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Dependence between renewable energy related critical metal futures and producer equity markets across varying market conditions

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A B S T R A C T

We study the dependence of renewable energy production-related critical metal futures and producer equity returns, compared to the non-renewable energy (oil and natural gas) and some other globally relevant commodity markets. We find different asymmetric and symmetric dependencies in these commodity markets. The dependence is asymmetric in the most important critical metal markets, i.e., of silver, copper, and platinum. Still, surprisingly, for example, in the oil market, the relationship is symmetric, and no relationship is found in the natural gas market. Furthermore, the oil and agricultural markets have homogenous dependence structures in most market conditions, so the information transmission channels in these markets seem to be highly efficient. Still, the critical metal markets seem inefficient in this respect. The short-term speculation effects from the precious metals-related stock market segment towards critical metals futures markets are strong compared to others. We suggest that the future regulation of the precious metals producer stock market sector should be tighter to reduce speculative spillovers from this market segment to the futures markets of these metals.

1. Introduction

Climate change and the issues related to energy security are the driving forces behind the currently heated discussions about the gradual shift towards renewable energy sources in the near future. In this process, electricity production technologies have a central role. However, these technologies are often heavily dependent on critical metals as inputs. As emphasized, for example by Grandell et al. [1, p. 53], ‘ … a metal is perceived critical if it is crucial for green energy technologies and if it is scarce by its geological occurrence. A shift in the global energy sector towards low carbon technologies will increase demand for these metals … ’ Grandell et al. also find that the most important critical metals are platinum, silver, and copper. Silver is in the direst situation regarding the mining and consumption needs because it is needed especially in solar energy, for example, in photovoltaic technologies and concentrated solar power production. It is also consumed in electronics, and therefore the expanding electric vehicle stock results in further demand for silver. As an example of the demand and supply conditions of critical metals, according to Ref. [1], the silver demand will exceed known global resources by more than 300% and currently classified reserves by almost 450% by the year 2050.

The main important grounding idea in our paper is that in addition to the globally most actively traded precious metal, gold, the most important critical metals (silver, platinum, and copper) are denoted as *precious metals*, too. Hence, they are also treated clearly as investment goods, i.e., assets, and not just (critical) inputs in the production of some increasingly important goods. Based on this, their dual role as a critical metal input for renewable energy production technologies, and as an asset, raises a prominent role of speculation to be addressed in connection to the markets where these commodities and shares of commons stocks of the firms producing goods related to these metals are traded.

This paper focuses on the connections between the stock market valuation of the critical (precious) metals-related producer firms and the pricing of these metals in their derivatives, i.e., futures markets. As already mentioned, in addition to the essential role of these precious metals in the production technologies related to green energy production, another unique feature regarding the commodity market segments analyzed in our paper is their apparent exposure to speculation. The Global Financial Crisis (GFC)

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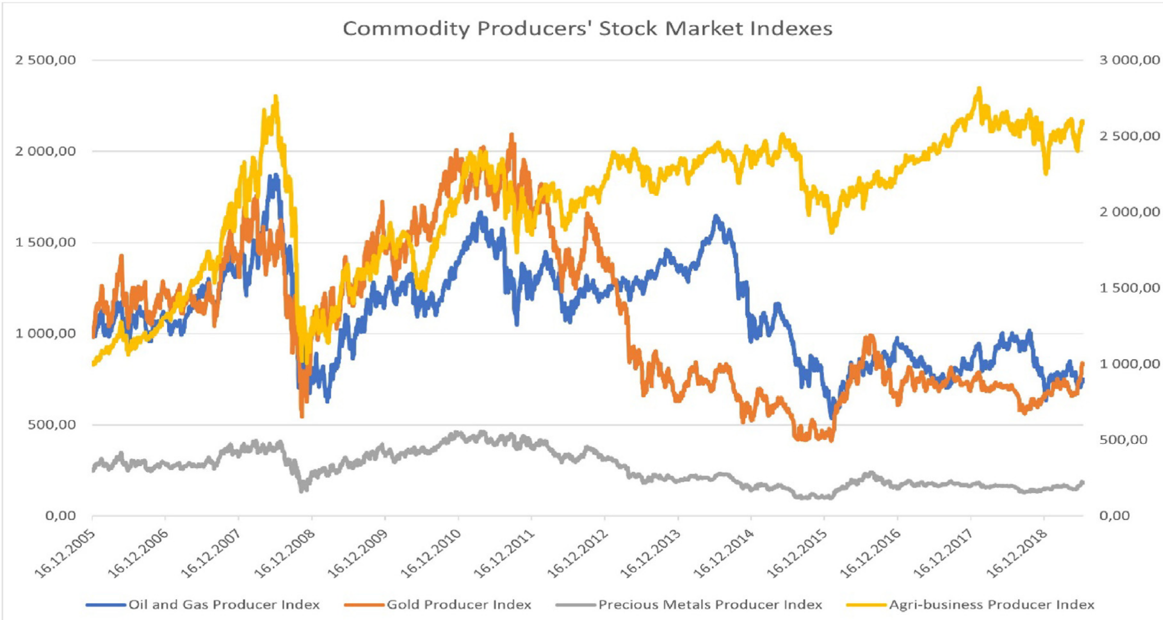

Fig. 1. Performance of the commodity producers' stock market valuation during the sample period 16/12/2005–28/6/2019.

in 2008 resulted from increased interconnections between various components of global financial markets that resulted in increased volatility in stock markets and commodity markets [2–6]. The increased volatility in the commodity markets during the GFC made researchers question the validity of the diversification argument [4]. The vast inflow of investments, especially in commodity market derivatives, also known as financialization, could contribute to this development [5,6].

Our paper focuses on the dependence in the traditional energy (oil and natural gas) sector and the globally most important agricultural products (corn, wheat and coffee) in comparison to the dependence in critical metal markets of silver, copper and platinum, and also of gold markets. We show that the dependence structures between the futures and stock markets in the most recent data from the traditional energy and agricultural sectors are very different compared to especially the renewable energy production connected segments of global commodity and stock markets. As we see from Fig. 1, the stock market valuation of oil and gas exploration firms experienced similar behavior as for example that of the precious metals and agribusiness firms around the period of GFC in 2007–2009. However, our results show that the dependency structure between the futures markets and the producer stock markets was clearly different in these market segments when the analysis focuses especially on the correlations between the extreme tail and other quantile observations of returns. Furthermore, the increased levels of volatility since the GFC in both the stock and commodity markets raise suspicion whether the cross-market linkages between these asset groups have changed over time and if there potentially could be signs of a financial contagion.

The previous literature has mainly focused on examining the volatility spillovers between commodity futures and stock markets, or the cross-market linkages between different commodity markets using aggregate index data like S&P500 index [4,7–9] and Dow Jones [8,10]. Another branch of literature has focused on the GFC's effects on co-movements between assets [3–5,11]. For example [3] find evidence for time-varying correlations between commodity and stock markets, where the GFC showed noticeable impact on the dependency structures.

As a completely new statistical approach compared to any other previous study mentioned above, we use a cross-quantilogram approach developed by Ref. [15] to accomplish the purpose of this study.[1] Furthermore, instead of focusing on the aggregate level market indices, we want to especially emphasize the dependence of the stock market segments of the commodity producer firms with respect to the global futures market of the commodity in question. More specifically, our chosen method allows for the dependency and directionality analysis between commodity futures and their corresponding producer equity index returns when they are in different quantiles, which essentially represent *different market conditions*. We examine the quantile dependencies at 1, 5 and 22 lags, which reflect the time horizons of one day, one week and one month. In practice, many of the previous studies, like [12–14] have focused on the relationships between the analyzed market segments using near-term implied volatility measures, like VIX from the stock market, and OVX from the oil market, and their effects on the stock market performance. However, we differ from these and all the other mentioned studies by focusing also on the tail dependencies of the *actual return distributions of the commodity market and the respective producers' stock market returns*. Nevertheless, because some parts of the previous literature have revealed the potential role of the effects of for example the Economic Policy Uncertainty (EPU) index developed by Ref. [19] (see e.g. Ref. [20]), we obviously have to control for the role of this kind of aggregate level uncertainty information in our analyses, too. This part of our analysis is based on using a *partial cross-quantilogram* method. As described in more details below, this enables the introduction of exogenous information (here in the form of VIX and EPU indexes) to the analysis of the tail dependence of the return variables focused.

[1] Previously this method has been used to analyze for example the dependence between clean anergy stocks and non-ferrous metal markets, real option market characteristics of gold markets, effects of euro currency on financial market dependence, and the dependence between developed and emerging stock markets [16–18]. However, according to our knowledge, this is the first paper to analyze the dependence between the critical metal market producer firms' valuation and the futures markets of these metals.

Furthermore, because already from Fig. 1 it is obvious that the varying market conditions might have introduced varying dynamic dependencies, too, we also allow for time-varying relationships between the analyzed market segments. This part of our analysis is based on using recursive subsample estimation procedure to attain time-varying dependence structures and to identify potential changes of cross-quantile correlations over time.

The main implications of our paper are as follows. The more detailed analysis of the return dependency in varying market conditions based on the revealed interrelationships of the returns in quantiles implies that the oil and also agricultural producer firms' extreme stock market returns, and their relevant futures market performances are symmetrically connected. That is, in extreme (either negative or positive) conditions in their futures markets, there are also extreme conditions in the corresponding producer's stock market returns, especially in the shortest, 1-day lag horizon. This dependence holds also in vice versa direction, but in comparison, in the market for the critical metals for renewable energy production this is not the case at all. The new information seems to transfer quickly to both the non-renewable energy market and agricultural products' futures contracts and the relevant equity indexes and hence, returns, but especially for the relationships in silver, platinum and copper futures markets and corresponding (precious metals) producer stock market segment, this is not the case. Hence, *the markets for the main renewable energy related critical metals advocated in Ref. [1] have clearly different dependence relationships compared to other main global commodity markets, and this raises serious concerns also for the need to control the adverse effects from stock market valuation of the producer firms of main critical metal markets for renewable energy production technologies.*

Especially for the platinum market we observe very strong asymmetries in the form of spillover effects in all market conditions from the producer stock market to the futures market returns, but basically nothing from the futures markets to the producer stock markets. For the general conclusion this result indicates our main new finding that also in extreme market conditions the pricing mechanisms work efficiently between oil and agricultural futures and producer stock indexes since this implies that also during extreme periods in markets, producers in the oil and agribusinesses base their production and storage decisions on looking at the prices of the futures contract. This seems not to be the case at all in the markets for precious, renewable energy production related critical metals. Furthermore, according to our results, the general market/economic uncertainty conditions do not have any role in these connections, i.e., the relationships especially for the oil and agribusiness markets hold when controlling both for the aggregate stock market (VIX) and aggregate real economic (EPU) uncertainty effects. Hence, these markets seem to be the most efficient in terms of symmetric information flows, whereas the critical metal markets involve much more asymmetric relationships between the futures market and relevant stock market segment developments. Hence, according to our results, the policy makers should put a lot of effort in controlling especially the very short-term speculative behavior in the precious, critical metals (especially platinum, silver, and copper) producer stock markets, because it seems that the relevant fundamental information in the futures market pricing mechanisms is very different compared to the information mirroring the producer firms' expected cash flows, that should be the main determinant of stock market prices. According to our main results it seems that the information in the futures market basically has no role to play in producer stock market pricing process for the precious, critical metals. However, basically in all market conditions, containing also potential speculation periods in stock markets, the producer stock market returns have very strong spillover effects for the corresponding futures markets of these metals. *Hence, in the critical metal market segment in general also the adverse commodity market price development can be seriously rooted to the speculation in the respective stock market sector.*

The reminder of the paper is organized as follows. Section 2 presents the data and methods for analyzing the dependency of futures market and producers' stock market performance in varying market conditions. Section 3 presents the main results and comparison to previous studies, and finally, Section 4 concludes the paper.

2. Material and methods

2.1. Data

Our data sample consists of the daily price and returns observations from December 16, 2005 to June 28, 2019, which gives us 3397 observations in total. All data are expressed in USD and retrieved from REFINITIV/Thomson Reuters Datastream. The sample period is chosen to include the global financial crisis of 2008 since the previous literature indicates that spillover between commodities and financial markets has increased after the crisis [11,21–23]. For comparison, in this paper, we contrast against each other the globally most important non-renewable energy sector (oil and natural gas), the agricultural business sector (corn, wheat, and coffee), and the renewable energy sector-related, critical metals, namely, platinum, silver, and copper. In addition, we also analyze the behavior of gold markets for comparison because gold is the most actively traded precious metal globally, and it also has a (more minor) role in some parts of renewable-energy-related production technologies [1]. However, as discovered by Grandell et al. [1], the platinum, copper, and silver markets constitute the most relevant segments of precious metals markets considered as critical in renewable energy production. All the considered commodity markets are globally significant, and their markets have distinctive characteristics.

We consider four globally important commodity stock indexes (oil and gas, gold, other precious metals, and agribusiness) to respectively represent the stock market performance of companies involved in the production and exploration of each of these commodity sectors. Our chosen indexes constitute some of the largest publicly traded commodity-producing companies, and each index exercises market-capitalization requirements for inclusion. On the other hand, the selected commodity futures contracts are continuous. At the start of a new month, the current finite future contract rolls over to extend the contract without expiring. Table 1 reports the descriptive statistics and correlation coefficients for the variables in our data.

Descriptive statistics reveal that the mean value of each asset return is close to zero, which is expected in a daily data set. While the majority of returns display positive mean values, natural gas futures market return has a slightly negative mean, and it has the largest standard deviation, too. This implies that the natural gas futures market has experienced more volatile market conditions during the sample period than the other futures contracts and producer stock markets. However, both aggregate uncertainty indexes (VIX and EPU) display larger standard deviations than the natural gas futures market returns, which indicates that the natural gas market has not experienced higher volatility than the overall stock markets or the aggregate economy.

Almost all commodity producer stock return series are characterized by negative skewness, except the Dow Jones Precious Metals Index. The negative skewness values indicate that the tails of the probability distribution of returns are skewed to the left. Almost half of the futures contract returns have negative skewness,

Table 1
Descriptive statistics and correlations.

i) Descriptive statistics

Series	Mean (%)	Std Dev (%)	Min	Max	Skewness	Kurtosis	Q(10)	ARCH(10)	JB	ADF(a)	ADF(b)	PP
Panel A: Producer Indices												
S&P Producers Oil and Gas	0.000	0.019	−0.175	0.133	−0.619	8.139	51.101***	3097.210***	9608.60***	−18.762(10)***	−18.773(10)***	−52.950***
S&P Producers Gold	0.000	0.023	−0.172	0.224	−0.067	7.040	69.540***	1927.271***	7028.600***	−20.673(8)***	−20.670(8)***	−54.272***
Dow Jones Precious Metals	0.000	0.025	−0.181	0.244	0.057	6.714	28.226***	1559.545***	6392.400***	−26.432(4)***	−26.429(4)***	−60.029***
S&P Producers Agribusiness	0.000	0.013	−0.165	0.103	−1.154	15.830	85.009***	2252.262***	36273.00***	−32.152(2)***	−32.161(2)***	−50.099***
Panel B: Futures Prices												
Crude Oil	0.000	0.023	−0.131	0.164	0.096	4.576	18.083***	1927.785***	2975.100***	−42.918(1)***	−42.915(1)***	−61.856***
Natural Gas	0.000	0.032	−0.181	0.268	0.552	5.109	32.450***	276.520***	3873.700***	−21.415(7)***	−21.414(7)***	−62.098***
Gold	0.000	0.012	−0.098	0.086	−0.321	5.551	17.075*	331.136***	4427.900***	−18.467(10)***	−18.529(10)***	−58.198***
Silver	0.000	0.021	−0.195	0.124	−0.864	7.081	15.777	375.098***	7531.300***	−29.772(3)***	−29.803(3)***	−60.050***
Platinum	0.000	0.015	−0.096	0.160	−0.069	7.140	15.581	359.086***	7230.000***	−40.390(1)***	−40.411(1)***	−55.637***
Copper	0.000	0.018	−0.116	0.117	−0.072	3.814	44.445***	2149.286***	2065.800***	−16.453(10)***	−16.466(10)***	−62.888***
Corn	0.000	0.019	−0.245	0.087	−0.626	10.025	11.590	29.585***	14468.00***	−32.799(2)***	−32.816(2)***	−56.950***
Wheat	0.000	0.021	−0.100	0.129	0.197	2.122	9.220	281.174***	661.160***	−41.935(1)***	−41.941(1)***	−58.041***
Coffee	0.000	0.019	−0.113	0.118	0.114	1.859	8.925	186.549***	498.130***	−32.866(2)***	−32.869(2)***	−60.206***
Panel C: Uncertainty Indices												
EPU	0.000	0.533	−3.148	3.216	0.039	1.745	548.579***	306.066***	433.310***	−26.118(10)***	−26.114(10)***	−143.200***
VIX	0.000	0.075	−0.351	0.768	0.987	6.554	68.959	221.194***	6643.100***	−21.415(9)***	−21.415(9)***	−65.803***

ii) Unconditional correlation matrix between producer index returns and relevant futures market returns

Producer Index\ Futures market	Crude Oil	Natural Gas	Gold	Silver	Platinum	Copper	Corn	Wheat	Coffee
S&P Producers Oil and Gas	0.916	0.448							
S&P Producers Gold			0.133						
Dow Jones Precious Metals				0.553	0.826	0.673			
S&P Producers Agribusiness							0.542	0.565	0.574

Notes: Panel i) shows descriptive statistics for the logarithmic returns (i.e., log changes in the case of uncertainty indices), measured in %-values. Time period is from December 16, 2005 to June 28, 2019, with 3397 observations per series, retrieved from REFINITIV/Thomson Reuters Datastream. In addition to standard descriptive statistics, we report the test statistics for the Ljung–Box (Q)-test for autocorrelation, ARCH–LM-test for heteroscedasticity, Jarque–Bera (JB) -test for normality, and the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests for testing the unit roots in the time series. ADF(a) refers to the test with intercept only, ADF(b) to the test with intercept and trend. Optimal lag length is determined based on Akaike Information Criterion and is presented in parenthesis. ***, **, * refer to 1%, 5% and 10% significance levels. Panel ii) presents correlations between producer index and commodity futures returns. Only correlations within the 'own' relevant sector are presented as they are the focus of this study and cross-sectoral correlations do not contribute noteworthy information. Furthermore, correlations between producer index returns and corresponding commodity futures returns within different sectors are not perfectly comparable as they are affected by the composition of the indexes and weights of each commodity in them.

and the other half experiences positive skewness, which indicates a probability distribution with tail extending to the right. Additionally, our data exhibit a higher probability of extreme events than a normal distribution, which is demonstrated by the high kurtosis values. The notably high kurtosis value in the S&P agribusiness index returns can be attributed to the unpredictability of inventory levels at pre-harvest periods due to the agribusinesses' exposure to weather conditions. In contrast, the only assets whose return kurtosis values are lower than three are the futures contracts for wheat and coffee, which means that these return distributions have thinner tails and are thus closer to being also normally distributed.

We also conducted some diagnostic tests to examine the time series characteristics of our data in more detail. The Jarque-Bera normality test values imply that the null hypothesis of the normal distribution can be rejected at one percent significance level for all series, confirming the non-normality of all stock market and futures market returns. We also tested for heteroskedasticity using the ARCH-LM test. Also in this case, the null hypothesis is rejected at a one percent significance level for all series, meaning that all return series might contain autoregressive conditional heteroskedasticity in their variances. Testing for the autocorrelation structure using the Ljung-Box-test suggests a serial correlation in the data generating processes, especially of the stock market returns, as the Q2-statistics for all producer index returns are statistically significant. The same inference applies to the futures market returns based on the Q2-test values, but not so clearly when using the standard Q-test statistics.

Instead of meeting the normality assumptions, the main requirement to employ the cross-quantilogram (CQ) method is that the analyzed time series must be stationary [15]. Therefore, the stationarity of the return series was tested using the Augmented Dickey–Fuller-test and the Phillips-Perron-test, which test for the existence of unit roots as the null hypothesis. The ADF-tests indicate stationarity of all the stock index and futures contract returns. The PP-test further confirms all the return time series' stationarity because the null hypothesis is clearly rejected in all cases. Finally, panel ii) in Table 1 displays the correlations between the producer stock index returns and the respective commodity futures returns. We observe the highest correlations between the crude oil futures and oil and gas producer index returns from the correlation matrix, indicating close to perfect correlations. We can also see from the table that the correlations are the lowest between the gold futures and gold producer sector index returns. The correlation in the gold market is close to zero, which suggests that the gold market contains attractive diversification (hedging) possibilities.

On the other hand, the platinum futures returns are most strongly correlated with the precious metal producer index returns out of all the precious, critical metal futures markets. In contrast, the silver futures returns are the least correlated with the producer stock market returns. In addition, it is worth noting that the correlations between the agriculture market futures returns and the agribusiness producer stock index returns are almost identical to each other, but most interestingly, to the corresponding correlation between the silver market futures and producer stock returns.

Hence, the average dependence in the whole sample observations without controlling the market conditions (based on quantiles of return distributions) might seem similar in the agricultural products and the analyzed renewable energy-related critical metals markets. However, next, we will describe in more detail our method to reveal the varying degrees of dependence in different market conditions.

2.2. Methods

The dependence structures and directional predictability between commodity futures and their corresponding producer equity markets are addressed using the cross-quantilogram approach developed by Ref. [15]. The quantilogram, developed by Ref. [24], is the predecessor of the cross-quantilogram model and it uses "quantile hits" in correlograms to measure the directional predictability of a stationary time series in different quantiles in a univariate setting. The quantilogram compares the correlations of the "quantile hits" to pointwise confidence intervals. The extended cross-quantilogram, on the other hand, employs a multivariate approach by examining the directional dependence of two time series using conditional quantiles. The cross-quantilogram distribution has good asymptotic properties and is therefore uniformly applicable over a variety of quantiles.

After reassuring that the variables follow a stationary stochastic process, the cross-quantilogram approach first estimates the "quantile-hits" between two events $\{y_{1t} \le q_1\ (\tau_1)\}$ and $\{y_{2t\text{-}k} \le q_2\ (\tau_2)\}$. This procedure is essentially the estimation of the serial dependence, and it incorporates any arbitrary pair of τ_t. The cross-correlations between different quantile-hits are later estimated, where the quantile-hit process for $i = 1{,}2$ is defined as $\{1[y_{it} \le q_{i,t}(\bullet)]\}$, where $1[\bullet]$ is the indicator function. Equation (1) captures the cross-correlations of the quantile-hit process for τ-quantile with k lead-lags periods to time t:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau 1}\left(y_{1t} - q_{1,t}(\tau_1)\right)\psi_{\tau 2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau 1}^2\left(y_{1t} - q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau 2}^2\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}}, \tag{1}$$

where y_{1t}, y_{2t}, …, y_{it} are stochastic stationary processes with the quantiles $q_{it}\ (\tau_t)$. The quantile, τ_t, is either conditional or unconditional to y_{it}, and $\tau \in \alpha$ and $0 < \alpha < 1$. We use the lag lengths $k = 1$, 5 and 22, which enable the analysis of cross-correlations on one day, five days (weekly), and 22 days (monthly) lag structures. The correlation of the quantile-hit process is denoted by $\rho_\tau(k)$ and its size is determined by the correlation coefficient, ψ_τ. The quantile hit process is defined by $\psi_{\tau 1}(y_{t1}\text{-}q_{1t}))1[y_{it} \le q_{it}(\tau_i)]\bullet\tau_i$, which can be represented as $\psi_\alpha = 1[u < 0]-\alpha$ (see Ref. [15]). In the context of our paper, y_1 could for example represent oil market futures return and y_2 could represent the oil and gas producer equity index return, or any other futures contracts and their corresponding producer index.

Assume for example that we want to examine the dependence structures between the non-renewable energy market variables in the quantile 0,05. We therefore assume y_1 has $q_1(0{,}05)$ at time t and y_2 has $q_2(0{,}05)$ at time t-1. We examine if the correlation of the quantile-hit process is $\rho_\tau(1) \ne 0$, which would imply that there is tail dependence between the oil futures and the oil and gas producer index returns. This result would further indicate that there is a one event directional predictability between the two markets in the 0.05 quantiles. In the case of $\rho_\tau(1) = 0$, this would entail no directional predictability between the two markets, and hence, no tail dependence would be evident either. In equation (2) we introduce the sample counterpart of the cross-quantilogram and it is computed to generate the empirical estimations of our study:

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T}\psi_{\tau 1}\left(y_{1t} - \hat{q}_{1,t}(\tau_1)\right)\psi_{\tau 2}\left(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi_{\tau 1}^2\left(y_{1t} - \hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi_{\tau 2}^2\left(y_{2t} - \hat{q}_{2,t}(\tau_2)\right)}}. \tag{2}$$

here the unconditional sample quantile of $y_{i,t}$ is denoted as $\hat{q}_i(\alpha_i)$ [15]. Next, the Ljung-Box test is computed with the objective of testing the validity of the null hypothesis through statistical inference. The null hypothesis is tested as $H_0 = \rho_\tau(1) = \ldots = \rho_\tau(\rho) = 0$, to examine if the conditional correlations are not statistically different from zero for some k $\in \{0, \ldots, \rho\}$. The null hypothesis is tested against the alternative hypothesis, $H_1 = \rho_\tau(k) \ne 0$, which entails evidence of statistically significant conditional correlations. The Ljung-Box-test for the maximum of lags p, with number of observations T, and model lags k is calculated based on:

$$\hat{Q}_\tau(p) = T(T+2)\sum_{k=1}^{p}\frac{\hat{\rho}^2(k)}{T-k}. \tag{3}$$

The cross-quantilogram output generates heat maps consisting of 121 squares that unveil different quantile combinations of our chosen variables. The X-axis and Y-axis in the heat maps represent the following quantile distribution between two variables: [q = (0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95)]. The cross-quantilogram approach enables analysis of cross-correlations in different market conditions since the lower quantiles 0.05 represent "bad" market conditions and the upper quantiles 0.95 display "good" market conditions. These extreme quantiles are often called the "tails" of the distributions. "Normal" market conditions are represented by the middle quantile, 0.5. These heatmaps effectively illustrate the unconditional bivariate cross-quantile correlation between two distributions and offer a complete picture of their dependence structures. The level of correlation is designated by the color scale, where the red color indicates a strong positive correlation and blue color represents strong negative correlation. Statistically insignificant results are set to zero and are represented by the green color. The statistical insignificance implies that there is no directional predictability between the quantiles of the variables of interest [15].

In our case, we introduce the EPU and VIX indexes as control variables for the economic policy and equity market uncertainties and examine their effect on the relationship between two events {y1t ≤ q1 (τ1)} and {y2t-k ≤ q2 (τ2)} between the time periods t and t-k. The partial cross-correlation is defined in equation (4), where = [(yτ3 − q3t(τ3)), …, ψ (yτn− qnt(τ3))]⊤ is a vector of all control variables.

Hence, we define the partial cross-correlograms based on

$$\rho_{\overline{\tau}|z} = -\frac{\rho_{\overline{\tau},12}}{\sqrt{\rho_{\overline{\tau},11}\rho_{\overline{\tau},22}}}. \tag{4}$$

By defining $h_t\ (\overline{\tau})$ now as a vector of quantile-hit processes, and letting $\overline{\tau} = (\tau_1, \ldots \tau_n)^\top$ compose a single set of quantiles, we are able to re-define $h_t\ (\overline{\tau}) = [\psi_{z1}(y_{\tau 3} - q_{3t}(\tau_3)), \ldots, \psi_{z2}(y_{\tau n} - q_{nt}(\tau_3))]^\top$. The partial cross-correlation can also be written as equation (5), where δ is a scalar parameter, so

$$\rho_{\overline{\tau}|z} = \delta\frac{\tau_1(1-\tau_1)}{\tau_2(1-\tau_2)}. \tag{5}$$

The predictability between two quantile hits can be estimated by testing the null hypothesis $\rho_{\overline{\tau}\overline{\tau}} = 0$, while controlling for the information given by $\overline{z}$.

Finally, based on simply viewing the time series development of our analyzed data, it is evident that the dependence between the return series is probably not time-invariant. Hence, at the final stage, we re-estimate the CQCs using a recursive subsample estimation process to attain time-varying dependence structures and identify potential cross-quantile correlations changes over time (see Uddin et al. [25]). This method facilitates analysis of the possible integration between futures returns with producer index returns over time. We start by estimating the first window of the CQC period, using a window length of 252 days. We subsequently add one day to the subsample and then perform new estimations using the same window length. Finally, this process is halted when the end of the subsample is reached. The recursive window estimation process generates blue lines representing time-varying CQCs in the recursive subsamples observed in Fig. 6 in the results section. The red lines are caused by a bootstrap procedure and illustrate 95% confidence intervals of no predictability between the variables. This means that the blue lines inside the red lines represent statistically significant results, and insignificant results are detected in cases where the blue lines go outside the confidence intervals. The bootstrapping procedure generates confidence intervals by taking our whole data sample as a proxy for the population and performing a range of iterations that provides broad information about the data. We choose to perform 500 bootstrap iterations to produce robust estimation results, and we select the five percent significance level for the statistical inference based on econometric standards.

3. Results and discussion

In reporting our results, we will highlight especially the differences between renewable energy-related critical metal (copper, platinum, and silver) markets and the other analyzed commodity markets. To assess the overall dependence structure within each commodity sector, we analyzed the directionalities going both ways. Hence, we study the directionality from the commodity futures to the producer equity index returns and the directionality from the producer equity index returns to the corresponding commodity futures returns. If there is spillover going both ways, the relationship is symmetric. However, if there is spillover only from one market to the other, the association is asymmetric.

Furthermore, the interpretations of the CQCs differ depending on which direction is examined. Panel a) of Figs. 2–5 always shows the spillover from commodity futures returns to respective producer equity index returns. Panel b) depicts spillover from producer equity returns to respective commodity futures returns. In panel a), the quantiles of the commodity futures returns are presented on the horizontal axis, and the quantiles of the producer equity returns

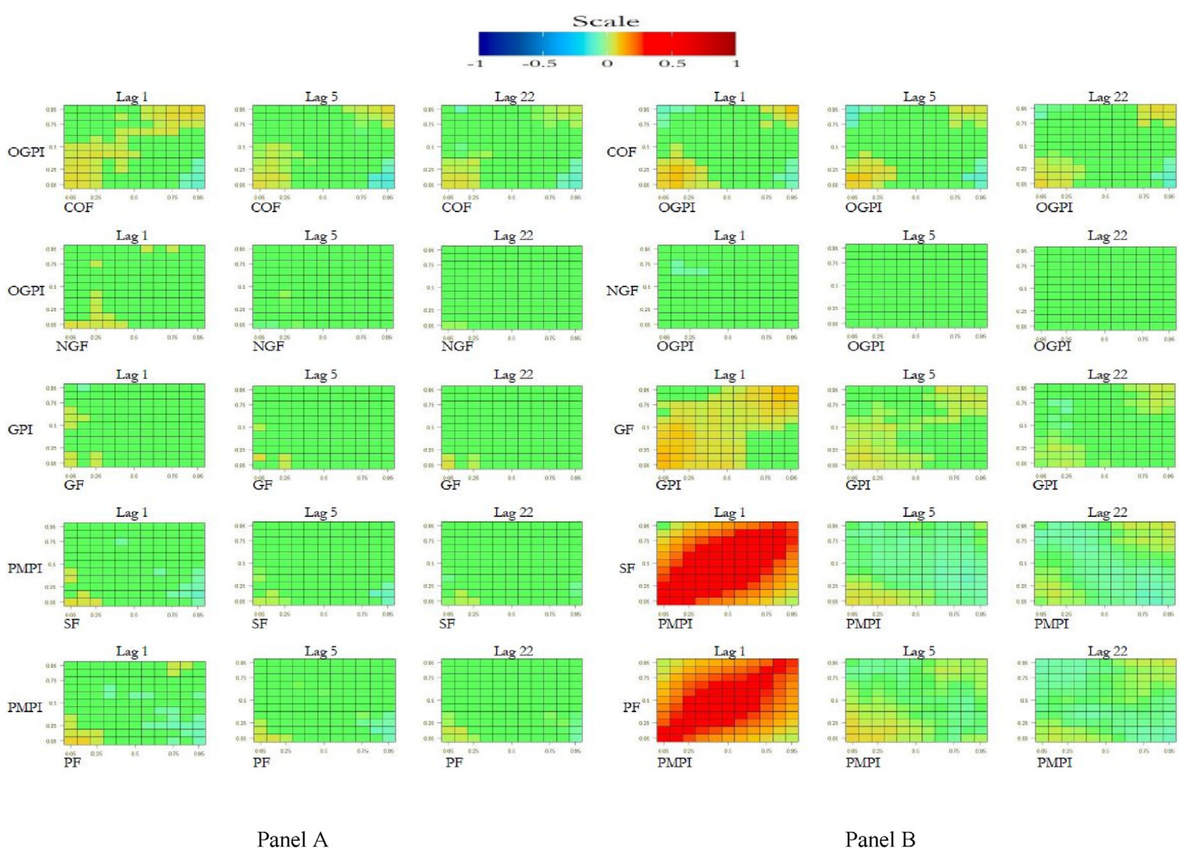

Fig. 2. Cross-quantile correlations between commodity futures returns and producer stock index returns for the oil and gas, gold, silver, and platinum futures markets, and respective producer stock markets.

Note: The figure depicts heatmaps from CQC-estimation. In Panel a) the horizontal axis represents quantiles of the commodity futures returns and vertical axis represents quantiles of the producer equity index returns in heatmaps illustrating spillover from futures to producer equity returns. In heatmaps depicting spillover from producer equity returns to commodity futures returns (Panel b) the horizontal axis represents quantiles of the equity returns and vertical axis represents the quantiles of the commodity futures returns. Hence, in Panel a) the upper left corner (0.05:0.95) represents low returns of commodity futures and high returns of the producer equities, whereas the upper right corner (0.95.0.95) represents high returns of both series, while the lower left corner (0.05:0.05) represents low returns of both series and finally the lower right corner (0.95:0.05) represents high returns of commodity futures and low returns of producer equity index. In Panel b, depicting spillover from producer index returns to commodity futures returns, the relation is opposite. The abbreviations are: OGPI - Oil and gas producer index, COF - Crude oil future, NGF - Natural gas future, GPI - Gold producer index, GF - Gold future, PMPI - Precious metals producer index, SF - silver future, PF - Platinum future.

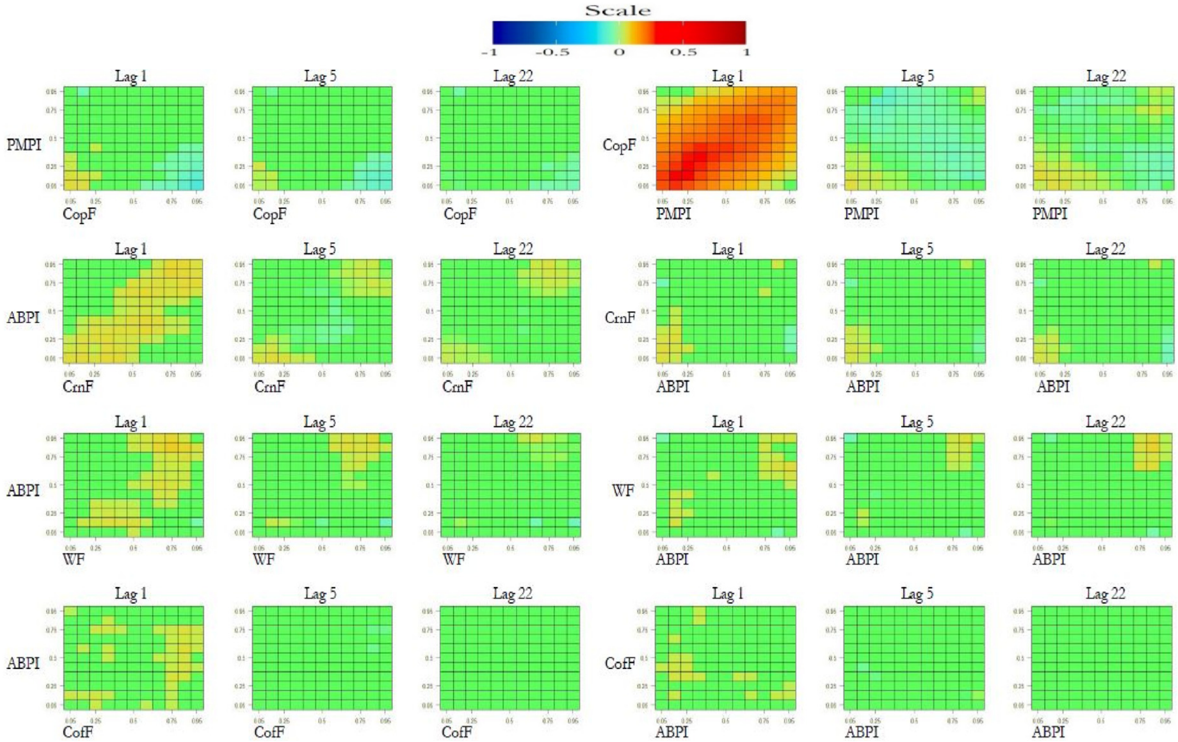

Fig. 3. Cross-quantile correlations between commodity futures returns and producer stock index returns for the copper, corn, wheat and coffee futures markets, and respective producer stock markets.
Note: See Fig. 2 for other descriptions, and the abbreviations are: PMPI - Precious metals producer index, CopF - Copper future, ABPI - Agribusiness producer index, CrnF - Corn future, WF - Wheat future, CofF - Coffee future.

are presented on the vertical axis. In panel b) the quantiles of the producer equity returns and the quantiles of the commodity futures returns are presented vice versa. Each panel displays CQCs over three-time horizons, i.e., lags of dependence. In Figs. 2 and 3, we chose to examine the CQCs on a daily (1 lag), weekly (5 lags), and monthly (22 lags) basis.

First of all, from Fig. 2, we see that the non-renewable energy (oil and gas) market dependencies are different from the renewable energy-related, i.e., critical metal market results, where there is much more asymmetry in the results in the latter case. The first row of Panel a) in Fig. 2 shows a mildly positive spillover from the oil futures returns to the producer equity returns across all quantiles at lag 1. Especially for the oil market, the effect is more pronounced in the tails of the distributions. Furthermore, the tail effect persists over 5 and 22 lags. The first row of Panel b) depicts similar results but mildly more pronounced negative dependencies in the opposite quantiles (0.00; 0.95, 0.95; 0.00) in longer lags. The results from Panel a) and b) both indicate positive cross-quantile correlations when the oil futures and corresponding equity index returns are in the upper and lower quantiles simultaneously. This indicates homogenous dependence structures between these asset segments of the oil market. In contrast to the cases of, e.g., gold and other precious/critical metal markets, this result also implies an asymmetric spillover relationship between crude oil and producer index returns in extreme market conditions. This means that the oil futures returns and the oil and gas producer equity index returns tend to similarly experience a “boom” and “bust” period.

In the second row of Panel a) in Fig. 2, the cross-quantile dependencies of natural gas futures on producer equity returns are vaguely positive in the lower quantiles at lag 1. We do not observe any statistically significant correlations between natural gas futures and producer equity returns when they are at their median to upper quantiles. There is no evidence of dependencies between these asset market segments when examining the reverse relationship. This result is also interesting when comparing it to the distinct tail dependence result for the oil futures and corresponding producer equity returns. The single weakly positive dependency of natural gas futures on the oil and gas producer equity returns may suggest that in bear market conditions, the natural gas futures are substituted for investments in the producer index.

The economic rationale behind the apparent tail effect results for the oil futures and producer equity returns may involve the oil market's risky nature, but also the vital role of oil market commodity prices in the stock market performance of the producer firms, too. Downturns in the oil market may affect investors' willingness to hold oil futures and stocks in the oil and gas producer index in a similar vein, as they might view both assets as equally risky. Therefore, investors might flee the oil market in general in bad market conditions. As discussed by Ref. [23], it might come down to the investment strategy among commodity index investors that affects the spillovers of crude oil and the producer index. They describe how commodity index investors' rebalancing strategies may connect the stock price fluctuations tightly with the commodity market price changes due to the restrictions concerning the size of their commodity position in their portfolio. Investors may reduce their commodity positions as a response to price declines in stocks, too. As a compensation, they might invest the proceeds from commodities in stocks instead, and in this way, the risk spillover caused by a price decline in stocks may transfer and cause a price decline in commodities, too. Similarly, a price increase in commodities may, in fact, be caused by an increase in stock prices, where investors might decide to take the proceeds from selling the stocks and invest them in commodities.

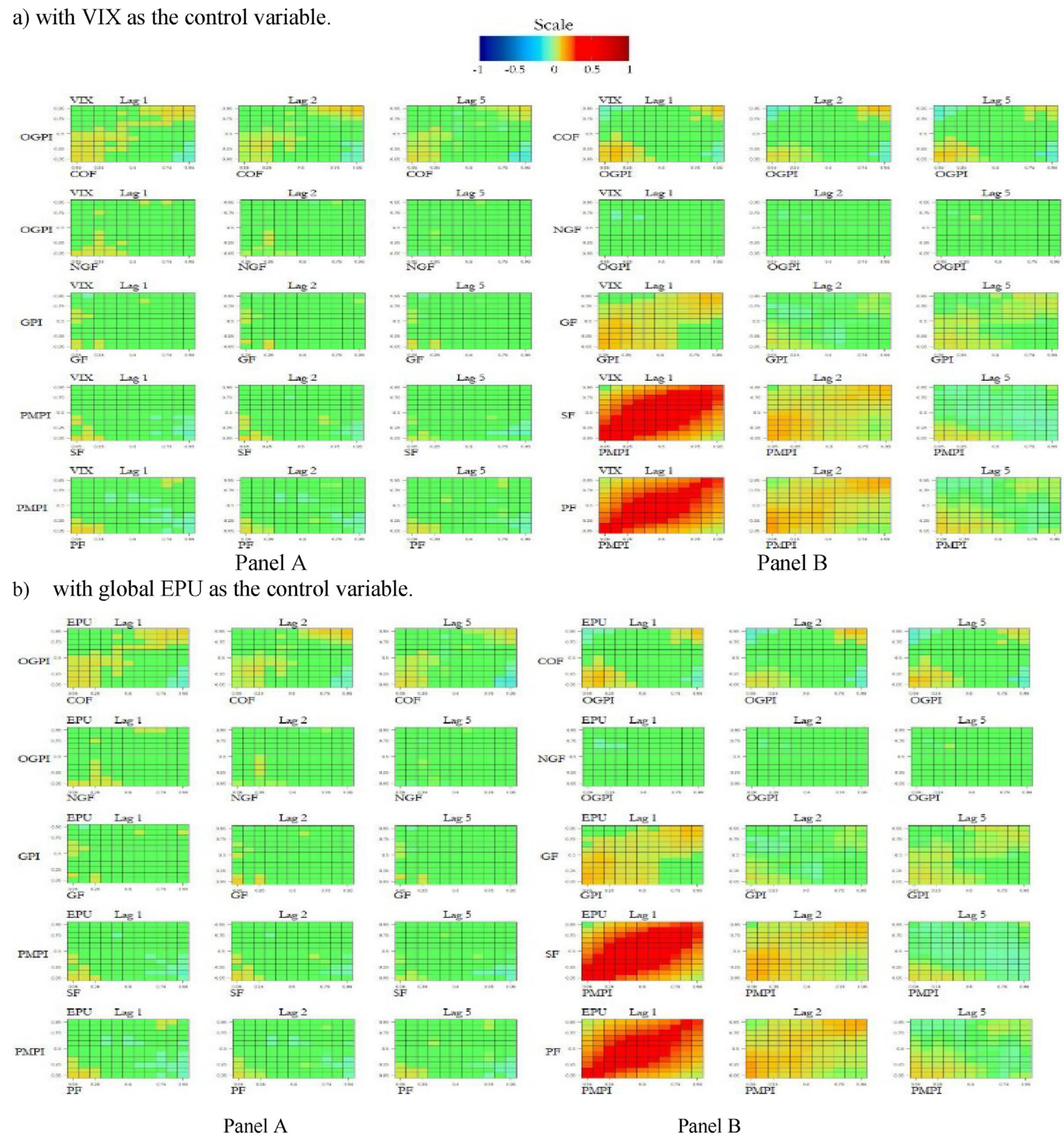

Fig. 4. Heatmaps from partial cross-correlogram estimation for oil, gas, gold, silver and platinum markets,
Note. See Figs. 2 and 3 for the notations in more details.

The clear tail effect between oil futures and producer equity returns may imply that the oil market operates more efficiently in good and bad market conditions than the natural gas market. This is because new information seems to transfer quickly to both oil future contracts and to the oil and gas producer equity index, and hence, to returns. Furthermore, this result may indicate that in extreme market conditions, the pricing mechanisms work efficiently between oil futures and the producer index since producers in the oil market base their production and storage decisions by looking at the prices of the futures contract. The futures contract prices' relevance in production decisions has been supported already by Ref. [26].

On the other hand, the negative correlations between oil futures and the producer equity returns in opposite quantiles (0.00; 0.95, 0.95; 0.00) may also suggest a speculation phenomenon in the oil market. Creti et al. [3] find evidence for speculation tendencies in the oil market. The correlations between oil and stock market prices declined when the equity prices decreased, especially during the GFC. In addition, the correlations between the two assets increased in periods when the equity prices increased, which is further signs of speculation, according to Ref. [3]. Our results show that when the producer stock portfolio has low returns there is a negative risk spillover also to the oil futures. However, there is also negative spillover from the oil futures to the producer index returns when they are in opposite quantiles. Consequently, this result could indicate signs of speculation in the oil futures and the oil and gas producer equity market because the two asset market segments seem to be clearly connected in tail conditions. Our finding of bidirectional spillover for the oil market relationships is consistent with previous studies [27,28]. Furthermore, our spillover results in opposite quantiles are in line with [29], who found that real stock returns are negatively correlated with positive oil price shocks. However, our results go against studies that show unidirectional

Fig. 5. Heatmaps for partial cross-quantilograms between commodity futures returns and producer stock index returns for the copper, corn, wheat and coffee futures markets, and producer stock markets
Note: See Fig. 2 for other descriptions, and the abbreviations are: PMPI - Precious metals producer index, CopF - Copper future, ABPI - Agribusiness producer index, CrnF - Corn future, WF - Wheat future, CofF - Coffee future.

spillover from oil to stock markets [7,30,31] or no spillover at all [32]. Differences in methodology and data samples may be reasons for diverging results.

Our results for the part of precious, critical metal markets considered are clearly different. First of all, we observe powerful spillover effects from the silver and platinum producer stock market returns basically in all market conditions. In contrast, the futures market seems not to affect almost at all the producer market stock returns in any quantile. Because we see this phenomenon so strong only at the shortest (daily) lag horizon, it implies that in the very short-term activities, the stock market investors seem not to take into account the information from the relevant futures markets at all. The futures market rates do not affect stock market performance almost in any market condition. Furthermore, in the stock market pricing process for the gold-related producer firms, it seems that also at the weekly horizon (5 trading days), there is spillover from the stock market returns to the futures returns, and especially for the tail observations in both ends of low/low and high/high returns. This is not so strongly evident anymore at the monthly lag horizon (22 trading days).

Our findings for the part of these other precious metals than the gold market are entirely new, so we do not have comparative results from the previous studies for the renewable energy production related critical metal markets. Finally, in Fig. 3, we plot similar graphs for the case of copper and agricultural (corn, wheat, and coffee) markets.

One set of the most strikingly new results is the findings obtained for the copper market. As emphasized by, e.g. Basak &

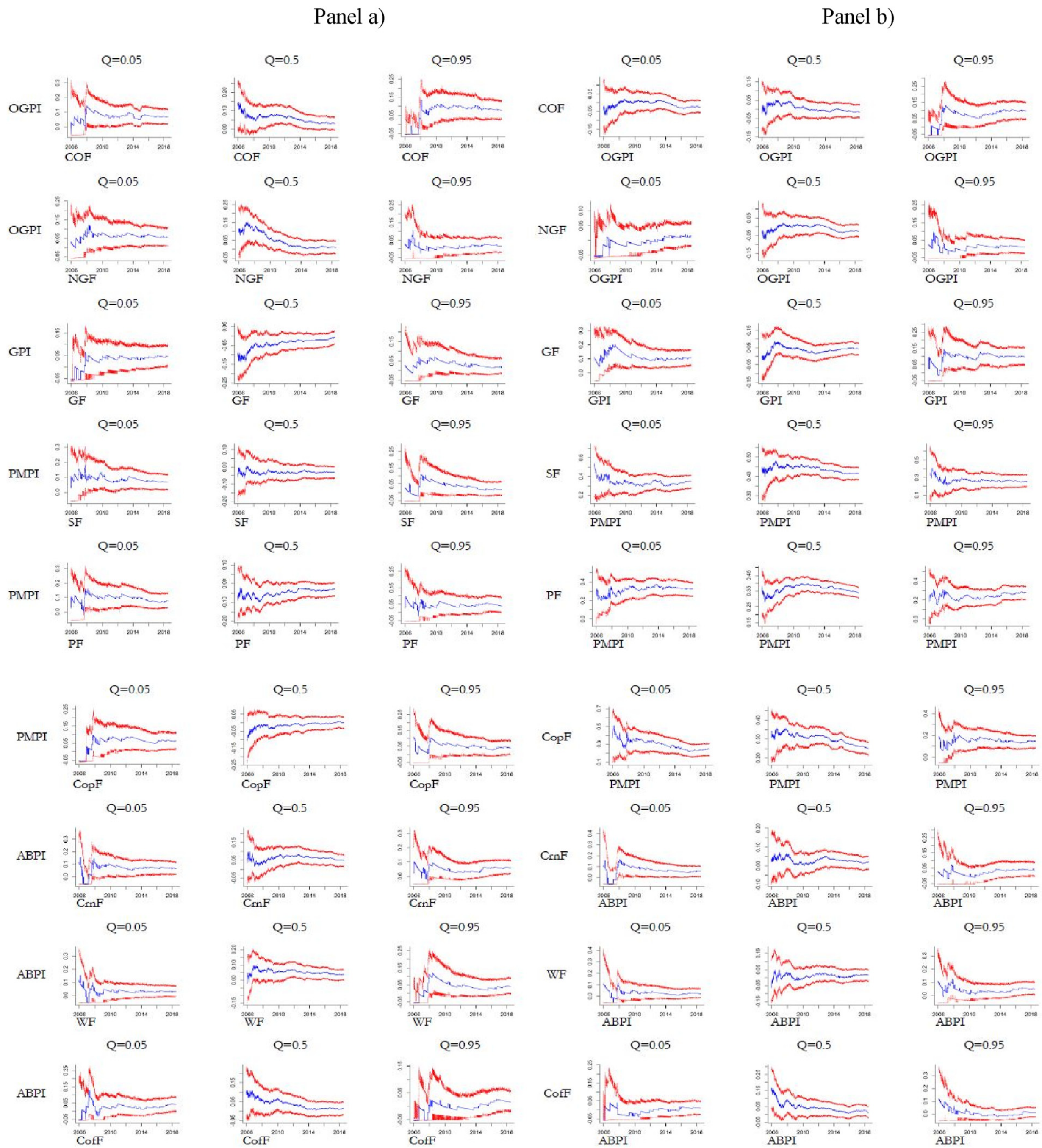

Fig. 6. Recursive rolling sample estimations for the dependence between commodity futures and producer stock index returns in the lowest, median and highest quantiles (Q = 0.05, 0.50, or 0.95)

Notes: For the abbreviations, see Figs. 2 and 3. Analogously to previous figures, Panel a) presents the result for the spillover from futures market to the producer stock market, and Panel b) vice versa. The figure presents CQC correlations from recursive rolling sample estimations. The length of the first window is 252 days, which further advances by one day. The columns show the results when both return distributions are at 5%, 50% and 95% quantiles. The blue lines are time-varying CQCs from the recursive subsamples, and the red lines are 95% confidence interval for the null hypothesis of no-predictability between the variables. The interval is derived from bootstrap procedure with 500 bootstraps.

Pavlova [33], copper has in many previous studies been denoted to serve as a general health indicator for the global economy given its wide use in the economy. More recently, for example, the Copper Alliance (see https://copperalliance.org/climate-week-nyc-2021/) stresses that one of the main distinguishing features of copper as a raw material compared to many other metals is that it is 100% recyclable and can be recycled over and over again without any loss of properties. In terms of the relevance for the renewable energy sector, this is important, since recycling electronics contributes to the circular economy, and globally, about 35% of copper demand is met with recycled copper. Because copper is a highly efficient conduit, it is used in renewable energy systems to generate power from solar, hydro, thermal and wind energy across the world.

Furthermore, many renewable energy systems use 12 times more copper than the traditional systems, and since renewable energy sources provide nearly about one-quarter of the world's power, copper plays an important role in making it as efficient as possible with minimal impact on the environment. Furthermore, copper can be found in essential parts of EVs, including the battery system, coils, windings, rotors, and connectors. Copper coils in an EV's motor convert electric energy to mechanical energy, while copper wire connects the electronics and battery packs. At the aggregate economy level, according to the latest European Commission Report on ‘Critical Raw Materials for Strategic Technologies and Sectors in the EU: A Foresight Study’ (see https://ec.europa.eu/growth/sectors/raw-materials/areas-specific-interest/critical-raw-materials_en), copper is the only raw material that is being used in all the modern-day technologies for the production of batteries, fuel cells, wind generators, traction motors, photovoltaics, robotics, drones, 3D printing, and ICT. The copper market is extremely important for the renewable energy and e-mobility sectors from the currently most important industry sectors.

Based on this increasingly important role of copper, it is relevant to track the connections of copper market price developments with the prominently speculative, producer-level stock market developments. Some of the most recent studies have revealed that copper's futures market price changes are somewhat strongly connected to the price development of oil and gold markets, too. For example, using extremely high-frequency, 1-min data from Sept 27, 2009, to July 1, 2020, for oil, copper, and gold futures prices [34], find that idiosyncratic jumps in oil and copper markets increase allocations to gold, but allocations to copper and oil are significantly affected by the systematic risks outlined in copper-gold and oil—gold pairs. This pushes risk-averse investors to oil from copper-gold and copper from oil—gold when systematic risks evolve. Furthermore, they postulate that the diversification benefits from price discontinuities are generally positive and driven by the idiosyncratic jumps in oil and copper markets when the minimum variance portfolio allocations are used. Hence, at least in high-frequency data, the connections between oil, gold, and copper markets seem to have strengthened during the latest sample periods. However, our paper differs in this respect, first of all, by focusing on the connections between the futures market and producer stock market valuations and extending the investors' investment horizons from daily to even monthly periods.

The first row in Fig. 3 presents CQCs between copper futures and precious metals producer stock index returns. Analogously to our previous results for the part of silver and platinum markets, the third precious, critical metal (copper) market dependence follows a fairly similar pattern. In Panel b) indicating spillover from stock markets to futures markets at lag 1, the CQC heatmap shows very strong positive correlations when the futures market returns and the producer stock index returns are in the lower quantiles, while the rest of the quantiles in overall do not show perhaps quite so strong, but sill, clearly positive correlations. In Panel a) presenting the spillover from the futures market to the stock market, we observe negative dependencies when the futures are in the higher quantiles (>0.75) and the producer index is in the lower quantiles (≈ 0.25). Also these negative correlations are more pronounced in the heatmap for copper compared to agricultural products. Again, the correlation structures for also the copper futures against the producer index returns dissipates in lags 5 and 22, which indicates that the dependence structures deteriorate over time (in weekly and monthly lag horizons). Furthermore, similarly to the case of other critical metals (silver and platinum) when analyzing the correlation at the 1-day lag horizon, we see that when the copper producer stock returns are at their highest levels in the most recent observations, the copper market futures returns are also at the highest values right after those, and there is even stronger correlation when both returns are at the lowest percentiles, indicating strong spillovers according to the first graph in Panel b) on the first row of Fig. 3. This again implies clear inefficiency in the pricing of copper market futures because the corresponding relationship is not observed when we analyze the spillover from the futures markets to the stock markets in Panel a). Hence, when the stock market segment is booming, the futures market is also strongly rising in the very near future, and when the stock market is bearish, the futures market is going down, too. However, when the corresponding change in the market conditions emanate from the futures market (based on fundamental demand/supply conditions for the copper metal market), the stock markets do not react to these almost at all, so the futures market information is not a priced factor in the stock market valuation of the precious metal producer firms.

Compared to the copper market, the cross-correlogram results for the agricultural product (corn, wheat and coffee) markets reported on the second, third and last rows in Fig. 3 reflect somewhat more positive correlations across almost all market conditions from all agriculture futures to the producer index returns at lag 1. However, also the dependence in all agricultural commodity markets disappears as we move to longer lags. In Panel b), we generally observe positive tail dependence at lag 1, but also this effect disappears at lags 5 and 22. Since the agribusiness producer index and agricultural futures returns reveal spillovers across different quantiles, this indicates that there are some heterogenous dependence structures in the agricultural commodity markets, too, but the strength (degree of correlation) of these dependencies is nowhere near the levels of critical metal market dependencies, especially for the spillover from stock market to the futures market.

In sum, we find very strong and positive cross-quantile correlations when examining the spillover from the critical precious metal producer index returns to the critical metal futures markets. These high correlations are predominant over all quantiles at lag 1. This finding implies that the producer stock markets strongly impact the returns in all critical metal futures in bearish, bullish and normal market conditions at lag 1. As we move to longer lags, the heatmaps reveal positive dependencies in only bearish and bullish market conditions for all three critical metals. The longer lags uniformly show negative or zero correlations in mean-to-mean quantiles and opposite quantiles. The futures and producer index returns in the precious, critical metals markets reveal spillovers across different quantiles, which means that there are heterogenous dependence structures in these markets.

Next, Figs. 4 and 5 show the results from our partial cross-correlogram analysis, where we have controlled for the effects of more general, aggregate level uncertainty, emanating from the stock markets (captured by the VIX index, Figs. 4a and 5a) and from the aggregate economies (measured by the Global EPU index of [19], Figs. 4b and 5b). For the purposes of examining the role of trading horizon, and since the strongest results were previously observed for the daily horizon, in Figs. 4 and 5 we also report the results for the trading periods of two and 5 days, so the longest horizon in these figures is now the weekly horizon.

Based on the reported PCQ heatmaps, we are able to say that our main results seem to hold even when controlling for the levels of more general uncertainty measures, both from the stock markets (Fig. 4a) and the aggregate economy (Fig. 4b). It seems that also the strong spillover effects observed previously from the stock markets for precious metal producer firms towards the platinum and silver futures markets would seem to start vanishing already at the 2-day trading horizon, so as already discovered earlier, we can confirm that also these effects are very short-term in nature. They are not dependent on the level of the general stock market or macroeconomic uncertainty. However, our main conclusions for non-renewable energy-related, especially the oil markets, remain the same because the heatmaps from partial analysis, allowing for the effects of exogenous variables (VIX and EPU), are almost identical to the case where we did not control for these. Hence, our previous conclusions and discussions for both the non-renewable and renewable energy-related critical metal market results still hold, even after controlling for the more general level uncertainty effects in all market conditions.

Furthermore, the extreme asymmetry in the spillover effects regarding the critical metal markets of platinum and silver is almost identical to our previous results without controlling for the general stock market and aggregate economy level uncertainty effects. Hence, it seems that the inefficiency of the futures market pricing mechanisms of critical metals is not rooted in the general stock market risk or aggregate economic uncertainty situations. The producer stock market returns are still strongly affecting the futures markets returns of, especially platinum and silver, at the shortest horizon of one day. Still, there is no spillover from the futures markets to producer stock markets.

Fig. 5 also delivers similar inference especially for the third critical metal, i.e., copper markets. For example, in the global corn markets, the returns of futures contracts have very short-term (at 1 day lag) effects also on the daily stock returns of the producer firms, but this is not the case in the dependence between the precious metal producer firms and copper futures returns. There we see again that the stock market returns have a strong positive correlation with the returns of futures contract at 1 day lag, but not vice versa. Hence, the previously observed strong asymmetry in the pricing of critical metal futures and producer firm stock returns is still clearly observed, even after controlling for either the effects from general stock market risk situation (Fig. 5a) or aggregate economic uncertainty (Fig. 5b).

In the final step of our empirical analysis, we focused on the time-variation in the revealed stock market vs. futures market return dependencies using a recursive window estimation with bootstrap iterations for the estimation procedure described in section 2 to reveal the degree of time-variation in the estimated dependencies.

Fig. 6 displays the CQC values from recursive window estimations when the return distributions of each pair are at the 5%, 50% and 95% quantiles, which represent bad, normal, and good market conditions. The first column of panels a) and b) in Fig. 6 depicts the recursive results for all commodity futures and producer indices when both variables are at their 5% quantile, indicating bearish market conditions. We find both positive and negative correlation structures among the commodity futures and corresponding producer futures prior to the Global Financial Crisis taking place in 2007. Despite the varying correlation structures prior to the GFC, we find that the cross-quantile dependence increases during the GFC when both returns are at their 5% quantile. This finding is evident for all sectors and assets in this market condition. In general terms, the degree of dependence increases during the GFC between the commodity futures and the commodity producer index returns and becomes stable afterwards. This increased connectedness between the market segments after the GFC could be a sign of financial contagion, when both asset returns are at their lowest quantiles. This finding may be attributable to investors' herding behavior and financial panic which increases volatility in financial turmoil and induces financial contagion, too. As stated by Ref. [35], the risk transmission between the asset classes might be set off by investors withdrawing investments from several markets at the same time. Investors might feel pressures in crisis periods due to leverage problems and therefore they might sell off assets in other markets in order to meet their margin requirements.

Our results may also be attributed to capital flight among investors. In financial turmoil, investors may redirect their investments from risky investments to safe havens, like the gold market. This activity could increase the volatility on the financial markets and entail a higher interaction between markets [36]. Since all commodity markets show positive volatility spikes during the GFC, this indicates that investors were redirecting their investments to the commodity sectors during the recent financial turmoil. Investors might have moved their funds to the commodity markets when there was a threat in the equity market [37] or unwind positions due to reduced risk appetite [38]. Our finding of increased volatility during the GFC aligns with previous literature [39–41].

The second column of panels a) and b) in Fig. 6 depicts the cross-quantile correlations when both assets are at their median quantiles showing that the cross-quantile correlations are around zero. This means that there is almost no mean-to-mean interdependence between the commodity futures and respectively producer index returns when both are at their 50% quantiles. However, there are slightly increasing positive correlations from gold, platinum and copper futures to the producer index after the GFC at the 50% quantiles. This finding could indicate growing connectedness between the precious, critical metals producer index and the critical metal futures returns after the GFC. This finding of gradually increasing price volatilities after 2008 between commodity and stock markets confirms recent literature [2,4,5]. The results reported in the third column of Fig. 6, when both returns are at their 95% quantiles, show volatility spikes around GFC and then the correlation structures stabilize around zero. The increased volatility during the GFC when commodity futures and producer indices are at their 95% quantiles might be explained by investors resorting to the commodity market as it could serve attractive diversification benefits in financial turmoil [42].

4. Conclusions

The main conclusion from our study is that during extreme market conditions, the dependence between commodity derivatives market returns and the corresponding producer equity index returns is very different in the non-renewable energy sector and other relevant global commodity markets compared to the markets for renewable energy-related, critical metals. More specifically, there is asymmetric dependence between commodity futures and producer equity returns in the precious, critical metals and gold markets. However, the relationship is symmetric in the oil market, and no relationship is found in the natural gas market. The oil market uncovers homogenous dependence structures, whereas the dependency structures are heterogeneous in the critical metals markets. However, the observed spillovers in all markets occur in the very short run, 1 day horizon, and dissipate more or less after a week, and even more clearly, after one month. This gives clear reasons for policymakers to try to control the effect of speculative behavior emanating from specific segments of the stock markets, especially in very short-term horizons. According to our results, a particular emphasis should be put on the short-term speculative behavior in the producer firm stock markets related to the production of critical metals for renewable energy production. However, because the oil market producer firms' extreme stock market returns and the crude oil futures market performance are symmetrically connected, there is no need for such strong interventions in these markets.

In other words, when there are extreme conditions in the oil futures markets, there are also extreme conditions in the oil producer's stock market returns, especially in the shortest horizon of 1 day, and vice versa, so the tail shocks of the return distribution emanating from the supply and demand conditions of the commodity markets seem to transfer to the stock markets, too, implying efficiency of the pricing mechanisms. New information seems to transfer quickly to both the oil futures contract prices and the oil and gas producer equity index, and hence, returns. On the other hand, especially for the relationships in silver, platinum and copper futures markets and corresponding producer stock market segment, this is not the case.

Finally, according to our results, the general market/economic uncertainty conditions do not have any role in these connections, i.e., the relationships especially for the oil market hold when controlling both for the aggregate stock market (VIX) and aggregate real economic (EPU) uncertainty effects. One of the main implications from all our analyses is that the policymakers should put a lot of effort into controlling especially the speculative behavior in the precious metals (especially silver, platinum, and copper) producer stock markets because it seems that the pricing kernels for the relevant fundamental information in the futures markets are very different compared to for example the information mirroring the producer firms' expected cash flows, that should be the main determinant of stock market prices.

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CRediT authorship contribution statement

Elin Borg: Data curation, Formal analysis, Investigation, Project administration, Software, Visualization, Writing – original draft. **Ilya Kits:** Data curation, Formal analysis, Investigation, Project administration, Software, Visualization, Writing – original draft, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Writing – original draft. **Juha Junttila:** Investigation, Project administration, Supervision, Validation, Writing – review & editing. **Gazi Salah Uddin:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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