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The impact of uncertainty shocks on energy transition metal prices

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ABSTRACT

We study whether uncertainty shocks are transmitted to energy transition metal (ETM) prices. Using a quantile vector autoregression model, we assess the impact on ETM price changes of shocks arising from economic policy uncertainty, climate policy uncertainty, geopolitical risk, financial market uncertainty, and oil price uncertainty. We document that the impact of uncertainty is U-shaped across ETM price quantiles, with modest effects in the intermediate quantiles and stronger impacts in the extreme, but mainly upper, quantiles. Climate policy uncertainty and geopolitical risk are the main uncertainty drivers in the extreme quantiles, while financial- and oil-related uncertainties have more pervasive effects in the intermediate quantiles. This evidence has implications for policymakers regarding the implementation cost of transition policies that generate uncertainties, and for investors in ETM futures markets regarding diversification and tail risk management decisions.

1. Introduction

The shift towards a net-zero carbon emissions world is metal intensive, given that new green technologies – such as electric vehicles, wind turbines, solar panels, batteries, and geothermal systems – require more metals (e.g., cobalt, lithium, nickel, aluminium, copper) than the fossil fuel alternatives. Those metals, called energy transition metals (ETMs), are called on to play a pivotal role in the transition to a low-carbon economy, and fluctuations in their prices are expected to have ramifications for the deployment of renewable energies and green technologies.

Economic, policy, and financial uncertainties around the market for ETMs, further reinforced by the transition to a low-carbon economy, potentially shape ETM prices in different ways. Depending on whether ETM use is limited to a few technologies (e.g., lithium, graphite, and cobalt) or to several technologies (e.g., also copper, and molybdenum), ETMs exhibit diverse demand risk profiles that may be affected by different low-carbon transition scenarios to a global warming maximum of 1.5ºC-2ºC (World Bank, 2020). Likewise, the ETM market is subject to supply risks, due to the geographical concentration of mining activities in a small number of developing countries. Trade disputes and social and economic tensions in producing countries could lead to geopolitical risks, with potential ramifications for the ETM supply chain and prices (Islam et al., 2023). In addition, since financial markets also play a crucial role in facilitating the transition process (Reboredo et al., 2020), the uncertainty in those markets might impact on investor willingness to fund investments in ETM mining activities or in renewable energies. Similarly, the funding of renewable energy projects might also be impacted by fluctuations in oil prices (Reboredo, 2015), with effects on the economic viability of renewable energy projects and thus on ETM prices.

In this research, we examine whether and how different kinds of uncertainty shocks shape ETM prices. Although overall uncertainty shocks lead to economic disruption (falls in output, investment, and productivity) and amplify recessions and recoveries (Bloom, 2009), we specifically identify and quantify different sources of uncertainty — including economic and climate policy uncertainty, geopolitical risk, financial market uncertainty, and oil price volatility — that could have a differential impact on the ETM market and contribute to ETM price fluctuations. This information is particularly useful for policymakers, as the way in which transition policies are implemented involves policy, economic, and financial risks that could be transmitted to ETM prices in different ways, potentially delaying the transition process through supply side issues. This transmission may differ depending on the way uncertainty shocks reverberate in different market conditions, making transition policies more or less burdensome and uncertain along the transition path to a low-carbon economy. Information on the transmission of uncertainty shocks to ETM prices is also useful for investors

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who operate in energy-related metal markets, given that uncertainty spills over from ETM prices into investments. Hence, specific risk management decisions are required to deal with diversification benefits and tail risks.

We model the relationship between ETM prices and different kinds of uncertainty using a quantile vector autoregression (QVAR) model (Cecchetti and Li, 2008; Chavleishviliy and Manganelli, 2019). The QVAR model considers the conditional quantile of a given series to be dependent on the lagged values of other series, and thus can explain whether and how average or extreme price movements in ETM prices are affected by past uncertainty shocks. This model thus accounts for the differential impact of uncertainty shocks on ETM markets, considering whether the ETM market is in a bullish, bearish, or calm state, and how investors' perceptions of uncertainty might differ. Furthermore, on the basis of the generalized forecast error variance decomposition from the QVAR model (Ando et al., 2022), we can construct a quantile-based connectiveness network that reports evidence on how the transmission of different kinds of uncertainty shocks diverge, depending on the shock size and ETM market boom and bust moments.

We conduct our empirical analysis using monthly information for different uncertainty indicators over the period 2007–2023, and ETM price information as represented by a basket of ETM futures contracts included in the Wisdom Tree Energy Transition Metals Commodity Index. Overall, our empirical evidence indicates that uncertainty plays an important role in shaping ETM price dynamics. Specifically, the impact of uncertainty is U-shaped across quantiles, with mild effects in the intermediate quantiles, and more intense effects in the extreme quantiles (predominantly in the upper quantiles). Likewise, we find that climate policy uncertainty and geopolitical risks are the main uncertainty drivers for the ETM market, mostly in the upper quantiles, while financial and oil uncertainty play a more prominent role in the intermediate quantiles. Likewise, economic policy uncertainty has an asymmetric impact on ETM price dynamics, with more pervasive effects in the extreme quantiles. We check whether and how this evidence differs over the sample period, documenting that our results on spillovers intensify during periods of heightened uncertainty, as was the case during the COVID-19 pandemic.

We contribute to the literature on the relationship between uncertainty and commodity metal markets (see literature review below) by specifically addressing how different sources of uncertainty could shape ETM prices under different market circumstances, thereby easing or hindering transition towards a low-carbon economy through the supply costs of the needed inputs. This information is particularly relevant in a context in which ETM demand is expected to be fuelled by the deployment of the renewable energies and green technologies necessary for low-carbon transition (Boer et al., 2023). Thus, uncertainty price effects on ETM prices — in particular under extreme market conditions — should be added to the expected demand price pressures on ETMs caused by growing demand.

Our evidence has clear takeaway messages for the design, implementation, and deployment speed of transition policies by policymakers, underlining the relevance of clarity, transparency, and predictability in order to avoid uncertainties associated with ETM price dynamics, and in turn, with the funding and profitability of the renewable energy deployment so necessary for the transition. Our analysis also provides useful information for risk management decision-making by investors operating in energy-related metal markets, in particular, in ETM futures markets. Abrupt uncertainty movements (a) generate tails risks that are enhanced in times of extreme ETM price movements; and (b) increase liquidity needs in ETM commodity futures, potentially causing a liquidity shock for investors when ETM price changes occur at the tails. Finally, our analysis also has implications for the modelling of energy transition effects. Integrated assessment models that consider energy transition in dynamic general equilibrium models (e.g., Nordhaus and Joseph Boyer, 2000; Hassler and Per Krusell, 2012) should take into account how uncertainties and policies surrounding the transition process itself impact on the price of the metal inputs needed for renewable energies, and consequently on inflation.

The remainder of the article is laid out as follows. In Section 2 we review the related literature. In Section 3 we present ETM price data and the main indices that reflect economic and financial uncertainties. In Section 4 we outline the QVAR model that characterizes dependence between ETM prices and uncertainty indicators in different quantiles, and describe how connectedness is computed for different quantiles on the basis of forecasted error variance decomposition. In Section 5 we present and discuss our empirical results on the quantile impact of uncertainty on ETM prices. Finally, Section 6 summarizes our analysis and concludes the paper.

2. Literature review

In this section, we briefly review previous literature on the impact of uncertainty on the market price of metals and on the market price of metals necessary for energy production.

Regarding the relationship between uncertainty and the price of precious metals, Raza et al. (2023) show that economic policy uncertainty enhances the volatility of precious metal prices, as exemplified by before and after the onset of the COVID-19 pandemic. Using a QVAR model to study the role of economic policy uncertainty in shaping connectedness between precious metals, Mokni et al. (2021) document that connectedness differs across market states and is driven by economic policy uncertainty. In contrast, from a quantile regression analysis, Reboredo and Uddin (2016) conclude that economic policy and financial uncertainty have a weak impact on metal futures, while Huynh (2020) reports that precious metal prices are mainly driven by financial market uncertainty and are relatively immune to economic policy uncertainty. Considering the effect of oil price uncertainty on precious metals, Rehman et al. (2018) document a positive effect of oil shocks on precious metal returns, reinforced during the 2008 global financial crisis.

A related strand of the literature specifically focuses on gold price dynamics and different sources of uncertainty. Gozgor et al. (2019) find that geopolitical risk explains the dynamics of gold prices, whereas Gkillas et al. (2020), through a quantile regression setup, show that geopolitical risk has predictive power regarding the conditional distribution of gold price volatility. Moreover, Beckmann et al. (2019) find a positive correlation between gold price changes and economic policy uncertainty. Similarly, in their investigation into the asymmetric effects of different uncertainty indicators on gold prices, Bilgin et al. (2018) find that gold prices go hand in hand with increased financial and economic uncertainty, and are less likely to fall when economic conditions improve. Interestingly, Chen et al. (2023) document that the gold price response to uncertainty is stronger in zero lower bound periods. Mokni et al. (2020) show that oil price shocks spill over to gold returns, and that this effect is modulated by economic policy uncertainty. Finally, from causality-in-quantile analyses of the impact of economic and equity market uncertainty on gold prices, Balcilar et al. (2016) and Raza et al. (2018) conclude that uncertainty raises gold price returns and volatility, mainly over the short run.

Focusing on metals specifically used for energy production, another branch of the literature explores how uncertainty shapes rare earth prices. Regarding trade policy uncertainty, Proelss et al. (2018) find that rare earth prices abruptly change their dynamics at times of World Trade Organization dispute resolutions. Analogously, Hau et al. (2022) document the existence of a relationship between rare earth prices and trade policy uncertainty over the long run but a weak association over the short run. Zhou et al. (2022) report that political risk spills over to rare earth prices, mainly during major economic and political events. Considering financial uncertainty, Reboredo and Ugolini (2018) confirm that volatility regimes in stock markets determine the size of the impact received and transmitted between rare earth and other markets. Finally, Song et al. (2021) demonstrate connectedness between rare earths and

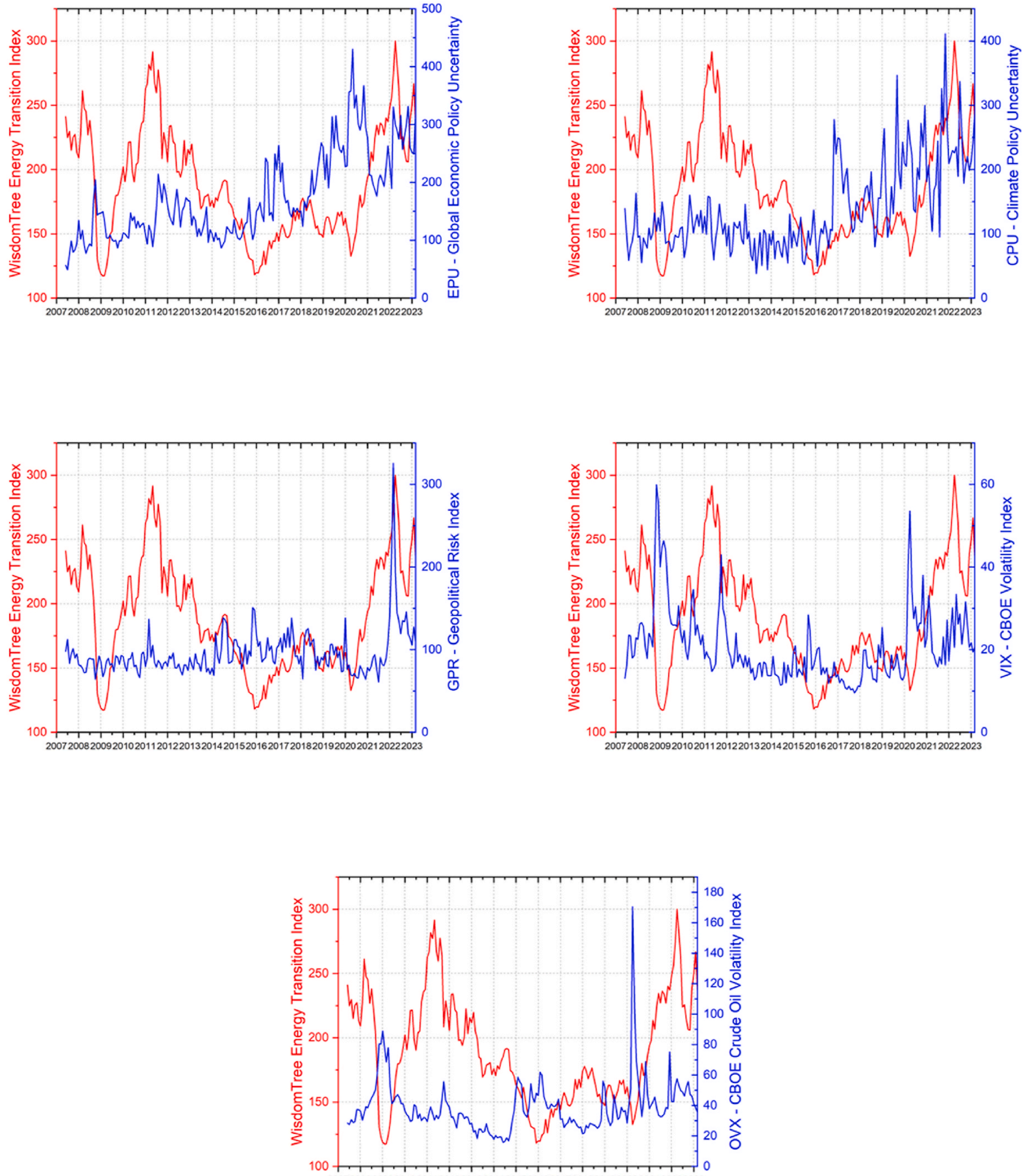


Fig. 1. The WisdomTree ETM commodity index (in red) and uncertainty indicators (in blue) June 2007–March 2023.

other commodity and financial markets shaped by uncertainty surrounding the COVID-19 pandemic, whereas Chen et al. (2022) show that rare earth markets are weakly connected with clean energy and fossil fuel markets.

As a result of climate change and the challenges posed by low-carbon transition, ETMs have been gaining prominence as key ingredients for the deployment of clean energies and green technologies, inspiring research to explore how their prices respond to different shocks. Boer et al. (2023) use scenario analysis to identify how demand shocks from an energy transition affect the prices of four ETM metals (copper, nickel, cobalt, and lithium), concluding that those metals can be expected to experience a huge increase in price and to become as important as oil for the global economy. Likewise, Ghosh et al. (2023) examine how changes in global economic sentiment are related to the price of five ETMs (aluminium, cobalt, copper, lithium, and nickel), finding that price shocks, except for cobalt, have an impact on sentiment that is accentuated under extreme market conditions. Using cross-quantilogram analysis, Karim et al. (2023) show that climate policy uncertainty is asymmetrically related to ETM prices. Moreover, Zhou et al. (2023), on examining how changes in physical and transition climate risks impact on carbon, energy, and metal markets, report evidence of more pervasive upside effects of physical risks and downside effects of transition risks.

Although the extant literature has explored the response of metal prices to different sources of uncertainty, no study to date has considered how different sources of uncertainty (e.g., economic, policy,

Table 1
Summary statistics for ETM price returns and uncertainty indicators.

	ETM	EPU	CPU	GPR	VIX	OVX
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Std. dev.	0.063	1.000	1.000	1.000	1.000	1.000
Minimum	−0.295	−1.676	−1.489	−1.241	−1.290	−1.373
Maximum	0.146	3.484	4.072	8.195	4.517	7.721
Skewness	−0.757	0.913	1.189	3.810	1.754	3.181
Kurtosis	5.391	3.173	4.268	27.531	6.950	21.737
Q(20)	29.593	1604.592	1071.800	209.144	498.702	254.049
	[0.240]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
PP	−12.157	−5.192	−8.136	−6.354	−4.898	−5.522
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Correlation matrix						
ETM	1					
EPU	−0.01	1				
CPU	0.01	0.72	1			
GPR	0.08	0.16	0.21	1		
VIX	−0.23	0.22	0.13	−0.10	1	
OVX	−0.17	0.40	0.24	0.00	0.73	1

Notes. This table presents descriptive statistics for logarithmic price changes computed for the WisdomTree Energy Transition Metals Commodity Index (ETM), and for the standardized value of uncertainty indices, including global economic policy uncertainty (EPU), climate policy uncertainty (CPU), geopolitical risk (GPR), CBOE Volatility Index (VIX), and CBOE Crude Oil Volatility Index (OVX). Data include monthly information from 1 June 2007 to 1 March 2023. Q(20) indicates the Ljung-Box statistic for serial correlation in returns (p-values for 20 lags in square brackets). PP denotes the Phillips-Perron unit root tests (p-values in square brackets). The correlation matrix reports the Pearson correlation for each pair of series indicated in the corresponding rows and columns.

financial, trade, or energy markets) contribute to movements in the market price of metals, and especially of ETMs, which are crucial metals expected to be affected by different kinds of uncertainties related to the transition towards a low-carbon economy. Our research fills this void in the literature by modelling the dependence between ETM prices and different uncertainty indicators in a multivariate QVAR setup, reporting evidence on the main uncertainty drivers of ETM prices.

3. Data

ETM market prices are represented by WisdomTree Energy Transition Metals Commodity Index values. This index comprises a basket of ETM futures contracts for transition-relevant metals —copper, silver, platinum, zinc, aluminium, nickel, lead, cobalt, tin, and lithium[1] — as essential metals for electric vehicles, charging stations, energy storage, and solar, wind, and hydrogen production. Therefore, an increase (decrease) in the value of this index indicates an increase (decrease) in ETM prices.

Our database also includes information on different economic and financial uncertainty indicators as follows. Economic uncertainty information includes information on global economic policy uncertainty (EPU), climate policy uncertainty (CPU) and geopolitical risk (GPR). Since EPU is well known to influence commodity markets (Huang et al., 2021), stock markets (Luo and Zhang, 2020), and the macroeconomy (Gu et al., 2021), and to shape asset correlations (Fasanya et al., 2021; Li and Peng, 2017), it might have a role to play in delimiting ETM price dynamics. Hence, we consider data from the global EPU index, as measured by Baker et al. (2016) using information on policy uncertainty gleaned from newspapers articles.

In addition, previous research (Faccini et al., 2021; Noailly et al., 2022) has documented that policies that deal with climate change and extreme weather change may lead to shocks that impact on investor attitudes to green investments, particularly investments in renewable technologies (Noailly et al., 2022), and consequently, uncertainty regarding climate policies may have direct and indirect impacts on ETM demand and supply, and thus, on ETM equilibrium prices. Our database therefore includes information on the CPU index as developed by Gavriilidis (2021) using the same approach as in Baker et al. (2016).

Finally, geopolitical turmoil and the resolution of disputes has an impact on trade flows of different minerals (Fan et al., 2023; Zheng-Zheng et al., 2023; Proelss et al., 2018), so those risks can also be expected to influence ETM price dynamics. Consequently, our database includes data on the GPR index created by Caldara and Iacoviello (2022) from newspaper articles on geopolitical events.

Financial uncertainty, which covers information on stock and oil price market volatility, has been documented to have macroeconomic effects (Bloom, 2009) and to impact on the pricing of stocks and metals (e.g., Ding et al., 2014; Otero and Reboredo, 2018; Pan, 2018). To assess whether financial uncertainty can capture ETM price fluctuations, we consider information on the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), computed from prices of near-term S&P500 options to reflect market expectations regarding 30-day forward-looking volatility. Likewise, since uncertainty in energy market prices affects investor expectations, inflation rates, and renewable energy and metal prices (Reboredo, 2015; Reboredo and Ugolini, 2016; Shao et al., 2021), it may be that oil price volatility could affect renewable technology deployment and ETM pricing; consequently, our database includes information on the CBOE Crude Oil Volatility Index (OVX) index, which is computed using crude oil options.

As information on the EPU, CPU, and GPR indices is available on a monthly basis, we run our analysis for monthly periods from 1 June 2007 to 1 March 2023, with the starting date of the sample determined by the availability of OVX data. Data for the CPU, CPU and GPR indices were obtained from the website www.policyuncertainty.com, while end-of-month data for ETM prices, VIX, and OVX were sourced from Bloomberg.

Fig. 1, which plots the temporal dynamics of ETM prices along with different uncertainty indices, shows that ETM price dynamics is not clearly associated with EPU and CPU dynamics (only in some periods do ETM prices and EPU and CPU move in tandem), and is not associated with GPR dynamics. The relationship between ETM prices and VIX is negative (the indices move in opposite directions), while the relationship with OVX is also negative and quite strong. Likewise, Fig. 1 graphically illustrates that ETM prices are more volatile than the uncertainty indices.

Table 1 reports descriptive statistics for ETM log price returns and for the standardized values of the uncertainty indices. The parameter estimates for those variables in the QVAR model can thus be interpreted as the ETM price response to one standard deviation in uncertainty shock.

[1] Prices of rare earth elements have not been included in our analysis since those metals are quite heterogeneous and are not expected to experience huge demand pressures in the transition to a low-carbon economy.

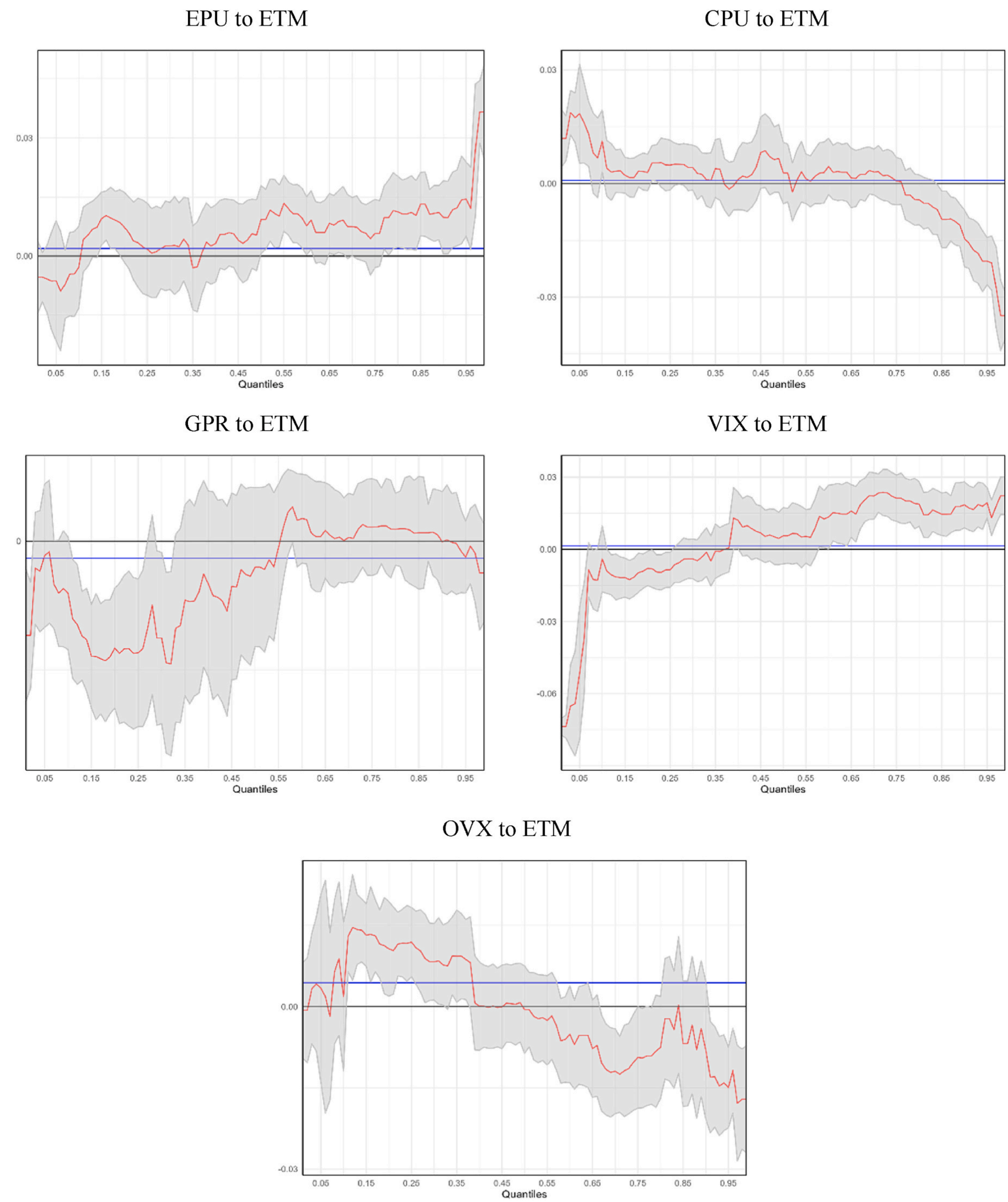


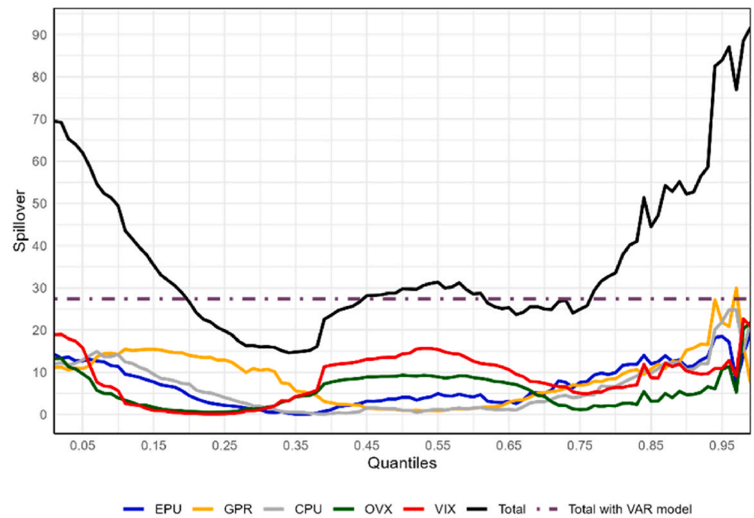
Fig. 2. Quantile VAR parameter estimates for the impact of uncertainty indicators on ETM prices in different quantiles.
Note. The blue line represents the parameter values obtained from a VAR model estimated with one lag.

ETM price returns have average monthly values close to zero, and ETM distribution is negatively skewed and shows fat tails. Regarding the uncertainty indices, their standardized values show temporal dependence and a distribution that is positively skewed and fat-tailed. According to the unit root test, all series are stationary. Finally, the Pearson correlation coefficient indicates that ETM price returns are negatively related to financial and oil price uncertainty, and unrelated to EPU, CPU, and GPR. Likewise, EPU and CPU show high linear dependence with financial uncertainty indicators, while GPR is unrelated.

4. Methods

We use a QVAR model to examine how economic and financial uncertainty shocks propagate to ETM prices. Introduced by Cecchetti and Li (2008), a QVAR model considers a quantile estimation approach in the context of a VAR model, where all variables are endogenously determined. On the basis of quantile forecast error variance decomposition from the QVAR model, we build a connectedness analysis between uncertainty and ETM prices in the spirit of the Diebold and Yilmaz (2014) approach, extended to QVAR models by Ando et al. (2022).

Panel A. Total spillovers from uncertainty indicators to ETM prices.



Panel B. Net spillovers from uncertainty indicators to ETM prices.

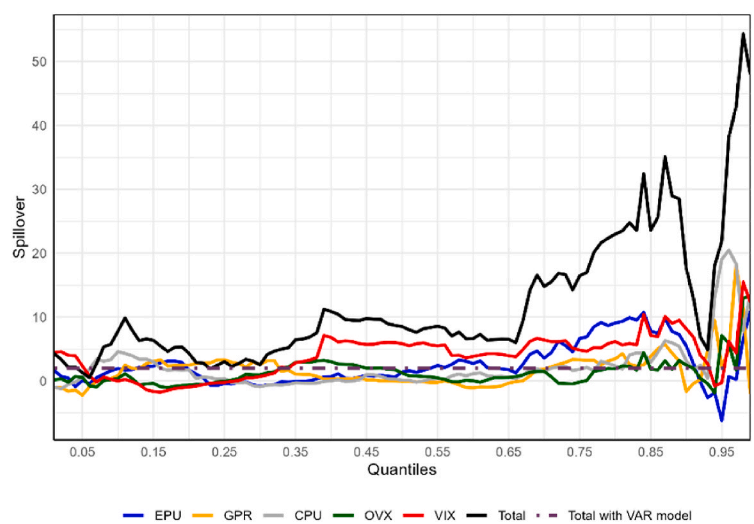


Fig. 3. Spillovers from uncertainty indicators to ETM prices in different quantiles.

4.1. The QVAR model

Let $y_t = \left(y_{1,t}, \ldots y_{k,t}\right)'$ be a kx1 vector of k endogenous variables at time $t = 1, \ldots, T$ (including information on ETM prices and uncertainty variables as discussed above), and let $\tau = (\tau_1, \ldots, \tau_k)'$ be a kx1 vector of quantiles of the conditional distribution of the variables included in y_t, with $\tau_s \in (0,1)$ for $s = 1, \ldots, k$. A QVAR model with p lags evaluated in the τ-th quantile is as follows:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} A_j(\tau) y_{t-j} + \varepsilon_t(\tau) \tag{1}$$

where $\mu(\tau)$ is a kx1 vector of intercepts at quantile τ, and $A_j(\tau)$ for $j = 1, \ldots, p$ is a kxk matrix of lagged coefficients at quantiles τ, where the element $a_{i,n}^{(j)}(\tau_i)$ accounts for the effect of the lag j of the variable n, $y_{n,t-j}$, on the τ_i-th quantile of the conditional distribution of the variable $y_{i,t}$. Thus, as the parameters of each equation may differ from the quantiles of the conditional distribution of the dependent variables, the QVAR model determines how a shock in the quantile of a variable (e.g., the median value) affects the quantile of another variable (e.g., the lowest or highest quantile). $\varepsilon_t(\tau)$ is a kx1 vector of residuals with the τ-th conditional quantile $Q_\tau\left(\varepsilon_t(\tau) \middle| y_{t-1}, \ldots, y_{t-p}\right) = 0$ when the conditional quantile model is correctly specified, and with a kxk variance-covariance matrix $\Sigma(\tau)$. Hence, the τ-th conditional quantiles of the dependent variable y_t are as follows:

$$Q_\tau\left(y_t \middle| y_{t-1}, \ldots, y_{t-p}\right) = \mu(\tau) + \sum_{j=1}^{p} A_j(\tau) y_{t-j} \tag{2}$$

For a given value of τ, and assuming that the value of p for the conditional mean model is valid for any conditional quantile, the model in Eq. (1) can be estimated using quantile regressions (see Cecchetti and Li, 2008), which are computed for the τ_i-th quantile of each variable i as:

$$\min_{\mu_i(\tau_i), a_{i,n}^{(j)}(\tau_i)} \sum_{t=1}^{T} \rho\left(y_{it} - \mu_i(\tau_i) - \sum_{j=1}^{p} \sum_{n=1}^{k} a_{i,n}^{(j)}(\tau_i) y_{t-j}\right) \tag{3}$$

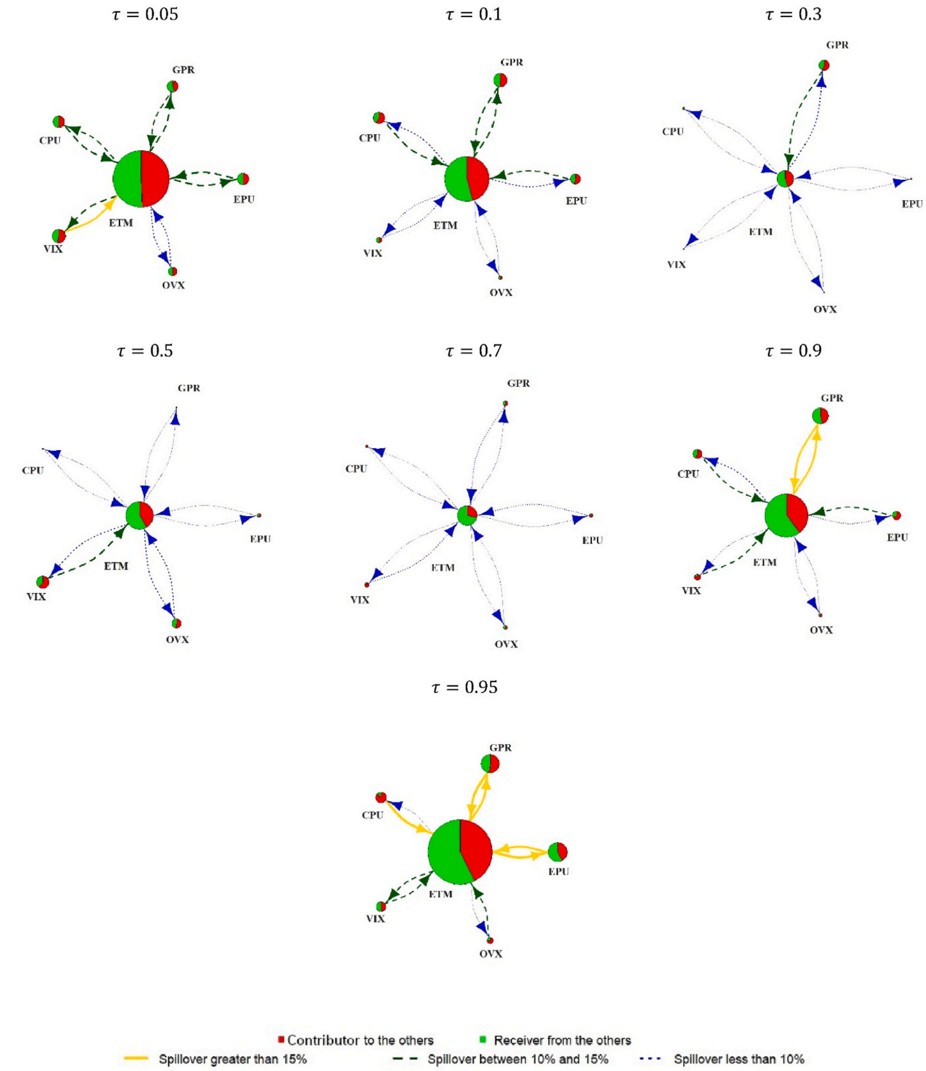


Fig. 4. Connectedness between ETM prices and uncertainty indicators in different quantiles.

where $\rho(x) = x\left(\tau_i - 1_{\{x<0\}}\right)$ is the usual check function for quantile regressions (see Koenker, 2005).

4.2. Quantile shock transmission

To assess the accumulated effects of a quantile shock over future horizons, we use Wold's representation of the QVAR(p) model in Eq. (1), which is given by:

$$y_t = \upsilon(\tau) + \sum_{h=0}^{\infty} \Psi_h(\tau)\varepsilon_{t-h}(\tau) \tag{4}$$

where $\Psi_h(\tau) = A_1(\tau)\Psi_{h-1}(\tau) + \cdots + A_p(\tau)\Psi_{h-p}(\tau)$ are the moving average (MA) coefficients, with $\Psi_0(\tau)$ equal to the kxk identity matrix and $\Psi_h(\tau) = 0$ for $h < 0$, and where $\upsilon(\tau) = \sum_{h=0}^{\infty}\Psi_h(\tau)\mu(\tau)$. Thus, the MA coefficient matrices contain information on the accumulated effects of shocks over a future horizon. As in Cecchetti and Li (2008), we assume that the quantile vector τ is fixed over the forecast horizon under analysis; hence, the vector of forecast errors for the prediction of y_{t+h}, conditional on information up to time $t-1$ and the τ-th quantile, is given by:

$$e_{t+h}(\tau) = \sum_{l=0}^{h} \Psi_l(\tau)(u(\tau) + \varepsilon_{t+h-l}(\tau)) \tag{5}$$

and the forecast error variance of this prediction derives as:

$$\Sigma_{e_{t+h}}(\tau) = \sum_{l=0}^{h} \Psi_l(\tau)\ \Sigma(\tau)\ \Psi_l'(\tau) \tag{6}$$

Now, using the h-step-ahead generalized forecast error variance decomposition by Pesaran and Shin (1998), the impact of a shock in the τ-th quantile of the variable j on variable i is given by:

$$\theta_{ij}^{(h)}(\tau) = \frac{\Sigma_{jj}(\tau)^{-1}\sum_{l=0}^{h}\left(e_i\Psi_l(\tau)\ \Sigma(\tau)e_j\right)^2}{\sum_{l=0}^{h} e_i'\Psi_l(\tau)\ \Sigma(\tau)\ \Psi_l'(\tau)e_i} \tag{7}$$

where e_i is a zero vector with 1 in the i-th position, and $\Sigma_{jj}(\tau)$ is the j-th diagonal element of $\Sigma(\tau)$. By considering $i, j = 1, \ldots, k$, we have all the elements of a kxk spillover matrix for y_t, where spillovers are evaluated in the τ-th quantile. We normalize the elements of this matrix by each row as $\widetilde{\theta}_{ij}^{(h)}(\tau) = \theta_{ij}^{(h)}(\tau)\,/\sum_{j=1}^{k}\theta_{ij}^{(h)}(\tau)$, so the sum of all components in a row equals 1. That is, this matrix accounts for the contribution of a shock in the quantile (e.g., the decile) of a variable on the quantiles of other variables (e.g., the median), providing thus a detailed picture of how changes in uncertainty may shape ETM price dynamics by considering the entire support of the distribution of ETM prices, and vice versa. Moreover, from the spillover matrix, we obtain details of the total information received by a quantile of the variable i from the quantiles of other variables as $C_{i\leftarrow j}(\tau) = \sum_{j=1, j\neq i}^{k}\widetilde{\theta}_{ij}^{(h)}(\tau)$, and the total information

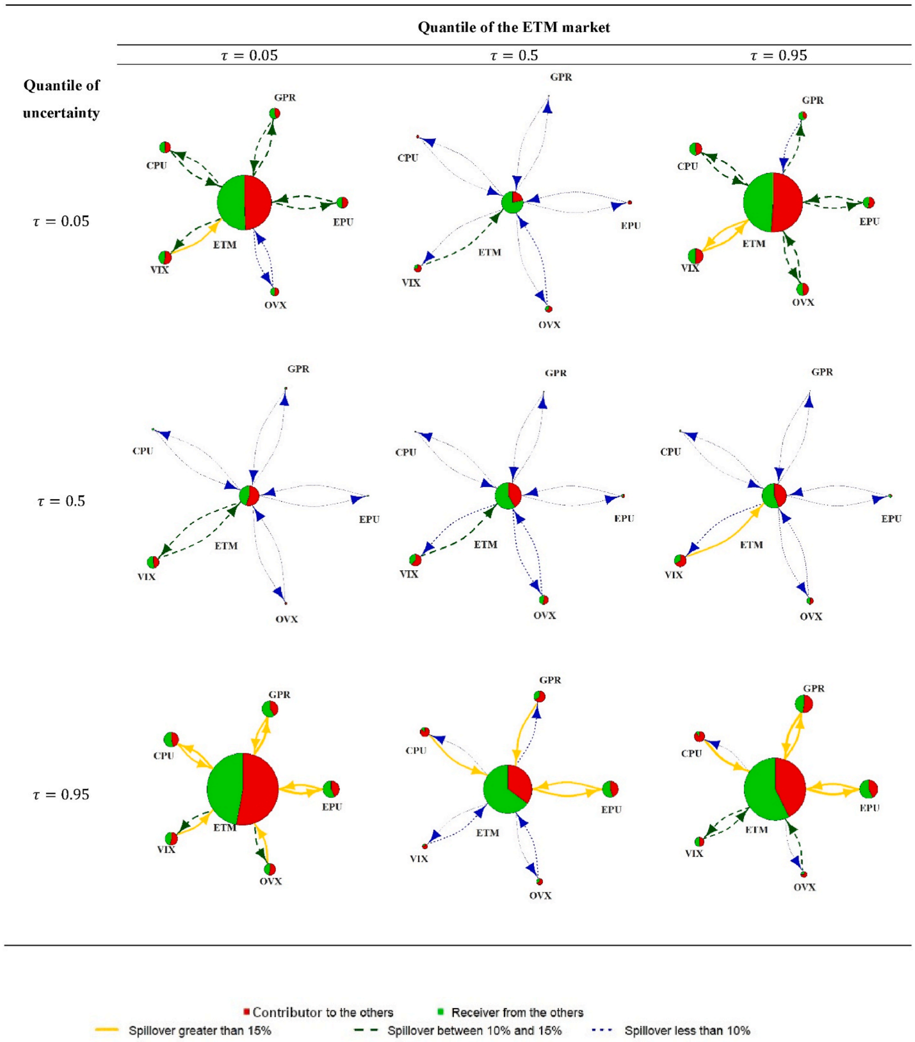


Fig. 5. Cross-quantile evidence of connectedness between ETM prices and uncertainty indicators.

transmitted by a quantile of the variable i to the quantiles of other variables as $C_{j\leftarrow i}(\tau) = \sum_{j=1, j\neq i}^{k} \widetilde{\theta}_{ji}^{(h)}(\tau)$. The difference between connectedness to and from others, $C_{j\leftarrow i}(\tau) - C_{i\leftarrow j}(\tau)$, is the net influence of the variable i on the network in the τ-th quantile.

5. Results and discussion

We estimate the QVAR model for the joint quantile dynamics between ETM price returns and uncertainty indices using one lag, selected according to the Bayesian information criterion (BIC) for a VAR model, and using a quantile range from 0.01 to 0.99 with quantile increments of 0.01. To compute spillovers, we consider forecast errors as per Eq. (5) for a 10-month horizon ($h = 10$).[2] Below we first present evidence for static spillovers and then for time-varying spillovers.

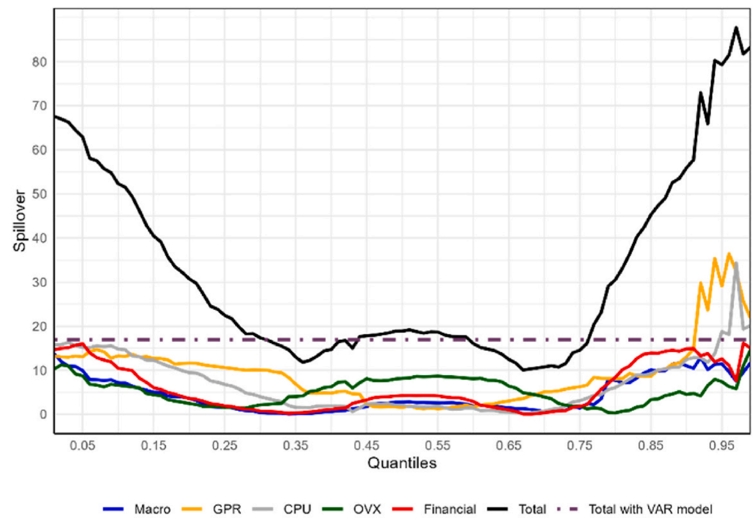
5.1. Evidence on static quantile-based spillovers

Fig. 2 presents estimations of the matrix $A_1(\tau)$ parameters that account for the effect of each uncertainty index on ETM prices in different quantiles τ (considering the same quantile value for both uncertainty and ETM price return series). The shading reflects the 68% confidence bands computed using the wild bootstrap procedure for quantile regressions as developed by Feng et al. (2011).[3] In addition, and for the purpose of comparison, we also report the parameter estimates that arise from the VAR model. Our evidence indicates that the impact of EPU on ETM is quantile dependent and asymmetric, with only the upper quantiles having a significant positive impact on ETM price dynamics. Similarly, the evidence for the CPU also indicates an asymmetric impact on ETM prices, i.e., a significant negative impact in the upper quantiles and a positive effect in the lower quantiles. As for the GPR, the estimated parameters point to negligible effects on ETM price dynamics, except for some lower-intermediate quantiles — consistent with the linear independence reported in the descriptive analysis of Table 1. In contrast, the evidence for the VIX indicates that financial uncertainty plays a relevant role in explaining ETM price dynamics for a wide set of upper and lower quantiles, and only has a negligible impact around the intermediate quantile; those impacts, besides, are asymmetric, with negative and positive parameter estimates in the lower and upper quantiles,

[2] The empirical evidence reported below is not sensitive to the choice of forecasting horizon. Results for horizons of 5, 20 and 30 months are available on request.

[3] For the sake of brevity, we only report evidence for estimated parameters of $A_1(\tau)$ that account for the direct effect of uncertainty on ETM prices. Information for the remaining parameters of this matrix and for parameters on cross-quantile effects between uncertainty and ETM prices is available from the authors on request.

Panel A. Total spillovers from uncertainty indicators to ETM prices.



Panel B. Net spillovers from uncertainty indicators to ETM prices.

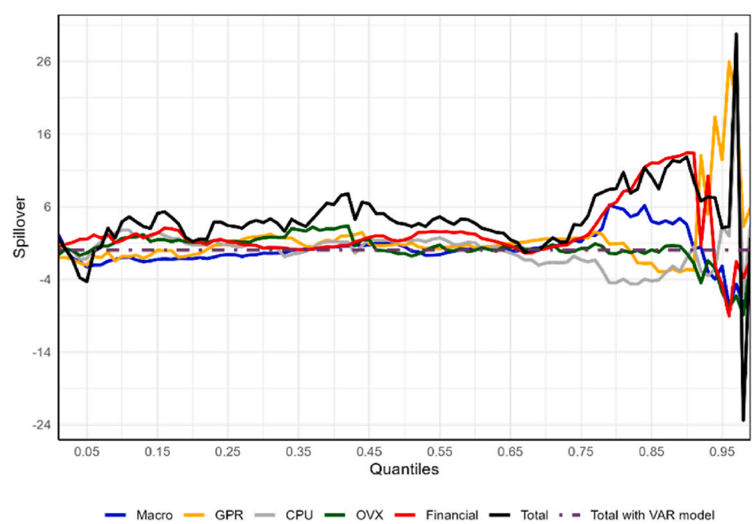


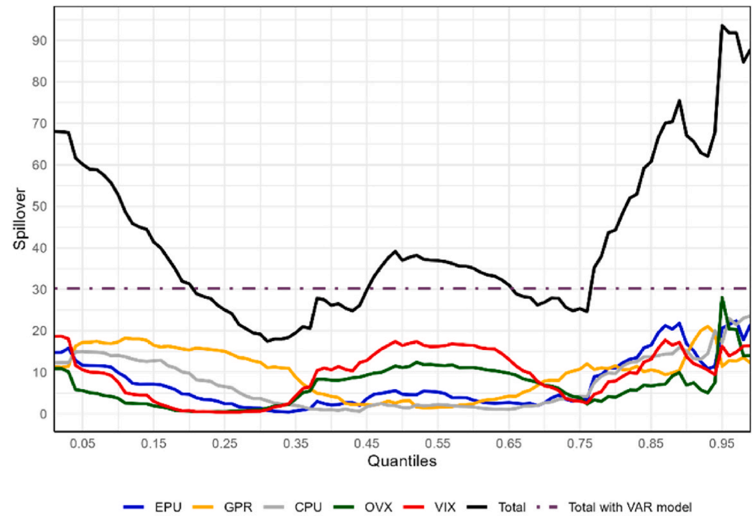
Fig. 6. Spillovers from uncertainty indicators using Macro and Financial Uncertainty Indices by Jurado et al. (2015) to ETM prices in different quantiles.

respectively. For oil price uncertainty, we find that only lower intermediate and upper quantile parameter estimates are significantly positive and negative, respectively, with no evidence of transmission effects from oil to ETMs for the remaining quantiles. Overall, parameter estimates indicate that uncertainty plays a significant role in shaping ETM price dynamics, and that those effects are quantile dependent and asymmetric, with ramifications for the size and strength of spillovers that we quantify below.

Fig. 3 presents evidence for the spillover effects from uncertainty to ETM prices in different quantiles. Fig. 3 Panel A shows that total spillovers from uncertainty to ETM prices are chiefly concentrated in the extreme quantiles, with relatively modest spillovers in the intermediate and around-intermediate quantiles. This evidence suggests that the impact of uncertainty differs across market states, consistent with previous results for precious metals reported by Mokni et al. (2021). Regarding the contribution of each uncertainty source, CPU and GPR are the main drivers of spillovers in the upper and lower quantiles, consistent with the fact that transition policies and trade or political disputes have a great impact on the deployment of renewable energies, and thus, on ETM demand. EPU has more influence on ETM prices in extreme quantiles, but a negligible impact in the intermediate quantiles. Moreover, financial market uncertainty, reflected in VIX and OVX indices, contributes greatly to ETM price changes, not only in the lower and upper quantiles, but also in the around-intermediate quantiles, consistent with the correlation evidence reported in Table 1. Overall, Panel A provides evidence that spillovers from different kinds of uncertainty to the ETM market are significant in extreme market conditions, but lower in calm markets, although financial and oil market uncertainty still have a bearing on ETM prices. This result is in line with previous evidence on the asymmetric impact of uncertainty on metal markets (e.g., Bilgin et al., 2018; Mokni et al., 2020; Raza et al., 2018) and on the impact of global sentiment on five ETMs as documented by Gosh et al. (2023). Finally, Fig. 3 Panel B shows that net (received minus transmitted) spillovers to the ETM market are asymmetric, with net positive effects in the upper quantiles and moderate effects in the remaining quantiles.

Fig. 4 graphically depicts ETM price connectedness with different uncertainty indicators at various quantile levels. Each node in this figure represents a series and the transmitted and received impacts of this

Panel A. Total spillovers from uncertainty indicators to ETM prices.



Panel B. Net spillovers from uncertainty indicators to ETM prices.

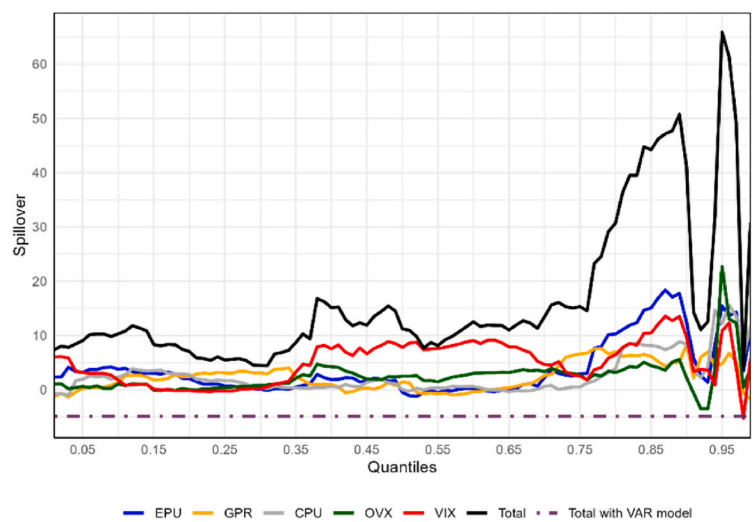


Fig. 7. Spillovers from uncertainty indicators to ETM prices in different quantiles considering the sample period 1 January 2010 to 1 December 2021.

series and the other series, with a relative size determined by the series contribution to the ETM market. The edges connecting the ETM market with different uncertainty indicators reflect the size of the transmitted/received impacts to/from the ETM market. Accordingly, the ETM market receives major impacts in the lower and upper quantiles, and only moderate impacts in the around-intermediate quantiles. In the lower quantiles, the ETM market is a near zero net transmitter of spillovers to the uncertainty indices, as impacts transmitted and received are similar. This situation is reversed for the upper quantiles, as the ETM market is a net receiver of spillovers from the uncertainty indicators. Fig. 4 also illustrates the fact that GPR, as an uncertainty source, is mainly relevant in the upper quantiles, and has minor relevance in the around-intermediate quantiles. This result is consistent with the fact that trade and political conflicts are influential when the ETM market is on the up, with prices reflecting scarcity. Similar evidence has been reported by Gkillas et al. (2020) for gold price volatility. Interestingly, Fig. 4 also shows that the relevance of CPU for ETM prices differs across quantiles: CPU is a net transmitter of effects to the ETM, with an intensity that increases by quantile. This result is consistent with the asymmetric effect of CPU on metal markets as reported by Karim et al. (2023). Hence, how climate polices are designed and the uncertainty surrounding their implementation have clear implications for the evolution of ETM prices. Finally, financial uncertainty affects ETM prices in all quantiles, with effects that intensify in the extreme upper and lower quantiles.

We finally examine to what extent the reported evidence may be affected by different circumstances in the ETM market, i.e., by different quantile levels of both ETM prices and uncertainty indicators. To that end, we evaluate the impact of the τ-th quantile of the uncertainty indicators on different quantiles of the ETM price returns. We graphically summarize our results in Fig. 5, which, like Fig. 4, accounts for all the ETM impacts transmitted to, and received from, the uncertainty indicators. Considered are different quantiles for ETM prices, indicated in the columns, and the quantile values of the uncertainty indices, reflected in the rows. The evidence confirms that extreme movements in the uncertainty indices have an impact on ETM prices that is independent of the bullish or bearish state of the ETM market. However, when the ETM market is calm, or when the uncertainty indicators are around their

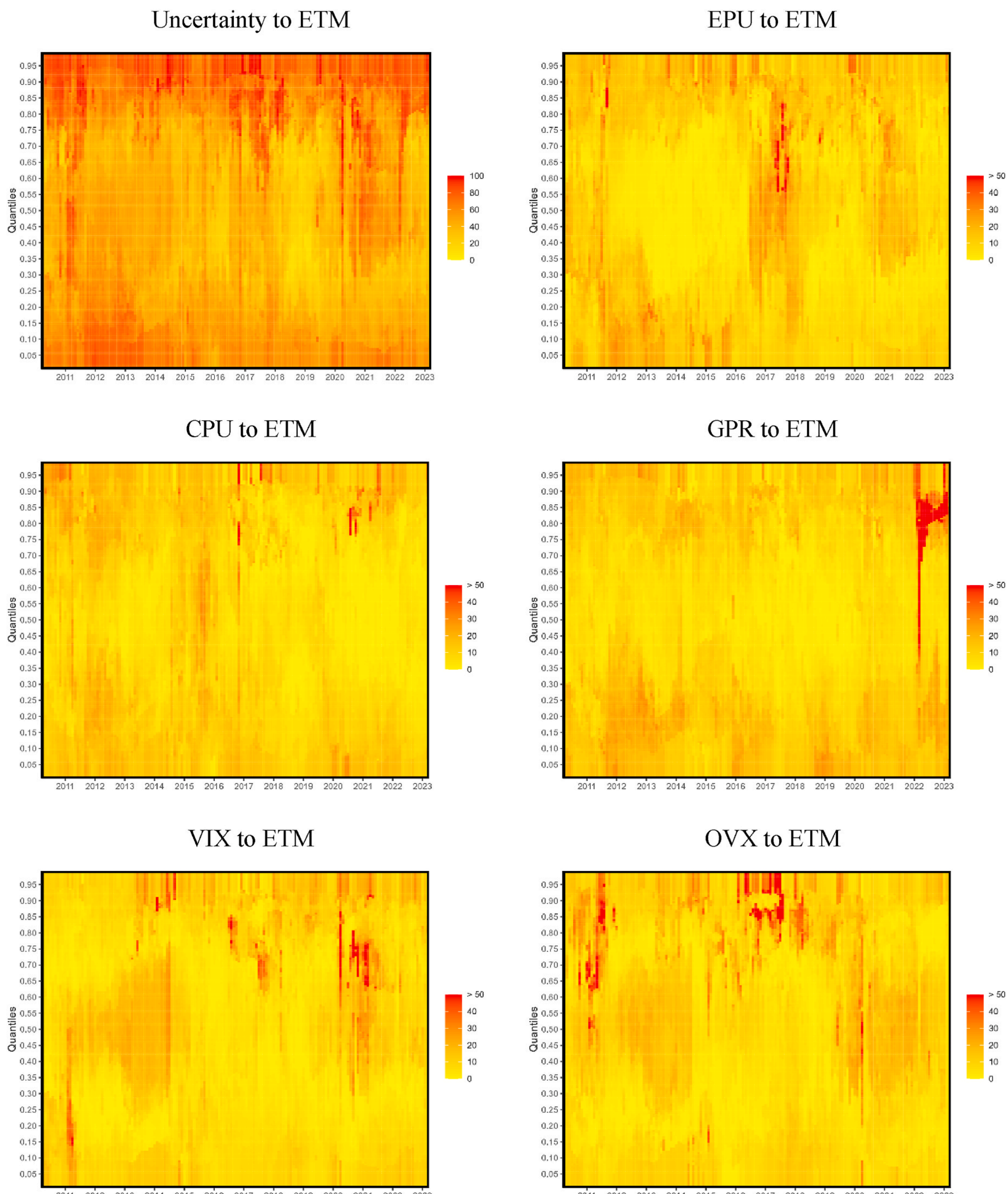


Fig. 8. Time-varying impacts from uncertainty indicators to ETM prices in different quantiles.

intermediate values, the relationship between ETM and uncertainty is weaker and, consistently, there is little evidence of spillovers between uncertainty and the ETM market.

5.2. Robustness check

We check the robustness of our previous results in two different ways. First, we consider different measures of uncertainty reported in the literature. Jurado et al. (2015) report a series of macro and financial uncertainty measures constructed from the forecast variance of a large set of variables. Likewise, Scotti (2016) describes an uncertainty index that is related to the state of the economy, while other authors use information of the forecast errors of professional forecasters (Jo and Sekkel, 2019); information on macroeconomic and professional forecasters (Rossi and Sekhposyan, 2015) or individual survey forecasts (Sheen and Wang, 2021). We run our model using information on macro and financial uncertainty by Jurado et al. (2015) to replace both EPU and OVX information. Fig. 6 illustrates that the above empirical results are insensitive to the use of alternative proxies for economic and financial uncertainty, indicated by the fact that the same U-shaped pattern reflects the information on economic and financial uncertainty.

Second, we check whether our results are impacted by the effects of the global financial crisis and the COVID-19 pandemic by restricting our sample to the period 2010–2021. Fig. 7 replicates the evidence in Fig. 4,

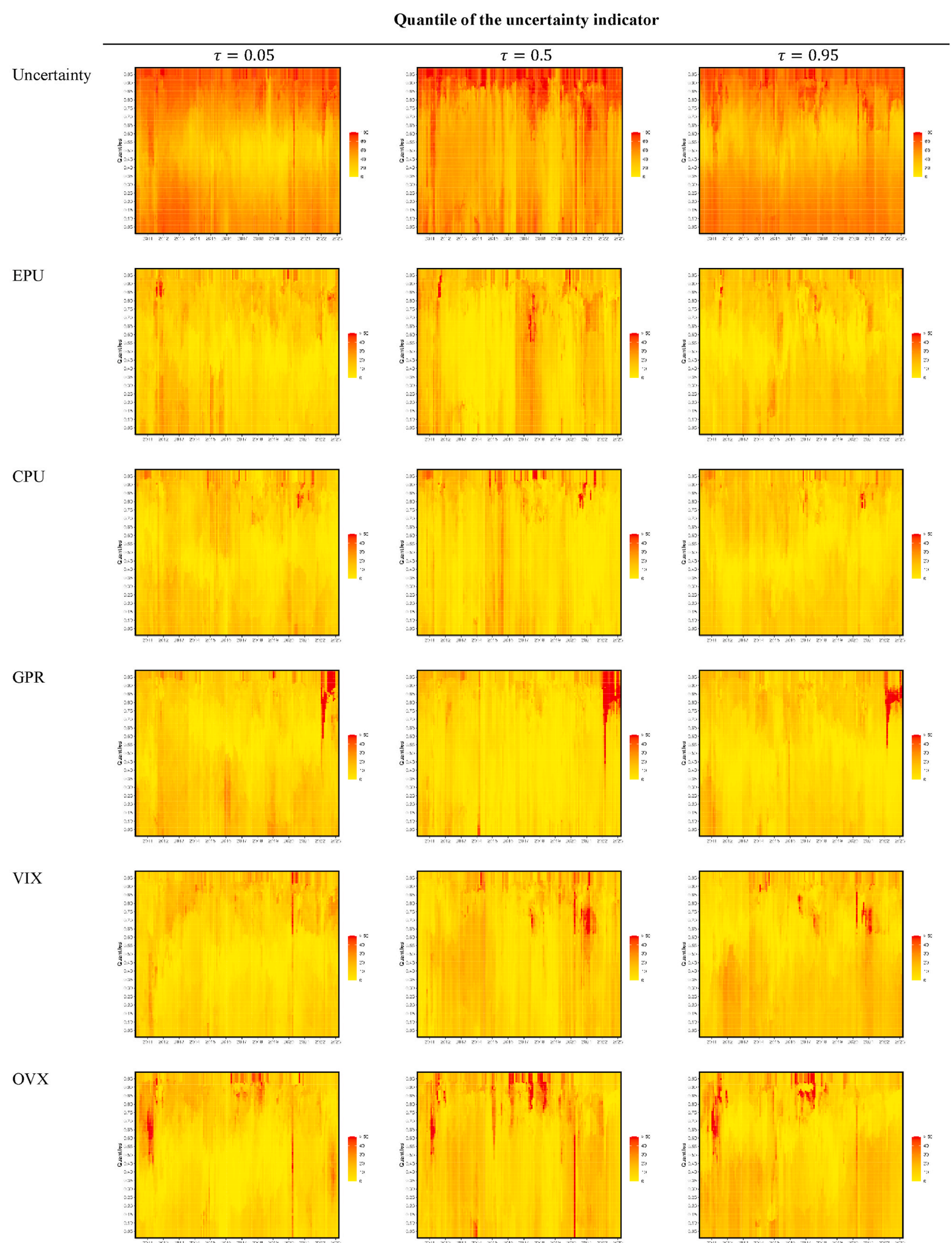


Fig. 9. Time-varying impacts from uncertainty indicator quantiles to ETM price quantiles.

showing that the spillover effects of different uncertainty sources are also U-shaped.

5.3. Evidence on time-varying quantile-based spillovers

As the impact of uncertainty on the ETM market may differ over the sample periods due to specific events (e.g., the COVID-19 pandemic), we examine to what extent our quantile evidence on the transmission of uncertainty shocks evolves over the sample period. Therefore, we run the QVAR model using a rolling window of 3 years (36 months), moved ahead on a month-by-month basis. For each window, we compute the value of quantile spillovers between the uncertainty indices and ETM prices.

Fig. 8 depicts spillover effects from uncertainty to ETM prices, showing that the uncertainty impact differs in intensity over the sample period, and that those effects are greater in the upper quantiles than in the lower quantiles. Likewise, the time-varying evidence confirms that the impact of uncertainty is much more moderate in calm markets.

Regarding different uncertainty indices, Fig. 8 indicates that EPU impact on the ETM market is mainly concentrated in the upper quantiles and varies over the sample period, with greater intensity in the second half of the sample; thus, the main effects are concentrated in 2017 and in the years immediately after COVID-19 pandemic onset. For CPU, we also find that its effects on ETM are chiefly concentrated in the upper quantiles — confirming thus its asymmetric impact — and that those effects are more intense in the latter years of the sample, mainly after the COVID-19 pandemic. Although the GPR impact is relatively moderate over the sample period and also through different quantiles, GPR was an important driver of ETM prices in the upper intermediate quantiles in the COVID-19 period, consistent with uncertainty regarding the outcome of the pandemic, trade tensions between the USA and China regarding raw materials, and the military conflict between Russia and Ukraine. As for financial and oil uncertainty, the impact of VIX and OVX is predominantly intense and time-varying for quantiles above the intermediate quantiles, confirming thus the asymmetric impact of this kind of uncertainty on ETM prices.

Finally, Fig. 9 reports graphical information on the time-varying spillover effects from uncertainty indices to different ETM price quantiles, considering different quantiles of the uncertainty indices, namely $\tau = 0.05, 0.5,$ and 0.95. The graphical evidence is consistent with the fact that effects are time-varying and asymmetric. Specifically, EPU has a time-varying impact that intensifies when the EPU and ETM quantiles increase, although this impact is mitigated in a bearish ETM market. A similar conclusion can be drawn for CPU but with a different intensity. For GPR, the evidence is consistent with that provided in Fig. 8: GPR has a significant impact in the upper ETM price quantiles in the latter years of the sample, confirming that this impact is independent of the GPR quantile. Finally, for VIX and OVX, the evidence in Fig. 7 indicates that, independently of their quantiles, those indices have a strong impact in the upper ETM price quantiles, and a lesser impact in the lower quantiles.

6. Conclusions

ETMs play a fundamental role in the transition to a low-carbon economy, as the net-zero emissions roadmap for 2050 involves the use of clean energies and green technologies that are more mineral-intensive than non-clean alternatives. Consequently, the demand for ETMs is expected to ramp up, although there is much uncertainty regarding the size of the demand and the capacity for meeting demand challenges. Therefore, economic and financial uncertainties that might emerge during the transition process could shape the dynamics of ETM prices.

In this article, we examine whether and how uncertainty shocks are transmitted to ETM prices. Considering different sources of uncertainty — including economic and climate policy uncertainty, geopolitical risk, and financial market and oil price volatility — we model the impact on ETM prices of uncertainty shocks of different sizes, as given by quantiles of uncertainty, and considering, in turn, those effects in bearish, bullish, and calm ETM markets. Using data for the period 2007–2023 and a QVAR model, we document that uncertainty shapes ETM price dynamics, with a U-shaped effect across quantiles of ETM price returns, i.e., the impact of uncertainty is modest in the intermediate quantiles, but intensifies in the extreme quantiles, and particularly in the upper quantiles. Furthermore, climate policy uncertainty and geopolitical risk are the main uncertainty drivers of ETM, principally in the upper quantiles, while economic uncertainty has an asymmetric impact on ETM prices, with more pervasive effects in the upper quantiles. In contrast, financial market and oil price volatilities mostly affect the intermediate and upper ETM price quantiles. Furthermore, in examining whether our quantile evidence differs over the sample period, we document that uncertainty spillovers intensify during periods of heightened uncertainty (such as the COVID-19 pandemic). Overall, our empirical results suggest that the impact of uncertainty shocks on ETM prices depends on the state of the ETM market and on the size and source of the uncertainty shock.

Our empirical evidence provides practical insights for portfolio and risk management decision-making by investors operating in the ETM futures market. Those investors are particularly exposed to upside risks arising from increased uncertainty, while, with the exception of energy prices, their exposure is less for downside risk. Our evidence can help investors elaborate hedging strategies based on anticipating the impact of uncertainty on the expected ETM value, which will differ depending on the state of the ETM market. Our results also have policy implications, in particular for the design and implementation of climate policies, as uncertainty surrounding those policies are transmitted to ETM prices, and so potentially hinder the energy transition process essential to a low-carbon economy. Finally, from our analysis it follows that the modelling of energy transition within integrated assessment models should account for the impact of uncertainty surrounding the transition process, as uncertainty could add costs to transition arising from the price of the necessary metal inputs for renewable energies.

CRediT authorship contribution statement

Juan C. Reboredo: Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Andrea Ugolini:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Data curation, Conceptualization.

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.

Data availability

Data will be made available on request.

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