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Are energy metals hedges or safe havens for clean energy stock returns?

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A R T I C L E I N F O

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A B S T R A C T

This paper examines the relationship between clean energy stock indices and energy metals that are sensitive to the growth in demand for clean energy solutions, and makes inferences about whether energy metals can act as hedges or safe havens for clean energy stock indices. The sample period is April 2011 to April 2021, a period which saw substantial investments into the clean energy industry as the capital deployed to clean energy generation during this period was about three times higher than the preceding decade. The main results indicate statistically significant non-linear relationships among the markets under study. All energy metals, except cobalt, have a significant positive linkage with clean energy stock indices and such associations do hold during episodes of high volatility. While none of the energy metals under study acts as a hedge for clean energy stock markets, the results support previous evidence on the hedging properties of precious metals, showing that gold and silver serve as hedges for certain clean energy stock indices. These results have important implications amid tremendous growth in clean energy stock investments and the repeating occurrence of periods of uncertainty.
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1. Introduction

Climate change and environmental degradation have been widely acknowledged by state actors, international organizations, and the general public as being urgent issues for the planet. Over the past 15 years, national governments, legislators, international organizations, and many industries have joined forces to find efficient and cleaner production solutions capable of reducing greenhouse gas (GHG) emissions. Accordingly, a large amount of investments have been poured into cleaner energies,[1] leading to the development of a new massive industry around clean energy. In academia, many previous studies shed light on how clean energy stocks are correlated with financial assets such as crude oil and other markets (e.g. Refs. [1–4]). Furthermore, the appearance of clean energy as an alternative to fossil fuels disrupts technology in a way akin to high growth technology companies. As such, it is hardly a surprise that most literature concerning the relationship between clean energy and other markets is focused on oil and technology companies. As investors opt out of fossil fuels and the clean energy sector matures, oil and technology stocks become less relevant for the sector [5,6] and the role of other (non-energy) commodities becomes more pertinent for market participants.

As the clean energy sector grows, so does the raw material demand for manufacturing clean energy solutions. Fig. 1 shows that certain metals are vital raw materials for producing clean energy solutions, which makes them subject to tremendous growth demand due to the wider adoption of clean energy technologies. In view of this, the prices and overall market dynamics of these energy metals are likely to see significant changes that influence the relationship between the metals and the clean energy markets. Notably, investors deploying a large pool of capital into clean energy are keen to understand the relationship clean energy companies have with energy metals. Precise knowledge of this association is particularly useful for diversifying the risk linked to clean energy assets. This is important given that clean energy stocks appear to be a relatively new asset class and therefore their markets can be extremely volatile [7]. It is, therefore, essential to understand how eco-friendly investors can diversify and hedge the

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[1] Over $15 trillion of investment into clean energy generation is needed to reach climate goals, to which hundreds of state parties are committed, and further hundreds of billions in investment is required to store the renewable energy generated from wind, solar, hydro, and biomass sources [5,40,41].

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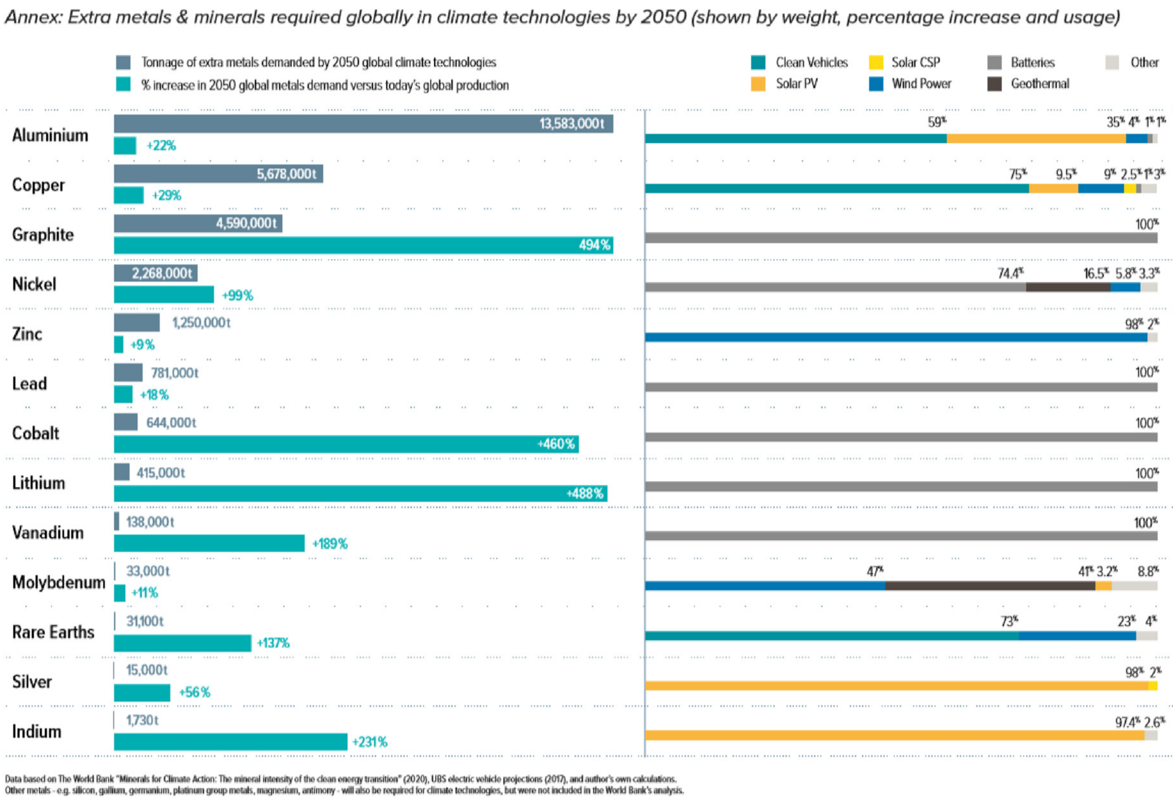

Fig. 1. Eurometaux [17] estimate of incremental impact on metals demand from clean energy solutions in 2050.

potential risk associated with clean energy indices. Such analyses are also important for policymakers, as they can build on the outcomes of our research to develop appropriate hedging strategies to evade the contagion risk emanating from volatile commodity markets.

However, proper knowledge of how investors holding assets in clean energy markets can hedge their risk is understudied, and none of the existing studies analyse the hedging performance of energy metals while analysing the risk linked to portfolios comprising clean energy assets. In fact, a growing body of literature exists on the material flows, supply constraints, and overall role of metals in the energy transition. In parallel, only a few studies focus on the relationship between clean energy stocks and metals, however they ignore the energy metals and clean energy markets, despite clean energy technologies using substantial amounts of metals as raw materials [8–14]. In this regard, Dutta [15] and Yahya et al. [3] provide two interesting studies on the relationship between clean energy stock prices and prices of metals, but their focus is limited to specific relationships and metals. Dutta [15] examines whether the stock returns of solar energy firms are sensitive to silver price volatility, while Yahya et al. [3] studies the cross-quantile dependence and causality between non-ferrous metals and renewable energy stocks.

In light of the above discussion and the gap in the literature on the clean stocks-energy metals nexus, this study addresses the question of whether energy metals act as hedges and/or safe havens for clean energy stocks. To the best of our knowledge, this is the first study to consider the relationship between clean energy stock returns and the prices of energy metals that are sensitive to the growth in demand for clean energy solutions. Accordingly, we make a novel extension to the existing literature focusing on clean energy stocks and other financial markets [1–4], and that considering the nexus of clean energy stock prices and metals prices [3,15]. On the methodological front, we employ a combination of suitable methods that involve the approach of Baur and McDermott [16] and the time-varying conditional analysis comprising hedging effectiveness and optimal hedge ratios. These methods have been used in various subsequent literature and their power to uncover evidence of hedge and safe haven properties of various assets cannot be overestimated.

While our paper is related to studies on the hedging and safe haven properties of gold (e.g. Refs. [16,18–21]), it is different not only in the use of multivariate GARCH models capable of providing time-varying conditional correlations and the application of hedging effectiveness and optimal hedge ratios, but also its focus on the universe of clean energy equities that has been volatile over the years [4,7]. In fact, we use the bivariate DCC-GARCH process and find evidence that the time-varying beta for the clean energy equity index remains high even when the market behaves normally. Notably, during crisis periods, the beta becomes extremely high (see Fig. A3). This further motivates our decision to find a proper hedge for these clean energy assets. This is also relevant given the growing concerns about climate change and energy security, which make eco-friendly investors consider green investments in their portfolios or maintain low-carbon portfolios.

Our main results show evidence that all the energy metals, except cobalt, have a significant positive relationship with clean energy stocks on average. Interestingly, silver and gold have a safe haven property for certain clean energy stocks. We extend our analysis and confirm our main findings by considering the hedge ratios and hedging effectiveness of gold, silver and Bitcoin during several sub-samples: Subsample I (the oil market crisis from October 2014 to March 2016), Subsample II (the pre-COVID period from April 2016 to January 2020), and Subsample III (the COVID-19 pandemic from February 2020 to April 2021).

The rest of the study is divided into sections. Section 2 reviews the literature on clean energy stocks, the properties of metals as hedges and safe havens, and the link between clean energy stocks and metals. Section 3 outlines the data and methodology. Section 4 presents and analyses the results. Section 5 extends the analysis to cover time-varying correlations and hedging effectiveness. Section 6 concludes.

2. Literature review

2.1. Clean energy stock prices and traditional energy

Given that the clean energy sector has already seen significant growth over the preceding 15 years, a growing number of studies examine the risk related to clean energy equities. One focus area of these studies is the link between traditional, fossil fuel based, energy markets and clean energy equities. Henrique and Sadorsky [22]; for example, argue that high oil prices work to the benefit of clean energy companies due to substitution. The authors include interest rates and technology stock prices in addition to oil price in their VAR model. Surprisingly, the results indicate that oil prices do not have a large impact on clean energy stock prices, while shocks to technology stock prices have an impact on clean energy stock prices.

Sadorsky [23] studies the determinants of clean energy company risk. The study uses the capital asset pricing model (CAPM) to investigate the impact of firm size, debt to equity ratio, R&D spending to sales ratio, sales growth, and oil price returns on the time varying systematic risk of clean energy companies. The results confirm the high risk of clean energy companies, indicating clean energy stocks to be twice as risky as the broader stock market. The study includes results from two augmented CAPM models that indicate a reduction in systematic risk as clean energy company sales grow. Notably, the findings from the augmented models also indicate that high oil price increases the systematic risk of clean energy companies.

Kumar et al. [24] investigate the relationship between clean energy stocks, technology stocks, interest rates, oil prices, and carbon prices. They hypothesize that high oil prices support substitution between traditional energy sources and clean energy even as they acknowledge that the link is not clear from previous academic literature. Results from the VAR-model used in the study confirm Henrique and Sadorsky's [22] findings, indicating a link between clean energy stocks and technology stocks. Kumar et al. [24] confirm the hypothesis of the substitution effect between clean and traditional energy. Bondia et al. [25] find a unidirectional short-run causality from technology stock prices to clean energy stock prices, thus confirming the perception of clean energy stocks as a subset of the wider technology sector stocks implied by Kumar et al. [24] and Henrique and Sadorsky [22]. The results also indicate a short-run unidirectional causality from oil prices to clean energy stock prices but do not indicate a long-run causality from any of the variables to clean energy stock prices.

More recent studies such as Ahmad [1] and Reboredo and Ugolini [2] show results that further strengthen the indication that oil prices have an impact on clean energy stocks. Reboredo and Ugolini [2] find that movements in energy prices, including oil prices, have an impact on clean energy stocks regardless of the direction, up or down, that prices move. The work of Ahmad [1] confirms the previously documented relationship between technology stocks and clean energy stocks, while suggesting a strong impact of oil prices on clean energy stocks. The study concludes that crude oil seems to be an effective hedge for stocks in both the technology and clean energy sectors. Sadorsky [26] provides similar evidence in terms of oil price's effectiveness in hedging clean energy stocks.

Dutta [27] is among the first to consider the link between oil price uncertainty and clean energy stocks. The study examines the link between implied volatility of oil prices, measured by the oil price volatility index (OVX), and realized volatility of clean energy stocks. The results indicate that clean energy stock returns are very sensitive to oil price uncertainty. The relationship is positive or in other words, increases in oil price uncertainty lead to increases in realized clean energy stock volatility. The findings of Ahmad et al. [7] also support the positive link, in line with Dutta [27]; between OVX and clean energy stock volatility. According to the study, clean energy stock price risk can be hedged by taking a long position on OVX. In fact, OVX is the third best among gold, bonds, VIX, climate credits and oil price, surpassed only by VIX and oil price.

A recent study by Henriques and Sadorsky [6] examines the implications of fossil fuel stock divestment from a portfolio returns perspective and finds evidence that, at least in the US stock market, it is possible for portfolios that include clean energy stocks instead of fossil fuels and utilities to reach higher risk-adjusted returns. The findings support the case for clean energy investments, not only as a social movement but as a movement with a capital investment returns driven rationale. If the capital markets for fossil fuels dry up due to pressure from stakeholders and lagging returns, the role of clean energy might also change from being an alternative source to the major source of energy. In such a scenario it is important to find alternative hedges for clean energy stock risk.

2.2. Precious metals as hedges for equities

The study of Baur and Lucey [18] is the first to formulate testable definitions for gold as a hedge, diversifier and safe haven, and explore whether gold acts as a safe haven for stocks and bonds. The study defines a hedge as an asset that is uncorrelated or negatively correlated with another asset on average, a diversifier as an asset that is positively but not perfectly correlated with another asset on average, and a safe haven as an asset that is uncorrelated or negatively correlated with another asset during market shocks. The results indicate that gold is an effective safe haven for stocks for a limited time period, around 15 trading days, after a large negative shock to equity markets in the US, UK and Germany. The results indicate that gold is a hedge for US and UK equities but not for equities in Germany and that gold is a more effective hedge or safe haven during bear markets than bull markets in all three equity markets.

Baur and McDermott [16] further contribute to studying gold as a safe haven for equities by examining the extent of protection gold provides. The study differentiates between weak and strong safe havens and expands geographically into 53 international equity markets. Their results indicate that gold is a strong safe haven for most of the developed equity markets included in the dataset. The results, however, also indicate that gold moves together with equity markets when there are extreme shocks to the global financial markets and gold provides only a weak safe haven to developing equity market risk.

Beckmann et al. [28] build upon Baur and McDermott's [16] approach by using a smooth transition regression model that splits the regression model into two regimes. One regime includes periods where stock returns are average and allows for the testing of gold as a hedge. The other regime includes periods where the differences between stock returns and average stock returns are large, which allows for the testing of gold as a safe haven. The data includes 18 individual markets and 5 regional indices in developed countries. Based on the modelling the authors conclude that gold acts as at least a weak hedge and safe haven in an overwhelming number of cases. The authors point out that gold's usefulness as a hedge or safe haven is dependent on the economic environment under observation but leave examination of individual economies outside the scope of the study.

Junttila et al. [29] study the cross-market link between gold and US aggregate stocks as well as US energy stocks. The findings are in line with earlier literature and suggest gold is a safe haven asset for the US aggregate stock market due to a negative return correlation between the two markets in times of financial crisis. Interestingly, the results indicate a strong time-variation in return correlations of commodity and stock markets. In other words, the negative correlation between gold and US stocks seems to have been higher during the crash following the dot-com bubble compared to the crash following the US housing bubble.

Batten et al. [30] examine the macroeconomic determinants of volatility for gold, silver, palladium and platinum prices. The authors use an array of macroeconomic variables such as consumer confidence, inflation, stock index prices, money supply, inflation, industrial production and the US dollar index to assess the root causes of volatility in precious metals. The authors find significant causality for all precious metals price volatilities except silver when testing all monetary and financial variables. Hillier et al. [31] examine precious metals (gold, silver and platinum) as assets in US equity and non-US equity portfolios jointly. The study finds that all precious metals included in the data have some potential for portfolio diversification. Furthermore, the results indicate that precious metals have some hedging properties especially during abnormal equity market volatility. Interestingly, the findings also indicate that a buy-and-hold approach to precious metals investment yields better results than a dynamic approach based on a short-term outlook.

Hood and Malik [19] study the hedging properties of various precious metals, following Bauer and McDermott's [16] methodology for defining hedges and safe havens, but expanding it to silver and platinum in addition to gold. The authors conclude that gold is the only precious metal that serves as a hedge and a weak safe haven for US equities.

More recently, a similar methodology made popular by Bauer and Lucy [18] has been used to investigate the time-varying safe haven qualities of precious metals. Lucey and Li [20] examine how the utility of gold, silver, palladium and platinum as safe havens for US stocks and bonds changes over time. The results indicate that there is strong time variance in the safe haven properties of each precious metal. Gold is more often useful as a safe haven than the other precious metals. Li and Lucey [21] build on Lucey and Li's [20] results on the time-varying nature of precious metals' safe haven properties. The 2017 study extends the examination to 11 countries and tries to identify the political and economic factors that might affect precious metals' safe haven properties. The results indicate that precious metals, on aggregate, provide a safe haven for stocks approximately 33% of the time.

2.3. Metals and renewable energy equities

Even though the expected growth in the demand for certain metals resulting from the rapid growth in clean energy technology adoption has been widely discussed among the public and in academic literature such as Moss et al. [13]; Habib et al. [11]; Kivinen et al. [12]; and Watari et al. [14]; the analysis of prices of metals and clean energy stocks has only come to prominence recently. In fact, to the best of the authors' knowledge, the first studies to consider any metals as hedges for clean energy stocks were published during the very last years of the 2010s.

Ahmed et al. [7] is among the first to study the link between metal prices and clean energy stocks in the context of a wider analysis of the usefulness of various financial assets, including gold, for hedging clean energy stock risk. The findings suggest that stock market volatility (VIX), oil prices and oil price volatility (OVX) are, in that order, the most effective hedges for clean energy stock risk. The results also indicate that gold is not a very effective hedge for clean energy stocks.

Bouri et al. [32] study the safe haven properties of gold and oil for clean energy stocks. The study uses two proxies for clean energy stocks, the S&P Global Clean Energy Index and the WilderHill Clean Energy Index. Based on the results, both oil and gold act as a weak safe haven for both indices. The results show that stock market index choice matters when analysing the link between clean energy stocks and commodity prices as oil is the better hedge for the Wilderhill Clean Energy Index, of the two, while gold is the better hedge for the S&P Global Clean Energy Index.

To the best of our knowledge, Dutta [15] appears to be the first to investigate the link between the prices of metals used as raw materials for clean energy solutions and prices of clean energy stocks. The author acknowledges this link and sets out to examine the link between uncertainty in the price of silver, measured by the silver volatility index (VXSLV), and the prices of solar energy stocks, measured by the Ardour Solar Energy stock index and MAC Global Solar Energy stock index. The results indicate that both the implied volatility of silver price, proxied by VXSLV and the realized volatility of silver price, proxied by squared returns, have negative and significant impacts on the prices of solar energy stocks. The results also suggest that the impact of VXSLV on solar energy stocks is symmetric.

More recently, Dutta et al. [33] examine the relationship of the volatility indices of three major commodities, gold, silver and oil, with clean energy stock prices. The authors set out to expand on the small number of studies that address how clean energy investors can reduce their downside risk. The study uses three indices to track clean energy stock prices. The findings indicate that each volatility index can be used effectively as a hedge for clean energy stock risk and the relationship between the volatility of each commodity and clean energy stock prices is negative. This holds true for each commodity/clean energy index pair. The study concludes that the oil volatility index is the most effective hedge for clean energy stocks, based on aggregate results from all three stock indices.

3. Data and methodology

3.1. Data

Aluminium, cobalt, copper, nickel, and silver are chosen to be included in the data, based on transparency of pricing, availability of data, and expected demand shock, measured by 2050 expected demand from clean energy solutions vs. 2019 production. Gold is included in the study for comparison purposes as the hedging and safe haven properties of gold are widely documented. All the metals included in this study are priced daily either on the London Metals Exchange (LME) or by the London Bullion Market Association (LBMA).

Clean energy, in the context of this paper, is used as an umbrella term covering industries that stand to benefit substantially from a societal transition toward lower emissions and pollution from the use of energy, i.e. the use of clean energy. Due to the varying ways in which companies contribute to the clean energy revolution, the umbrella covers not only companies that generate and store clean energy but also companies that produce products and services that enable the efficient generation and consumption of clean energy. This wide-ranging umbrella can be roughly divided into:

(i) Clean Energy Production: The producers of clean (i.e. low emission) energy, or manufacturers relevant to clean energy such as the makers of turbines and rotors used for wind power, makers of solar photovoltaic panels and suppliers of clean energy systems, and the makers of biofuels derived from renewable vegetable crops, as examples.

(ii) Energy Storage: Manufacturers of advanced batteries, materials and solutions that store energy in traditional and novel ways. Because most renewable power cannot be generated at all times (i.e. solar power works only when the sun is shining and wind power only when there is wind), joining renewable power with energy storage systems provides flexibility for the energy consumer.

(iii) Energy Conversion: Manufacturers of devices that convert an assortment of inputs into the more desired electrical, motive, lighting, or other power wherever needed. This includes whole conversion systems such as electrical vehicles as well as more focused solutions such as advanced motors and materials for conversion to an intended electrical or mechanical power.

(iv) Power Delivery and Conservation: Manufacturers of solutions that improve efficiency and conservation to reduce energy consumption. Such solutions include inverters and equipment for power conditioning, and in transport, power management for hybrid, hydrogen and fuel cell vehicles.

(v) Greener Utilities: Utilities that emphasize cleaner methods of making electric power including wind, solar, biogas, geothermal, hydro and others that can prevent pollution.

(vi) Cleaner Fuels: Producers of various liquid, solid and other biofuels derived from renewable sources such as cellulosic, sugar, algae, or other feedstock as well as biomass and waste to energy.

The WilderHill Clean Energy Index (ECO) and S&P Global Clean Energy Index (SPGCE) are used as proxies to capture the wide clean energy sector. The other three indices focus more directly on one specific value chain under the wider umbrella. MAC Global Solar Energy (MAC) is a proxy for the solar energy industry including all solar technologies, the entire value chain from manufacturing of equipment used in solar plants to installations and operations of solar plants. The Kensho Electric Vehicles Index (SPKEV) is a proxy for the clean mobility industry as its constituents represent companies focused on producing electric road vehicles and associated subsystems, powertrains, energy storage systems, and charging infrastructure. The NASDAQ OMX Wind Index (GRNWIND) meanwhile covers the wind energy sector value chain from the manufacturing of equipment used in wind farms to the installation and operation of wind farms, as well as supporting services. Due to the global nature of clean energy value chains, the indices refer to companies from several geographies and stock exchanges. We believe this is beneficial because including the leading companies instead of focusing on one geography makes the indices better proxies for the global clean energy industry.

In this study, we consider daily data for all metals and indices covering the period from March 31, 2011 to April 23, 2021. It is worth noting that SPKEV was launched on May 15, 2013, and thus the sample period for SPKEV is from May 15, 2013 to April 23, 2021. All indices and metals included in the study are priced in USD, which eliminates potential currency issues from data. The period under study is particularly interesting for two reasons: (i) the sample contains the COVID-19 crisis, the most recent shock to the financial markets; and (ii) the clean energy sector has experienced significant growth and investment during the last decade. Each of the metal indices under study is plotted against the various clean energy stock indices (Figs. 2–7).

Descriptive statistics for all metals price returns are presented in Panel A of Table 1. Cobalt has the highest average return during the sample period and the second highest single best daily return during the period. Silver returns have the highest standard deviation as well as the highest single best day and lowest single worst day. Interestingly, most of the metals have a median daily return of 0. Copper and gold are the only metals to have a median daily return other than 0. This could be due to the copper and gold markets simply being larger and more liquid. In 2015 Visual Capitalist[2] estimated gold to be the largest metal market and copper to be the third largest metal market as measured in US dollars. The aluminium market, however, was almost the same size as copper market. The Jarque-Bera test rejects the null hypothesis that the return indices follow a normal distribution. We further note that, based on both the Phillips-Perron (PP) test and augmented Dickey-Fuller (ADF) test, all the return series appear to be stationary.

Descriptive statistics for all the clean energy stock index returns are presented in Panel B of Table 1. SPKEV has the highest average return, while ECO has the highest single best daily return and the lowest single worst daily return during the period. MAC returns have the highest standard deviation during the period. As with the metals price returns, both unit root tests confirm that each series is stationary. All the indices fail to satisfy the normality assumption.

Table 2 shows the unconditional correlations between the metals and clean energy stock indices. We find that cobalt has the lowest correlations (insignificant) with the stock returns, while copper maintains the highest correlations with clean energy assets.

3.2. Methodology

To test whether an energy metal index is a hedge or safe haven for a clean energy subsector or clean energy stocks in general, we distinguish between a hedge and a safe haven following the framework of Baur and McDermott [16] and Baur and Lucey [18].

3.2.1. Hedge

A strong (weak) hedge is an asset that is negatively correlated (uncorrelated) with another asset on average. In other words, during normal market circumstances a hedge provides return diversification benefits. As such, a hedge does not need to provide returns diversification during unusual market circumstances, such as extreme declines in prices.

3.2.2. Safe haven

A strong (weak) safe haven is an asset that is negatively correlated (uncorrelated) with another asset during unusual market circumstances, such as extreme declines in prices. In other words, during unusual market circumstances a safe haven provides protection benefits. As such, a safe haven does not need to provide returns protection during normal market circumstances.

Accordingly, the econometric approach applied in this paper is built on a model that regresses metal price returns to stock returns in the same period. This is done for all six metals and five clean stock indices, a total of 30 separate regression models that each follows the mean equation:

$$r_{metal,t} = a + b_t r_{index,t} + \varepsilon_t \quad (1)$$

where $r_{metal,t}$ is the log-return of the metal price at time t, $r_{index,t}$ is the return of the index at time t, α and b_t are the coefficient parameters to estimate, and the error term is ε_t. Parameter b_t is estimated by the equation:

[2] https://www.visualcapitalist.com/size-oil-market/.

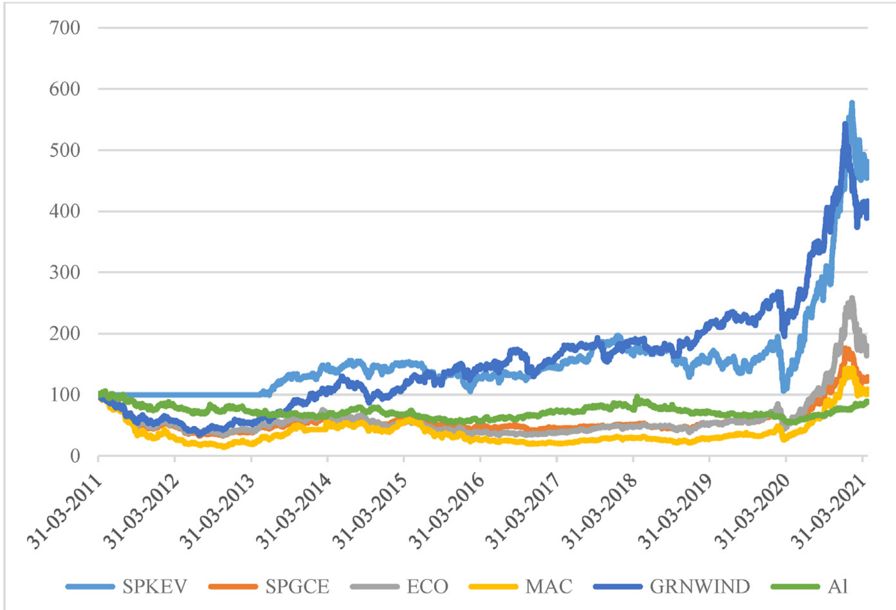

Fig. 2. Aluminium LME price and clean energy indices (indexed, March 31, 2011 = 100).

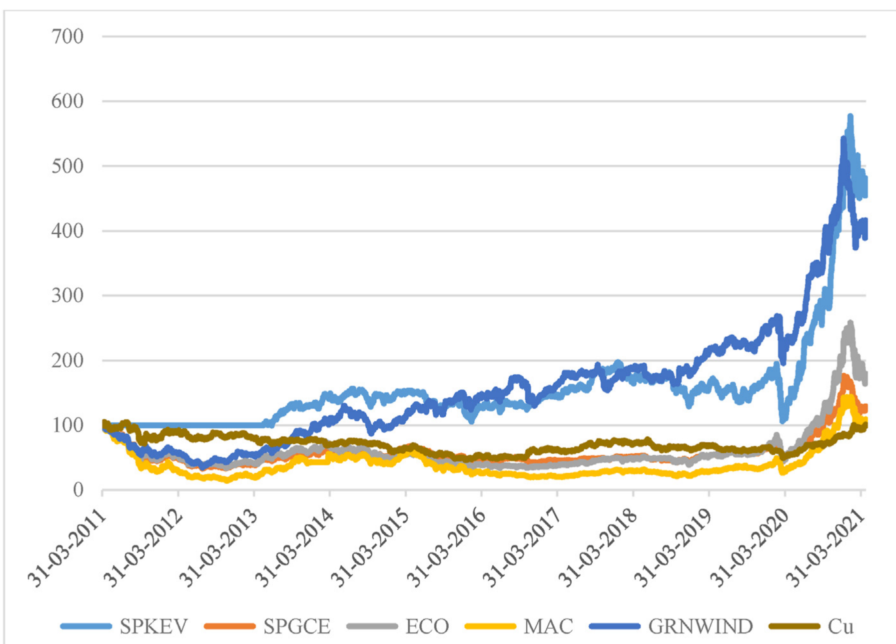

Fig. 3. Copper LME price and clean energy indices (indexed, March 31, 2011 = 100).

$$b_t = c_0 + c_1 D\left(r_{index} q_{q5}\right) + c_2 D\left(r_{index} q_{q2.5}\right) + c_3 D\left(r_{index} q_{q1}\right) \quad (2)$$

where the coefficient parameters to estimate are c_0, c_1, c_2 and c_3. To differentiate between hedges and safe havens, the dummy variables D are defined. The dummy variables capture the periods when clean energy indices' returns fall below the 5%, 2.5% or 1% worst quantile threshold of the sample period. The dummy variable, thus, denotes periods when investors would likely seek safe haven from clean energy indices. $D(\ldots)$ is estimated as:

$$D(r_{index} q_x) = \begin{cases} 1 \text{ if } r_{index,t} < r_{index} q_x \\ 0 \text{ if } r_{index,t} \geq r_{index} q_x \end{cases} \quad (3)$$

where $r_{index} q_x$ is the worst x return quantile threshold of either 5%, 2.5% or 1%.

To account for heteroscedasticity in the data, a GARCH (1,1) model, specified below, is used to estimate the error term:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \quad (4)$$

If one of the coefficients c_1, c_2 or c_3 in Eq. (2) is significantly

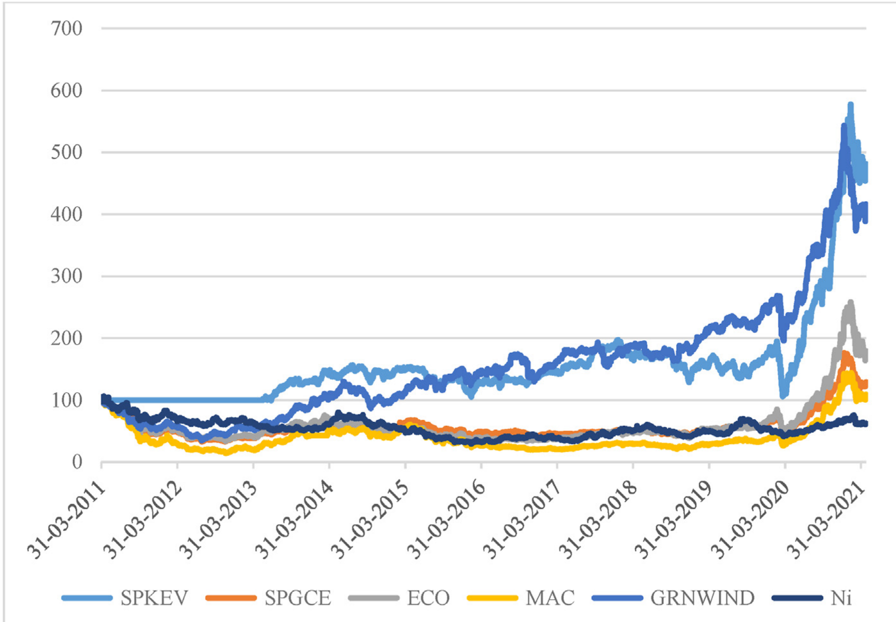

Fig. 4. Nickel LME price and clean energy indices (indexed, March 31, 2011 = 100).

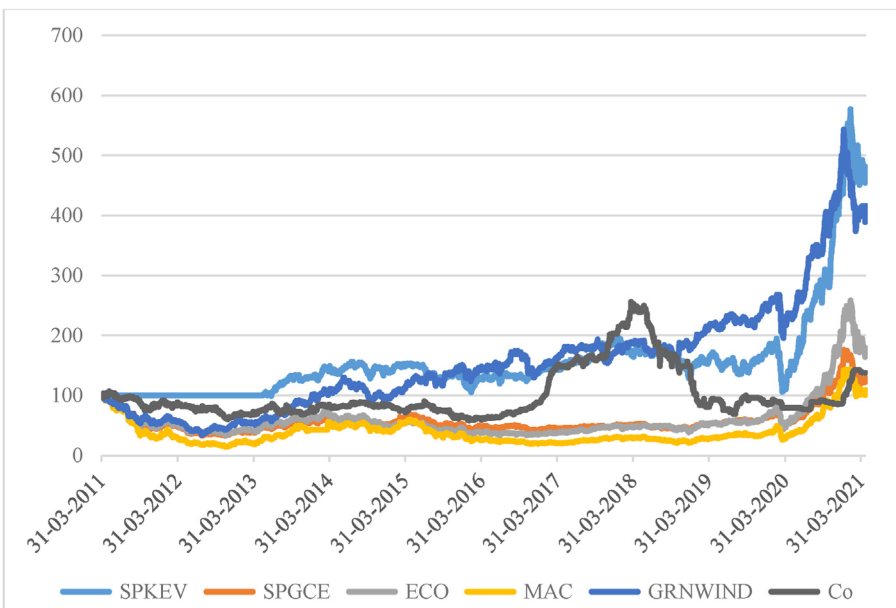

Fig. 5. Cobalt LME price and clean energy indices (indexed, March 31, 2011 = 100).

different from zero, it is an indication of a non-linear link between the returns of the metal and the asset. Following the definition of a hedge and a safe haven given above, the results from the models are interpreted based on the coefficients and their statistical difference from zero. If the parameters in Eq. (2) are non-positive, the metal is a weak safe haven for that particular clean energy sector. If the parameters in Eq. (2) are negative and a statistically significant difference from zero is obtained, the metal is a strong safe haven for that particular clean energy sector. If c_0 is zero (negative) and the sum of c_1, c_2 and c_3 does not positively exceed c_0 the metal in question acts as weak (strong) hedge for the clean energy sector.

4. Empirical results

This section presents the results of, in total, 30 regression estimates. Each metal is separately estimated with each stock index using the regression model given by Eqs. (1)–(4). Table 3 shows estimates for c_0 and the estimated effects of negative shocks to market circumstances. The estimated effect of negative shocks is computed for each quantile, where the sum of c_0 and c_1 is the effect for the 5th quantile, the sum of c_0, c_1 and c_2 is the effect for the 2.5th quantile, and the sum of c_0, c_1, c_2 and c_3 is the effect for the 1st quantile.

There is evidence of a non-linear relationship between each of

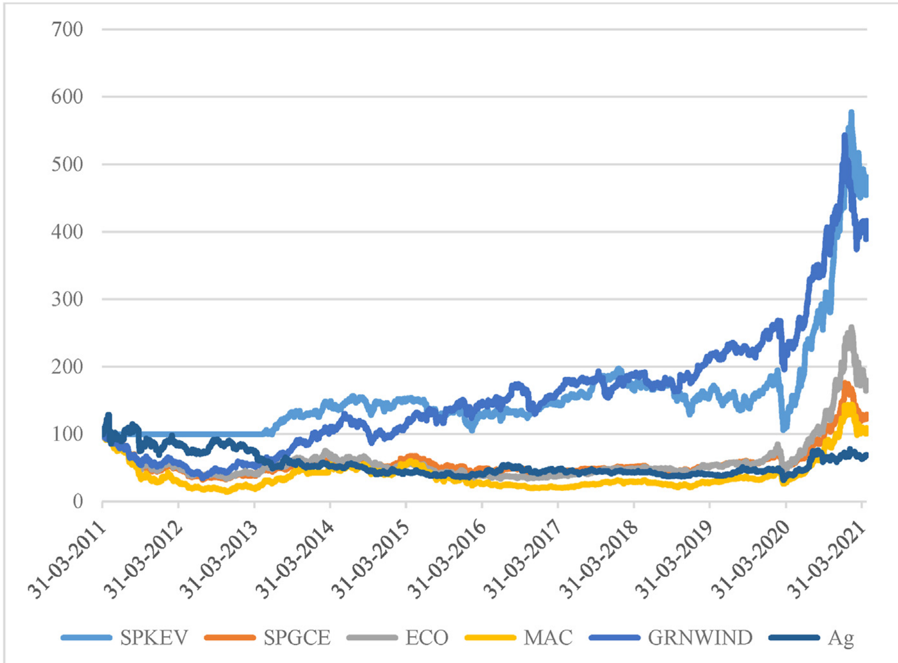

Fig. 6. Silver LBMA price and clean energy indices (indexed, March 31, 2011 = 100).

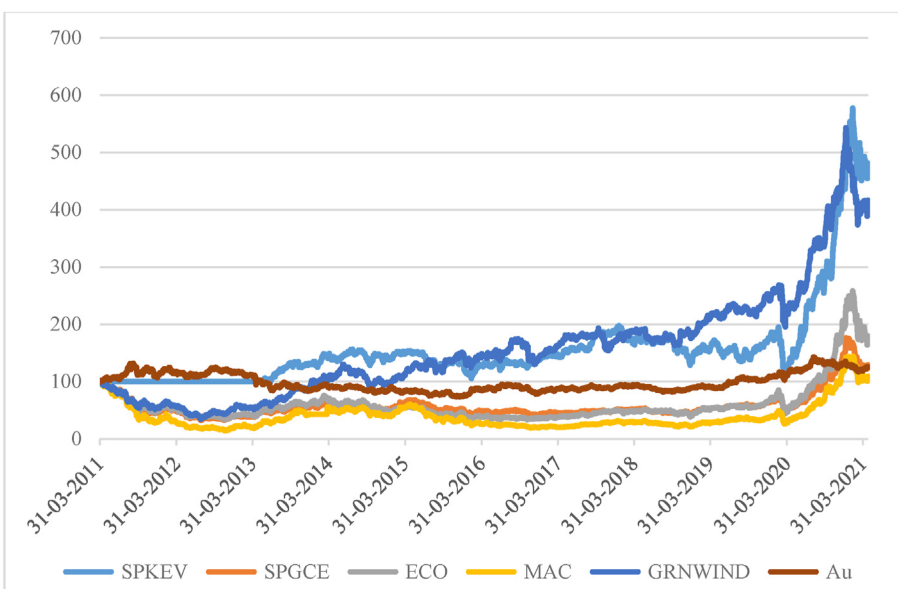

Fig. 7. Gold LBMA price and clean energy indices (indexed, March 31, 2011 = 100). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the metals and clean energy stocks, as for every metal at least one of the coefficients c_1, c_2 or c_3 is significantly different from zero with at least one clean energy index. The evidence for the non-linearity of the relationship is weakest for aluminium and strongest for silver. The weakest evidence of any significant relationship with clean energy stocks comes from the cobalt estimates.

Starting with aluminium, there is a strong positive relationship between aluminium and all clean energy subsectors on average. There is also an indication at the 10% significance level that aluminium tends to correlate with ECO, one of the two indices proxying the aggregate clean energy sector, during the worst market shocks. As such, the results show that aluminium does not have any hedging or safe haven uses for clean energy stocks. The strong positive relationship might indicate that aluminium prices are driven by aggregate clean energy solutions demand rather than aluminium prices having a large effect on the profitability and value of clean energy stocks. Given that, according to Eurometaux [17]; aluminium demand is the most diversified between clean energy subsectors, and the high positive coefficients with ECO and SPGCE in the hedge column of Table 3, there is some support for this indication. The large volume of clean energy sector investments during 2010–2019 highlighted in the supplementary material to

Table 1
Descriptive statistics of daily returns.

Panel A: Metal indices

	Silver	Aluminium	Gold	Cobalt	Copper	Nickel
Mean	0.005%	0.003%	0.014%	0.027%	0.009%	−0.042%
Median	–	–	0.020%	–	0.003%	–
Maximum	18.963%	6.604%	5.582%	12.500%	6.908%	8.792%
Minimum	−17.79%	−7.53%	−9.66%	−14.55%	−7.78%	−100.00%
Std. Dev.	1.99%	1.19%	1.00%	1.70%	1.31%	2.69%
Skewness	0.344	0.259	0.615	0.254	0.017	20.216
Kurtosis	16.730	5.289	9.847	16.174	5.791	752.131
J-B test	9806.04***	617.26***	956.24***	20699.3***	248.24***	193.35***
ADF test	−10.548***	−28.97***	−50.768***	−8.216***	−17.948***	−28.97***
PP test	−53.45***	−51.745***	−50.781***	−58.234***	−53.127***	−51.745***

Panel B: Clean energy indices

	ECO	SPGCE	MAC	SPKEV	GRNWIND
Mean	0.042%	0.021%	0.018%	0.093%	0.071%
Median	0.118%	0.074%	0.052%	0.141%	0.084%
Maximum	14.332%	11.665%	12.699%	11.355%	8.026%
Minimum	−15.00%	−11.75%	−13.90%	−12.13%	−12.44%
Std. Dev.	2.00%	1.49%	2.24%	1.73%	1.63%
Skewness	0.275	0.419	0.033	0.228	0.275
Kurtosis	8.975	10.738	6.905	10.477	6.875
J-B test	4100.16***	7722.61***	2020.02***	3657.75***	2628.74***
ADF tests	−9.903***	−18.332***	−9.118***	−11.427***	−12.676***
PP test	−49.991***	−47.321***	−43.05***	−45.027***	−44.529***

Notes: J-B test refers to the Jarque-Bera test. *** indicates statistical significance at the 1% level.

Table 2
Correlation matrix.

	Silver	Aluminium	Gold	Cobalt	Copper	Nickel
ECO	0.11***	0.12***	0.05**	0.01	0.25***	0.23***
SPGCE	0.18***	0.13***	0.10***	0.02	0.27***	0.27***
MAC	0.13***	0.10***	0.06***	0.03	0.22***	0.22***
GRNWIND	0.12***	0.14***	0.06***	0.02	0.19***	0.18***
SPKEV	0.09***	0.13***	0.01	0.01	0.26***	0.23***

Notes: This Table displays the unconditional correlations between metals indices and clean energy stock indices. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

this paper might contribute to aluminium demand and consequently the strong positive relationship with the aggregate clean energy market. As such, favourable market conditions could override the negative effect on clean energy companies resulting from higher aluminium prices.

Copper yields similar results to aluminium as the coefficients in the hedge column are positive, albeit higher on average, and statistically significant at the 1% level with all clean energy indices. Copper also has strong positive relationships with ECO, MAC and SPKEV during extreme market shocks at the 1% significance level, indicating that copper has an even stronger link with the aggregate clean energy sector than aluminium and particularly with the clean vehicles and solar energy sectors, which are expected to be the two largest sources of copper demand of the wider clean energy sector in the future. Based on the positive coefficients on average and during extreme shocks, copper is not a hedge or a safe haven for clean energy stocks.

It is noteworthy that already in 2020, a large share of copper demand comes from power and electricity related solutions as well as the electric parts of vehicles.[3] The results are in line with the hypothesis that, while the growing demand for clean energy solutions drives copper demand and prices higher, the potential impacts on clean energy stock values and profitability could be

[3] See supplementary materials for more details.

Table 3
Regression results for safe haven and hedge assessment.

	Hedge	Safe haven quantiles		
		0.05	0.025	0.01
Aluminium				
ECO	0.119[c]	0.100	0.146	0.065[a]
SPGCE	0.194[c]	0.206	0.176	0.152
MAC	0.104[c]	0.122	0.113	0.082
GRNWIND	0.157[c]	0.182	0.181	0.141
SPKEV	0.105[c]	0.098	0.053	0.084
Cobalt				
ECO	−0.004	0.007	−0.006	0.036
SPGCE	0.010	−0.123[b]	0.030	0.047
MAC	0.008	0.025	0.036	0.037
GRNWIND	0.010	−0.015	0.014	0.030
SPKEV	−0.012	0.099[b]	0.024	0.050
Copper				
ECO	0.183[c]	0.207	0.092[b]	0.238[c]
SPGCE	0.282[c]	0.344	0.258	0.319
MAC	0.155[c]	0.147	0.098	0.235[c]
GRNWIND	0.202[c]	0.121[a]	0.222	0.228
SPKEV	0.170[c]	0.143	0.171	0.269[b]
Gold				
ECO	0.025[b]	−0.021[a]	−0.025	0.037[a]
SPGCE	0.094[c]	0.019	−0.051	0.016[a]
MAC	0.04[c]	0.038	−0.06[c]	0.055[c]
GRNWIND	0.063[c]	0.006	0.044	−0.004
SPKEV	−0.023[b]	−0.055	−0.055	0.061[a]
Nickel				
ECO	0.216[c]	0.277	0.111[a]	0.261[a]
SPGCE	0.345[c]	0.328	0.503	0.319[b]
MAC	0.064[c]	0.100	0.119	0.080
GRNWIND	0.157[c]	0.232	0.204	0.364
SPKEV	−0.022	0.077	−0.104	−0.010
Silver				
ECO	0.051[c]	0.010	0.269[c]	0.346[b]
SPGCE	0.204[c]	0.190	0.092	−0.039[b]
MAC	0.081[c]	0.175[b]	0.052[c]	0.384[c]
GRNWIND	0.151[c]	0.060	0.237[b]	−0.128[c]
SPKEV	0.039[a]	−0.132[c]	0.124[c]	0.443[c]

[a] Statistical significance at the 10% level.
[b] Statistical significance at the 5% level.
[c] Statistical significance at the 1% level.

mitigated by the strength of the aggregate demand for clean energy solutions that use copper as a raw material.

The third base metal included in this study, nickel, has a similar relationship with the aggregate clean energy sector to copper and aluminium, with one notable exception. As with copper and aluminium, the main sources of demand for nickel currently originate from construction, manufacturing and infrastructure end-uses. In this light, it is not surprising that nickel on average has positive coefficients, which are all significant at the 1% level, with 4 of the 5 clean energy indices. The coefficients are even higher than the corresponding coefficients of copper and aluminium. Furthermore, nickel has a strong positive relationship during the most extreme, 1st quantile, market shocks with both indices representing the aggregate clean energy sector, ECO and SPGCE. Based on the coefficients from the regression model, nickel does not serve as a hedge or a safe haven for aggregate clean energy stocks but the results for clean vehicle stocks are not as conclusive. While copper and aluminium have a strong positive relationship with SPKEV, the proxy for clean vehicles, nickel, in contrast, has a negative coefficient on average and in the two quantiles that represent the most acute shocks to clean energy stocks. What makes this observation interesting is that clean vehicles are, at the time of writing, mainly powered by batteries. According to Wentker et al. [34]; nickel prices have a noticeable impact on cathode active material (CAM) prices and high-nickel CAMs are more affected by nickel price fluctuations than CAMs with other cathode chemistries. According to Fraser et al. [10]; most automotive OEMs are, at the time of writing, planning to use mainly high-nickel cathodes such as NCM 811, LNO, or NCMA.

As such, the impact of nickel prices on battery costs and subsequently EV industry profitability are likely to become even more noticeable. The impacts of nickel prices are likely to be more pronounced in upstream parts of the value chain, such as precursor CAM, CAM, and battery manufacturing, as the cost of the procured nickel dilutes further downstream due to the increasing proportion of other costs. It is unfortunate that there is no stock index that isolates the CAM or battery manufacturing subsectors that feed the clean vehicle sector, from the aggregate clean energy sector stocks.

From Table 3, it is noticeable that cobalt yields very little in terms of statistically significant results with clean energy stocks. Cobalt is the other metal in this study expected to be most impacted by the growth in battery demand, but the only positive and statistically significant coefficient cobalt has is with SPKEV, 5th quantile returns, indicating that cobalt has a positive relationship with SPKEV during extreme market conditions but not during the most extreme market conditions.

All in all, there is very little evidence of a significant relationship between cobalt and clean energy stocks, compared to the other metals in this study. The only other index that yields statistically significant coefficients with cobalt is SPGCE, again with the 5th quantile returns only, but in contrast to SPKEV the coefficient with SPGCE implies a negative relationship. There are several cobalt market specific factors that might explain cobalt's perceived lack of relationship with clean energy stocks.

Notably, cobalt is produced mostly as a by-product of other metals. That is, cobalt supply is not, at least not entirely, driven by pure cobalt demand, which might explain the lack of evidence for a connection between cobalt prices and the primary demand sources of cobalt. Brink et al. [9]; identify additional factors that are likely to be larger drivers of cobalt pricing than conventional market economics. According to their study, the two additional factors are: (i) the cobalt market is highly concentrated; and (ii) cobalt production is for the most part located in countries with medium to very weak political stability. The study concludes that the cobalt market operates under high supply chain disruption risk due to the three above-mentioned factors. Based on these general characteristics of the cobalt market, it is not surprising that we find little statistically significant evidence of a relationship between cobalt price and clean energy stocks. Fig. 5 illustrates the most recent, 2018, price spike and the detachedness between cobalt and clean energy stock indices.

In line with previous literature the best hedge and best safe haven, of the metals included in this study, are both precious metals. Silver has a significant positive relationship with all the clean energy stock indices, on average, implying that silver is not a hedge for clean energy stocks. The results indicate that silver is the best safe haven for clean energy stocks of the metals in the dataset, as silver has a significant negative relationship with both SPGCE and GRNWIND during the most extreme, 1st quantile, shocks to clean energy stocks. Silver also has a significant negative relationship with SPKEV during lesser, 5th quantile, market shocks. Silver has a significant positive relationship with MAC, the proxy for PV solar stocks on average and during all the various market shock levels. The results for the relationship between MAC and silver prices are in line with Dutta [15]; that silver price uncertainty has a significant negative effect on solar energy stock prices. It seems quite natural that silver prices have the most significant relationship with solar energy stocks, due to solar being the largest silver demand driver of the clean energy subsectors.

Even though gold is not identified as a metal with a large demand growth impact from clean energy, it is included in this study as a benchmark for the so-called energy metals. Gold is the only metal of the group that has significant potential as a hedge, even though it is not for the aggregate clean energy stock market. Gold has a significant, at the 5% level, negative relationship with SPKEV on average, indicating it is a hedge for SPKEV. The relationship, however, turns to significantly, at the 10% level, positive during times of extreme shocks to clean energy stocks. Gold has a highly significant positive relationship with all the other clean energy indices included in this study on average. Interestingly, gold does not have as pronounced hedge and safe haven properties for clean energy stocks as previous studies document for aggregate stock markets (see section 2.2). This finding supports the note made by Dutta [15]; that several recent studies have found the hedging properties of precious metals to have weakened during the last decade. Gold has a significant negative relationship with ECO during lesser, 5th quantile, market shocks and a similar yet more significant negative relationship with MAC during 2.5th quantile market shocks, indicating that gold has some safe haven properties.

5. Time-varying correlations and hedging effectiveness

In order to investigate how the association between metal prices and clean energy stock returns evolves over time, we employ the DCC-GARCH model for estimating the time-varying correlations among the indices. The DCC estimates are used to compute the hedging effectiveness. Such analyses shed light on how precious metals (gold and silver) can hedge the clean energy equity risk. Note that we include Bitcoin in our analysis to compare the results with gold and silver.[4] Previous literature argues that Bitcoin often serves as a hedge for energy commodities [33,35].

The DCC-GARCH process assumes the form:

$$R_t = L + \tau R_{t-1} + \varepsilon_t \tag{5}$$

[4] The data on Bitcoin are considered for the period from 01.10.2014 to 23.04.2021 given that the return observations before 2014 were very low and close to zero.

$$\varepsilon_t = H_t^{1/2}\eta_t \tag{6}$$

where R_t is a matrix of logarithmic differences for the indices used, L designates a matrix of fixed parameters, τ is a matrix of coefficients gauging the influence of own-lagged and cross mean transmission, ε_t is the noise term, and η_t is a matrix of *iid* innovations. Moreover, $H_t^{1/2}$ refers to the matrix of conditional volatilities which is further decomposed as:

$$H_t = D_t R_t D_t \tag{7}$$

$$D_t = diag\left(\sqrt{h_t^s}, \sqrt{h_t^m}\right) \tag{8}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{9}$$

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1 \xi_{t-1}\xi'_{t-1} + \theta_2 Q_{t-1} \tag{10}$$

In Eq. (8), h_t^s and h_t^m are the conditional volatilities of clean energy stock and metal/Bitcoin markets, respectively. We define h_t^s and h_t^o as:

$$h_t^s = d_s^2 + b_{11}^2 h_{t-1}^s + b_{21}^2 h_{t-1}^m + a_{11}^2 \varepsilon_{s,t-1}^2 + a_{21}^2 \varepsilon_{m,t-1}^2 \tag{11}$$

$$h_t^m = d_m^2 + b_{12}^2 h_{t-1}^s + b_{22}^2 h_{t-1}^m + a_{12}^2 \varepsilon_{s,t-1}^2 + a_{22}^2 \varepsilon_{m,t-1}^2 \tag{12}$$

Additionally, in Eq. (10), Q_t is the time-varying conditional correlation of residuals, θ_1 and θ_2 are non-negative scalar parameters such that $\theta_1 + \theta_2 < 1$ for the model to be stationary, and Q_0 is the matrix of unconditional correlations for the standardized noise ξ_t. Then, pairwise dynamic conditional correlation is given by:

$$\rho_t = \frac{h_t^{sm}}{\left(\sqrt{h_t^s}\ \sqrt{h_t^m}\right)} \tag{13}$$

where, h_t^{sm} represents the conditional covariance between the clean energy asset and gold/silver/Bitcoin. Note that the parameters of the DCC-GARCH model are estimated using the quasi-maximum likelihood estimation technique.

Figs. 8–10 depict the time-varying correlations among the indices. It is noteworthy that we estimate these correlations between gold/silver/Bitcoin and clean energy equities because our earlier analysis shows that gold and silver perform better than aluminium, cobalt, copper and nickel as safe haven assets for clean energy stock markets. In particular, our objective is to examine whether the findings of Section 4 hold when employing a multivariate GARCH process. We also investigate whether Bitcoin has better safe haven properties than gold and silver. Such hedging strategies could have important implications for investors participating in the metal and clean energy sectors.

As shown by the plots in Fig. 8, gold appears to have positive correlations with the clean energy stock indices during the period February 2020 to May 2020. Notably, the National Bureau of Economic Research (NBER) defines this time as the major economic crisis period due to the COVID-19 pandemic. Therefore, gold does not seem to act as a hedge or safe haven asset for the renewable energy assets during the COVID-19 pandemic. Fig. 9 shows similar evidence for the silver market, implying that neither gold nor silver would act as a hedge or safe haven asset for clean energy stocks during health crisis periods. Fig. 10 shows that Bitcoin also maintains a positive linkage with the renewable energy stock indices during the COVID-19 crisis period. However, the correlations between Bitcoin and the stocks tend be lower at the end of April 2020, which is not the case for gold or silver, indicating that cryptocurrency might perform better than metal markets during pandemic. The portfolio hedging analyses shed further light on this issue.

In line with Ku et al. [36]; we compute the hedging effectiveness for portfolios including clean energy assets and gold/silver/Bitcoin[5] as:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{14}$$

where, $Var_{unhedged}$ indicates the variance of the unhedged portfolio including only clean energy assets and Var_{hedged} refers to the corresponding variation in the combined portfolio including both clean energy assets and gold/silver/Bitcoin. Note that a higher HE index indicates better risk reduction and greater hedging efficiency. Var_{hedged} is given by:

$$Var_{hedged} = \left(\omega_t^{sm}\right)\left(\omega_t^{sm}\right)^2 h_t^s + \left(1-\left(\omega_t^{sm}\right)^2\right) h_t^m + 2\omega_t^{sm}\left(1-\omega_t^{sm}\right) h_t^{sm} \tag{15}$$

where ω_t^{sm} is the optimal weight of clean energy equities in the combined portfolio, defined as:

$$\omega_t^{sm} = \frac{h_t^s - h_t^{sm}}{h_t^s - 2h_t^{sm} + h_t^m} \tag{16}$$

Table 4 shows the results of the portfolio hedging analyses. We consider three sample periods for the analyses: Subsample I, from October 2014 to March 2016, when global oil markets experience a sharp price decline due to a strong US dollar, an oversupply of crude oil, declining demand and the Iran nuclear deal [37]; Subsample II, from April 2016 to January 2020, which we refer as the pre-COVID period; and Subsample III, from February 2020 to April 2021 the period of the COVID-19 pandemic. It is worth mentioning that, while we present these results only for ECO and SPGCE, we find similar results for other clean energy stock indices. Table 4 reveals several interesting outcomes. Firstly, both gold and silver outperform Bitcoin during the oil market crisis period. Secondly, Bitcoin performs better than silver during the pre-COVID period, although gold emerges as the best hedge. Thirdly, Bitcoin outperforms both metals during the pandemic. Hence, Bitcoin appears to be a more efficient hedging instrument than gold during health crises. Chemkha et al. [38] report similar results for the S&P 500 index, arguing that the ability of Bitcoin to outperform gold could be attributed to the little dependence between cryptocurrencies and stock markets. Gold seems to be more volatile than Bitcoin during pandemic periods, as evidenced by the realized volatility plots of

[5] As mentioned, clean energy stocks, being a new asset class, can be highly volatile. To shed light on the riskiness of this new asset class, we estimate the time-varying betas for each clean energy stock index considered in this study. Fig. A3 shows these betas. We estimate the betas using the bivariate DCC-GARCH process. In particular, we employ DCC models to find the conditional covariance between a specific clean energy stock index and the market portfolio returns, then divide the covariance matrix by the estimated conditional variance matrix of the market portfolio returns. Notably, we consider the S&P 500 index as the market portfolio. The plot shows that all the clean energy stock indices appear to be highly volatile during crisis periods including the oil market crisis (2014–2016) and COVID-19 pandemic. During the normal periods, most of the indices remain quite volatile.

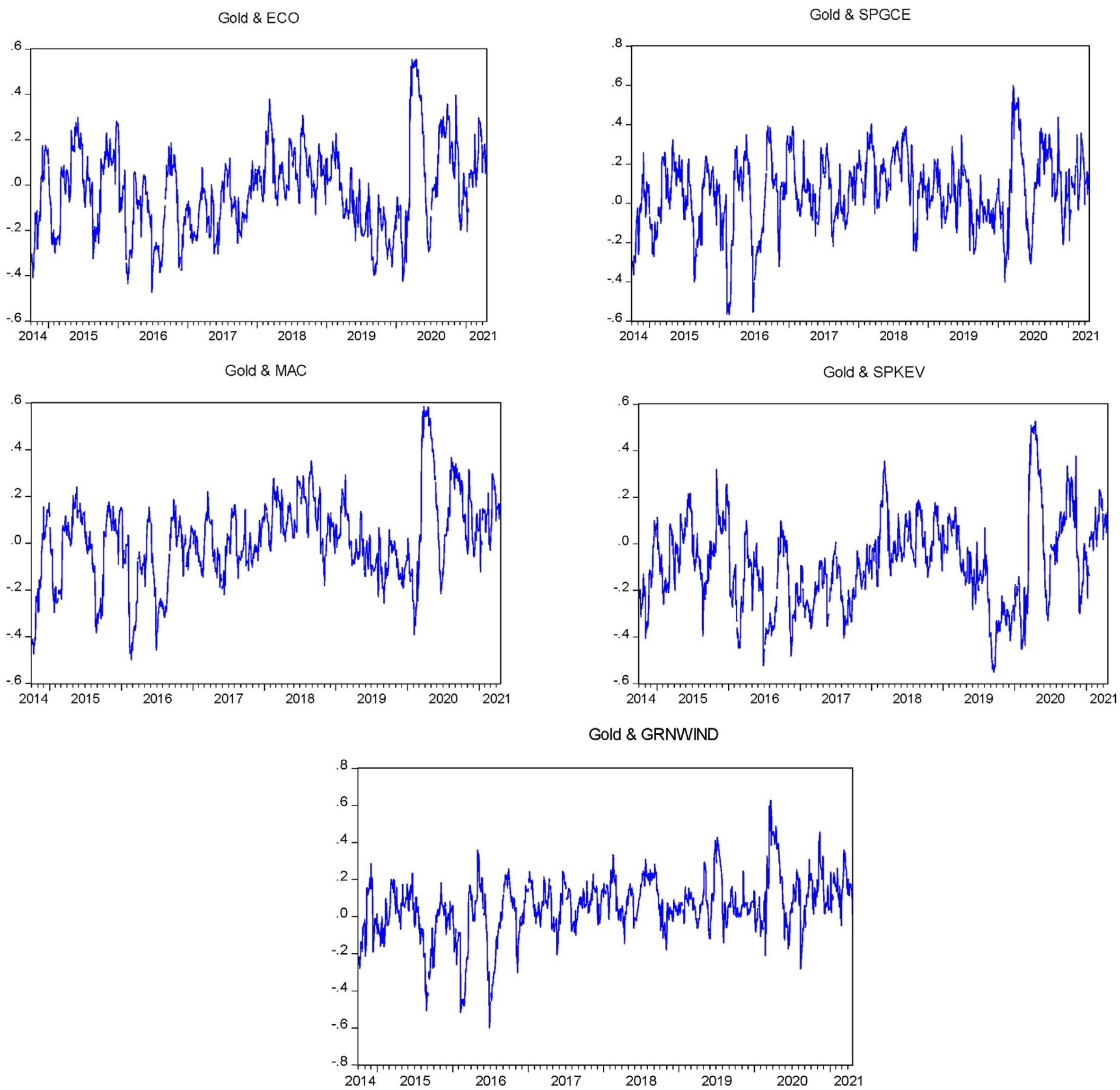

Fig. 8. DCC correlations between gold and clean energy equities. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

these indices[6] (see Appendix A). Hence, these findings have important implications for investors looking for appropriate assets to hedge the downside risk linked to clean energy equities.

Next, we extend our analysis by computing the optimal hedge ratios for these assets. In line with Junttila et al. [29]; we use the formula:

$$\beta_t = \frac{h_t^{sm}}{h_t^m} \quad (17)$$

To reduce the risk of a portfolio of two assets, a long position of \$1 taken in any given clean energy asset should be hedged by shorting β_t dollars in the gold/silver/Bitcoin market. As suggested by López, Cabrera and Schulz [39]; the lower the hedge ratio, the less expensive the hedge. The hedge ratios shown in Table 5 reveal that the Bitcoin-stock pairs represent a better hedging strategy than the gold-stock or silver-stock pairs during the pandemic. For example, over the COVID-19 period, a long position of \$1 in the ECO index can be hedged with a 18.56 (23.88) cent short position in Bitcoin (gold). The gold-stock pairs, however, offer more effective hedging strategies during the oil market crisis period. We note that the optimal hedge ratios for Bitcoin/gold/silver tend to increase significantly during the crises.

6. Conclusions

The motivation behind this study is to examine, for the first time, the relationship between the metals expected to be most impacted by the clean energy transition, and the stocks of clean energy companies. Given that previous studies, for the most part, focus on the relationship between clean energy stocks, technology stocks, and oil prices, this paper contributes to the existing literature by widening the scope to energy metals. More concretely, the study addresses the question of whether energy metals act as

[6] Figs. A1 and A2 depict the realized volatility of the metal and stock indices, respectively. It is evident from Fig. A2 that the volatility of the clean energy stock indices increases substantially following the COVID-19 outbreak around early 2020. However, Fig. A1 shows that while gold, silver and copper become volatile during the pandemic, aluminium, cobalt and nickel exhibit high volatility during the oil market crisis and pre-COVID period.

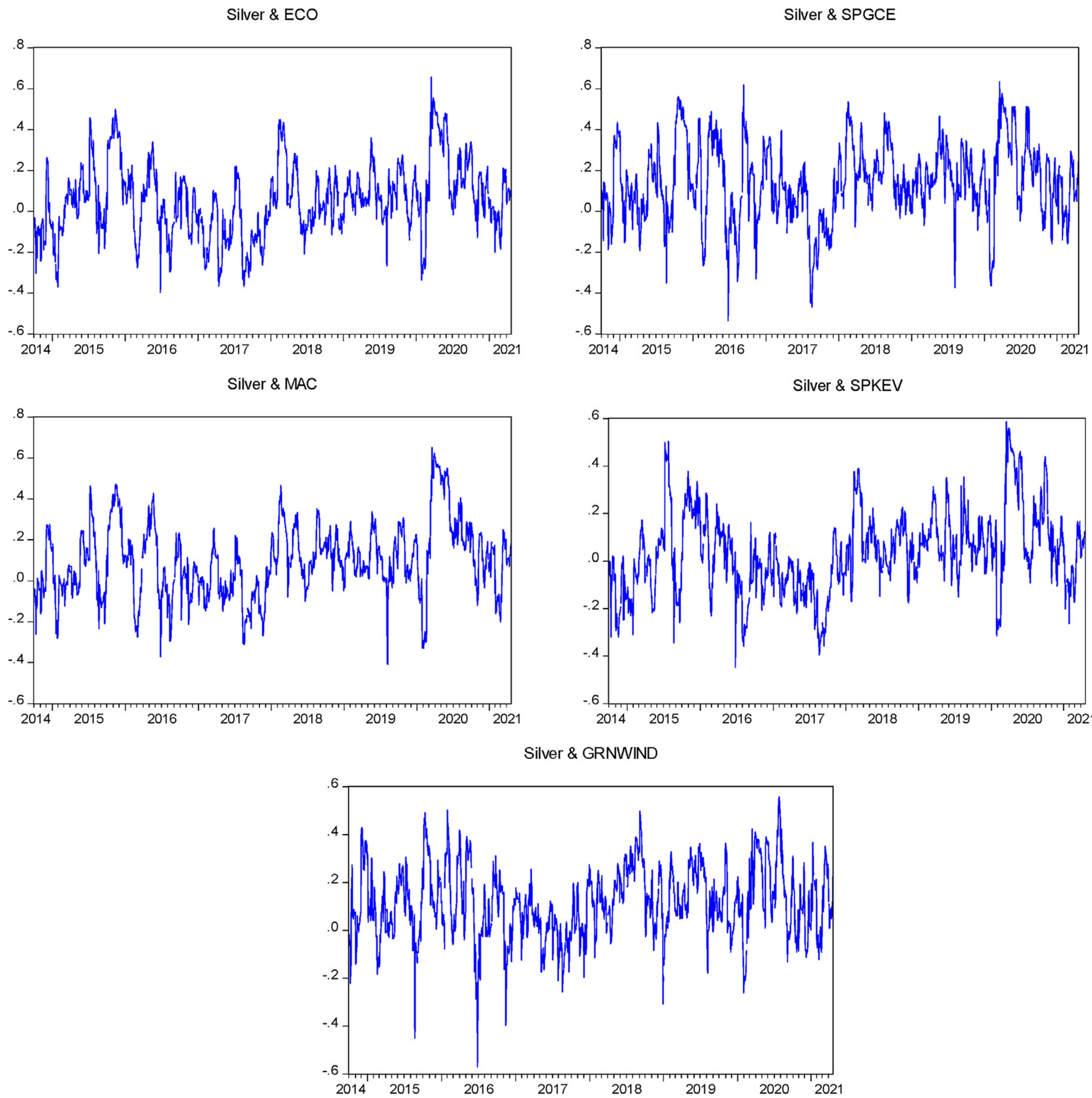

Fig. 9. DCC correlations between silver and clean energy equities.

hedges and/or safe havens for clean energy stocks.

Our main results indicate a statistically significant non-linear relationship between the returns of the majority of the metals under study and the clean energy stock indices. All the energy metals, except cobalt, have a significant positive relationship with clean energy stocks on average. Evidence from the regression estimates shows that the positive relationship is also present during extreme market shocks in most cases. None of the energy metals act as hedges for clean energy stocks but the study supports the existing literature on the hedging properties of gold and silver, as we find evidence of gold and silver serving as hedges for stocks in certain clean energy subsectors.

As a by-product of testing the research hypothesis, this study summarizes the findings on the current and expected dynamics of certain energy metal markets and clean energy markets from previous studies and sector relevant reports. By analysing the empirical results from the regression model and the information on energy metal market dynamics, we highlight several issues that might influence the relationship between energy metals and clean energy stocks. Further examination of these issues and the testing of hypotheses is outside of the scope of this study. We argue, however, that it is important to highlight these topics for the benefit of future research in the sector. The issues include the role of supply and demand in determining the relationship between energy metal prices and clean energy companies. In the case of cobalt, we postulate that supply factors might play far too large a role in determining the price, and lead to a decoupling from the demand for clean energy solutions. One potential topic of study could be the determinants of cobalt price, for which this study provides multiple possible factors to analyse. In the case of the base metals in this study, we postulate that the extreme growth in the demand for clean energy solutions might mitigate the negative impact on profitability of growing raw material costs resulting from higher metal prices. Another topic of study could be testing this hypothesis at a later date, as the industry matures and the high demand growth, that is likely driving stock prices, eases. Furthermore, we highlight the decreasing impact of metal prices moving downstream. For example, changes in nickel prices likely have a larger impact on the profitability of a cathode manufacturer than an electric vehicle manufacturer. We argue that isolating the clean

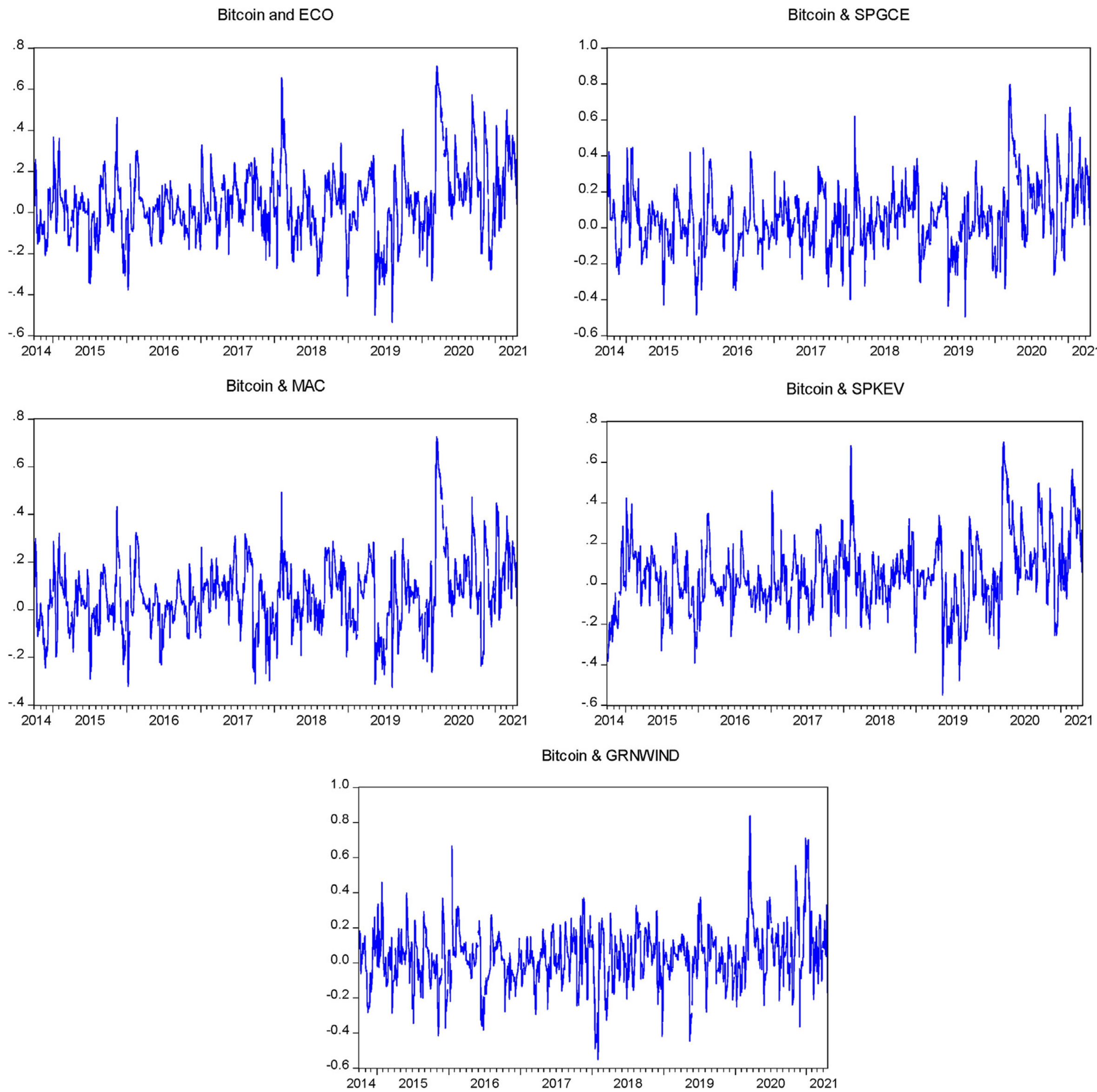

Fig. 10. DCC correlations between Bitcoin and clean energy equities.

Table 4
Analysis of hedging effectiveness (%).

Sample period →	Subsample I	Subsample II	Subsample III
Panel A: ECO index			
Gold	18.01	22.46	7.59
Silver	14.99	13.43	5.27
Bitcoin	11.35	15.08	10.02
Panel B: SPGCE index			
Gold	17.48	23.06	7.68
Silver	14.19	13.34	5.14
Bitcoin	12.76	17.22	10.87

Notes: This table gives the hedging effectiveness results. Subsample I is the period from October 2014 to March 2016, the oil market crisis; Subsample II is April 2016 to January 2020, the pre-COVID period; Subsample III is February 2020 to April 2021, the COVID-19 pandemic.

Table 5
Optimal hedge ratios.

Sample period →	Subsample I	Subsample II	Subsample III
Panel A: ECO index			
Gold	0.1752	0.0058	0.2388
Silver	0.1945	0.0189	0.2641
Bitcoin	0.2076	0.0284	0.1856
Panel B: SPGCE index			
Gold	0.1721	0.0073	0.2253
Silver	0.1956	0.0196	0.2501
Bitcoin	0.2141	0.0314	0.1898

Notes: This table gives the optimal hedge ratios. Subsample I the period from October 2014 to March 2016, the oil market crisis; Subsample II is April 2016 to January 2020, the pre-COVID period; Subsample III is February 2020 to April 2021, the COVID-19 pandemic.

energy subsector as close to the first degree of separation from metal production as possible could yield better results. This topic could be examined in multiple ways, such as whether the degrees of separation influence the impact of metal price changes on clean energy company profitability. As profitability is only one determinant of value, and subsequently stock price, the determinants of clean energy stock prices and the role of metals as determinants could be studied further. Such a study could start from, or expanded to, any of the clean energy subsectors and the corresponding raw material value chains. With better information about the role of metals in determining clean energy company profitability and value, a similar methodology to the one used in this study could be used to test hedging and safe haven properties more accurately.

Although this study opens the discussion around the quantitative association between energy metal prices and clean energy companies, and addresses the potential inferences regarding hedging and safe haven attributes, it has several limitations, many of which are, directly or indirectly, caused by the early stage of development of the clean energy sector. There are few stock indices to choose from, and the isolation of specific subsectors, as in the case of nickel and battery cathodes, is extremely cumbersome, if not impossible, with publicly available information. In addition, many of the energy metals are not traded on public markets, which results in multiple problems with the data. For example, graphite and lithium are not traded in liquid marketplaces that produce daily data, but data is available from vendors who aggregate information from customs data and industry surveys. This leads to opaque and infrequent data points, which cannot be used very reliably in quantitative studies. As the clean energy sectors, along with the mining and metal subsector providing raw materials for generating new energy, mature, more data is likely to become available and empirical research on the topic could become easier and more reliable.

Credit author statement

Robert Gustafsson: Conceptualization; Formal analysis; Writing - original draft; Final Revision. Anupam Dutta: Conceptualization; Validation; Writing - original draft. Elie Bouri: Writing; Editing; Final Revision; Project administration.

Declaration of competing interest

The authors declare no conflict of interest.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.122708.

Appendix A

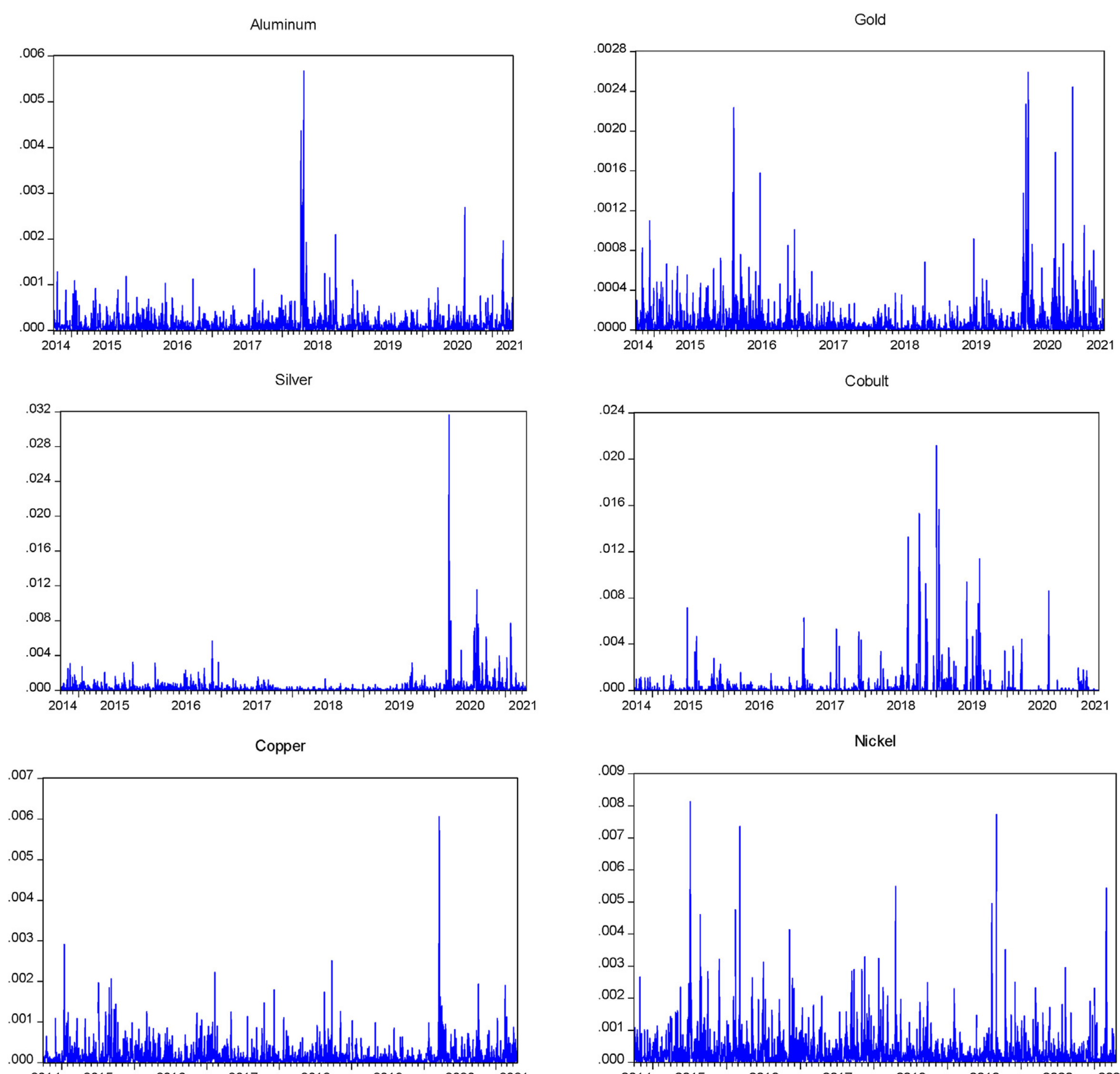

Fig. A1. Realized volatility of metal indices.

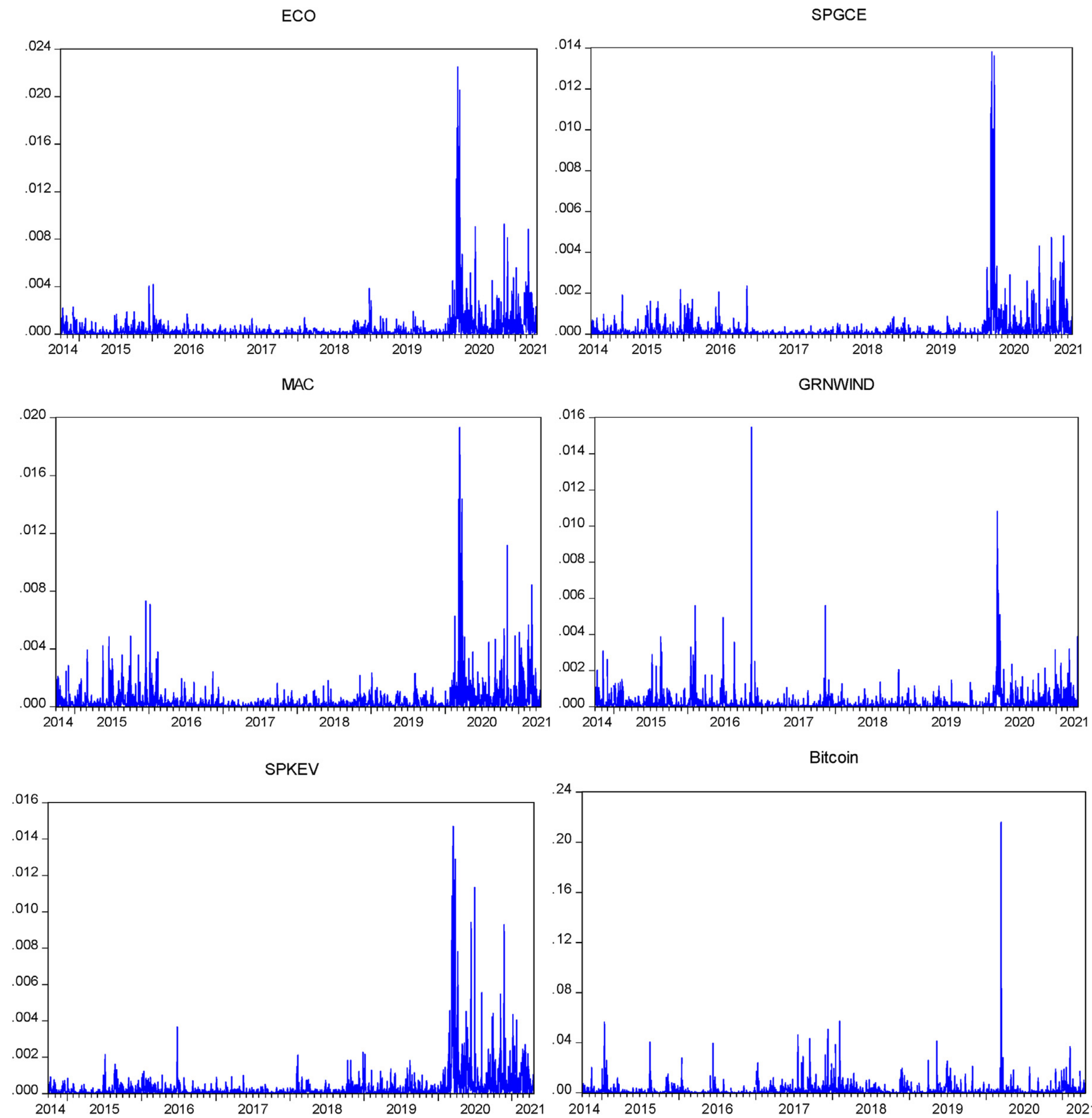

Fig. A2. Realized volatility of clean energy stock indices.

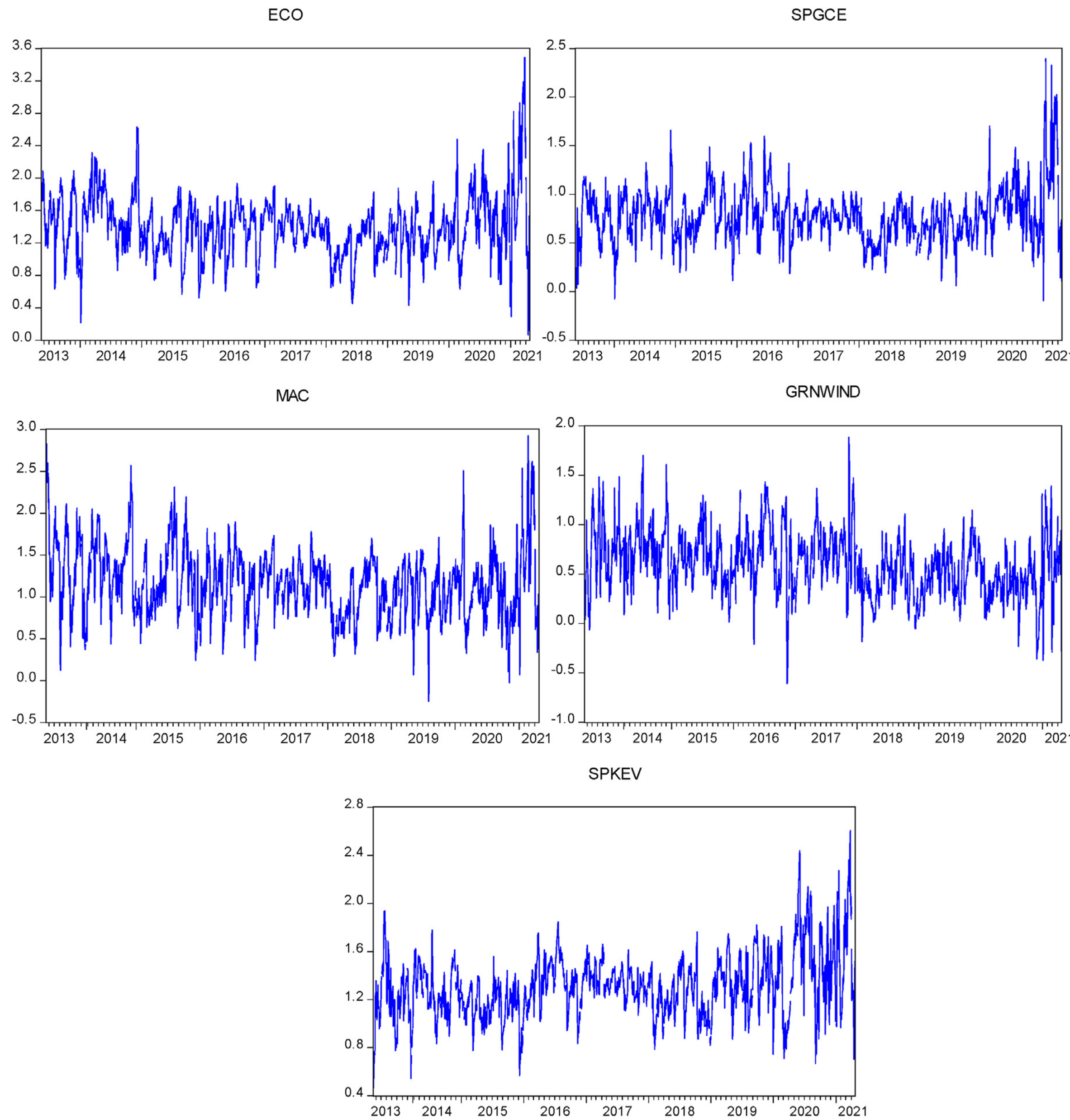

Fig. A3. Time-varying betas for clean energy stock indices.

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