Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company’s public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Rare earth and financial markets: Dynamics of return and volatility connectedness around the COVID-19 outbreak

Ying Song a,1, Elie Bouri b, Sajal Ghosh c,∗, Kakali Kanjilal d

a Department of Economics & Management, Nanchang Hangkong University, China
b School of Business, Lebanese American University, Lebanon
c Management Development Institute Gurgaon, Gurugram, 122001, India
d International Management Institute New Delhi, New Delhi, 110016, India

ARTICLE INFO

Keywords:
Rare earth metals
Clean energy stocks
Crude oil
TVP-VAR
Return and volatility connectedness
COVID-19
Network of connectedness

ABSTRACT

This study examines the return and volatility connectedness between the rare earth stock market and clean energy markets, world equity, base metals, gold, and crude oil. Using daily data from September 21, 2010 to August 28, 2020, a time-varying parameter vector autoregression (TVP-VAR) approach to connectedness is applied to uncover the dynamics of connectedness during the entire period and the COVID-19 pandemic period. Volatility connectedness is generally stronger than return connectedness. However, the return and volatility connectedness pattern varies over the full sample period, exhibiting a significant spike following the abrupt COVID-19 outbreak in February–March 2020. The rare earth index shows a close interdependence with the clean energy, world equity, and oil indexes during the outbreak of the pandemic, though it mostly remains a return and volatility receiver over the entire period. During the COVID-19 outbreak, the rare earth stock index becomes more central to the network of connectedness for both return and volatility, showing strong interdependence with that of crude oil prices. Our findings help investors understand diversification benefits and investment protection. They support policymakers in developing strategies for lessening import dependence on rare earth metals.

1. Introduction

Do financial markets reflect the evolving uncertainty of rare earth materials and their transmission mechanisms to clean energy and other commodities? This is a timely and key research question, especially in light of the supply chain disruptions of rare earth materials (REMs) amid the US-China trade embargo of 2019 and the COVID-19 pandemic of 2020. Our current research examines the dynamics of return and volatility spillovers between the rare earth index and five key financial markets covering clean energy, world equity, base metals, gold, and crude oil from September 21, 2010 to August 28, 2020.

REMs have emerged as an integral part of modern life because of their distinctive physicochemical properties. The world’s aspiration for a transition to clean energy away from fossil fuels necessitates the development of a new market for REMs (Hodgkinson and Smith, 2018) because REMs are key to the production of solar cells, wind turbines, and electric vehicles,2 for which there are few or no substitutes (Buchholz and Brandenburg, 2018; Müller et al., 2016; Riesgo García et al., 2017). Apart from being critical metals for the de-carbonization of the energy sector, these metals are also increasingly used in electronic, aerospace, healthcare, military, and other high-tech strategic applications (Müller et al., 2016). The demand for REMs is expected to increase by around 34 percent by 2040 for cleaner energy production alone (Nassar et al., 2016). Furthermore, the growing emphasis on clean energy also

1 Ying Song is grateful for the grant from the humanities and social sciences Foundation of High Education of Jiangxi Province (No. JC19131).
2 Reuter et al. (2013) identify dysprosium, europium, terbium, yttrium, praseodymium and neodymium, and two metals (gallium and tellurium) as ‘critical’.

https://doi.org/10.1016/j.resourpol.2021.102379
Received 24 January 2021; Received in revised form 19 September 2021; Accepted 20 September 2021
Available online 1 October 2021
0301-4207/© 2021 Elsevier Ltd. All rights reserved.
increases the demand for some base metals, the basic pillars of clean energy technologies (Grandell et al., 2016). Naturally, a robust supply chain of these strategic metals could assure a sustainable clean energy transition.

China’s dominance in the production and processing of REMs (Buchholz and Brandenburg, 2018; Mancheri et al., 2019) has posed a big threat to its supply chains. The embedded risk of REMs is reflected in the financial markets. The prices of REMs have experienced huge fluctuations in the past years and are expected to do so in the future because of huge demand growth, supply constraints, geopolitical risk, and market disruptions (Proehs et al., 2020; Schmid, 2019; Smith Stegen, 2015). Due to their strategic significance, REMs possess huge potential to evolve as a separate commodity asset class, which may be intrinsically risky (Cox and Kynicky, 2018; Fernandez, 2017; Proehs et al., 2020).

The ongoing US-China trade embargo represents additional stress on the renewable energy sector and REMs (He, 2018; Lee et al., 2020; Rogers et al., 2019). Notably, the COVID-19 outbreak makes the subject more critical because companies are now actively looking to diversify their supply chains away from China. Moreover, the market for renewable energy has shown higher resilience compared to other fossil fuel markets, which have witnessed a slump in demand during the pandemic (Kim and Karpinski, 2020). The IEA (Kim and Karpinski, 2020) predict that solar and wind capacities will double between 2020 and 2025, indicating a renewed importance of REMs.

Apergis and Apergis (2017) argue that rare earth prices are determinants of renewable energy consumption, whereas Baldi et al. (2014) highlight key economic and financial issues about rare earth materials and clean energy industries. However, research investigating the interlinkages of the rare earth index with various market indexes such as base metals, global commodities, and gold has not garnered sufficient attention in the academic world, barring a few works (Chen et al., 2020; Fernandez, 2017; Reboredo and Ugolini, 2020). Notably, these studies overlook the study of both return and volatility spillovers and the effects of stressful periods such as the COVID-19 outbreak on the dynamics and network of connectedness. In this paper, we study return and volatility transmission between the rare earth index and five key indexes, namely the clean energy index, MSCI world equity index, S&P global base metal index, global gold index, and global oil index, representing stock and commodity markets. The study period is September 21, 2010 to August 28, 2020, covering the unprecedented COVID-19 outbreak. Such a detailed analysis is important for portfolio managers in terms of diversification benefits and investment protection by showing the time-variation of both return and volatility connectedness between REMs and key financial instruments during normal and stressful periods such as COVID-19, which helps refine investment and risk management decisions. Our analysis also assists policymakers in evaluating policy decisions regarding investments in clean energies and REMs. The findings carry especially meaningful implications for investors and policymakers in the clean energy domain.

Our study advances the academic literature in the following ways. Firstly, the study is timely as the data span encompasses not only the peak of US-China trade tensions starting in 2019 but the outbreak of COVID-19 in 2020, during which financial markets experienced large price swings and extreme volatility. The beginning of the period also marks a critical juncture for rare earth markets when China introduced a stringent export policy. In light of the COVID-19 pandemic, the current study is very relevant because of two countervailing effects. The supply chains of REMs have been disrupted, which increases the uncertainty of REM stocks. A possible cartelization of these critical metals may increase their price, dampening the prospect of clean energy projects. On the contrary, the higher resilience of the renewable energy market compared to the fossil fuel market during the pandemic poses potential future challenges to REMs (Kim and Karpinski, 2020). So, the COVID-19 outbreak, coupled with increasing tension in the US-China trade relationship, may alter earlier empirical findings, revealing a new dynamic between rare earth and other financial instruments. Secondly, unlike previous works (Chen et al., 2020; Fernandez, 2017; Reboredo and Ugolini, 2020), we evaluate the dynamics of both return and volatility connectedness of the rare earth index and the five indexes using the novel time-varying parameter vector autoregression (TVP-VAR) approach (Antonakakis et al., 2018, 2020), which overcomes the shortcomings of the rolling window analysis of connectedness such as the arbitrary choice of rolling window size and the loss of observations. Thirdly, we explore the time-varying return and volatility connectedness of the rare earth index with various market indexes in total and net connectedness spillover, where the role of each index is evaluated as a receiver or a transmitter. This is conducted for the entire sample as well as for the COVID-19 period separately. So, unlike previous studies, we delve into the return and volatility dynamics of the network of six indexes in every possible way (e.g., Reboredo and Ugolini, 2020) and consider the unprecedented COVID-19 outbreak.

Our study offers some intriguing empirical evidence for both return and volatility connectedness. During the entire sample period, results of return connectedness suggest that the REM index shares the utmost connection with the base metal index, followed by the world equity index, both as a receiver and a transmitter. Gold appears to be the least connected index in the system. Overall, the base metals, world equity, and crude oil indexes play a transmitter role more than a receiver role. In contrast, the REM index is the largest receiver of return spillovers, followed by gold and clean energy. The volatility connectedness results indicate stronger connectedness among the world equity index, base metal index, and crude oil index. The crude oil index is the largest net transmitter, followed by the world equity index, while the gold and rare earth indexes remain the largest net receivers of volatility spillovers. The clean energy and REM indexes do not seem to be closely connected in either return or volatility. They stay mostly on the receiver side, catching volatility spillover from the world equity, crude oil, and base metal indexes. Crude oil leads the list in volatility transmission to others, followed by world equity and base metals. A separate return and volatility transmission analysis for the COVID-19 period indicates a stronger level of system-wide connectedness, with a noticeable change in the roles of the clean energy and crude oil indexes. Our main findings corroborate with Reboredo and Ugolini (2020), who find an interdependence among these indexes during unstable periods. During COVID-19, clean energy becomes a net transmitter of return spillovers altering the dominance of the crude oil index. However, the crude oil index takes the lead in net volatility transmission during the pandemic period. Other noteworthy results emerge during the COVID-19 period. After playing a marginal role during the full sample period, the REM index becomes more central to the network of connectedness during the COVID-19 period for both return and volatility. Importantly, during COVID-19, the REM, clean energy, and volatility indexes are connected strongly, transmitting return and volatility spillovers to each other, unlike in the full sample period during which the world equity index plays a central role connecting with the REM and clean energy indexes. Interestingly, the weak link between the REM and clean energy indexes becomes much stronger during the COVID-19 pandemic. This outcome concords with the findings of Chen et al. (2020) for the financial market in China but differs from Reboredo and Ugolini (2020), who find that REM is impacted by crude oil, clean energy, and world equity indexes.

\footnotesize 3 \footnotesize For example, solar photovoltaics (SPV) and wind energy require non-ferrous elements such as silicon, copper, silver, tin, cobalt, manganese, chromium, molybdenum, nickel, barium, indium, gallium, selenium, cadmium, and tellurium, while energy storage and electrical grids need aluminum, copper, germanium, steel, zinc, tin, lithium, cobalt, nickel, manganese, vanadium, and chromium among others.

\footnotesize 4 \footnotesize Illegal mining, which represents 30–40% of total mining activity, often depresses the market price thereby making the sector less profitable (Packey and Kingnorth, 2016). REM mining and processing have higher ecological impacts than other common metals (Wong et al., 2016).
with no feedback effects.

The emergence of rare earth metal as the central nodal point, which starts to share a strong connection with clean energy during the COVID-19 outbreak, is a significant addition to the existing limited literature. The results are logical because of the well-established and strong association of the rare earth market with the clean energy index, world equity index, and base metal index, which are intrinsically connected elements in the financial markets. These findings are not in line with previous studies (e.g., Reboredo and Ugolini, 2020), potentially due to the fact that the uncertainty due to COVID-19 coupled with stress in the trade relationship between the US and China truly capture the underlying market sentiments about rare earth usage in clean energy applications. We believe that the finding shall hold true in normal circumstances because a surge in demand for REMs is expected as many governments put clean energy transitions at the heart of their economic stimulus packages (Kim and Karpinski, 2020).

For the rest of the paper, Section 2 reviews the related literature on rare earth and financial markets. Section 3 presents the time-varying approach of connectedness used to study return and volatility transmission. Section 4 describes the dataset. Section 5 discusses empirical outcomes on return and volatility connectedness for the full sample and COVID-19 periods. Section 6 concludes.

2. Literature review

Previous studies point to the importance of rare earth metals for the transition of clean energy (Apergis and Apergis, 2017; Baldi et al., 2014; Chen et al., 2020; Münberger and Johansson, 2019; Wang et al., 2019). Accordingly, some research http://www.sciencedirect.com.mdilibrary.

remotexs.in/science/article/pii/S0301420719308311 - bib1 has explored the interdependence of REM (e.g., cerium, terbium, europium, yttrium, dysprosium, neodymium, and praseodymium) prices with clean energy stocks. For example, Baldi et al. (2014) establish an inverse relationship between dysprosium and neodymium prices and the clean energy index for January 2006 to September 2012. Apergis and Apergis (2017) find a negative relationship between REM prices and renewable energy consumption at the global and regional levels over the period 2004 to 2016.

However, studies examining the interconnectedness of the rare earth index with various market indexes such as base metal, global commodities, and gold are largely limited. Rare earth as a critical element and its historical evolution was first analysed in detail in the work of Fernandez (2017). Using pairwise correlations, Fernandez (2017) concludes that REM indexes move more closely with industrial metals and the general commodity index than with precious metals over the period January 2008 to December 2016. Chen et al. (2020) explore the volatility spillover of the Brent oil price, Mainland new energy index, and world equity index, world base metal index, world gold index, and global oil index) using a time-varying connectedness approach that overcomes the issues associated with rolling window analysis. Our sample period is September 21, 2010 to August 28, 2020, covering the COVID-19 outbreak.

3. Methods

The connectedness approach of Diebold and Yilmaz (2014) is the workhorse of modelling return and volatility spillovers among financial and economic variables. It is built on generalized forecast error variance decompositions (GFEVD) that are computed from a generalized vector autoregressive (VAR) process. Notably, the time-varying (dynamic) version of the Diebold and Yilmaz (2014) approach can be conducted using a rolling window analysis, which involves an arbitrary choice of window size and a subsequent loss of observations equal to the size of the window. To address these shortcomings, Antonakakis et al. (2020, 2018) propose a time-varying connectedness approach based on a TVP-VAR, which overcomes the shortcomings associated with rolling window analysis.5

Following Antonakakis et al. (2020, 2018), we employ the TVP-VAR approach to study the connectedness of both return and volatility series. Specifically, the TVP-VAR (1), suggested by the Bayesian information criterion (BIC), is given by:

\[
Y_t = \beta_1 Y_{t-1} + \epsilon_t; \epsilon_t | F_{t-1} \sim N(0, S_t) \tag{1}
\]

\[
vec(\beta_t) = vec(\beta_{t-1}) + \nu_t; \nu_t | F_{t-1} \sim N(0, RV_t) \tag{2}
\]

where \(Y_t\) and \(Y_{t-1}\) are \(N \times 1\) dimensional endogenous variable vectors; \(\epsilon_t\) is the \(N \times 1\) dimensional disturbance term, normally distributed with an \(N \times N\) dimensional variance-covariance matrix, \(S_t\); \(\beta_t\) is the \(N \times N\) dimensional VAR coefficient matrix; \(\nu_t\) denotes an \(N^2 \times 1\) disturbance vector that follows a normal distribution and has an \(N^2 \times N^2\) dimensional variance-covariance matrix, \(RV_t\).

In order to compute the GFEVD, the TVP-VAR is transformed into its vector moving average (VMA) representation using the Wold representation theorem:

\[
Y_t = \sum_{i=1}^{p} \beta_i Y_{t-i} + \epsilon_t = \sum_{i=1}^{m} A_i \epsilon_{t-i} \tag{3}
\]

Using the unscaled GFEVD \((\theta_{ij}^U(H)):\n
\[
\theta_{ij}^U(H) = \frac{\sum_{t=1}^{H} \sum_{t=1}^{H} (\epsilon_t A S A_t')}{\sum_{t=1}^{H} \sum_{t=1}^{H} (\epsilon_t A S A_t')^2} \tag{4}
\]

we compute the scaled GFEVD \((\theta_{ij}^S(H))\) to make sure that each row sums

5 This approach has been used by Bouri et al. (2021b).
up to unity, indicating that all variables explain 100% of variable $i$'s forecast error variance (Antonakakis et al., 2020).

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^{k} \theta_{ij}(H)} \quad (5)$$

where, $\sum_{j=1}^{k} \theta_{ij}(H) = 1$, $k$ and $e_i$ is a vector with one on the $i^{th}$ element and zero otherwise; $\tilde{\theta}_{ij}(H)$ represents a measure of the pairwise directional connectedness from index $j$ to index $i$ at horizon $H$.

Within the framework of Diebold and Yilmaz (2014), we use the GFEVD to compute various connectedness measures. Starting with the system-wide connectedness across all indexes under study (TCL), it is given by:

$$TCl_i = \frac{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \theta_{ij}(H)} \times 100 \quad (6)$$

The total directional connectedness of index $i$ to all other indexes ($C_{\bullet,i}(H)$), also known as total directional connectedness to others (TO), is defined as:

$$C_{\bullet,i}(H) = \sum_{j=1}^{N} \tilde{\theta}_{ij}(H) \times 100 \quad (7)$$

The total directional connectedness of all indexes to index $i$ ($C_{i,\bullet}(H)$), also known as total directional connectedness from others (FROM), is defined as:

$$C_{i,\bullet}(H) = \sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) \times 100 \quad (8)$$

Finally, the net total directional connectedness ($C_{i,i}(H)$) can be regarded as the influence index $i$ has on the analysed network. It is obtained from the difference between TO and FROM as follows:

$$C_{i,i}(H) = C_{\bullet,i}(H) - C_{i,\bullet}(H) \quad (9)$$

4. Data and some preliminary analyses

4.1. The dataset

Our daily dataset covers the global Rare Earth/Strategic Metals Index (REMX) and five various global indexes, namely the WILDERHILL Clean Energy Index (ECO), MSCI World Equity Index (MSCI), S&P/TSX Global Base Metals Index (SPGBM), the S&P/TSX Global Gold Index (SPGOLD), and the S&P Global Oil Index (SPOIL). The choice of these indexes is motivated by a previous study (Reboredo and Ugolini, 2020).

Data series are extracted from Bloomberg over the period September 21, 2010 to August 28, 2020, with the beginning of the sample set by data availability for the six indexes under study. The beginning of the study period is further guided by the disruption caused in the REM markets by China’s export policy towards the end of 2010, which caused a dramatic rise in REM prices from the last quarter of 2010 (Fernandez, 2017). There was a sharp fall in imports of rare earth metals from China across the globe during 2011–2012, a trend which reversed in 2013. The COVID-19 pandemic also overlaps with the data period. Fig. 1(a) shows a chronological plot of REMX and the five indexes under study. REMX seems to move in tandem with SPGOLD. Although the dynamics with the rest of the indexes appear to be mixed, synchronous upward movements of ECO, MSCI, and SPGOLD are apparent from 2016. The increasing trend in SPGBM since 2016 is not sustained after 2017. SPOIL shows a fall from 2018 after a period of steady recovery during 2016-17 following a downturn in 2014. Notably, all six indexes exhibit joint down movement during the COVID-19 outbreak from early 2020, which reflects the impact of the pandemic on the dynamics of the indexes. The impact of the COVID-19 outbreak is more apparent on the return series (Fig. 1(b)) and the volatility series (Fig. 1(c)). A close look at the volatility series (Fig. 1(c)) indicates that the most volatile period in the rare earth market was in 2011, following China’s strict export policy for REMs. ECO, MSCI, and SPGOLD also exhibited a volatility pattern in 2011.

4.2. Statistical properties of the data

The statistical properties of the daily logarithmic returns for the six indexes under study are given in Table 1a. The average returns are negative for four indexes (REMX, SPOIL, SPGOLD, and SPGBM) and positive for the rest (ECO, MSCI). The highest (lowest) standard deviation is reported for SPGOLD (MSCI), while the standard deviation of REMX stands between them. Excess kurtosis and negative skewness are omnipresent. The normality of the unconditional distribution is rebutted, as evidenced by the Jarque-Bera statistics. The Phillips–Perron (PP) test statistics show that all return series are stationary at the 1% level of significance.

The summary statistics of the volatility series, as measured by squared returns, are shown in Table 1b. Notably, the highest (lowest) average volatility is reported for SPGOLD (MSCI). For all volatility series, the skewness and kurtosis values are high. All volatility series are stationary, as shown by the PP statistics.

The correlation coefficients for the returns are shown in Table 2a. They are all positive. The highest correlation is between MSCI and SPOIL (0.778), while the lowest correlation is between MSCI and SPGOLD (0.207). REMX has its strongest correlation with MSCI (0.630) and SPGBM (0.610), and its weakest correlation with SPGOLD (0.224). ECO, SPGOLD, and SPOIL share the highest correlation with MSCI (0.768, 0.770, 0.778). SPGOLD has the least linear association with all five indexes.

The correlations between the volatility series are shown in Table 2b. The lowest correlation is for the pair REMX-SPGOLD (0.241), while the highest correlation is for the pair ECO-MSCI (0.859). SPGBM shows a high level of association in volatility with ECO, MSCI, and SPOIL.

5. Empirical results

5.1. Connectedness analyses – return series

Table 3 shows the full sample results for the return connectedness of REMX with the other five indexes, and vice versa, based on GFEVD using the TVP-VAR approach (Antonakakis et al., 2018) with a lag length of order one (BIC). GFEVD generates a $6 \times 6$ matrix shown in the first six rows and columns of Table 3. The numbers in each row of the $6 \times 6$ matrix represent the total variation in returns (%) for each index explained by its own variance and the variance of the other five indexes. Each row in the matrix adds up to 100. For example, the contribution from the five indexes to REMX amounts to 61.563%, and the rest, 38.437%, is explained by REMX itself. The numbers in each column show the contribution of each index on the other five indexes, including its own variance. For example, REMX contributes 44.951% in total to the other five indexes.

Table 3 shows that own connectedness seems to be larger than pairwise connectedness, especially for SPGOLD (67.461%), implying its ability to explain a large portion of its return connectedness. For other indexes, the own connectedness dynamics are below 40%, suggesting...
that the largest portion of return connectedness is explained by return spillovers from the other indexes in the system. For REMX, own return connectedness is 38.437%, implying that the cross-index return connectedness comprises useful incremental information for determining returns. Overall, the highest pairwise connectedness is from MSCI to SPOIL (21.117%) and from SPOIL to MSCI (20.539%). The lowest two return spillovers are from SPGOLD to ECO and MSCI (2.136% and 2.358%, respectively). To REMX, the highest pairwise return connectedness emanates from SPGBM (18.452%), followed by MSCI (14.887%), SPOIL (13.149%), and ECO (10.869%). The lowest return connectedness of REMX is with SPGOLD (4.207%). Furthermore, REMX has the highest return contribution to SPGBM (11.962%) and MSCI (10.387%). This finding is in line with Reboredo and Ugolini (2020), who establish the importance of SPGBM in explaining REMX and vice versa, although our estimates suggest a stronger connection.

For the return connectedness from all indexes to a specific index (contribution FROM others), MSCI ranks first, receiving 67.338% of spillover from the other indexes, followed by SPGBM (66.994%), SPOIL (65.939%), REMX (61.563%), and ECO (60.796%). SPGOLD receives the least from other indexes (32.539%). As for the total directional connectedness from the return of one particular index to that of the other five indexes (Contribution TO others), SPGBM is the largest contributor (83.538%), followed by MSCI (76.609%), and SPOIL (73.649%). The contribution of SPGOLD remains the smallest (18.69%). In this regard, the contribution of REMX is moderate (44.951%), standing as the second lowest. Interestingly, SPGBM, MSCI, and SPOIL play the role of transmitter more than receiver in terms of their total network connectedness. The net spillover effect is another measure used to explain the dynamics among the indexes. The last row of Table 3 is derived by deducting the contributions FROM others from the contributions TO others. The net spillover effect shows evidence in accordance with the total spillover effect. We find that the largest net transmitter of returns is SPGBM (16.544%), followed by MSCI (9.272%), and SPOIL (7.71%). Conversely, the largest net receiver of returns is REMX (−16.611%), followed by SPGOLD (−13.849%), and ECO (−3.066%). The average value of the total connectedness index amounts to 59.19%, reflecting a large degree of interdependence among the returns of the six indexes.

We present the dynamic net return connectedness in Figure A.1 in the Appendix. Based on the patterns of connectedness, we see three groups of indexes: the first includes net receivers of return spillovers for the full sample period, such as REMX and SPTGOLD; the second includes net transmitters of return spillovers, such as MSCI, SPOIL, and SPGBM, although SPOIL becomes a net receiver towards the end of the sample period; the third includes only one index (ECO) that acts as a net receiver of return spillovers during most of the sample period before becoming a net transmitter during the COVID-19 period. REMX becomes a strong receiver after 2015. Accordingly, transmitters of return spillovers should be monitored by investors and regulators if the historical pattern underlined by the system of return connectedness continues into the future.

To better understand the stability of the return connectedness among the six indexes under study, we present the time-variation in the total connectedness index. Fig. 2 shows that the total return connectedness index oscillates between 40% and 74%. A major peak is seen around mid-January 2012. This may be due to a decline in metal and energy...
prices along with a strong recovery in global equity markets post-2011. Furthermore, 2011 marks a shift in China’s export policy regarding REMs. Conversely, a major trough is seen around November 2017, when all the indexes exhibit growth momentum, indicating a relatively low volatility phase. Notably, from early February to late March 2020, which coincides with the COVID-19 outbreak, the total connectedness index spikes from 50 to over 71%, reflecting a spike in the level of integration among the return series. A few months later, the index retraces some of its upside movement but remains relatively high at around 65%. The results suggest that in a turbulent global environment, the indexes demonstrate stronger connectedness. This result is generally comparable to Reboredo and Ugolini (2020).

To consider more stylized facts with the return and volatility of the six indices under study, including volatility clustering, time-variations in conditional volatility, long memory, and fat tails, we employ GARCH and FIGARCH processes under the framework of the Dynamic Equicorrelation (DECO) model of (Engle and Kelly, 2012).

The estimation results of the AR(1)-FGARCH(1,d,1)-DECO model on the return series are presented in Table 4, where we report the results of mean and variance equations and the average correlation. The AR(1) parameter is positively significant, except for SPGOLD. Most of the ARCH and GARCH coefficients from the AR(1)-FIGARCH(1,d,1) variance equation are significant. There is evidence of a high level of persistence in all cases, as shown by the significance of the fractionally integrated coefficient (d). Regarding the DECO equation, the coefficient Alpha (0.025) is significant, suggesting evidence of short-term shocks across the return series. The coefficient Beta (0.975) is very close to one and significant, reflecting the prevalence and persistence of the long-run volatility. The sum of Alpha and Beta coefficients is slightly below one, suggesting an integrated equicorrelation. The average conditional correlation is moderate (0.345), mimicking that shown in Table 2.

As indicated by Aboura and Chevallier (2013), “the ‘natural’ way of looking at the DECO dynamics is to look at the equicorrelation”. Therefore, we mainly focus on the plot of return equicorrelation in Fig. 3, which shows time-varying patterns ranging between 0.22 and 0.75. A major trough preceded the abrupt of the COVID-19 outbreak followed by a major spike, suggesting an increase in the level of market integration during stress periods (Reboredo and Ugolini, 2020) like the COVID-19 outbreak. In fact, the spike in the level of correlation between the indices decreases the potential of diversification benefits during stress periods.

5.2. Connectedness analyses – volatility series

We present in Table 5 the volatility connectedness measures of the TVP-VAR estimates of squared returns. The numbers in Table 5 can be interpreted along similar lines to those in Table 3. The GFEVD estimates of the volatility connectedness measures indicate that own connectedness is greater than pairwise connectedness. It is mostly much higher than that reported for the return

---

7 We have assumed a student t distribution for the distributional innovations.

8 We thank an anonymous reviewer for suggesting the application of the equicorrelation model of Engle and Kelly (2012). To conserve space, readers interested in reading more about the AR(1)-GARCH(1,1)-DECO and AR(1)-FGARCH(1,d,1)-DECO models can refer to previous studies (Engle and Kelly, 2012; Mensi et al., 2019; Nasreen et al., 2020).
series, except for SPGOLD (62.119% vs. 67.461%). For REMX, its own dynamics are at 51.148%, suggesting that 49% of volatility connectedness can be explained by volatility spillovers from the volatilities of other indexes. The lowest value of own connectedness is for MSCI (35.514%). These results are quite comparable to those shown for the return series (Table 3). However, for pairwise volatility connectedness measures, including contributions FROM others’ contribution TO others, and net spillovers, the picture differs. The top three for pairwise...
volatility connectedness are from SPOIL to MSCI (22.259%), from MSCI to SPOIL (20.52%), and from SPOIL to SPGBM (20.347%). The lowest volatility transmission is between REMX and SPGOLD (2.853, 2.869). Overall, the results indicate a stronger connectedness in volatility among MSCI, SPGBM, and SPOIL, as with the return series. REMX makes very low contributions to other indexes, the maximum being to MSCI (9.014%). The volatility connectedness of REMX FROM and TO other market indexes is consistently lower than for the return series. ECO and REMX do not seem to be closely connected either in return or volatility. REMX receives more volatility spillover from MSCI (13.431%), SPOIL (13.18%), and SPGBM (11.722%) than it transmits to the others, even lower than the transmission of its return spillover to SPGBM (7.677% vs. 1.1962%). MSCI (64.486%) and SPOIL (62.846%) are the biggest receivers of contributions from other indexes. Like the return connectedness, SPGOLD (37.881%) receives the minimum. SPOIL is the largest contributor TO others (81.970%), followed by MSCI (75.244%) and SPGBM (67.738%). In contrast, SPGOLD is the smallest contributor (21.445%). The contribution of REMX (33.220%) is lower than that for the return series (44.951%). Analysing the results of net volatility transmission shown in the last row of Table 4, we find that the largest net transmitter of volatility is SPOIL (19.123%), followed by MSCI (10.758%), and SPGBM (7.375%). Likewise, the largest net receiver of volatility spillover is SPGOLD (−16.436%), followed by MVREMX (−15.632%), and ECO (−5.188%). The average total connectedness index is 55.38%, which is slightly lower than that for the return series. This result adds to previous findings that ignore the volatility connectedness among rare earth stocks and financial markets (Reboredo and Ugolini, 2020). Notably, our analysis in the next sections reveals the dynamics of the volatility connectedness during the COVID-19 period, an unexplored research topic.

Figure A.2 in the Appendix presents the net volatility connectedness. From the patterns of net volatility connectedness, we see the net receivers of volatility spillovers (REMX and SPGOLD) and the net

| Table 2a | Correlation matrix among daily returns - full sample. |  |
| REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM |  |
| REMX | 1 | | | | | |
| ECO | 0.506 | 1 | | | | |
| MSCI | 0.630 | 0.768 | 1 | | | |
| SPOIL | 0.544 | 0.652 | 0.778 | 1 | | |
| SPGOLD | 0.224 | 0.220 | 0.207 | 0.261 | 1 | |
| SPGBM | 0.610 | 0.712 | 0.770 | 0.755 | 0.401 | 1 |

Notes: This table shows the pairwise Pearson correlation coefficients among the daily return series. The sample period is September 21, 2010 to August 28, 2020.

| Table 2b | Correlation matrix among daily volatility – full sample. |  |
| REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM |  |
| REMX | 1 | | | | | |
| ECO | 0.480 | 1 | | | | |
| MSCI | 0.516 | 0.859 | 1 | | | |
| SPOIL | 0.404 | 0.636 | 0.659 | 1 | | |
| SPGOLD | 0.241 | 0.401 | 0.392 | 0.399 | 1 | |
| SPGBM | 0.514 | 0.767 | 0.752 | 0.766 | 0.493 | 1 |

Notes: This table shows the pairwise Pearson correlation coefficients among the daily volatilities, as measured by squared returns of the six indexes. The sample period is September 21, 2010 to August 28, 2020.

volatility connectedness are from SPOIL to MSCI (22.259%), from MSCI to SPOIL (20.52%), and from SPOIL to SPGBM (20.347%). The lowest volatility transmission is between REMX and SPGOLD (2.853, 2.869). Overall, the results indicate a stronger connectedness in volatility among MSCI, SPGBM, and SPOIL, as with the return series. REMX makes very low contributions to other indexes, the maximum being to MSCI (9.014%). The volatility connectedness of REMX FROM and TO other market indexes is consistently lower than for the return series. ECO and REMX do not seem to be closely connected either in return or volatility. REMX receives more volatility spillover from MSCI (13.431%), SPOIL (13.18%), and SPGBM (11.722%) than it transmits to the others, even lower than the transmission of its return spillover to SPGBM (7.677% vs. 11.962%). MSCI (64.486%) and SPOIL (62.846%) are the biggest receivers of contributions from other indexes. Like the return connectedness, SPGOLD (37.881%) receives the minimum. SPOIL is the largest contributor TO others (81.970%), followed by MSCI (75.244%) and SPGBM (67.738%). In contrast, SPGOLD is the smallest contributor (21.445%). The contribution of REMX (33.220%) is lower than that for the return series (44.951%). Analysing the results of net volatility transmission shown in the last row of Table 4, we find that the largest net transmitter of volatility is SPOIL (19.123%), followed by MSCI (10.758%), and SPGBM (7.375%). Likewise, the largest net receiver of volatility spillover is SPGOLD (−16.436%), followed by MVREMX (−15.632%), and ECO (−5.188%). The average total connectedness index is 55.38%, which is slightly lower than that for the return series. This result adds to previous findings that ignore the volatility connectedness among rare earth stocks and financial markets (Reboredo and Ugolini, 2020). Notably, our analysis in the next sections reveals the dynamics of the volatility connectedness during the COVID-19 period, an unexplored research topic.

Figure A.2 in the Appendix presents the net volatility connectedness. From the patterns of net volatility connectedness, we see the net receivers of volatility spillovers (REMX and SPGOLD) and the net

![Graph](image-url)
The third group of indexes, including ECO, MSCI, and SPGBM, are sometimes net transmitters and sometimes net receivers, especially ECO, which becomes a net transmitter of volatility spillovers during the COVID-19 outbreak. Based on these findings, investors and regulators should monitor net volatility transmitters for the sake of market stability.

The total volatility connectedness index (Fig. 4) is time-varying and ranges between the mid-30s to 71%. However, it reached 81% during the COVID-19 outbreak when uncertainty shattered the financial market suggesting an abrupt increase in the level of integration among the volatility series. REMX shows maximum volatility during the pandemic period (Kim and Karpinski, 2020), followed by SPGBM, and ECO due to supply chain disruptions, the halting of mining operations, and the worldwide lockdown effect (Kim and Karpinski, 2020). At the end of our sample, around late August 2020, the index settles to around 67%. The outcomes are similar to those for return connectedness, where the indexes show a high level of integration during turbulent periods. Notably, the indexes are more deeply connected in volatility transmission than in returns. Our findings corroborate the results of Reboredo and Ugolini (2020), who find stronger linkages among these indexes during unstable periods.

The estimation results of the AR(1)-GARCH(1,1)-DECO model are presented in Table 6. The AR(1) parameters are positive and significant, except for SPGBM. Most of the ARCH and GARCH coefficients are significant. Regarding the DECO equation, there is evidence of persistence and long-run volatility, as evidenced by the coefficient Beta (0.978), which is highly significant and very close to one. The positive dynamic Equicorrelation coefficient (0.155) implies a moderate degree of integration in the correlation across the six volatility series.

| The AR-FIARCH | REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM |
|---------------|------|-----|------|-------|--------|--------|
| Constant      | -0.054 | 0.026 | 0.059*** | 0.030 | -0.012 | 0.002 |
| AR(1)         | 0.207*** | 0.062*** | 0.145*** | 0.113*** | -0.005 | 0.067*** |
|ARCH           | 0.520*** | 0.468*** | 0.504*** | 0.611*** | 1.062*** | 0.554*** |
| GARCH         | 0.723*** | 0.220*** | 0.115 | 0.241*** | -0.005 | 0.257*** |

| The DECO     | Equicorrelation | 0.345*** |
|--------------|-----------------|---------|
| Alpha        | 0.025***        |         |
| Beta         | 0.970***        |         |
| Log Likelihood | -23259.990   |         |

Notes: This table presents coefficients estimates of the AR-FIARCH-DECO model based on the return series, where the AR-FIARCH model is estimated in the first stage and DECO equicorrelation model is estimated in the second stage. The sample period is September 21, 2010 to August 28, 2020. *** denotes the statistical significance at the 1% level.

![Fig. 3. The return equicorrelation.](image)

| Table 4 Estimates of the AR(1)-FIGARCH(1,1)-DECO model for the return series. |
|-------------------------------------|-----|-----|-----|-----|-----|-----|
| REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM |
|-------|-----|------|-------|--------|--------|
| Constant | -0.054 | 0.026 | 0.059*** | 0.030 | -0.012 | 0.002 |
| AR(1) | 0.207*** | 0.062*** | 0.145*** | 0.113*** | -0.005 | 0.067*** |
| ARCH | 0.520*** | 0.468*** | 0.504*** | 0.611*** | 1.062*** | 0.554*** |
| GARCH | 0.723*** | 0.220*** | 0.115 | 0.241*** | -0.005 | 0.257*** |

| The DECO | Equicorrelation | 0.345*** |
|-----------------|---------|
| Alpha | 0.025*** |
| Beta | 0.970*** |
| Log Likelihood | -23259.990 |

Notes: This table presents coefficients estimates of the AR-FIARCH-DECO model based on the return series, where the AR-FIARCH model is estimated in the first stage and DECO equicorrelation model is estimated in the second stage. The sample period is September 21, 2010 to August 28, 2020. *** denotes the statistical significance at the 1% level.

| Table 5 Static connectedness measures of volatility series - full period. |
|-------------------------------------|-----|-----|-----|-----|-----|-----|
| REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM |
|-------|-----|------|-------|--------|--------|
| REMX | 51.148 | 7.651 | 13.431 | 13.180 | 2.869 | 11.722 | 48.852 |
| ECO | 5.837 | 42.152 | 18.666 | 16.011 | 4.144 | 13.191 | 57.848 |
| MSCI | 9.014 | 15.004 | 35.514 | 22.259 | 3.691 | 14.519 | 64.486 |
| SPOIL | 7.839 | 12.028 | 20.52 | 37.154 | 4.863 | 17.596 | 62.846 |
| SPGOLD | 2.853 | 6.684 | 7.460 | 10.173 | 62.119 | 10.710 | 37.881 |
| SPGBM | 7.677 | 11.294 | 15.167 | 20.347 | 5.879 | 39.637 | 60.363 |
| Contribution TO others | 33.220 | 52.661 | 75.244 | 81.970 | 21.445 | 67.738 | 332.277 |
| Contribution including own | 84.368 | 94.812 | 110.758 | 119.123 | 83.564 | 107.375 | TCI = 55.38% |
| Net spillovers | -15.632 | -5.188 | 10.758 | 19.123 | -16.436 | 7.375 |

Notes: See notes to Table 3.
Looking at the volatility equicorrelation plotted in Fig. 5, there is evidence of time-varying patterns ranging between 0.09 and 0.57. Notably, a large spike trough coincides with the abrupt COVID-19, suggesting an increase in the level of market integration. In addition, the level of volatility equicorrelation eased toward the end of the sample period around August 2020, yet it remains relatively high. This finding is generally comparable to that shown in Fig. 3 and indicates the contagious effects across the volatility series during times of stress.

5.3. Connectedness during the COVID-19 period

To better understand the connectedness of REMX with the other five indexes during the COVID-19 outbreak, we study the period 2 January to August 28, 2020 separately. The correlation coefficients between the return (volatility) series during the COVID-19 period are presented in Appendix Table A.1 (A.2). Both tables show stronger correlation coefficients than during the full sample period. We also present the descriptive statistics of daily returns and volatility of the rare earth stock index and the indices of clean energy, world equity, base metals, gold, and crude oil during COVID-19 outbreak in Appendix Table A.3 and Table A.4, respectively.

We regress the total connectedness index of return series on a dummy variable representing the COVID-19 outbreak to show the impact of the pandemic on the dynamics of the total connectedness across the return series. We do this for the total connectedness index of the volatility series too. The results are not reported here, but they are available upon request from the authors. They show that both total connectedness indices have increased following the abrupt of the pandemic, as indicated by the significant and positive coefficient associated with the dummy variable. Notably, the dummy variable coefficient is much stronger for the total volatility connectedness (9.960 and a t-statistic of 15.125) than that for the total return connectedness (4.831 and a t-statistic of 7.363). To further capture the dynamics of returns and volatility connectedness during the unprecedented period of the COVID-19 outbreak, we rerun the TVP-VAR model for both return and volatility series from January 2, 2020 to the end of the sample period i.e., August 28, 2020. The results presented in Table 7 show stronger return connectedness measures, including the total connectedness index, which increases from 59.19% to 66.52%. In fact, the results underline the greater effect of extreme shocks such as COVID-19 on the system of return connectedness. The contributions TO others and contributions FROM others are much stronger than for the full sample period, with no major shift in the role of these indexes. For instance, SPGBM contributes the maximum variance to others, followed by MSCI, as in the full sample, but during the pandemic period, SPGBM explains a total of 93.148% compared to 83.538% in the full sample. Similarly, MSCI contributes 85.95% as opposed to 76.609% in the full sample period. Notably, ECO (82.491% vs. 57.73%) becomes a prominent contributor to others during the COVID-19 period. This is further reflected in net volatility transmission, where ECO is a net transmitter of spillovers, and SPOIL becomes a net receiver of spillovers during COVID-19. These results are not surprising given previous evidence that connections among markets tend to intensify during crisis periods (Reboredo and Ugolini, 2020) and the prominence of ECO over SPOIL in the financial market (Bouri et al.,

Notes: See notes to Figure 2.

Table 6
Estimates of the AR-GARCH(1,1)-DECO model for the volatility series.

|                  | REMX | ECO  | MSCI  | SPOIL | SPGOLD | SPGBM |
|------------------|------|------|-------|-------|--------|-------|
| **The AR-GARCH** |      |      |       |       |        |       |
| Constant         | 1.755*** | 2.200*** | 0.806** | -0.219 | 4.193*** | 3.262*** |
| AR(1)            | 0.139*** | 0.175*** | 0.570*** | -0.448* | 0.244** | -0.072 |
| ARCH             | 0.022**  | 0.065*** | 0.108*** | 0.203   | 0.059*** | 0.116** |
| GARCH            | 0.977*** | 0.934*** | 0.891*** | 0.796*** | 0.940*** | 0.883*** |
| **The DECO**     |      |      |       |       |        |       |
| Equicorrelation  | 0.155*** |        |       |       |        |       |
| Alpha            | 0.008*      |        |       |       |        |       |
| Beta             | 0.978*** |        |       |       |        |       |
| Log Likelihood   | -41826.871 |  |       |       |        |       |

Notes: This table presents coefficients estimates of the AR-GARCH-DECO model, where the AR-GARCH model is estimated in the first stage and DECO equicorrelation model is estimated in the second stage. The sample period is September 21, 2010 to August 28, 2020. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
2019; Ferrer et al., 2018; Nasreen et al., 2020).

The effect of the COVID-19 outbreak on the connectedness measures is also much stronger for the volatility series. Table 8 shows that the total volatility connectedness index spikes from 55.38% to 78.08%. The cross-index volatility connectedness becomes larger to the detriment of the own volatility connectedness. For example, the total volatility contribution from the five indexes to REMX is 82.446% compared to 48.852% during the entire sample period. A similar trend is observed for the other indexes. SPGOLD (37.881%) receives the minimum contribution from others in the full sample compared to 79.651% in the COVID-19 period. These findings align with Reboredo and Ugolini (2020), who establishes that the transmission from indexes other than the SPGBM increases substantially in the high volatility state. Interestingly, the volatility transmission from REMX (19.591%) to others is minimum during the COVID-19 outbreak. So, REMX becomes a larger net volatility receiver (−62.856%), followed by SPGOLD (−20.989%). SPOIL (32.329%), SPGBM (22.929%), and MSCI (20.187%) remain the three largest net volatility transmitters, with SPOIL taking the first position in the COVID-19 period. The role of ECO reverses from a net receiver (−5.188%) to a net transmitter (8.405%) of volatility spillover in the pandemic period. The outcomes are quite similar to those for the return variability transmission in terms of stronger connectedness during the COVID-19 outbreak. However, it is apparent that SPOIL (32.329%) continues to take the lead in net volatility transmission during the pandemic, although it becomes a net receiver in terms of return connectedness. EO (8.405%) ranks fourth as a net transmitter of volatility spillover, directing crude oil dominance in volatility transmission to the financial markets. Our findings are generally comparable to the works of Dutta et al. (2020), Lundgren et al. (2018); Uddin et al. (2019), and Zhang and Broadstock (2020).

We graphically represent the connectedness between the six indexes during both the full sample period and the COVID-19 period for both returns and volatilities. Fig. 5 and 6 generally show that the connectedness varies between the return and volatility series periods. The network of return connectedness (Fig. 4(a)) shows a weak system-wide connectedness. The return spillovers are strong among SPGBM, MSCI, ECO, and SPGOLD, but SPGBM is the recipient of return spillover from SPOIL, SPGBM, MSCI, and ECO. REMX is connected to SPGOLD via SPGBM. REMX shows a weak connectedness with ECO and SPOIL.

The patterns of volatility connectedness are shown in Fig. 6(b). They exhibit some similarities with Fig. 6(a), although stronger connectedness emerges, especially between REMX and ECO and, to a lesser extent, REMX and SPGOLD.

During the COVID-19 outbreak, the returns and volatility connectedness networks become more complex, reflecting a much stronger system-wide connectedness. After playing a marginal role during the full sample period, REMX becomes central to the network of connectedness during the COVID-19 period, for both return and volatility, even though it acts as a leading receiver of spillovers. Fig. 7(a) shows that the graphical visualization of return connectedness is powerful across REMX, ECO, MSCI, SPGBM, and SPGOLD, consistent with Table 7. Similar yet somewhat stronger connectedness is revealed in Fig. 7(b) for the volatility series, indicating the intensity brought about by COVID-19 on the system of volatility connectedness. Higher degrees of co-movement among markets during turbulent periods align with previous research (e.g., Reboredo and Ugolini, 2020). Importantly, during the COVID-19 period, REMX, ECO, and MSCI are interconnected strongly, transmitting return and volatility spillovers to each other, unlike in the total sample period where MSCI plays a central role connecting with REMX and ECO. SPOIL is interlinked with REMX, ECO, and MSCI, mostly in the volatility spillover effect. The results are similar to those shown in Table 8 and support the works of Chen et al. (2020), who suggest that the volatility between crude oil and clean energy gets passed through China’s rare earth market. The weak link between REMX and ECO becomes much stronger over the COVID-19 period. Our results show a close bond between REMX and ECO during the COVID-19 period when volatility is highly pervasive in the financial markets, which broadly falls in line with Apergis and Apergis (2017), who find a long-term relationship between rare earth prices and renewable energy consumption in a not-so-disruptive economic environment. However, this finding differs from Reboredo and Ugolini (2020), who show that REMX is impacted by oil, clean energy, and MSCI with no feedback spillovers from REMX. Our findings indicate that the COVID-19 outbreak has shaped the dynamics of connectedness between rare earth stocks and financial markets, leading to a feedback effect.

Accordingly, our analysis extends previous findings (e.g., Reboredo and Ugolini, 2020) that generally suggest a very weak connection between REMs and key financial instruments such as crude oil and clean

Table 7

| Contribution TO others | REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM | Contribution FROM others |
|-----------------------|------|-----|------|-------|--------|-------|-------------------------|
| 62.856                | 8.405| 20.187| 37.144| 112.776| 78.081| 118.791|
| 48.852                | 11.341| 20.663| 37.144| 112.776| 78.081| 118.791|
| 52.920                | 82.491| 85.95| 66.191| 18.426| 93.148| 399.126|
| 82.446                | 85.95| 85.95| 85.95| 85.95| 85.95| 85.95|
| 32.329                | 9.288| 20.905| 14.48| 2.911| 21.459| 73.174|
| 12.309                | 9.288| 20.905| 14.48| 2.911| 21.459| 73.174|
| 9.235                | 27.462| 21.988| 31.889| 3.153| 21.446| 68.111|
| 11.225                | 27.462| 21.988| 31.889| 3.153| 21.446| 68.111|
| 52.920                | 82.491| 85.95| 66.191| 18.426| 93.148| 399.126|
| 52.920                | 82.491| 85.95| 66.191| 18.426| 93.148| 399.126|

Table 8

| Contribution TO others | REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM | Contribution FROM others |
|-----------------------|------|-----|------|-------|--------|-------|-------------------------|
| 62.856                | 8.405| 20.187| 37.144| 112.776| 78.081| 118.791|
| 48.852                | 11.341| 20.663| 37.144| 112.776| 78.081| 118.791|
| 52.920                | 82.491| 85.95| 66.191| 18.426| 93.148| 399.126|
| 82.446                | 85.95| 85.95| 85.95| 85.95| 85.95| 85.95|
| 32.329                | 9.288| 20.905| 14.48| 2.911| 21.459| 73.174|
| 12.309                | 9.288| 20.905| 14.48| 2.911| 21.459| 73.174|
| 9.235                | 27.462| 21.988| 31.889| 3.153| 21.446| 68.111|
| 11.225                | 27.462| 21.988| 31.889| 3.153| 21.446| 68.111|
| 52.920                | 82.491| 85.95| 66.191| 18.426| 93.148| 399.126|
| 52.920                | 82.491| 85.95| 66.191| 18.426| 93.148| 399.126|

Notes: The sample period is January 2, 2020 to August 28, 2020.
Fig. 5. The volatility equicorrelation.

Fig. 6a. Graphical representation of return connectedness during the full period.

Fig. 6b. Graphical representation of volatility connectedness during the full period.

Fig. 7a. Graphical representation of return connectedness during the COVID-19 period.

Fig. 7b. Graphical representation of volatility connectedness during the COVID-19 period.
energy markets and, therefore, the possibility of using these two markets as hedging instruments for REMs. Our findings successfully establish a relatively strong connection between REMs and the markets of clean energy, world equity, and base metals, which are found to be interlinked. They provide evidence that extreme market events can later create the dynamics of returns and volatility spillovers, which concords with Bouri et al. (2021a).

6. Conclusion

The widespread application of REMs in cleaner energy production and some strategic sectors of the economy make these specific metals critical to modern society. The growing importance of REMs has resulted in phenomenal growth in demand, drawing attention from global investors. Although REMs are available in many geographical locations, China enjoys a near-monopoly in supply. Notably, the outbreak of COVID-19 has caused precariousness in the supply chains of REMs, evident in price oscillations. As a result, REMs can evolve as an attractive asset class that is inherently risky. This characteristic of REMs warrants in-depth exploration of the dynamics of their return and volatility spillovers to other financial instruments, and vice versa, a new arena of research. In this study, we investigate the time-varying return and volatility transmission of the rare earth stock index with the clean energy index, world equity index, global base metal index, gold index, and global crude oil index for the period September 21, 2010 to August 28, 2020 using the TVP-VAR connectedness approach. We undertake the same investigation during the COVID-19 pandemic separately. One of our work’s unique contributions is its examination of both return and volatility spillovers when the global focus on REMs is at its peak; hence the current study helps establish landmark findings for the financial markets and advances the less explored existing literature with its methodological aptness and empirical findings.

Our main results suggest that, for the full sample period, the base metals, world equity, and crude oil indexes are the main transmitters of return spillovers, whereas REMX is the main receiver of return spillover, followed by gold and clean energy. The crude oil and world equity indexes demonstrate the strongest link, while the gold index is the least connected instrument. The volatility connectedness results also indicate a stronger connectedness among base metals, world equities, and crude oil, with gold and rare earth indexes being the largest net receivers of volatility. Interestingly, the clean energy and rare earth indexes are weakly linked in terms of both return and volatility for the full period. They stay mostly on the recipient side, receiving volatility spillovers from base metals, world equities, and crude oil. During the COVID-19 period, some interesting findings emerge. The network shows stronger connectedness both in return and volatility, suggesting higher market integration in these turbulent days. REMX becomes more central to the network of connectedness for both return and volatility. Notably, REMX, clean energy, and world equities are interconnected, transmitting return and volatility spillovers to each other, unlike the full sample period. Crude oil is also strongly interconnected with REMX, clean energy, and world equities based on volatility transmission.

Overall, our analysis adds to the academic literature, which establishes rare earth metal as the central nodal point, connected with clean energy stocks and the key commodity market, barring gold. Our results contest the previous finding that REMs function as an independent market entity having a weak connection with key financial instruments such as base metals, clean energy, crude oil, and gold (Reboredo and Ugolini, 2020). The results are intuitive, as REMs, base metals, and clean energy are fundamentally connected. The emergence of REMs as the central point primarily manifests its vital role in the transition from fossil fuels to cleaner energy and other critical industrial applications across the globe. Amid the COVID-19 outbreak and rising negative sentiments for China, importers of REMs realize the significance of indigenous production and recycling of REMs to attain supply chain security. Global investors have also become more interested in investing in clean energy sectors and divesting traditional fossil fuels, which intensifies the growth in demand for REMs and makes these strategic metals an attractive investment without ignoring the risk due to their tenuous supply chains.

The empirical evidence has meaningful implications for investors and policymakers. For investors, our findings matter to portfolio and risk management as they suggest that crude oil and clean energy cannot act as hedges against the risk of REMs, and neither world equities nor base metals can play that role. Notably, gold appears to be the only hedging instrument for REMs, implying that investors can use gold to prevent the risk from REMs; however, with gold receiving significant volatility spillover from other commodity indexes, the REM index may soon catch the trend. Furthermore, the fact that return volatility spillovers are time-varying implies that investors might need to adopt a dynamic approach for managing the risk spillovers between the REM index and other assets when they are combined in one portfolio. This is very relevant during turbulent periods. The evidence of a strong interdependence between rare earth and crude oil markets points to higher market integration and thereby to low possibilities for diversification. Based on our evidence, investors should be cautious when investing in the market of REMs as it does not function as an independent market anymore, especially during the COVID-19 outbreak. Accordingly, investors should eventually search for a new hedging instrument for REMs and clean energy other than gold, which might open new research paths dealing with this emerging evidence. This is relevant given that investors may think that "the sectors thriving on rare earth are insulated from the price fluctuations of this critical element and hence may ponder investing in these indexes without considering the potential supply risk of rare earth elements" (Bouri et al., 2021a). With the outbreak of COVID-19, the global supply chain of REMs is disrupted due to many countries’ complete or partial lockdown and halting the mining operations. Apart from that, many companies associated with REM mining have decided to slash their budgets for planned investments (Kim and Karpinski, 2020). An escalated demand for REMs is predictable as the economic stimulus package provided by many governments place clean energy transition as one of the objectives. It is aligned with the IEA’s (International Energy Agency’s) prediction on the requirement of rare earth and other strategic metals for a clean energy transition that forecasts a quadruple rise by 2040 than their current level of consumption under “Sustainable Development Scenario (SDS)” (IEA, 2021). Moreover, IEA predicts that key REMs like neodymium and dysprosium will face supply shortages (IEA, 2021). Interestingly, the policymakers must ensure an alternative green supply chain for REMs and their indigenous mining and recycling projects to successfully implement the clean energy transition. They also need to make sure that the investment in the sector remains uninterrupted and sustainable. Socially responsible investing options like green bonds can play a major role in this regard. Such measures may help to reinforce less dependence on China for the supply of REMs.

Future studies can consider applying a structural VAR version of the TVP-VAR approach (Chan et al., 2020) or a frequency approach of connectedness (Barunik and Krehlik, 2018). Another possibility is to uncover tail dependency between the rare earth stock market and the markets of clean energy, world equity, base metals, gold, and crude oil using conditional quantiles and tail dependence (Bouri and Jalkh, 2019). For a more in-depth study, researchers can conduct empirical analyses involving high-frequency data (Qu et al., 2021).

CRediT authorship contribution statement

Ying Song: Software, Validation, Formal analysis, Data curation, Writing – review & editing. Elie Bouri: Conceptualization, Data curation, Validation, Formal analysis, Writing – review & editing, Project administration. Sajal Ghosh: Conceptualization, Validation, Writing – original draft, Writing – review & editing, Supervision, Project administration. Kakali Kanjilal: Conceptualization, Validation, Writing – original draft, Writing – review & editing, Project administration.
Appendix

Table A.1
Correlation matrix among daily returns - COVID-19 period

|       | REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM |
|-------|------|-----|------|-------|--------|-------|
| REMX  | 1    |     |      |       |        |       |
| ECO   | 0.632| 1   |      |       |        |       |
| MSCI  | 0.696| 0.894| 1    |       |        |       |
| SPOIL | 0.566| 0.686| 0.711| 1     |        |       |
| SPGOLD| 0.254| 0.381| 0.311| 0.297| 1      |       |
| SPGBM | 0.660| 0.88 | 0.893| 0.780| 0.408  | 1     |

Notes: The sample period is January 2, 2020 to August 28, 2020.

Table A.2
Correlation matrix among daily volatility - COVID-19 period

|       | REMX | ECO | MSCI | SPOIL | SPGOLD | SPGBM |
|-------|------|-----|------|-------|--------|-------|
| REMX  | 1    |     |      |       |        |       |
| ECO   | 0.623| 1   |      |       |        |       |
| MSCI  | 0.636| 0.903| 1    |       |        |       |
| SPOIL | 0.588| 0.646| 0.639| 1     |        |       |
| SPGOLD| 0.444| 0.651| 0.610| 0.603| 1      |       |
| SPGBM | 0.605| 0.841| 0.803| 0.847| 0.740  | 1     |

Notes: See notes to Table A.1.

Table A.3
Statistical properties of daily returns - COVID-19 period

|       | Mean | Median | Max | Min | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | PP |
|-------|------|--------|-----|-----|-----------|----------|----------|-------------|----|
| REMX  | 0.008| −0.100 | 6.453| −8.116| 2.523     | −0.323   | 3.816    | 7.404**     | −12.668*** |
| ECO   | 0.312| 0.552  | 13.399| −16.239| 3.839     | −1.146   | 7.336    | 164.403***  | −14.138*** |
| MSCI  | 0.022| 0.137  | 8.059| −9.997| 2.082     | −1.171   | 10.031   | 375.304***  | −15.203*** |
| SPOIL | −0.276| −0.370| 13.797| −21.865| 3.654     | −1.673   | 13.097   | 773.102***  | −11.199*** |
| SPGOLD| 0.226| 0.213  | 12.360| −14.007| 3.510     | −0.322   | 5.711    | 53.064***   | −11.795*** |
| SPGBM | −0.031| 0.039  | 16.627| −16.478| 3.887     | −0.622   | 8.060    | 185.537***  | −15.717*** |

Notes: The sample period is January 2, 2020 to August 28, 2020. The PP test is conducted with a trend and intercept; lag length is selected based on Schwarz information criterion (SIC). **, *** indicate statistical significance at 5% and 1% levels.

Table A.4
Statistical properties of daily volatility - COVID-19 period

|       | Mean | Median | Max | Min | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | PP |
|-------|------|--------|-----|-----|-----------|----------|----------|-------------|----|
| REMX  | 6.324| 2.136  | 65.875| 0.002| 10.638    | 2.912    | 12.786   | 886.268***  | −11.791*** |
| ECO   | 14.747| 3.357  | 263.707| 0.000| 35.959    | 4.520    | 25.457   | 4004.537*** | −13.252*** |
| MSCI  | 4.310| 0.502  | 99.934| 0.000| 12.955    | 5.462    | 35.648   | 8099.116*** | −11.034*** |
| SPOIL | 13.346| 1.490  | 478.061| 0.000| 47.298    | 7.159    | 62.777   | 25818.720***| −12.559*** |
| SPGOLD| 12.295| 3.410  | 196.189| 0.003| 26.467    | 4.165    | 23.295   | 3288.631*** | −9.489***  |
| SPGBM | 15.016| 3.901  | 276.461| 0.001| 40.076    | 4.865    | 28.362   | 5042.500*** | −12.270*** |

Notes: The sample period is January 2, 2020 to August 28, 2020. The PP test is conducted with a trend and intercept; lag length is selected based on Schwarz information criterion (SIC). *** indicates statistical significance at the 1% level.
Fig. A.1. Net directional return connectedness - full period.
Fig. A.2. Net directional volatility connectedness - full period.

References

Aboura, S., Chevallier, J., 2013. An equicorrelation measure for equity, bond, foreign exchange and commodity returns. Appl. Econ. Lett. 20 https://doi.org/10.1080/13504851.2013.829192.

Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J. Risk Financ. Manag. https://doi.org/10.3390/jrfm13040084.

Antonakakis, N., Gabauer, D., Gupta, R., Plakandaras, V., 2018. Dynamic connectedness of uncertainty across developed economies: a time-varying approach. Econ. Lett. https://doi.org/10.1016/j.econlet.2018.02.011.

Apergis, E., Apergis, N., 2017. The role of rare earth prices in renewable energy consumption: the actual driver for a renewable energy world. Energy Econ. https://doi.org/10.1016/j.eneco.2016.12.015.

Apergis, N., Bonato, M., Gupta, R., Kyei, C., 2018. Does geopolitical risks predict stock returns and volatility of leading defense companies? Evidence from a nonparametric approach. Defence Peace Econ. 684–696.

Baldi, L., Peri, M., Vandone, D., 2014. Clean energy industries and rare earth materials: economic and financial issues. Energy Pol. https://doi.org/10.1016/j.enpol.2013.10.067.

Barunik, J., Krehlik, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. J. Financ. Econom. 16, 271–296. https://doi.org/10.1093/jjfinec/nby001.

Bouri, E., Jalkh, N., Dutta, A., Uddin, G.S., 2019. Gold and crude oil as safe-haven assets for clean energy stock indices: blended copulas approach. Energy 178, 544–553. https://doi.org/10.1016/j.energy.2019.04.155.

Bouri, E., Kanjilal, K., Ghosh, S., Roubaud, D., Saeed, T., 2021a. Rare earth and allied sectors in stock markets: extreme dependence of return and volatility. Appl. Econ. https://doi.org/10.1080/00036846.2021.1927971.

Bouri, E., Cepni, O., Gabauer, D., Gupta, R., 2021b. Return connectedness across asset classes around the COVID-19 outbreak. Int. Rev. Financ. Anal. 73, 101646 https://doi.org/10.1016/j.irfa.2020.101646.

Buchholz, P., Brandenburg, T., 2018. Demand, supply, and price trends for mineral raw materials relevant to the renewable energy transition wind energy, solar photovoltaic energy, and energy storage. Chem. Ing. Tech. https://doi.org/10.1002/ cite.201700098.

Chan, J.C.C., Eisenstat, E., Strachan, R.W., 2020. Reducing the state space dimension in a large TVP-VAR. J. Econom. 218 https://doi.org/10.1016/j.jeconom.2019.11.006.

Chen, Y., Zheng, B., Qu, F., 2020. Modeling the nexus of crude oil, new energy and rare earth in China: an asymmetric VAR-BEKK (DCC)-GARCH approach. Resour. Policy. https://doi.org/10.1016/j.resourpol.2019.101545.

Cox, C., Kynicky, J., 2018. The rapid evolution of speculative investment in the REE market before, during, and after the rare earth crisis of 2010–2012. Extr. Ind. Soc. https://doi.org/10.1016/j.exis.2017.09.002.

Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econom. https://doi.org/10.1016/j.jeconom.2014.04.012.

Dutta, A., Jana, R.K., Das, D., 2020. Do green investments react to oil price shocks? Implications for sustainable development. J. Clean. Prod. 2661 https://doi.org/10.1016/j.jclepro.2020.121956.

Engle, R., Kelly, B., 2012. Dynamic equicorrelation. J. Bus. Econ. 30 (2), 212–228. https://doi.org/10.1080/07350015.2011.652048.

Fernandez, V., 2017. Rare-earth elements market: a historical and financial perspective. Resour. Policy. https://doi.org/10.1016/j.resourpol.2017.05.010.

Ferrer, R., Shahzad, S.J.H., L´opez, R., Jareno, F., 2018. Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Econ. 76, 1–20. https://doi.org/10.1016/j.eneco.2018.09.022.

Grandell, L., Lehtila, A., Kivinen, M., Koljonen, T., Kihlman, S., Lauri, L.S., 2016. Role of critical metals in the future markets of clean energy technologies. Renew. Energy. https://doi.org/10.1016/j.renene.2016.03.102.

He, Y., 2018. The trade-security nexus and U.S. policy making in critical minerals. Resour. Policy. https://doi.org/10.1016/j.resourpol.2018.07.010.
Mancheri, N.A., Sprecher, B., Bailey, G., Ge, J., Tukker, A., 2019. Effect of Chinese Månberger, A., Johansson, B., 2019. The geopolitics of metals and metalloids used for the Li, W., 2021. COVID-19 and asymmetric volatility spillovers across global stock markets. Y. Song et al.

Packey, D.J., Kingsnorth, D., 2016. The impact of unregulated ionic clay rare earth mining in China. Resour. Policy. https://doi.org/10.1016/j.resourpol.2016.03.003, Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. J. Bus. 53 https://doi.org/10.1086/296071.

Proots, J., Schweizer, D., Seiler, V., 2020. The economic importance of rare earth elements volatility forecasts. Int. Rev. Financ. Anal. https://doi.org/10.1016/j.irf.2019.01.010.

Qu, F., Chen, Y., Zheng, B., 2021. Is new energy driven by crude oil, high-tech sector or low-carbon notion? New evidence from high-frequency data. Energy 230, 120770. https://doi.org/10.1016/j.energy.2021.120770.

Rebrodeo, J.C., Ugolini, A., 2020. Price spillovers between rare earth stocks and financial markets. Resour. Policy. https://doi.org/10.1016/j.jresourpol.2020.101647.

Reuter, M.A., Hudson, C., van Schalk, A., Heitkam, K., Meskers, C., Hegelsken, C., 2013. Metal recycling: opportunities, limits, infrastructure. A Report of the Working Group on the Global Metal Flows to the International Resource Panel [WWW Document]. UN Environ. Program. URL https://www.resourcepanel.org/reports/metrecycling. 1.4.21.

Riesgo García, M.V., Kremien, A., Manzanedo del Campo, M.A., Menéndez Álvarez, M., Gent, M.R., 2017. Rare earth elements mining investment: it is not all about China. Resour. Policy. https://doi.org/10.1016/j.jresourpol.2017.05.004.

Rogers, J., Stringer, D., Ritchie, M., 2019. China gears up to weaponize rare earths dominance in trade war [WWW Document]. Bloom. Quint. URL https://www.bloombergquint.com/global-economics/china-gears-up-to-weaponize-rare-earth-s-dominance-in-trade-war#:~:text=(Bloomberg)–Beijing%20is%20gearing%20deepening%20trade%20with%20Washington.&text=The%20world’s%20biggest%20producer%2C%20China%20electric%20vehicles%20and%2C%201.4.21.

Schmid, M., 2019. Mitigating supply risks through involvement in rare earth projects: Japan’s strategies and what the US can learn. Resour. Policy. https://doi.org/10.1016/j.jresourpol.2019.104157.

Smith Stegen, K., 2015. Heavy rare earths, permanent magnets, and renewable energies: an imminent crisis. Energy Pol. https://doi.org/10.1016/j.enpol.2014.12.015.

Uddin, G.S., Rahman, M.L., Hedstrom, A., Ahmed, A., 2019. Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes. Energy Econ. 80, 743–759. https://doi.org/10.1016/j.eneco.2019.02.014.

Wang, P., Chen, L.Y., Ge, J.P., Cai, W., Chen, W.Q., 2019. Incorporating critical material cycles into metal-energy nexus of China’s 2050 renewable transition. Appl. Energy. https://doi.org/10.1016/j.apenergy.2019.113612.

Weng, Z., Häse, N., Mudd, G.M., Jowitt, S.M., 2016. Assessing the energy requirements and global warming potential of the production of rare earth elements. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2016.08.132.

Zhang, D., Broadstock, D.C., 2020. Global financial crisis and rising connectedness in the international commodity markets. Int. Rev. Financ. Anal. https://doi.org/10.1016/j.irf.2018.08.002.