.55	-1.17	24.37	23.72	-0.65
Industrial Metals	24.51	51.61	27.10	21.01	30.40	9.39

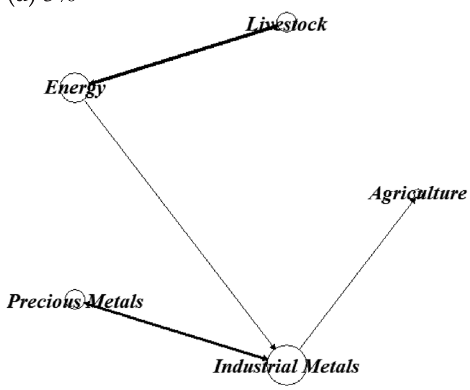
Table VII: The tail risk connectedness at 20% and 80% thresholds

	Lower tail dependence (20%)					
	Pro			*Covid*		
Commodities	*To*	*From*	*Net*	*To*	*From*	*Net*
Agriculture	16.92	10.43	-6.49	16.92	10.43	-6.49
Livestock	0.00	18.75	18.75	0.00	18.75	18.75
Energy	36.97	12.07	-24.90	36.97	12.07	-24.90
Precious Metals	19.19	16.52	-2.67	19.19	16.52	-2.67
Industrial Metals	26.91	42.22	15.31	26.91	42.22	15.31
	Upper tail dependence (80%)					
	Pro			*Covid*		
Commodities	*To*	*From*	*Net*	*To*	*From*	*Net*
Agriculture	8.97	19.11	10.14	14.55	14.15	-0.40
Livestock	8.91	4.04	-4.87	6.60	21.02	14.42
Energy	36.45	16.85	-19.60	45.03	12.48	-32.55
Precious Metals	17.73	30.98	13.25	13.13	22.95	9.82
Industrial Metals	27.94	29.03	1.09	20.69	29.40	8.71

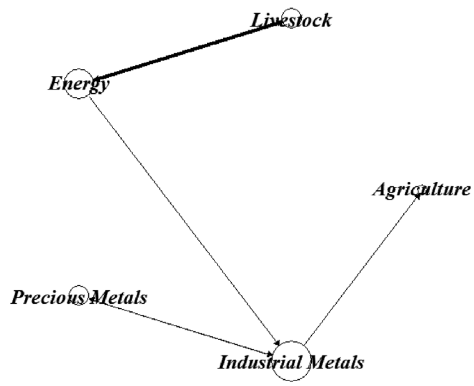
Table VIII: The tail risk connectedness at 40% and 60% thresholds

	Lower tail dependence (40%)					
	Pro			*Covid*		
Commodities	*To*	*From*	*Net*	*To*	*From*	*Net*
Agriculture	16.57	20.48	3.91	16.57	20.48	3.91
Livestock	8.95	11.07	2.12	8.95	11.07	2.12
Energy	37.21	10.39	-26.82	37.21	10.39	-26.82
Precious Metals	15.15	18.85	3.70	15.15	18.85	3.70
Industrial Metals	22.12	39.21	17.09	22.12	39.21	17.09
	Upper tail dependence (60%)					
	Pro			*Covid*		
Commodities	*To*	*From*	*Net*	*To*	*From*	*Net*
Agriculture	20.10	20.24	0.14	25.05	18.98	-6.07
Livestock	2.75	4.45	1.70	2.58	4.17	1.59
Energy	32.19	16.53	-15.66	30.20	15.50	-14.70
Precious Metals	18.20	20.28	2.08	17.07	19.02	1.95
Industrial Metals	26.76	38.51	11.75	25.10	42.31	17.21

(a) 5%

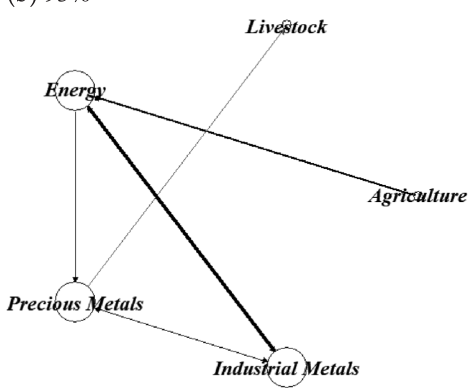


(a1) pro-COVID

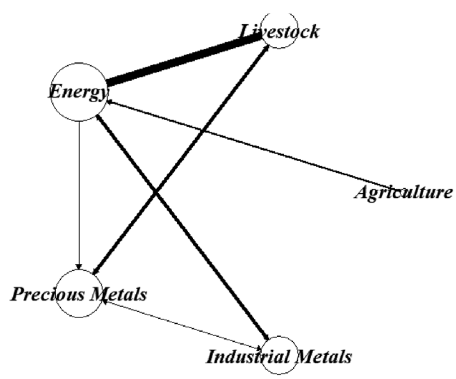


(a2) COVID

(b) 95%



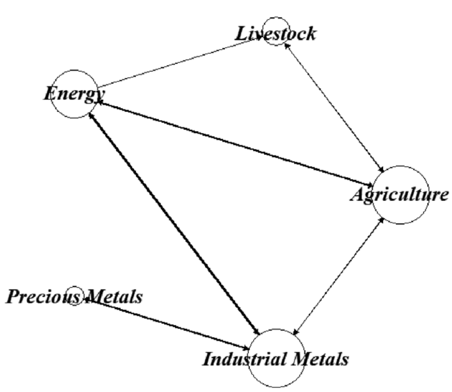
(b1) pro-COVID



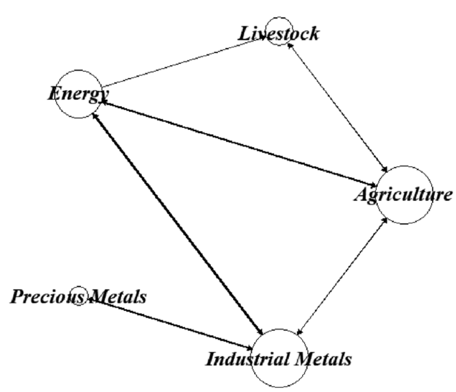
(b2) COVID

Figure 1: Tail-risk dependence networks at: (a) 5% (b) 95%

(a) 10%

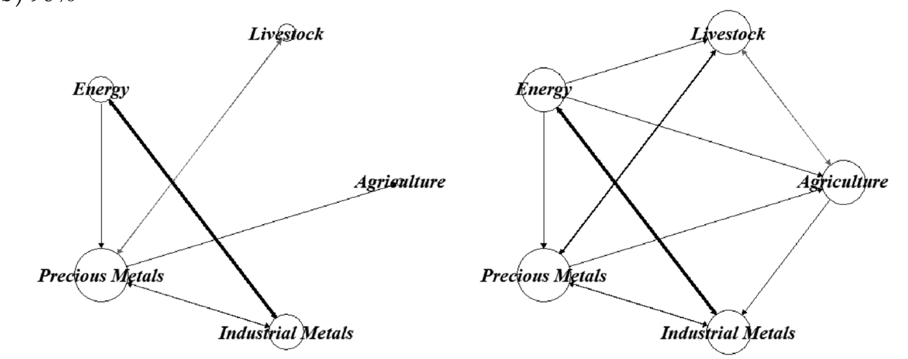


(a1) pro-COVID



(a2) COVID

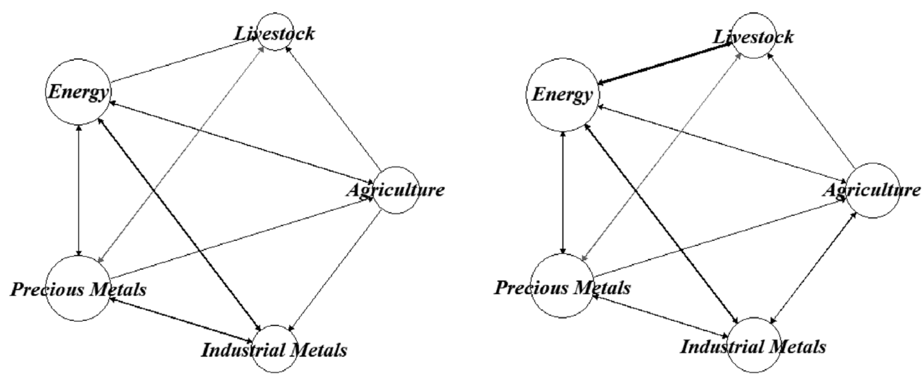
(b) 90%



(b1) pro-COVID (b2) COVID

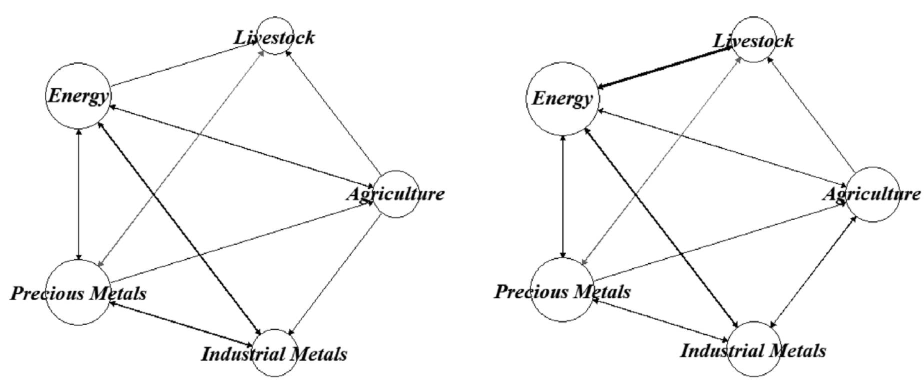
Figure 2: Tail-risk dependence networks at: (a) 10% (b) 90%

(a) 20%



(a1) pro-COVID (a2) COVID

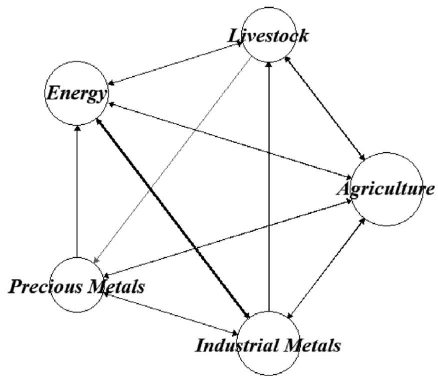
(a) 80%



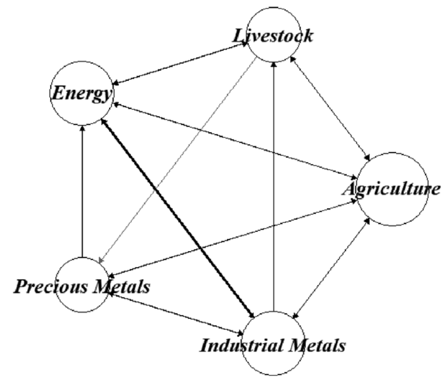
(b1) pro-COVID (b2) COVID

Figure 3: Tail-risk dependence networks at: (a) 20% (b) 80%

(a) 40%

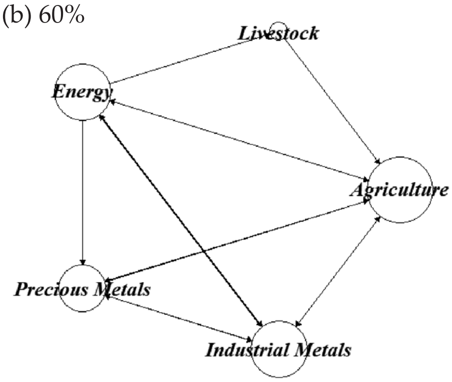


(a1) pro-COVID

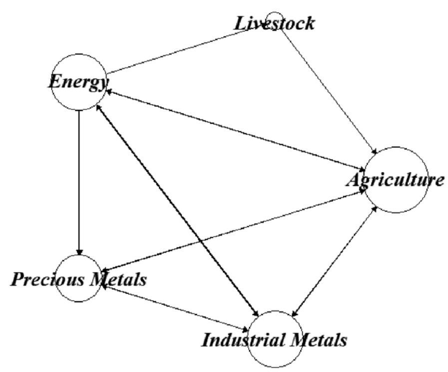


(a2) COVID

(b) 60%



(b1) pro-COVID



(b2) COVID

Figure 4: Tail-risk dependence networks at: (a) 40%   (b) 60%

dependence and between the livestock market with either the precious metals or the agriculture market. Thus, in euphoric economic periods investors should exclude these combinations in their portfolios in order to avoid losses.

(b) In all cases examined and based on the calculation of the net-degrees, energy sector has appeared as receiver of other commodity sectors' burst or boom. This finding, that energy commodities are the main extreme events receivers, characterises them as the most unstable components of commodity markets and thus exposes their holders in high risk.

(c) COVID has made a thing in the tail risk connectedness network of the US commodity sectors in the upper tail thresholds, meaning on a general welfare in the commodities. In this context, investors' trading strategies in booms of commodities have changed during COVID.

There are potential avenues for future research. The first may involve the examination of tail interdependence in other set of financial markets. Moreover, it could be applied for the risk dependence of commodities with other financial assets or taking into account different uncertainty periods.

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APPENDIX

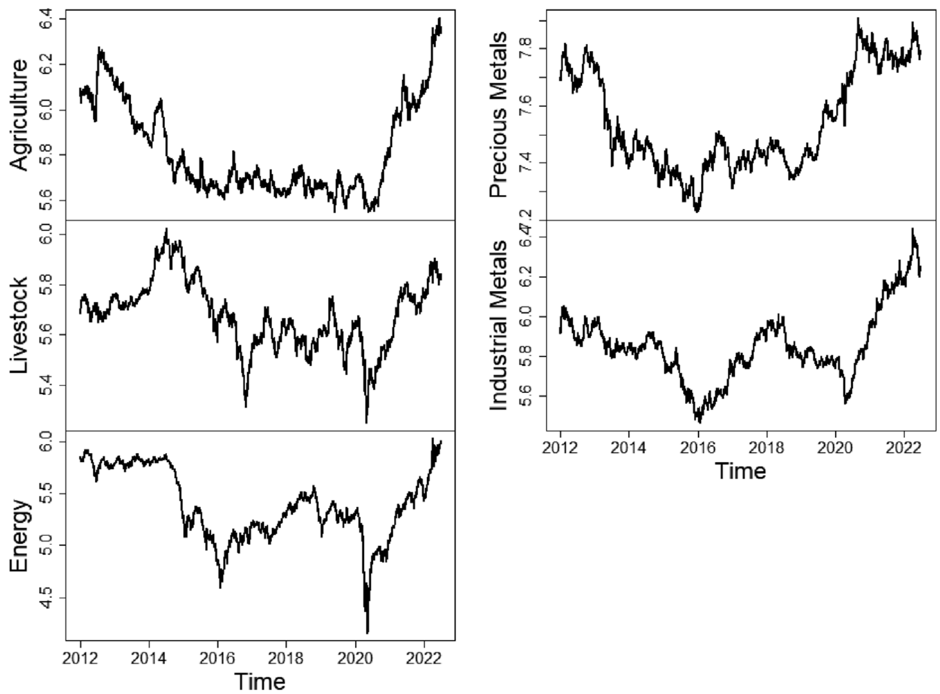

Figure A1. Natural logarithms of prices

Table AI: Summary statistics and tests on the distributions of logarithmic price returns

Statistic	*Agriculture*	*Livestock*	*Energy*	*Precious Metals*	*Industrial Metals*
Mean	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.001	0.000	0.000
SD	0.011	0.010	0.022	0.011	0.011
Minimum	-0.053	-0.062	-0.302	-0.101	-0.041
Maximum	0.050	0.053	0.160	0.057	0.050
1st Quartile	-0.007	-0.006	-0.009	-0.005	-0.006
3rd Quartile	0.006	0.006	0.010	0.005	0.006
Skewness	0.082 (0.08)	-0.305 (<0.01)	-1.418 (<0.01)	-0.594 (<0.01)	-0.013 (0.79)
Kurtosis	4.904 (<0.01)	5.551 (<0.01)	27.010 (<0.01)	9.839 (<0.01)	4.132 (<0.01)
Normality	0.982 (<0.01)	0.976 (<0.01)	0.853 (<0.01)	0.938 (<0.01)	0.990 (<0.01)

Note: The *p*-values for skewness, kurtosis, and normality have been obtained using the tests by d'Agostino (1970), Anscombe and Glynn (1983), and Shapiro and Wilks (1965), respectively.