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Tail risks of energy transition metal prices for commodity prices

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ABSTRACT

Energy transition requires huge amounts of critical metals —called energy transition metals (ETMs)— to deploy clean energy technologies. The growing demand for ETMs and uncertainties regarding the path to net-zero emissions could cause ETM price oscillations, with potential effects on the prices of other commodities. We explore whether upward and downward movements in ETM prices have a neutral effect on the level and volatility of energy and non-energy commodity prices. By characterizing the conditional dependence between ETM and commodity prices, we document that, except for natural gas, extreme ETM price changes have a non-neutral effect on commodity prices, although this effect vanishes for non-extreme price movements. The implications of this evidence for investors operating in commodity markets are evaluated in terms of commodity risk-adjusted returns, commodity tail risk, and liquidity needs for trading in commodity futures contracts.

1. Introduction

The net zero emissions roadmap for 2050 (European Green Deal, 2019; IEA, 2021; European Commission, 2020) involves a lengthy ramp-up in the use of energy transition metals (ETMs). Renewable energies, electric vehicles, and hydrogen need more metals than fossil fuels (Boer et al., 2024; IEA, 2021; Hund et al., 2023; World Bank, 2020). Electric car batteries need lithium, nickel, manganese, and cobalt (Guzmán et al., 2022), while wind turbines and solar panels use large quantities of iron ore, copper, aluminium, silver, silicon, and zinc (Huber and Steininger, 2022). Indeed, ETMs are called on to play a pivotal role in the clean energy transition that is necessary to meet net-zero emissions targets, reshaping mining activities, investments, and ETM prices.

The deficient supply of, and growing demand for, ETMs is expected to lead to price pressures (Boer et al., 2024), which, in turn, could have unexplored side effects on the prices of other commodities. Commodity markets are intrinsically connected through economic and financial channels such as production cost structures across different commodities, substitution between mining activities, supply-demand shocks, and financialization of commodities. Therefore, a key unexplored question is to what extent swings in ETM prices, arguably triggered by the net-zero emissions roadmap, could be transmitted to other commodity prices. Assessing the impact of ETM price oscillations on other commodity prices potentially provides useful information for investors on the viability of certain activities (e.g., the development of lower-grade mineral deposits) in terms of plugging money into mining activities and commodities, and for policymakers regarding the viability and side effects of climate transition policies, and also in terms of funding activities that are aligned with net-zero emissions targets.

In this paper, we study whether ETM price swings have a neutral effect on the prices of other energy and non-energy commodities. Specifically, we test this neutrality hypothesis by examining whether upward or downward movements in ETM prices have a neutral effect on the level and volatility of commodity prices. Using copula functions we model the dependence structure between the prices of ETMs and the prices of different kinds of commodities (including crude oil, natural gas, industrial metals, precious metals, and agricultural commodities) and obtain the conditional distribution of commodity price changes with respect to ETM price changes. From that conditional distribution, we then quantify how abrupt upward or downward changes in ETM prices impact on the expected value and the volatility of price returns for

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different commodities.

Our empirical evidence for the period 2012–2023 reveals that the structure of dependence between ETM and commodity prices varies across different commodities and in some cases fluctuates over time. ETM dependence is strong on industrial and precious metals, but is weaker on crude oil and agricultural commodities; in contrast, ETM and natural gas prices show average and tail independence. The analysis of extreme changes in ETM prices shows that upward and downward ETM price movements have a dissimilar impact on the expected change in commodity prices, with a weak asymmetric tail impact (except for natural gas). In contrast, movements in ETM prices around their median values have negligible effects on commodity prices. Commodity price volatility is also impacted by extreme ETM price fluctuations, with notable differences in size across commodities. This empirical evidence rejects our null hypothesis of neutrality of ETM prices for all commodity prices, except for natural gas prices, for which we find no evidence of an impact of ETM price changes on the expected value or volatility.

We perform back-of-the-envelope calculations to assess the economic and financial implications of our empirical results for commodity investors in terms of the following impacts of ETM price shocks: on the expected risk-adjusted returns for commodities, on the tail risk of commodity returns, and on liquidity needs to uphold positions in commodity futures contracts. We document that risk-adjusted returns and tail risk exposure in commodity markets could be improved if investors consider ETM markets, and that abrupt changes in ETM prices have sizeable effects on liquidity needs in commodity futures contracts.

Our research belongs in the literature that examines the price behaviour of metals used for energy production. In considering the relationship between new energy and rare earth elements used to produce clean energies and technologies, Baldi et al. (2014) and Apergis and Apergis (2017) document that peaks in rare earth prices have a negative impact on the performance of renewable energy indices and deplete long-run renewable energy consumption in high-income regions. Similarly, Chen et al. (2020) show that the dynamic correlation between rare earth and new energy markets is high. Using firm level data, Zheng et al. (2021) explore connectedness between rare earth and clean energy markets, finding that size volatility spillovers between those markets differ across time. In a similar vein, Hanif et al. (2023) report that return and volatility spillovers between rare earth and renewable energy stocks increased during the COVID-19 pandemic.

Another literature strand explores the behaviour of rare earth prices. Proelss et al. (2018, 2019) report that rare earth prices exhibit volatility persistence and are sensitive to World Trade Organization dispute resolution. Moreover, rare earth prices affect the stock price dynamics of companies involved in rare earth mining (Fernandez, 2017). Zhou et al. (2022) further show that political risk is a relevant driver of rare earth stock prices, mainly at times of high political uncertainty, while Hau et al. (2022) report that the long-run dynamics of rare earth prices is tied to trade policy uncertainty and market conditions. Finally, focusing on the financial aspects of rare earths, Reboredo and Ugolini (2018) examine price transmission between rare earth stocks and base metals, gold, clean energy, oil, and stock markets under different volatility regimes, showing that spillover effects between those markets increase during a high-volatility regime. Regarding the COVID19 pandemic, Song et al. (2021) present evidence of strong return and volatility connectedness between rare earth, commodity, and financial markets.

A related strand of the literature analyses the relationship between clean energy and by-product metals, which are crucial for the development of clean energy technologies (Jordan, 2018; Valero et al., 2018; Elshkaki and Shen, 2019). Song et al. (2022) report evidence on time-varying co-movement between the main by-products and clean energy markets, predominantly explained by clean energy market dynamics. Considering the main by-product metals, Shao et al. (2020) show that there is two-way nonlinear Granger causality between them, both in the short and medium terms, while Shammugam et al. (2019) prove that joint consumption is the main cause of causality between by-product metals.

Our related research contributes to the previous literature by assessing how swings in ETM prices could impact on the prices of other commodities. We report empirical evidence on the tail risk effects of ETM prices that are particularly informative and relevant in the transition to a low-carbon economy in which ETM prices are expected to be specifically affected by transition policies and their speed of implementation (Boer et al., 2024). Likewise, our analysis provides useful information for investors operating in commodity markets, in terms of the impact of ETM price fluctuations on risk-adjusted commodity returns and on the tail risks of commodities, and also in terms of the impact of ETM price changes on the liquidity needs of commodity futures contracts.

The remainder of the paper is laid out as follows. Section 2 presents metrics for the tail risk impacts of ETM prices on commodity prices and volatility, and characterizes those metrics in terms of bivariate dependence as given by copula functions. Section 3 describes the main features of price data for both ETMs and commodities. Section 4 presents evidence for the conditional distribution of commodity prices and the effects of extreme ETM price changes on commodity prices. Section 5 explores the implications of the empirical results for risk and liquidity management by commodity investors. Finally, Section 6 summarizes our empirical results and concludes the paper.

2. Empirical methodology

2.1. Measuring the tail risk impact of ETM prices on commodity prices

We assess the impact of extreme upward and downward movements in ETM prices on the expected value and on the variance of commodity price returns as follows.

Let r_{ETM} be ETM price returns, and let r^{α}_{ETM} and r^{β}_{ETM} be the lower and upper quantiles of r_{ETM}, such that $P(r_{ETM} \le r^{\alpha}_{ETM}) = \alpha$ and $P\left(r_{ETM} \ge r^{\beta}_{ETM}\right) = \beta$, reflecting extreme downward and upward ETM price changes, respectively, for low values of α and β. Thus, the expected impact of a downward α-quantile movement in ETM prices on commodity price returns (r_c) can be computed in terms of the conditional expectation of commodity returns as:

$$E(r_c | r_{ETM} \le r^{\alpha}_{ETM}) = \int_{-\infty}^{\infty} r_c f(r_c | r_{ETM} \le r^{\alpha}_{ETM}) dr_c, \tag{1}$$

where $f(r_c | r_{ETM} \le r^{\alpha}_{ETM})$ is the conditional density of r_c, which can be written as $F_{ETM|c}(r^{\alpha}_{ETM}) f_c(r_c)/\alpha$, where $F_{ETM|c}(\cdot)$ and $f_c(\cdot)$ are the conditional distribution and the marginal density of ETM and commodity price returns, respectively. Similarly, for an upward β-quantile movement in ETM prices, the expected impact can be defined by considering the conditional density in Eq. (1) as $f\left(r_c \middle| r_{ETM} \ge r^{\beta}_{ETM}\right)$, which, in turn, can be written as $\left(1 - F_{ETM|c}\left(r^{\beta}_{ETM}\right)\right) f_c(r_c)/\beta$.

We also consider the impact of extreme downward and upward ETM price changes on the volatility of commodity price returns; for a downward movement it is given by:

$$\sigma^2_{c|r_{ETM} \le r^{\alpha}_{ETM}} = E(r_c^2 | r_{ETM} \le r^{\alpha}_{ETM}) - E(r_c | r_{ETM} \le r^{\alpha}_{ETM})^2, \tag{2}$$

whereas for an upward movement, it is given by:

$$\sigma^2_{c|r_{ETM} \ge r^{\beta}_{ETM}} = E(r_c^2 | r_{ETM} \ge r^{\beta}_{ETM}) - E(r_c | r_{ETM} \ge r^{\beta}_{ETM})^2. \tag{3}$$

Therefore, to assess the impact of extreme ETM price movements on commodity prices, we need information on the marginal density of r_c, and on the conditional distribution $F_{ETM|c}(\cdot)$ so as to have the conditional density of commodity returns, and we then solve Eq. (1) and Eqs. (2) and (3) for the impacts of ETM extreme price changes on the expected commodity returns and volatility.

2.2. Modelling conditional distributions

The conditional distribution can be characterized in terms of copula functions[2] as follows. Let C be a copula function such that the joint distribution between r_{ETM} and r_c is $F(r_{ETM}, r_c) = C(F_{ETM}(r_{ETM}), F_c(r_c))$, where $F_{ETM}(r_{ETM}) = u_{ETM}$ and $F_c(r_c) = u_c$ are the marginal distributions of ETM and commodity price returns, respectively. Hence, the conditional distribution of ETM is drawn from the conditional copula as $C_{ETM|c} = \partial C(u_{ETM}, u_c)/\partial u_c$.

Drawing the conditional distribution from copulas has two main advantages. First, copulas offer flexibility in modelling conditional dependence, given that they independently characterize marginal and dependence features of data; they thus account for tail dependence between variables, given that the joint density between r_{ETM} and r_c, $f(r_{ETM}, r_c)$, can be decomposed as $c(u_{ETM}, u_c)f(r_{ETM})f(r_c)$, where $c(u_{ETM}, u_c)$ denotes the copula density. Second, copulas allow straight computation of the conditional expectation stated in Eq. (1), which, for downward and upward ETM price changes, respectively, are given by[3]:

$$E\left(r_c \middle| r_{ETM} \le r_{ETM}^{\alpha}\right) = \frac{1}{\alpha}\int_0^1 F_c^{-1}(u_c)C_{ETM|c}(\alpha|u_c)du_c, \tag{4}$$

$$E\left(r_c \middle| r_{ETM} \ge r_{ETM}^{\beta}\right) = \frac{1}{\beta}\int_0^1 F_c^{-1}(u_c)\left\{1 - C_{ETM|c}((1-\beta)|u_c)\right\}du_c. \tag{5}$$

Similarly, the conditional expectations in Eq. (2) for downward and upward ETM price changes, respectively, are given by:

$$E\left(r_c^2 \middle| r_{ETM} \le r_{ETM}^{\alpha}\right) = \frac{1}{\alpha}\int_0^1 F_c^{-1}(u_c)^2 C_{ETM|c}(\alpha|u_c)du_c, \tag{6}$$

$$E\left(r_c^2 \middle| r_{ETM} \ge r_{ETM}^{\beta}\right) = \frac{1}{\beta}\int_0^1 F_c^{-1}(u_c)^2\left\{1 - C_{ETM|c}((1-\beta)|u_c)\right\}du_c, \tag{7}$$

while the second expectation components in Eqs. (2) and (3) derive from Eqs. (4) and (5).[4]

2.3. Modelling marginals

To account for the tail risk effects of ETM price changes on commodity prices and volatility we also need information on the marginal distribution functions. We characterize the marginal distributions of ETM and commodity price returns assuming that the dynamics of those returns at any time t is given by an autoregressive moving average (ARMA) model of order m and r:

$$r_{j,t} = \varphi_0 + \sum_{q=1}^{m} \varphi_q r_{j,t-q} + \sum_{k=1}^{k} \varphi_k \varepsilon_{j,t-k} + \varepsilon_{j,t}, \tag{8}$$

where $j = ETM, c$, and φ_q and φ_r denote the parameters of the AR and MA components of the model. $\varepsilon_{j,t}$ is the stochastic component with mean zero and time-varying variance $\sigma_{j,t}^2$, whose dynamics is delimited by a generalized autoregressive conditional heteroskedasticity (GARCH) model:

$$\sigma_{j,t}^2 = \omega_0 + \sum_{k=1}^{K} \beta_q \sigma_{j,t-k}^2 + \sum_{h=1}^{H} \alpha_h \varepsilon_{j,t-h}^2, \tag{9}$$

where ω_0, β_q and α_h are the parameters of the volatility model. Moreover, the standardized value of $x_{j,t}$ $\left(\varepsilon_{j,t}/\sigma_{j,t}\right)$ is assumed to have a Hansen (1994) skewed-t density:

$$f(x_{j,t}; \vartheta, \lambda) = \begin{cases} bc\left(1 + \dfrac{1}{\vartheta - 2}\left(\dfrac{bx_{j,t} + a}{1 - \lambda}\right)^2\right) & \text{for } x_{j,t} < -\dfrac{a}{b} \\ bc\left(1 + \dfrac{1}{\vartheta - 2}\left(\dfrac{bx_{j,t} + a}{1 + \lambda}\right)^2\right) & \text{for } x_{j,t} \ge -\dfrac{a}{b} \end{cases} \tag{10}$$

where ϑ $(2 < \vartheta < \infty)$ and λ $(-1 < \lambda < 1)$ are the degrees of freedom and symmetry parameters, respectively, and where a, b, and c are constants such that $a = 4\lambda c\left(\frac{\vartheta-2}{\vartheta-1}\right)$, $b^2 = 1 - 3\lambda^2 - a^2$ and $c = \Gamma\left(\frac{\vartheta+2}{2}\right)/\sqrt{\pi(\vartheta-2)}\Gamma\left(\frac{\vartheta}{2}\right)$. This distribution converges to the standard normal distribution when $\lambda \to 0$ and $\vartheta \to \infty$, and to the symmetric Student-t distribution when $\lambda = 0$ and ϑ is finite.

2.4. Estimation

We estimate the parameters of the marginal distribution by maximum likelihood, and then, using pseudo-sample observations from the marginals, as given by the integral probability transformations of standardized price returns, we estimate copula parameters by maximum likelihood (Joe and Xu, 1996). To account for dependence between ETM and commodity price returns, we use different copula models that capture different forms of average and tail dependence between variables. Table 1 summarize the main characteristics of the copula functions, including the Gaussian, Student-t, Clayton, Gumbel, BB1, and SJC copulas, dealing with tail independence, symmetric tail dependence, lower tail dependence, and upper tail dependence. Furthermore, we consider that the copula parameters may be time-varying, with the dynamics described in Table 1.

The number of lags for the mean and variance of returns is selected using the Akaike information criterion (AIC), while the best copula fit is selected using the AIC corrected for small sample bias (Breymann et al., 2003; Reboredo, 2011).

3. Data

The database comprises information on a basket of ETM futures contract prices for transition relevant metals —including cobalt, lithium, nickel, copper, lead, aluminium, silver, zinc, tin, and platinum— that are essential ingredients for the development of electric vehicles, charging stations, energy storage, and solar, wind, and hydrogen production.[5] We use information on the diversified basket of those metals, constituting the basis of the distinctive WisdomTree Energy Transition Metals Commodity Index. This index tracks ETM market performance, so an increase (decrease) in its value represents an increase (decrease) in ETM market prices.

The database also includes information on global commodity prices, represented by the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI), a widely known benchmark that tracks the prices of nearby futures contracts for commodities, including 6 energy products (WTI and Brent crude oil, RBOB gasoline, heating oil, gasoil, and natural gas), 5 industrial metals (aluminium, copper, lead, nickel, and zinc), 8 agricultural products (Chicago wheat, Kansas wheat, corn, soybeans, cotton, sugar, coffee, and cocoa), 3 livestock products (live cattle, feeder cattle, lean hogs), and 2 precious metals (gold and silver). Representations of those 24 commodities weighted by world production in 2022 are 53.48%, 12.71%, 20.48%, 7.36%, and 5.97%. We also take specific information on energy and non-energy commodity prices as represented

[2] For an analysis of copulas, see Nelsen (2006).

[3] The derivation of those equations is reported in the Appendix.

[4] Proofs for the conditional expected value of the square commodity returns are reported in the Appendix.

[5] Further details on the uses of transition metals can be found in European Commission (2020).

Table 1
Copula functions.

	Copula model	τ_L	τ_U
Gaussian	$\Phi(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \rho)$	if $\rho = 1$ then 1, 0 otherwise	if $\rho = 1$ then 1, 0 otherwise
Student-t	$T(T^{-1}(u_1; \eta), T^{-1}(u_2; \eta); \rho, \eta)$	$2t_{\eta+1}\left(-\sqrt{\frac{(\eta+1)(1-\rho)}{1+\rho}}\right)$	$2t_{\eta+1}\left(-\sqrt{\frac{(\eta+1)(1-\rho)}{1+\rho}}\right)$
Clayton	$(u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}}$	$2^{-\frac{1}{\theta}}$	0
Gumbel	$\exp\left(-\left((-\log u_1)^{\theta} + (-\log u_2)^{\theta}\right)^{\frac{1}{\theta}}\right)$	0	$2 - 2^{\frac{1}{\theta}}$
BB1	$\left(1 + \left[(u_1^{-\theta} - 1)^{\delta} + (u_2^{-\theta} - 1)^{\delta}\right]^{1/\delta}\right)^{-\frac{1}{\theta}}$	$2^{-\frac{1}{\theta\delta}}$	$2 - 2^{\frac{1}{\delta}}$
SJC	$0.5(C_{JC}(u_1, u_2; \tau_L, \tau_U) + C_{JC}(1-u_1, 1-u_2; \tau_L, \tau_U) + u_1 + u_2 - 1)$, where $C_{JC}(\cdot) = 1 - \left(1 - \{[1-(1-u_1)^{\kappa}]^{-\gamma} + [1-(1-u_2)^{\kappa}]^{-\gamma} - 1\}^{\frac{-1}{\gamma}}\right)^{\frac{1}{\kappa}}$ for $\kappa = 1/\log_2(2-\tau_U)$ and $\gamma = 1/\log_2(\tau_L)$	τ_L	τ_U

Notes. τ_L is lower tail dependence and τ_U is upper tail dependence: $\tau_L = \lim_{u\to 0} P\left(X \le F_X^{-1}(u) \middle| Y \le F_Y^{-1}(u)\right)$ and $\tau_U = \lim_{u\to 1} P\left(X \ge F_X^{-1}(u) \middle| Y \ge F_Y^{-1}(u)\right)$. $\Phi(\cdot,\cdot)$ and $T(\cdot,\cdot)$ denote the cumulative distribution functions of the normal and Student-t distribution. Time-varying copulas follow by assuming that the copula parameters have dynamics as follows: (a) for the Gaussian and Student-t copulas, $\rho_t = \Lambda\left(\psi_0 + \psi_1\rho_{t-1} + \psi_2\sum_{j=1}^{q}\varphi^{-1}(u_{1,t-j})\varphi^{-1}(u_{2,t-j})\right)$, where $\Lambda(x) = (1-e^{-x})(1+e^{-x})^{-1}$ is the modified logistic transformation to keep the value of ρ_t within (−1,1); (b) for the Clayton, Gumbel, and BB1 copulas, $\theta_t = \Lambda_2\left(\omega + \beta\theta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q}|u_{1,t-j} - u_{2,t-j}|\right)$, and $\delta_t = \Lambda_2\left(\overline{\omega} + \overline{\beta}\theta_{t-1} + \overline{\alpha}\frac{1}{q}\sum_{j=1}^{q}|u_{1,t-j} - u_{2,t-j}|\right)$ where $\Lambda_2(x) = 1 + \frac{99}{1+\exp(-x)}$; and (c) for the SJC copula, $\tau_{U,t} = \Lambda_2\left(\overline{\omega} + \overline{\beta}\tau_{t-1}^{U} + \overline{\alpha}\frac{1}{q}\sum_{j=1}^{q}|u_{t-i} - v_{t-i}|\right)$ and $\tau_{L,t} = \Lambda_2\left(\omega + \beta\tau_{t-1}^{L} + \alpha\frac{1}{q}\sum_{j=1}^{q}|u_{t-i} - v_{t-i}|\right)$, where $\Lambda_2(x) = (1+e^{-x})^{-1}$ is the logistic transformation used to keep τ_U and τ_L within (0,1). For the estimation of dynamic models q is set to 10.

by S&P GSCI components. Energy commodity future prices are represented by the S&P GSCI Crude Oil Index (crude oil) and the S&P GSCI Natural Gas Index (natural gas), while non-energy commodity future prices are represented by the S&P GSCI Industrial Metals Index (industrial metals), the S&P GSCI Precious Metals Index (precious metal), and the S&P GSCI Agriculture and Livestock Index (agriculture).

We source weekly data for all indices from Bloomberg for the period 6 January 2012 to 13 June 2023, using the USD as the base currency. The temporal dynamics of all the analysed indices is plotted in Fig. 1, which shows that transition metal prices and the general commodity index S&P GSCI share similar trends but different price dynamics around those trends. This figure also shows that the dynamics of ETM prices is weakly related to that of crude oil prices but independent of the dynamics of natural gas prices, while those energy commodities exhibit higher volatility than the ETM prices. As reflected in Fig. 1, and as would be expected, the relationship between ETMs and industrial metals is quite close, given that both indices share some common metals (e.g., copper, aluminium, and nickel), although in different proportions. Likewise, the nexus between ETM and precious metal prices is positive and reasonably strong, whereas the link between ETM and agricultural prices is relatively weak.

Table 2 presents information on the statistical features of ETM and commodity price returns, computed as the first difference of the log value of the indices. ETM and commodity prices show near zero weekly returns. Energy commodity prices exhibit the greatest volatility, while non-energy commodities are less volatile than ETMs. All series display fat tail distributions, and exhibit negative skewness, with the exception of ETMs, industrial metals, and agriculture. Consistently, the Jarque-Bera (JB) test rejects normality. Furthermore, except for crude oil, there is no evidence of serial dependence; the ARCH test points to the presence of conditional heteroskedasticity in the series; and unit root and stationary tests point to the fact that all return series are stationary. Finally, the Pearson correlation coefficient indicates that ETM price returns are closely related to industrial metals and are linearly dependent on precious metals and agriculture. For energy commodities, the correlation coefficient points to linear independence between ETM and natural gas price returns, and positive dependence between ETM and crude oil price returns.

4. Empirical evidence

We first provide evidence on the fit of the marginals and copula estimates, then report evidence of the estimated conditional marginal densities for commodity prices, and, finally, report results on the impact of upward and downward ETM price movements on the expected value and volatility of commodity prices.

4.1. Evidence for marginal and copula models

Parameter estimates and goodness-of-fit tests for the marginal models in Eqs (8)–(10) for ETM and commodity price returns are presented in Table 3. For all models, we choose the optimal number of lags in the mean and variance equations that minimize the AIC criterion. Empirical estimates indicate that all series, with the exception of precious metals, exhibit serial independence, and the volatility parameter estimates indicate that volatility dynamics is well described by a GARCH model with Student-t distribution, asymmetric for commodities, crude oil, and industrial metals. Analysis of the model residuals reveals that, according to the Ljung-Box (LB) and the ARCH-Lagrange multiplier (ARCH-LM) tests, neither serial correlation nor conditional heteroskedasticity remain in the residuals. Furthermore, the Kolmogorov-Smirnov (KS), Cramér-von Mises (CvM), and Anderson-Darling (A-D) tests indicate non-significant differences between the empirical and theoretical distributions of the model residuals, indicating that the marginal models are correctly specified.

From the estimated marginal models, we obtain pseudo sample

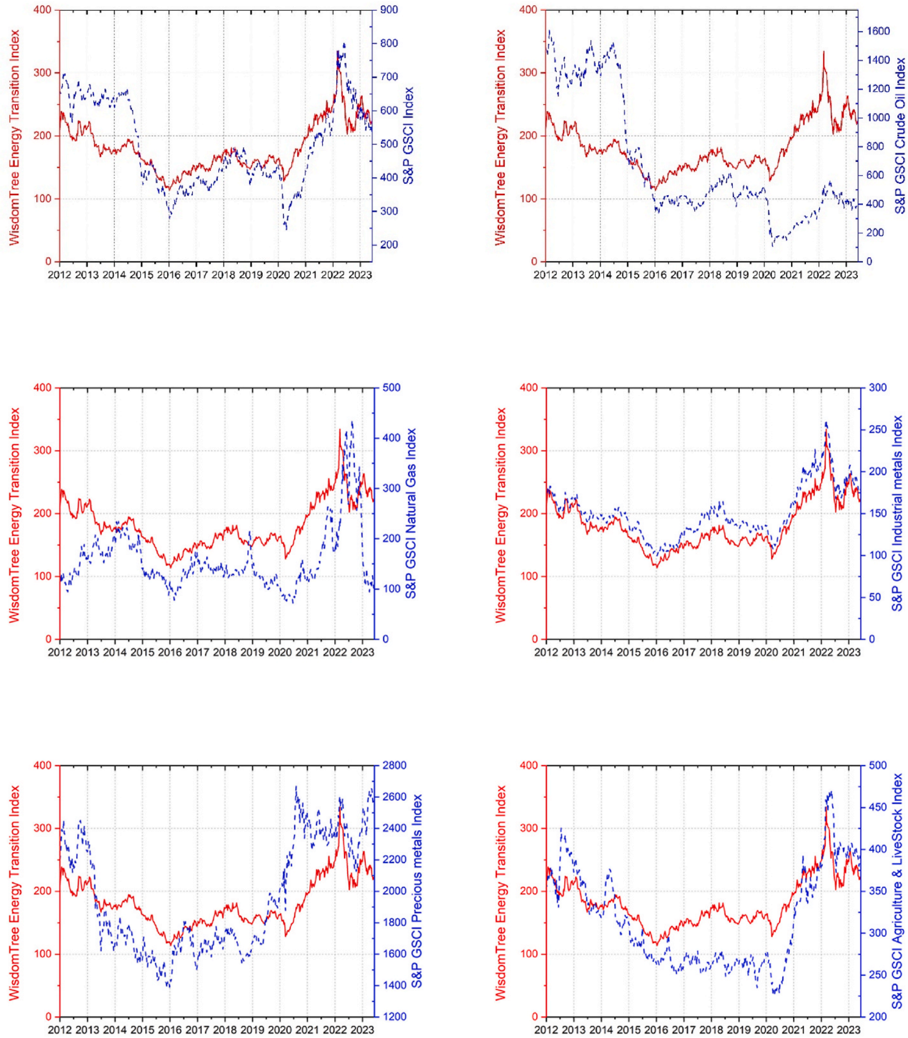


Fig. 1. Time series plot of the WisdomTree Energy Transition Metals Commodity Index (in red) and commodity price indices (in blue).

observations to estimate all the parametric copula models presented in Table 1. For each pair composed of ETM and different commodity price returns, Table 4 presents the best fitting copula models and the corresponding parameter estimates. Consistent with the correlation information reported in Table 2, we find evidence of positive dependence for all pairs, with the exception of natural gas, whose price dynamics is independent of ETM prices. Dependence is constant over the sample period for the general commodity index, crude oil, and agriculture, but fluctuates for natural gas, industrial metals, and precious metals. Tail dependence is rather weak and symmetric for agriculture and natural gas, whereas it is strong and somewhat symmetric for the general commodity index and crude oil. For industrial metals, we find evidence of strong and symmetric tail dependence, while tail dependence is asymmetric for precious metals, with lower tail dependence that is stronger than upper tail dependence.

4.2. Evidence on conditional marginal densities for commodity prices

Using the above information on the marginal and copula models, we obtain the conditional density of r_c at different moments of the sample period for ETM α- and β- quantiles, i.e., $f\left(r_c \middle| r_{ETM} \leq r^{\alpha}_{ETM}\right)$ and $f\left(r_c \middle| r_{ETM} \geq r^{\beta}_{ETM}\right)$, respectively, taking $\alpha = \beta = 0.10$. For the sake of comparison, we also compute the value of the conditional density of r_c assuming that ETM prices move around their median values, i.e., $f\left(r_c \middle| r^{0.45}_{ETM} \leq r_{ETM} \leq r^{0.55}_{ETM}\right)$. Those conditional distributions, displayed in Fig. 2, reveal that: (a) the conditional distributions change over the sample period, which is consistent with the time-varying nature of volatility and, in some cases, with changes in dependence; (b) ETM quantiles have a symmetric impact (except for precious metals, where the impact is asymmetric) on the conditional distributions, displacing them to the left and right when ETM prices experience downward and upward price movements, respectively; and (c) conditional distributions exhibit different volatility and tail patterns depending on whether the impact comes from a downward or upward movement in ETM prices.

Observing Fig. 2, Panel A shows that commodity prices are particularly affected by downward ETM price movements, and that the distribution is negatively skewed, while upward ETM price movements also have an impact on the conditional distribution, but with a slightly weaker effect on the tails than in the case of downward movements. Also, commodity price volatility is remarkably impacted by the onset of the COVID-19 pandemic, although that effect was cancelled a year later. Similar effects can be observed for crude oil in Panel B, with even lower intensity in the tails. Regarding natural gas, the conditional densities in Panel C fully reflect its independence from ETM prices, as abrupt changes in ETM prices, whether upwards or downwards, have negligible effects on the conditional density of natural gas price returns. Panel D, for industrial metal prices, shows that both downward and upward ETM price movements clearly displace the conditional distributions to the left and right, respectively, and that the conditional distributions are skewed and exhibit time-varying volatility and heavy tails; this is consistent with

Table 2
Summary statistics for ETM and commodity price returns.

	ETM	S&P GSCI	Crude oil	Natural gas	Industrial metals	Precious metals	Agriculture
Mean	0.000	0.000	−0.002	0.000	0.000	0.000	0.000
SD	0.025	0.029	0.054	0.067	0.024	0.022	0.021
Minimum	−0.105	−0.146	−0.390	−0.282	−0.095	−0.103	−0.069
Maximum	0.113	0.183	0.276	0.231	0.115	0.110	0.106
Skewness	0.092	−0.191	−1.087	−0.241	0.261	−0.123	0.019
Kurtosis	4.517	7.202	12.186	4.151	4.305	5.143	4.957
JB	58.198*	443.569*	2220.350*	38.771*	49.190*	115.980*	95.420*
Q(20)	23.464	31.871	45.002	22.395	24.059	23.086	37.121
	[0.550]	[0.162]	[0.008]	[0.613]	[0.516]	[0.573]	[0.056]
Q2(20)	205.855	92.586	432.639	146.607	115.498	102.733	86.424
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH-LM	98.814	51.884	215.894	68.121	75.796	85.765	64.389
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−7.520	−7.372	−7.120	−8.052	−7.341	−8.249	−8.077
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
PP	−23.185	−22.694	−21.326	−23.944	−23.486	−24.797	−25.663
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
KPSS	0.175	0.157	0.098	0.055	0.142	0.249	0.232
Correlation matrix							
Transition metals	1						
S&P GSCI	0.46	1					
Crude oil	0.34	0.90	1				
Natural gas	0.06	0.27	0.16	1			
Industrial metals	0.90	0.47	0.34	0.09	1		
Precious metals	0.52	0.20	0.12	−0.05	0.29	1	
Agriculture	0.28	0.42	0.19	0.12	0.28	0.12	1

Notes. The table presents descriptive statistics for logarithmic price changes computed from the WisdomTree Energy Transition Metals Commodity Index (ETM) and the S&P GSCI and its components, namely, crude oil, natural gas, industrial metals, precious metals, and agriculture. Data is sampled on a weekly basis, from 6 Jan 2012 to 13 June 2023. JB denotes the Jarque-Bera statistic for the null of normality, with the asterisk (*) indicating rejection of the null at the 1% level. Q(20), $Q^2(20)$, and ARCH-LM indicate the Ljung-Box statistics for serial correlation in returns and in squared returns, and Engle's autoregressive conditional heteroskedasticity-Lagrange multiplier test for heteroskedasticity, respectively, all computed with 20 lags and p-values as reported in square brackets. The null hypothesis of a unit root is tested using the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, with p-values as reported in square brackets. The null of trend stationarity is tested using the one-sided Kwiatkowski-Phillips-Schmidt-Shin test (KPSS), with critical values of 0.73, 0.46, and 0.34 for the 1%, 5%, and 10% confidence levels, respectively. The correlation matrix reports the Pearson correlation for each series pair indicated in each row and column.

strong positive dependence between ETMs and industrial metals. For precious metals, Panel E shows that the conditional density is asymmetrically impacted by ETM price movements, with downward ETM price movements displacing the distribution to the left, and with upward ETM price movements having a more moderate impact on the distribution; this evidence is consistent with the asymmetric dependence between ETMs and precious metals as given by the time-varying SJC copula. Finally, as shown in Panel F, the conditional distribution of agriculture is displaced by extreme movements in ETM prices, even though the size of those impacts is moderate and nearly symmetric, consistent with the symmetric tail dependence between ETMs and agricultural commodities.

4.3. Evidence on tail risk effects of ETM prices on commodity prices

Using the information on the conditional distributions, we compute the impact of downward and upward ETM price movements on the expected commodity price returns, as per Eqs. (4) and (5), and on commodity price volatility, as per Eqs. (2) and (3), for the confidence levels $\alpha = \beta = 0.10$.

Fig. 3 shows the effect of extreme ETM price movements on the mean and volatility of commodity price returns over the sample period, along with the respective effects of around-median ETM price changes and unconditional mean and volatility values of commodity price returns. For the commodity price index, the evidence in Panel A points to the fact that downward ETM price movements have a more pervasive effect than upward movements, while moderate changes in ETM prices have a negligible effect, overtly reflecting low dependence between ETM and commodity prices. Similarly, the evidence for volatility shows that only extreme changes in ETM prices have an impact on commodity price volatility; downward movements have a significant impact, but upward movements only have a mild impact. Furthermore, our empirical estimates indicate a more sizeable impact of ETM prices on commodity prices around the times of the COVID-19 pandemic and the military conflict between Russia and Ukraine.

Fig. 3 also shows the effect of changes in ETM prices on different kind of commodities. The evidence in Panel B shows that upsurges in ETM prices have a positive impact on crude oil price returns, of a smaller size, however, than the impact of abrupt drops in ETM prices, particularly at times of high uncertainty such as the COVID-19 pandemic. This evidence is possibly explained in terms of the economic viability of the substitution between renewable and non-renewable energy resources when ETM prices are particularly low or high. Likewise, we find that the impact of extreme ETM price movements on crude oil volatility is higher during ETM price downturns than during upturns, when volatility is similar to when ETM price movements are moderate. For natural gas, the evidence in Panel C indicates that extreme ETM price movements have no effect on natural gas price volatility, and that the impact on the expected return value is negligible and fails to reflect the effects of the COVID-19 pandemic and of the Russia-Ukraine military conflict. This result is consistent with the independence between ETM and natural gas prices as reported in Table 4. Panel D, for industrial metals, shows that, consistent with the high degree of symmetry in the dependence on ETMs, extreme ETM price oscillations have sizeable impacts on the expected value of industrial metal prices. However, and in contrast to what happens with the general commodity index and crude oil, extreme movements in ETM prices have quite similar impacts on industrial metal price volatility. Moreover, the effects of COVID-19 and the Russia-Ukraine military conflict are barely reflected in the impact of ETM prices on industrial metal prices. For the precious metals, Panel E indicates that abrupt changes in ETM prices have a notable impact, and that this impact is symmetric. Likewise, ETM price swings affect precious metal price volatility, with ETM price downturns having more sizeable effects on volatility than ETM price upturns. Finally, for agricultural price changes,

Table 3
Estimates of the marginal models for commodity price returns.

	Transition metals	S&P GSCI	Crude oil	Natural gas	Industrial metals	Precious metals	Agriculture
Mean							
φ_0	0.000	0.000	−0.001	0.000	0.000	0.000	0.000
	(-0.135)	(-0.443)	(-0.506)	(0.140)	(0.232)	(0.117)	(-0.160)
Variance							
ω	0.071*	0.214	1.737	1.804**	0.145	0.093	0.743***
	(1.732)	(1.068)	(1.464)	(2.168)	(1.716)	(0.998)	(3.445)
α_1	0.152***	0.084**	0.182***	0.102***	0.049***	0.096*	0.178***
	(2.618)	(2.123)	(2.612)	(3.338)	(2.931)	(1.652)	(4.131)
β_1	0.955***	0.893***	0.760***	0.860***	0.927***	0.939***	0.652***
	(83.680)	(15.020)	(7.386)	(22.320)	(37.920)	(27.830)	(9.385)
λ	0.056	−0.215***	−0.175***	−0.035	0.120**	−0.076	−0.088
	(1.011)	(-2.992)	(-3.279)	(-0.539)	(1.962)	(-1.438)	(-1.437)
ϑ	12.878**	7.260***	5.836***	10.572***	9.963***	7.558***	6.747***
	(2.055)	(2.904)	(3.638)	(2.809)	(2.514)	(3.741)	(3.587)
LogLik	1388.76	1325.44	1011.76	802.22	1395.49	1464.41	1514.30
LJ	17.264	21.418	21.399	8.525	18.731	11.877	23.359
	[0.30]	[0.12]	[0.12]	[0.90]	[0.23]	[0.54]	[0.08]
LJ^2	16.089	3.986	10.804	6.507	18.133	16.674	12.068
	[0.19]	[0.99]	[0.63]	[0.93]	[0.15]	[0.16]	[0.52]
ARCH	0.922	0.246	0.771	0.428	1.006	1.108	0.739
	[0.54]	[0.99]	[0.71]	[0.97]	[0.45]	[0.35]	[0.75]
KS	0.99	0.83	0.74	0.98	0.71	0.96	0.97
CvM	0.97	0.78	0.70	0.97	0.94	0.97	0.98
AD	0.98	0.84	0.71	0.99	0.96	0.99	0.99

Notes. The table presents estimates of the marginal models as per Eqs. (6)–(8) for the WisdomTree Energy Transition Metals Commodity Index (Transition metals) and the S&P GSCI and its components, namely, crude oil, natural gas, industrial metals, precious metals, and agriculture. Standard errors are reported in round parentheses, with ***, **, and * denoting estimate significance at the 1%, 5%, and 10% levels. Volatility models for ETMs and precious metals have 2 lags in the autoregressive conditional heteroskedasticity (ARCH) component (the second parameter estimate is not reported), and the model for the mean of precious metals has 1 lag (not reported) in the autoregressive (AR) and moving average (MA) components. LogLik denotes the value of the log-likelihood function, while LJ and LJ2 denote the Ljung-Box statistics for serial correlation of the residuals and squared residuals of the model, respectively, both computed with 20 lags. ARCH-LM refers to Engle's autoregressive conditional heteroskedasticity-Lagrange multiplier test which was computed with 20 lags. KS, CvM, and AD denote the Kolmogorov–Smirnov, Cramér-von Mises, and Anderson–Darling tests for adequacy of the skewed-t distribution model, with p-values (in square brackets) below 0.05 indicating rejection of the null hypothesis of adequate model specification.

Table 4
Estimates for the best fitting copula models between ETM and commodity price returns.

Copula: ETM with	Copula model	Parameter estimates		AIC
S&P GSCI	BB1	$\theta = 0.385$***	$\delta = 1.182$***	−145.18
		(0.089)	(0.052)	
Crude oil	BB1	$\theta = 0.324$***	$\delta = 1.100$***	−86.49
		(0.076)	(0.043)	
Natural gas	TVP-Student t	$\psi_0 = 0.170$***	$\psi_1 = 0.139$	−6.83
		(0.133)	(0.103)	
		$\psi_2 = -1.254$***	$\eta = 6.383$***	
		(0.499)	(2.077)	
Industrial metals	TVP-Student t	$\psi_0 = 6.209$***	$\psi_1 = -0.071$**	−1007.56
		(2.898)	(0.041)	
		$\psi_2 = -3.447$	$\eta = 6.492$***	
		(3.286)	(1.855)	
Precious metals	TVP-SJC	$\overline{\varpi} = 1.735$***	$\overline{\beta} = -10.372$***	−187.69
		(0.484)	(3.147)	
		$\overline{\alpha} = -2.829$***	$\omega = -0.441$	
		(0.973)	(0.818)	
		$\beta = 4.373$***	$\alpha = -4.148$	
		(1.867)	(0.475)	
Agriculture	BB1	$\theta = 0.245$***	$\delta = 1.067$***	−49.93
		(0.055)	(0.035)	

Notes. For each ETM and commodity price returns pair indicated in the first column, this table presents maximum likelihood parameter estimates for the best fitting copula model, selected from the copula models presented in Table 1 according to the AIC criterion. Standard errors are reported in round parenthesis, with *** and ** denoting estimate significance at the 1% and 5% levels, respectively.

Panel F indicates that the impact of extreme ETM price movements is somewhat asymmetric, with downward ETM prices having a more sizeable impact, yet smaller in size than for the other commodities; this is consistent with the fact that ETM-agriculture dependence is lower than for other commodities. Similarly, upturns and downturns in ETM prices have a mild asymmetric impact on agricultural price volatility, consistent with the asymmetric dependence indicated by the BB1 copula.

Overall, except for natural gas prices, our evidence points to the fact that extreme ETM price movements play a distinctive role in shaping the dynamics of commodity prices and volatility. However, this effect dissipates when ETM prices move around their median values, with the conditional and unconditional dynamics of commodity prices and volatility becoming rather indistinguishable. Likewise, abrupt ETM price changes have some asymmetric impacts, as evidenced by the COVID-19 pandemic.

5. Implications for commodity investors

Our analysis of tail risk effects of ETM prices for commodity prices has implications for risk and liquidity management in commodity markets. Investors are usually concerned with the impact of shocks on their investment positions in terms of both the expected risk-adjusted returns and downside/upside risks, and also in terms of liquidity needs to uphold open positions in commodity futures contracts. As a result, we assess the implications of ETM price shocks in those three scenarios.

5.1. Impact on risk-adjusted return

We consider the returns impact (RI) of ETM price changes as the difference between the conditional and unconditional expected commodity returns adjusted by the respective volatility as:

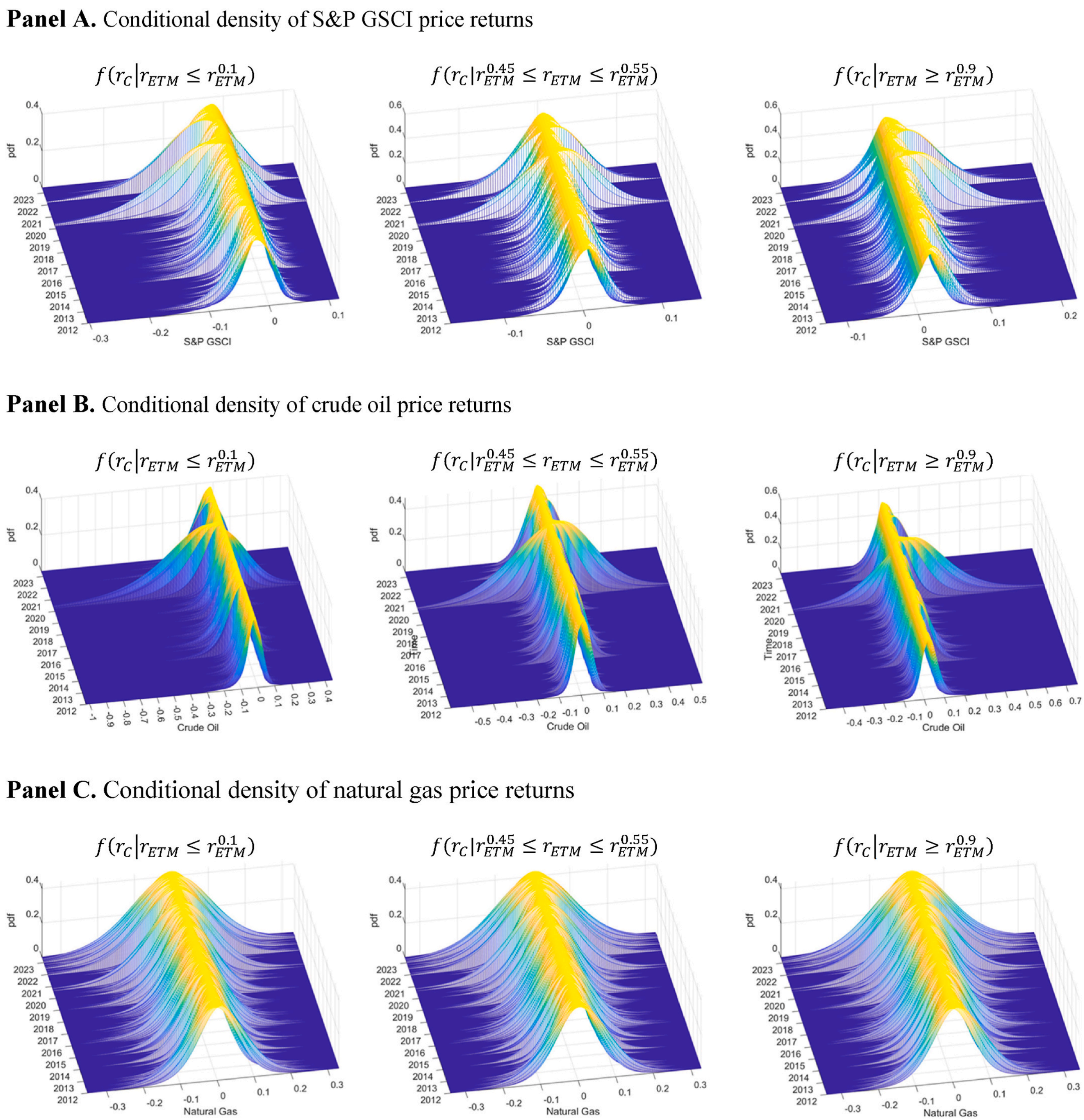
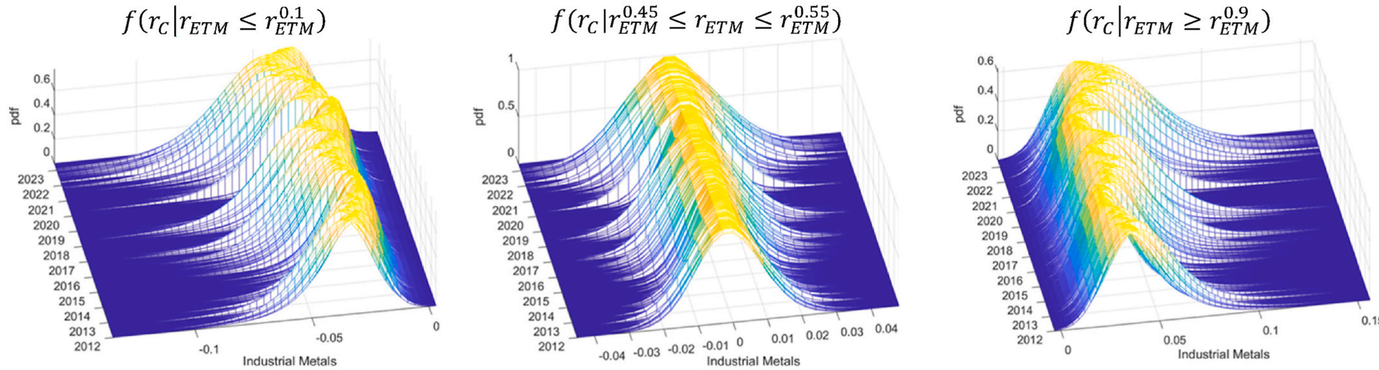


Fig. 2. Estimates of the conditional density of commodity price returns.

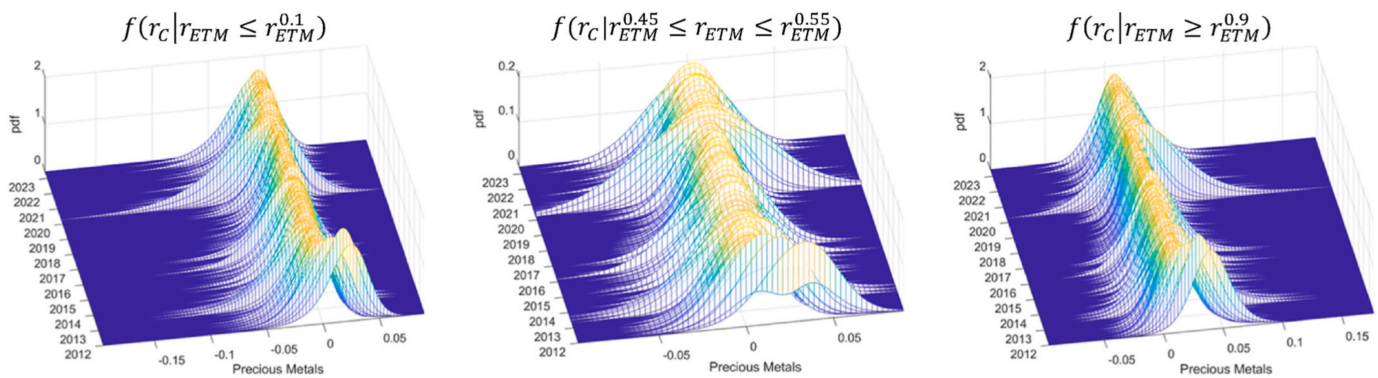
$$\mathrm{RI} = \frac{E\left(r_c \middle| r_{ETM} \leq r_{ETM}^{\alpha}\right)}{\sigma_{c|r_{ETM} \leq r_{ETM}^{\alpha}}} - \frac{E(r_c)}{\sigma_c} \tag{11}$$

where $E(r^c)$ and σ_c are the expected value and the standard deviation (SD) of returns when commodity and ETM price returns are independent, computed from the marginal distribution of commodity price returns from Eqs. (8)–(10), and where $E\left(r_c \middle| r_{ETM} \leq r_{ETM}^{\alpha}\right)$ and $\sigma_{c|r_{ETM} \leq r_{ETM}^{\alpha}}$ are the conditional expected value and SD of those returns when commodity and ETM price returns are dependent, computed from the conditional dependence between commodity and ETM price returns considering a downward ETM price movement. Therefore, the first term in Eq. (11) provides information on risk-adjusted returns for a given downside movement in ETM prices, while the second term indicates what the value of those risk-adjusted returns would be under independence between commodity and ETM price returns. Hence, positive (negative) values of RI indicate that a downward ETM price change increases (reduces) the risk-adjusted commodity price returns. Likewise, we can obtain the RI for an upward price movement in ETM prices by replacing $E\left(r_c \middle| r_{ETM} \leq r_{ETM}^{\alpha}\right)$ with $E\left(r_c \middle| r_{ETM} \geq r_{ETM}^{\beta}\right)$ and $\sigma_{c|r_{ETM} \leq r_{ETM}^{\alpha}}$ with $\sigma_{c|r_{ETM} \geq r_{ETM}^{\beta}}$.

Panel D. Conditional density of industrial metal price returns



Panel E. Conditional density of precious metal price returns



Panel F. Conditional density of agricultural price returns

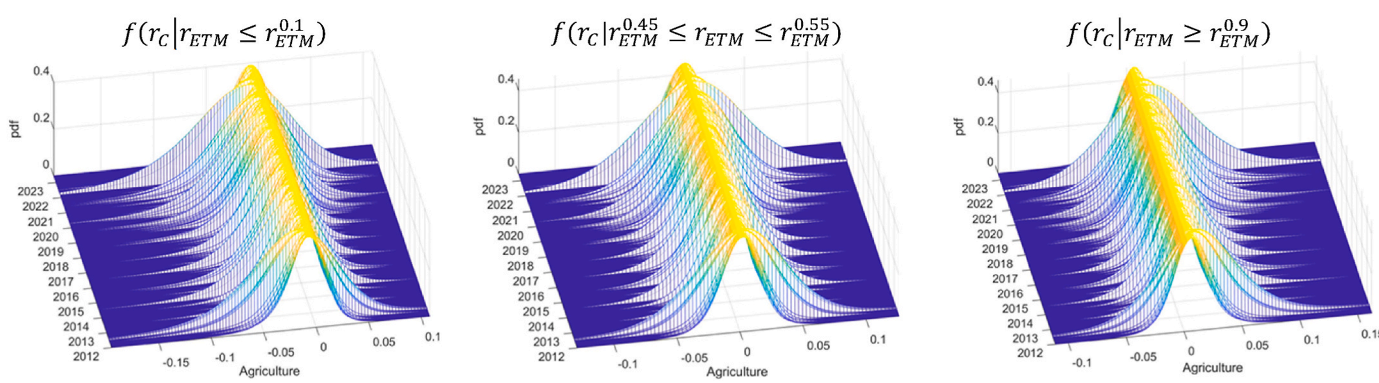


Fig. 2. (*continued*).

Fig. 4 presents evidence on the tail risk impact of ETM price changes on risk-adjusted commodity returns. The evidence in Panels A and B indicates that investors in natural gas and agricultural commodity markets could ignore swings in ETM prices as having hardly any impact on positions. However, for investors in the general commodity index and in crude oil, abrupt changes in ETM prices have an important impact on positions, reducing or increasing the risk-adjusted returns when ETM prices move downwards and upwards, respectively. The more pervasive effects of ETM price fluctuations are for investors with industrial and precious metal positions. Changes are especially abrupt in the case of precious metals, the result of high volatility due to their role as production inputs and as hedging and safe-haven assets.

5.2. *Tail risk impact*

We consider the tail risk impact (TRI) to be the difference between the unconditional and conditional tail risk, i.e.:

$$\mathrm{TRI} = E\left(r_c \middle| r_{ETM} \leq r_{ETM}^{\alpha}, r_c \leq r_c^{\gamma}\right) - E\left(r_c \middle| r_c \leq r_c^{\gamma}\right) \tag{12}$$

where $E\left(r_c \middle| r_{ETM} \leq r_{ETM}^{\alpha}, r_c \leq r_c^{\gamma}\right)$ and $E(r_c|r_c \leq r_c^{\gamma})$ are the conditional and unconditional tail values-at-risk, respectively. $E(r_c|r_c \leq r_c^{\gamma})$ can be computed from the marginal distribution of commodity returns as $\frac{1}{\gamma}\int_{-\infty}^{r_c^{\gamma}} r_c f_c(r_c) dr_c$, whereas $E\left(r_c \middle| r_{ETM} \leq r_{ETM}^{\alpha}, r_c \leq r_c^{\gamma}\right)$ is derived from Eq. (4) as $\frac{1}{\alpha\gamma}\int_0^{\gamma} F_c^{-1}(u_c) C_{ETM|c}(\alpha|u_c) du_c$. Hence, TRI accounts for the impact of

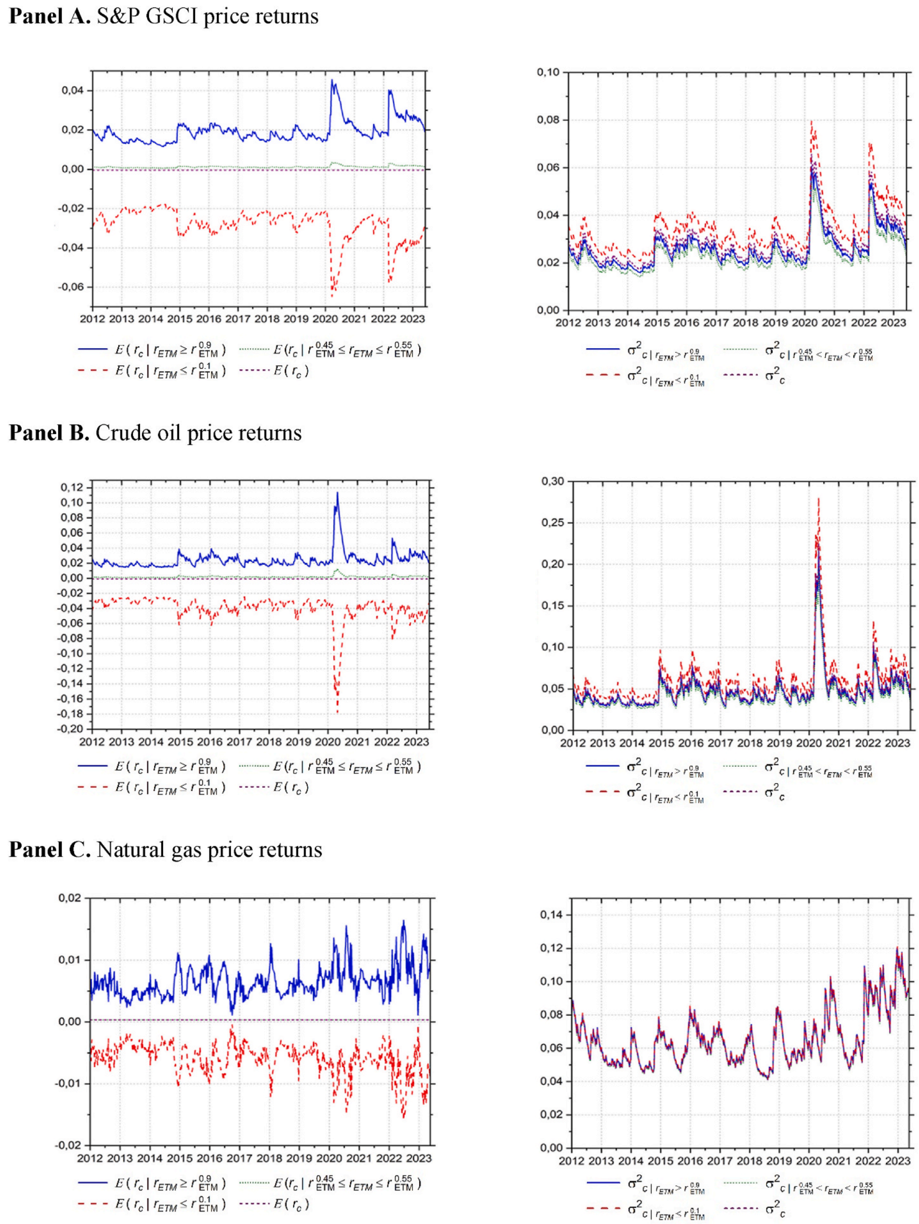


Fig. 3. Impact of ETM price changes on commodity price means (left) and volatilities (right).

ETM downward price changes in terms of differences in the expected returns in the tails of the conditional and unconditional commodity price returns; positive (negative) values of TRI indicate that a downward ETM price change increases (reduces) the tail risk of commodity price returns. In a similar way, we can consider the TRI for an upward movement in ETM prices by replacing $E\left(r_c \middle| r_{ETM} \le r_{ETM}^{\alpha}, r_c \le r_c^{\gamma}\right)$ with $E\left(r_c \middle| r_{ETM} \ge r_{ETM}^{\beta}, r_c \ge r_c^{\gamma}\right)$, and $E(r_c|r_c \le r_c^{\gamma})$ with $E(r_c|r_c \ge r_c^{\gamma})$.

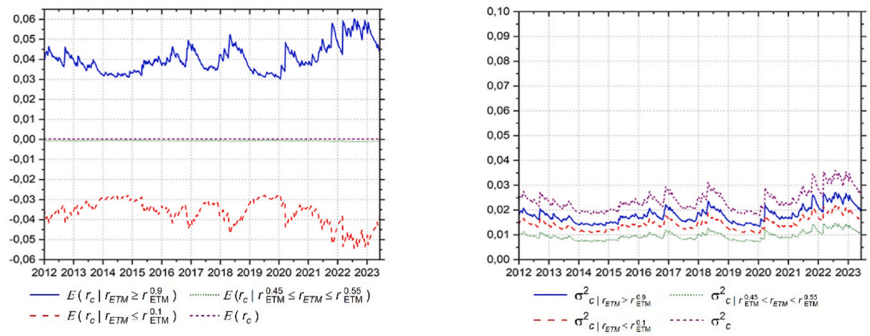
For $\alpha = \beta = \gamma = 0.1$, Fig. 5 presents evidence for TRI over the sample period, indicating that extreme ETM price changes have low impacts on the tails of natural gas and agricultural commodities, consistent with the graphical evidence presented in Fig. 2. For the general commodity price index and for crude oil, the impact of abrupt changes in ETM prices is sizeable, with increases in the value of conditional expected shortfall of around 20% and 10% for downward and upward movements in ETM prices, respectively. Moreover, this impact is considerably higher at the onset of the pandemic and of the Russia-Ukraine military conflict. Our estimates for industrial and precious metals indicate that the expected shortfalls for those commodities are particularly affected by extreme ETM prices, increasing the expected returns in tails by around 20% and 30% when ETM prices experience downward and upward price movements, respectively. However, for oil prices, we find that ETM prices increase the expected returns in tails by around 30% and 15% when ETM prices experience downward and upward price movements, respectively. Overall, our estimates point to the fact that extreme ETM price changes contain relevant information for the management of tail risk in commodity futures.

5.3. *Liquidity needs*

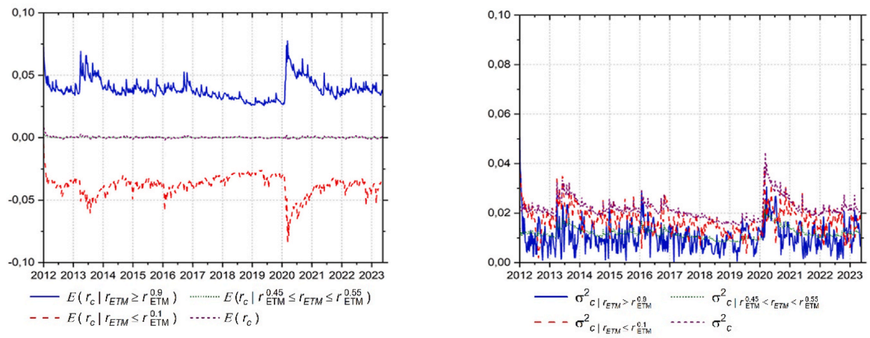
We assess how ETM extreme price changes could impact future liquidity needs, and thus generate a potential liquidity shock for investors trading in commodity futures. Liquidity constraints could force investors to close their positions in commodity futures or to sell portfolio assets to meet their liquidity needs.

To estimate potential future exposure based on asset volatility and

Panel D. Industrial metal price returns



Panel E. Precious metal price returns



Panel F. Agricultural price returns

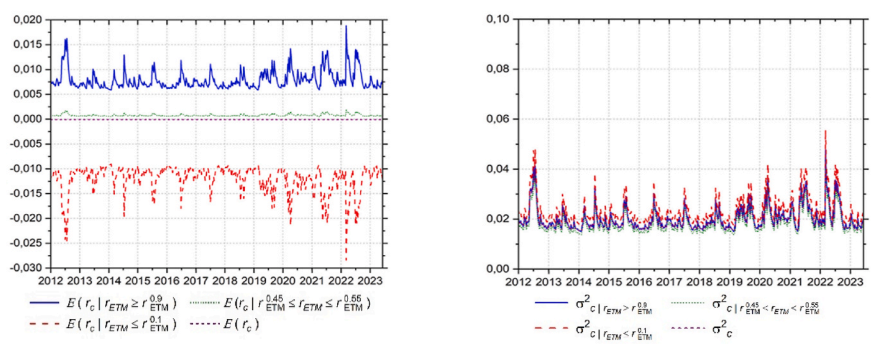


Fig. 3. (*continued*).

(a) Downward movement in ETM prices (b) Upward movement in ETM prices

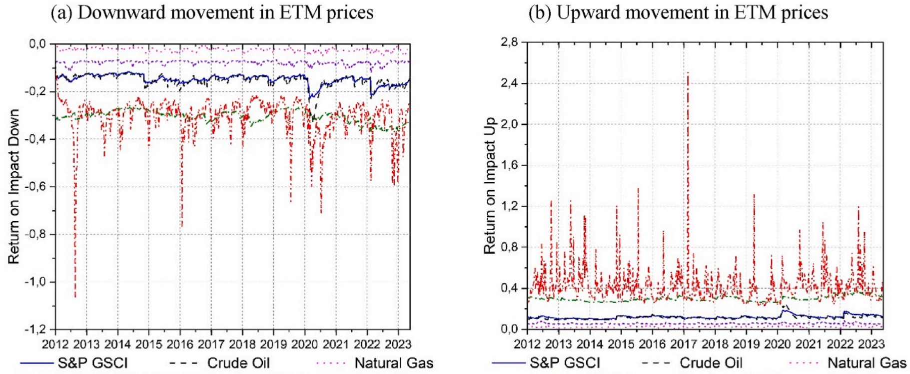


Fig. 4. Tail risk impact of ETM price on risk-adjusted commodity returns. (a) Downward movement in ETM prices (b) Upward movement in ETM prices.

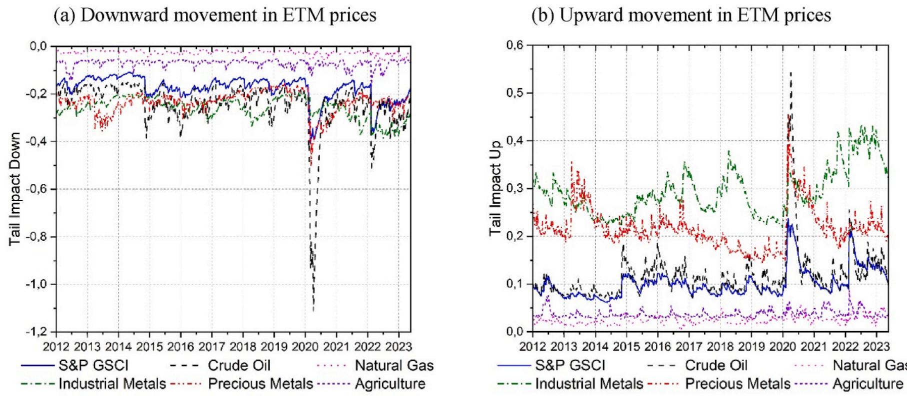


Fig. 5. Tail risks impact of ETM price changes on the tail risk of commodity returns.

how quickly it could be liquidated, we follow the SPAN risk system introduced by the Chicago Mercantile Exchange in 1988. SPAN, an industry-standard method to determine initial margin for futures,[6] is derived from 3-times volatility based on the historical realization of returns in an exponentially weighted moving average (EWMA) model:

$$\sigma_t = \sqrt{(1-\lambda)\sum\nolimits_{i=1}^{52} \frac{\lambda^{i-1}\left(r_{t-i}-\overline{r}\right)^2}{\left(1-\lambda^{52}\right)}} \tag{13}$$

with a lambda parameter of 0.99 (see Canadian Derivatives Clearing Corporation, 2023). Using weekly returns and assuming a liquidation period of one week to settle losses in the portfolio (Boudiaf et al., 2023), we obtain an indicator on the difficulty of liquidating a (defaulted) position as the margin interval (MI), i.e., $\mathrm{MI}_t = 3\sigma_t$, which, along with the notional value of the position (P), determine the margin requirement (MR) to open a position in futures at time t as:

$$\mathrm{MR}_t = \mathrm{MI}_t * \mathrm{P}_t. \tag{14}$$

Once the position is re-evaluated, the investor should provide enough collateral to the clearing house to fulfil the new margin. Moreover, profits and losses from a future position imply cash settlements that could lead to additional liquidity requests when the position experiences losses. Therefore, liquidity claims follow from the combination of the change in MR and the returns between two periods, i.e.:

$$\textit{Liquidity needs}_t = \Delta\mathrm{MR}_t - \Delta\mathrm{P}_t. \tag{15}$$

Thus, returns are preceded by a minus, as profits and losses decrease and increase liquidity needs, respectively.

To estimate liquidity needs, we determine the value of commodity returns conditional on ETM prices experiencing downward or upward movements, using the marginal and copula models for commodity and ETM price returns. From those values, and the value of the change in MR, we can evaluate how an abrupt change in ETM prices impacts on liquidity needs.

Fig. 6 depicts actual liquidity needs over the sample period along with liquidity needs considering extreme ETM prices for alpha and beta values of 0.1, and for an initial exposure of 100 USD. For all the commodities, we find that liquidity needs increase when ETM prices experience upward movements; crude oil and industrial metals exhibit the highest liquidity needs, with increments of between 350 and 400 basis points. For the S&P GSCI, liquidity increments are around 300 basis points, for precious metals between 180 and 200 basis points, and for agricultural commodities around 100 basis points. In contrast, ETM price changes have a negligible impact on natural gas liquidity needs, which fluctuate around 50 basis points. Overall, this evidence points to the fact that ETM price fluctuations have sizeable implications for trade in commodity futures contracts.

6. Conclusions

A large number and variety of critical metals are required for the transition towards a clean energy system, which is more metal-intensive than fossil fuels, and which would reduce CO2 emissions and enable convergence to a low-carbon economy. Supported by policies focused on net-zero emissions, ETMs are gaining prominence in the world mineral industry, and arguably, the evolution of ETM prices is tied to the implementation and the uncertainty of transition polices, shaping ETM demand and supply. ETM prices are thus expected to fluctuate widely, and those price fluctuations may be transmitted to the prices of other commodities through the different economic and financial channels that link commodity markets.

In this research we have examined to what extent ETM price changes could impact the prices of other energy and non-energy commodities, including oil, natural gas, industrial metals, precious metals, and agricultural commodities. We have characterized the structure of dependence between ETM price changes and price changes for each commodity, and have evaluated the impact of extreme upward and downward ETM price movements on the expected price returns and price volatilities of the different commodities. We document that abrupt changes in ETM prices have non-neutral effects on the prices of other commodities, as upward and downward price changes in ETM determine price dynamics for all the commodities, with the only exception of natural gas prices. However, movements in ETM prices around their median values have negligible effects on commodity prices. Therefore, depending on how transition policies affect ETM prices, they could have ramifications for the commodity markets. We also confirm that extreme changes in ETM prices have a sizeable impact on commodity price volatility, but this impact is negligible when ETM price changes oscillate around median values.

Finally, we assess the implications of our evidence for commodity investors, documenting that information on ETM prices is useful for investors in terms of risk-adjusted returns and risk management. With the exception of natural gas, positions in ETM markets could improve performance and reduce tail risks for investments in different commodities. Likewise, we find that ETM price information is useful for liquidity management in relation to trade in commodity futures, as liquidity needs are found to increase with extreme ETM price fluctuations.

[6] This methodology is frequently employed by central clearing houses to compute margining for derivatives in equities and agricultural and energy-related commodities (see Bank for International Settlements, 2022). See Boudiaf et al. (2023) for a summary of the methodologies used by clearing houses depending on the derivative type.

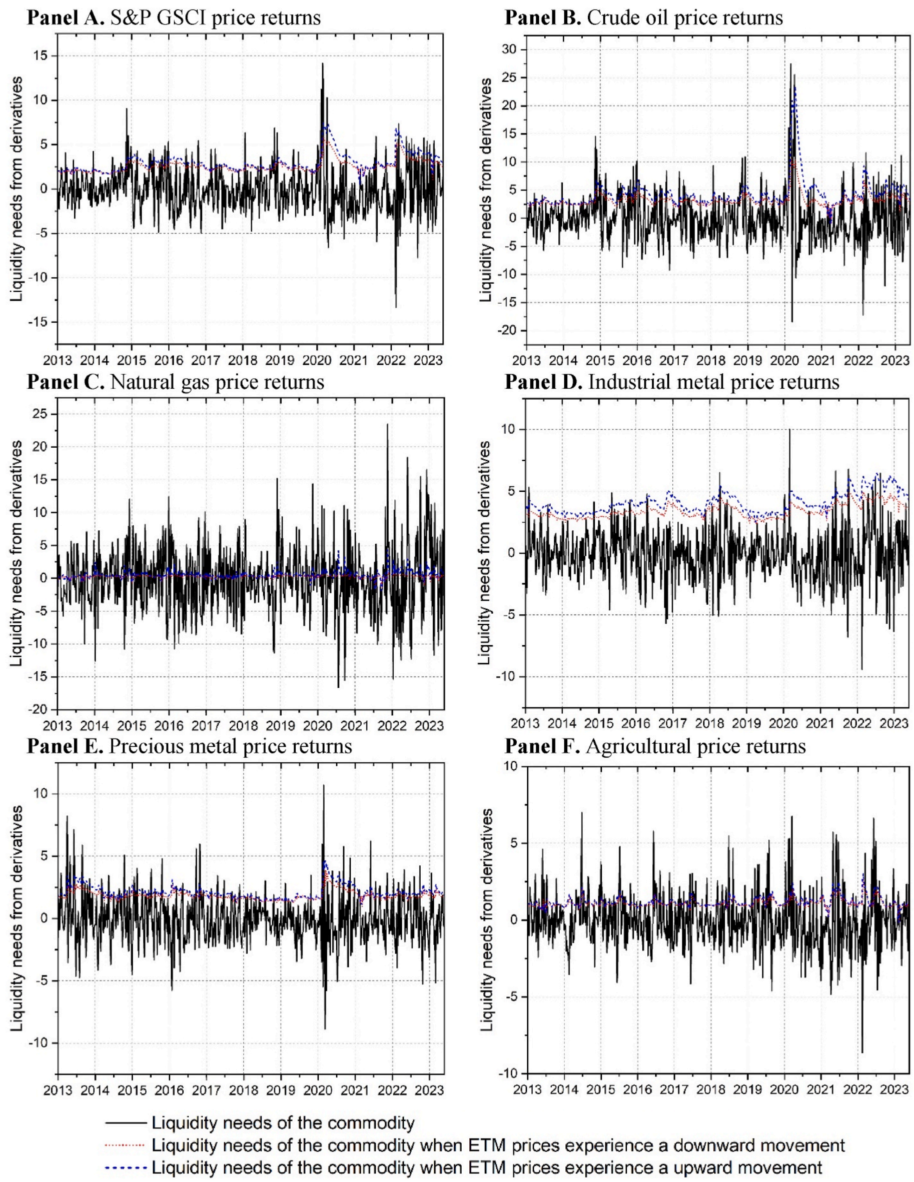


Fig. 6. Liquidity needs in commodity futures positions due to ETM price changes.

CRediT authorship contribution statement

Juan C. Reboredo: Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Andrea Ugolini:** Conceptualization, Data curation, Investigation, Methodology, Software, Supervision, Validation, Writing – original draft. **Javier Ojea-Ferreiro:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Writing – original draft.

Declaration of competing interest

All authors have collaborated in the production of this article and approved the final version of the manuscript that is being submitted. They warrant that the article is the authors' original work, hasn't received prior publication and isn't under consideration for publication elsewhere.

The validity of this research is not influenced by a secondary interest, such as financial gain. Authors have not financial/personal interest or belief that could affect their objectivity.

Data availability

The authors do not have permission to share data.

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Appendix

A. Proof of Eq. (2). Following Reboredo et al. (2022), the conditional density $f(r_c|r_{ETM} \le r_{ETM}^{\alpha})$ can be written as:

$$f(r_c|r_{ETM} \le r_{ETM}^{\alpha}) = \frac{P(r_{ETM} \le r_{ETM}^{\alpha}, r_c)}{P(r_{ETM} \le r_{ETM}^{\alpha})} = \frac{P(r_{ETM} \le r_{ETM}^{\alpha}|r_c)f_c(r_c)}{\alpha} = \frac{C_{ETM|c}(\alpha|F_c(r_c))}{\alpha}f_c(r_c),$$

where the third equality follows from the definition of a conditional copula. Thus:

$$E(r_c|r_{ETM} \le r_{ETM}^{\alpha}) = \int_{-\infty}^{\infty} r_c f(r_c|r_{ETM} \le r_{ETM}^{\alpha})dr_c = \int_{-\infty}^{\infty} r_c \frac{C_{ETM|c}(\alpha|F_c(r_c))}{\alpha} f_c(r_c)dr_c = \frac{1}{\alpha}\int_0^1 F_c^{-1}(u_c)C_{ETM|c}(\alpha|u_c)du_c,$$

where the last equality follows from the fact that $u_c = F_c(r_c)$, with $du_c = f_c(r_c)dr_c$ and $r_c = F_c^{-1}(u_c)$.

B. Proof of Eq. (3). The conditional density $f\left(r_c\middle|r_{ETM} \ge r_{ETM}^{\beta}\right)$ can be written as:

$$f(r_c|r_{ETM} \ge r_{ETM}^{\beta}) = \frac{P(r_{ETM} \ge r_{ETM}^{\beta}, r_c)}{P(r_{ETM} \ge r_{ETM}^{\beta})} = \frac{P(r_{ETM} \ge r_{ETM}^{\beta}|r_c)f_c(r_c)}{\beta} = \frac{1 - P(r_{ETM} \le r_{ETM}^{\beta}|r_c)}{\beta}f_c(r_c) = \frac{1 - C_{ETM|c}((1-\beta)|F_c(r_c))}{\beta}f_c(r_c).$$

Hence:

$$E(r_c|r_{ETM} \ge r_{ETM}^{\beta}) = \int_{-\infty}^{\infty} r_c f(r_c|r_{ETM} \ge r_{ETM}^{\beta})dr_c = \int_{-\infty}^{\infty} r_c \frac{1 - C_{ETM|c}((1-\beta)|F_c(r_c))}{\beta} f_c(r_c)dr_c = \frac{1}{\beta}\int_0^1 F_c^{-1}(u_c)\{1 - C_{ETM|c}((1-\beta)|u_c)\}du_c$$

where the last equality follows from the fact that $u_c = F_c(r_c)$, with $du_c = f_c(r_c)dr_c$ and $r_c = F_c^{-1}(u_c)$.

C. Proof of Eqs. (4)-(5). To compute $\sigma^2_{c|r_{ETM} \le r_{ETM}^{\alpha}}$ we need information about $E(r_c^2|r_{ETM} \le r_{ETM}^{\alpha})$ (the value of $E(r_c|r_{ETM} \le r_{ETM}^{\alpha})$ is already available from Eq. (1)), which is:

$$E(r_c^2|r_{ETM} \le r_{ETM}^{\alpha}) = \int_{-\infty}^{\infty} r_c^2 f(r_c|r_{ETM} \le r_{ETM}^{\alpha})dr_c = \int_{-\infty}^{\infty} r_c^2 \frac{C_{ETM|c}(\alpha|F_c(r_c))}{\alpha} f_c(r_c)dr_c = \frac{1}{\alpha}\int_0^1 F_c^{-1}(u_c)^2 C_{ETM|c}(\alpha|u_c)du_c$$

Likewise, to compute $\sigma^2_{c|r_{ETM} \ge r_{ETM}^{\beta}}$ we need information about $E(r_c^2|r_{ETM} \ge r_{ETM}^{\beta})$, which is:

$$E(r_c^2|r_{ETM} \ge r_{ETM}^{\beta}) = \int_{-\infty}^{\infty} r_c^2 f(r_c|r_{ETM} \ge r_{ETM}^{\beta})dr_c = \int_{-\infty}^{\infty} r_c^2 \frac{1 - C_{ETM|c}((1-\beta)|F_c(r_c))}{\beta} f_c(r_c)dr_c = \frac{1}{\beta}\int_0^1 F_c^{-1}(u_c)^2\{1 - C_{ETM|c}((1-\beta)|u_c)\}du_c .$$

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