Carbon Credit Futures as an Emerging Asset:
Hedging, Diversification and Downside Risks

Abstract

Even though carbon futures as a new asset have attracted the attention of scholars, there have been few attempts to investigate potential benefits of investing in carbon credits. In this study, we analyse the feasibility of hedging and diversifying stocks with carbon futures. We adopt the dynamic conditional correlation (DCC) models which allow us to compute time-varying optimal hedge ratios, optimal weights and portfolio returns. These hedging and portfolio metrics are then compared with those derived for commodity futures. Our main results suggest that including a small portion of carbon futures in a stock portfolio provides hedging benefits and reduces overall risk for a given level of expected return. The COVID-19 outbreak seems to have changed the hedging dynamics and the hedging capability of carbon futures is impaired during the pandemic. In terms of diversification benefits, our results show that adding carbon to a stock portfolio improves the risk-adjusted performance overall. We further examine economic benefits as a measure of hedging performance and find evidence of positive utility gains that are strongly dependent on investors' risk aversion. Comparing the performance of carbon futures with commodities, hedging effectiveness of carbon futures is not as high as that of precious metals and agriculture futures, however, carbon credits outperform energy futures in terms of hedging and diversification.

1. Introduction

Global warming and climate change have been a serious threat for the environment in the last couple of decades. Since the mid-20th century, increasing temperatures have been menacing the global climatic system. The main cause of global warming is attributed to man-made emissions of greenhouse gases. Starting heavily with industrialization, fossil fuel consumption to generate energy for manufacturing, transportation, heating, and electricity, along with hasty urbanization causing deforestation are seen as the major reasons of carbon emissions. Authorities have initiated a range of policies to prevent carbon emissions to mitigate the damages of global heating[1]. Carbon pricing that can be applied either as carbon taxes or emissions trading systems is one of the most efficient solutions to facilitate the transition towards low-carbon industries by providing an economic incentive.

Emissions trading systems are also known as cap and trade (CAP) or emissions trading scheme (ETS) under which the central authority allocates a limited number of carbon permits. According to this system, carbon releasing companies must hold permits to cover their emissions. Thus, through a market-based system, polluters are allowed to adjust their carbon emissions permits by trading carbon allowances. As the cost of carbon increases, carbon-releasing companies are forced to shift their operations to greener applications. Established emissions trading systems come along with exchange-listed futures that enhance market efficiency through price formation and liquidity which resultantly allure investors to actively trade. The value of traded global carbon permits grew by 164% in 2021 and reached to $851

[1] The United Nations Framework Convention on Climate Change (UNFCCC) has been established to prevent "dangerous human interference with the climate system" and 154 states signed the Earth Summit in 1992. The Kyoto Protocol superseded in 1997, and the Paris Agreement in 2015 replaced the Kyoto Protocol with 194 countries and the European Union signing the treaty. The Kyoto Protocol has propelled the creation of the carbon credit markets and the emissions trading systems (see among others, Balcilar et al., 2016).

billion. Since the launch of the EU ETS, carbon emissions have become a factor of production and tradable commodity (Gronwald et al., 2011; Wen et al., 2017). The carbon market with its recent history provides new opportunities for market participants, however, its price dynamics should be well understood in order to develop relevant investment decisions and risk management strategies. Unlike bonds and stocks which pay interest and dividends, respectively, carbon allowances do not provide interim cash flows, instead investors can collect the resale price, which is determined by demand and supply forces (Benz and Truck, 2009; Fan et al., 2014). Demand for carbon may arise from energy consumption, economic activity, and investments, however, it is supplied by regulating bodies only, which is rather unique (Seifert et al., 2008; Alberola et al., 2008).

In light of the above discussions, a new market for a new asset[2] has emerged and been growing steadily, attracting investors who seek hedging benefits and asset-level diversification which provides significant advantages over country-level diversification in a world of globalization.[3] Carbon futures are used by financial market participants for hedging to facilitate risk mitigation and transfer (Narayan and Sharma, 2015; Schultz and Swieringa, 2014). Besides, with the involvement of institutional investors including hedge funds, pension funds and carbon funds, carbon markets have received considerable interest from market players who want to extend their investment opportunities, even though they do not have any emission reduction obligations (Afonin et al., 2018). As pointed out by Dutta (2018), financial institutions constitute a weighty group of investors in the European emission market that make use of the EUAs as an effective tool for portfolio diversification and as a part of socially responsible investing strategy.[4] Therefore, the increasing role of institutional investors in carbon markets supplements liquidity and enhances profitability (Jaraite-Kazukausk and Kazukauskas, 2015; Hintermann, 2017; Makridou et al., 2019).

Recently, scholars have dedicated efforts to study the interactions between carbon markets and financial assets from the perspective of portfolio construction and risk management. Narayan and Sharma (2015) confer that carbon and related derivatives are used for “different investment operations, such as portfolio diversification, arbitrage, hedging, and speculation”. However, the vast majority of the literature in this field investigate the linkages between carbon and energy markets (Reboredo, 2013; Boersen and Scholtens, 2014; Sousa et al., 2014; Hammoudeh et al., 2015; Yu and Lo, 2015; Kanamura, 2016; Zhang and Sun, 2016; Wen et al., 2017). We still do not have a very good understanding of potential benefits of investing in carbon for investors. Even though some studies examine carbon allowances as a hedging instrument for clean energy stocks (e.g. Ahmad et al., 2018; Jiang and Ma, 2022), these studies do not offer a complete picture. Given that carbon allowances have weak linkages with macroeconomic variables and financial markets (e.g. Chevallier, 2009; Tan et al., 2020), there may be some hedging and diversification benefits to exploit for equity market investors, which has been largely ignored in previous research. In addition, the bulk of prior studies focus on EUA carbon allowances,

[2] According to Fan et al. (2014) it could be expected that “existing finance theories, concepts and tools would not be applicable in this market”.
[3] As suggested by Singh et al. (2019), globalization has caused asset-level diversification to become more efficient than country-level diversification in portfolio construction.
[4] See Viteva et al. (2014) among others on the discussion of socially responsible investing strategies adopted by investors.

whereas global carbon markets could offer investors various other investment opportunities in carbon credits that can be useful in risk management and portfolio diversification.[5]

This study analyses carbon credit futures as an emerging financial asset. Given the distinctive and unique features of carbon allowances as a tradable asset, we believe that investigating the investment characteristics of carbon futures deserves a special attention and can provide useful information for financial market participants. Our main aim is to assess the hedging and diversification benefits of global carbon allowances for stock portfolios (MSCI Asia Pacific, MSCI Europe, MSCI North America, and NASDAQ green stocks). For this purpose, first, we compute hedge ratios, hedging effectiveness and optimal weights based on Engle's (2002) Dynamic Conditional Correlation (DCC)-Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and then estimate portfolio metrics and utility gains of hedged portfolios. We also compare hedging and diversification performance of carbon futures to that of commodity futures (agriculture, energy, and precious metals). More specifically, this paper attempts to implement hedging strategies using carbon allowances that improve the efficiency of risk management and minimize the overall portfolio risk. Such a contribution is eminent for market players in terms of building accurate portfolio construction strategies and pricing related financial derivatives. In our case, hedging can be considered as a special case of asset allocation that involves carbon/commodity futures and equities. However, as suggested by Wang et al. (2015), hedging is slightly different from asset allocation in the sense that hedgers try to minimize their losses by taking an offsetting position and thus they are less concerned about the returns they get than the risks they may face. Mean-variance portfolio investors that seek diversification, on the other hand, strive to reduce risk without sacrificing the potential for higher gains when they construct their portfolios. Since hedging is return neutral, we also investigate if the hedged portfolios provide diversification and positive economic benefits.

We contribute to the emerging literature of energy finance in several dimensions. First, to the best of our knowledge, we use a global carbon index for the first time in the existing literature as the previous work largely focuses on European Union Allowances (EUAs) used in the European Union Emissions Trading Scheme (EU ETS), which was launched in 2005 and constitutes a first example. More specifically, we use the IHS Markit Global Carbon Index which is the first benchmark and liquid investable index designed to track global carbon credits established on July 31, 2014. Therefore, this study extends the relevant literature and enhances our understanding of benefits of investing in global carbon allowances by examining their hedging and diversification potential in greater depth. Second, as stated earlier, even though some papers investigate the links between carbon allowances and financial assets, these studies largely focus on clean energy equities or electricity companies (e.g. Oberndorfer, 2009; Kumar et al., 2012; Moreno and da Silva, 2016; Dutta et al., 2018; Ahmad et al., 2018; Wang and Cai, 2018; Ji et al., 2019; Xia et al., 2019; Hanif et al., 2021). There are also some studies exploring the hedging potential of energy and carbon futures for mitigating carbon price risk (see among others Balcilar et al., 2016; Philip and Shi, 2016; Wen et al., 2017; Chai and Zhou, 2018; Lee and Yoon, 2020). However, relatively very few empirical works analyse the performance of carbon futures as a standalone investment (Zhang et al., 2017; Afonin et al., 2018). Therefore, our paper fills this gap by exploring the performance of global carbon futures not only for green

[5] Apart from EUA, there are also national or sub-national systems operating in other countries, including Canada, China, Japan, New Zealand, South Korea, Switzerland, the United Kingdom and the United States.

stocks but also for conventional stock portfolios. Third, our sample period that runs from July 31, 2014 to July 30, 2021 covers the COVID-19 period and we examine how the hedging and diversification dynamics have changed during the pandemic. Understanding cross-market interactions during market turmoil is crucial for investors and portfolio managers, particularly in terms of risk management (Huynh et al., 2022). In this way, our study provides updated and fresh evidence for hedging and diversification characteristics of carbon futures before and after the pandemic which is rather in dearth. Fourth, unlike most of the previous studies that focus on symmetric variance reductions, we also consider downside risk measures, such as Value-at-Risk (VaR) and Conditional Value at Risk (CVaR). More specifically, we further investigate whether an investor with a proportion of wealth allocated to carbon credits and stocks can reduce their exposure to downside risk relative to an unhedged stock-only portfolio.

Our results show that carbon is a relatively cheap hedge overall, however, optimal hedge ratios display considerable volatility over time and significantly depend on the market state. During the COVID-19 pandemic, hedging becomes more expensive and hedging effectiveness falls, showing that hedging capability of carbon futures is impaired. Our findings also indicate that the Modified Conditional Value-at-Risk (MCVaR), capturing skewness and kurtosis of the losses beyond the VaR level, generates better results in terms of hedging effectiveness. The results also provide evidence of positive utility gains for portfolios consisting of carbon and stocks; however, the economic benefits are significantly dependent on the level of risk aversion and market state. As for the diversification benefits, adding carbon futures to stock portfolios improves portfolio performance in the full sample and pre-COVID periods; however, the portfolio performance of carbon futures deteriorates during the pandemic, particularly for European and North American stocks. Lastly, when we compare the performance of carbon futures with commodities, we observe that hedging effectiveness of carbon is not as high as those of precious metals and agriculture futures, nevertheless, carbon credits outperform energy futures in terms of hedging and diversification benefits.

The remainder of this paper is organized as follows. Section 2 reviews the work in related literature. Section 3 presents the data with descriptive statistics. Section 4 discusses the research model and results of the analyses. Section 5 concludes the findings.

2. Literature Review

This section surveys several strands of the literature relevant to carbon as a financial asset. The first strand of the literature investigates the relationship between carbon and energy markets. As suggested by Dai et al. (2021), empirical studies that analyse the effects of carbon trading on macroeconomy and financial markets largely focus on energy industry. The linkages between carbon and energy markets have been studied extensively with the execution of different quantitative techniques (Keppler and Mansanet-Bataller, 2010; Byun and Cho, 2013; Sousa et al., 2014; Yu and Lo, 2015; Zhang and Sun, 2016; Balcilar et al., 2016; Wen et al., 2017; Uddin et al. 2018; Ji et al., 2018; Wang and Guo, 2018). Taking a closer look at the relevant literature, existing research substantiates significant interactions whereby the results predominantly suggest that energy markets, specifically fossil fuels, significantly affect carbon prices (Mansanet-Bataller et al., 2007; Alberola et al., 2008; Bredin and Muckley, 2011; Creti et al., 2012). Empirical research also shows that oil and carbon markets are positively associated, as a surge in oil demand spouts energy consumption along with carbon emissions leading to higher carbon prices (Kanen, 2006; Zhang et al., 2017). Byun and Cho (2013) forecast the volatility of the carbon market using the volatilities of Brent oil, coal, natural gas, and electricity prices. Their findings reveal that Brent oil, coal and electricity have a strong predictive power for the volatility of carbon futures. Balcilar et al. (2016) examine the energy and carbon markets with a focus on risk spillovers and dynamic hedging strategies. They provide evidence of time-varying correlations between carbon and energy futures and volatile hedging effectiveness of carbon allowances. In another study, Tan and Wang (2017) investigate the dependence between the EU ETS and energy markets and confirm significant linkages arising from production-restrain, substitution and aggregated-demand effects. In a similar study, Ji et al. (2018) show that Brent oil prices significantly affect carbon markets, wherein the volatility connectedness is higher than the return connectedness.

The second strand of the literature analyses univariate dynamics of carbon prices. Examining the presence of outliers in carbon price volatility, Chevallier (2011a) detects instabilities in carbon volatility, which can be explained by growing uncertainties in post-Kyoto negotiations. In another study, Chevallier (2011b) adopts non-parametric modelling and report strong heteroskedastic and asymmetric behaviour of carbon prices. In a similar study, Chang et al. (2017) explore the price dynamics of the China-wide emissions trading scheme (CETS). Their results imply that the emissions allowances display significant dynamicity, asymmetric leverage and regime-switching effects. Creti and Joëts (2017) test for multiple bubbles in EUA carbon prices and provide evidence of different episodes of price bubbles. They also find that these bubbles seem to be related to energy and environmental policy announcements. In a more recent study, Dutta (2018) examines jumps in EUA prices and shows that jumps do exist in the carbon market. He further contends that outliers and time-varying jumps should be incorporated into the modelling of carbon market risk.

The third and emerging strand of the literature investigates the links between financial markets and carbon markets and/or hedging and diversification benefits of carbon as an investment vehicle. Our paper mostly relates to this stream of the literature. Table 1 provides a summary of key relevant works. As can be seen, most of the empirical studies in this area focus on clean energy equities or electricity companies. In addition, the literature cites mixed results regarding portfolio performance of carbon. For example, Zhang et al. (2017) suggest that including carbon credits into stock portfolios reduces the overall portfolio risk as the relative independence of the carbon market from financial assets helps to diversify. Afonin et al. (2018) provide a contrasting evidence and find that European carbon emissions offer diversification benefits only during phase 1 (2005-2007), however these benefits disappear for phase 2 (2008-2012) and phase 3 (2013-2020). In another study, Dutta et al. (2018) find insignificant relation between carbon emissions and clean energy equity returns, whereas volatility linkages are significant. They also show that portfolio diversification benefits are attainable for investors in the EUAs. In a more recent study, Hanif et al. (2021) provide implications in terms of portfolio management based on dynamic spillovers and copula functions. They state that the inclusion of carbon allowances in clean energy stock portfolios may provide diversification benefits, particularly during bearish market periods and investors contemplating to invest in carbon must hedge against price fluctuations in clean energy equities. Some studies also argue that carbon and stock prices are connected via energy prices within the nexus of economic and financial environment; increases in oil demand drive up energy prices, invoking a negative influence on economic growth, firm value, and leverage, which in turn depresses stock prices (Arouri and Nguyen, 2010; Zhang et al., 2017). However, from a different perspective, higher energy demand may lead to higher carbon allowance prices, creating an economic incentive to reduce emissions which would directly affect firm valuation (Wen et al., 2020; Jimenez-Rodriguez, 2019).[6]

[Insert Table 1 here]

Overall, the survey of literature shows a dearth of empirical studies on hedging and diversification potential of carbon futures for equity portfolios. Prior studies largely focus on clean energy or electricity companies to analyse benefits of investing in carbon markets. The recently established carbon credit markets position carbon futures as an emerging investment alternative with a particular stance in asset management and allocation since their weak association with macroeconomic factors and other financial securities situates them as potential hedging instruments in portfolio design (Alberola et al., 2008; Chevallier, 2009). Despite of the abundance of studies that examine the links between energy and carbon markets, empirical work analysing the interactions between carbon and stock prices and hedging/diversification benefits of carbon as a financial asset are relatively rarer in the existing literature. A deeper understanding of the interactions between equities and carbon credits would equip investors with enhanced skills in optimising investment and hedging strategies. Therefore, we contribute to the existing literature by assessing the portfolio performance of carbon futures and providing updated evidence regarding how the portfolio performance of carbon have changed during the COVID-19 pandemic.

3. Data and Summary Statistics

The data used in this study are listed in Table 2. The study period runs from July 31, 2014 to July 30, 2021, which covers the COVID-19 pandemic. The data are daily and retrieved from Bloomberg. Figure 1 depicts the time series of daily prices for carbon futures. The graphical illustration shows that carbon prices are stable from mid-2014 to mid-2017 and show a strong upward trajectory since mid-2017 due to positive developments in the carbon markets, such as more effective carbon tax policy reforms and the introduction of the Market Stability Reserve (MSR). The global carbon market experiences a fall during March 2020 after the WHO declared COVID-19 a pandemic, however it appears that it quickly recovered and entered a new period of price growth. It even hits a record high level in mid-2021 with increased financial investment in the carbon allowance markets. We also argue that the increased carbon prices can be attributed to governments' actions; market participants have clear signals from governments that they will continue to decarbonize the economy and the supply of carbon allowances will be reduced more rapidly in the years ahead in line with 2030 climate target plan and 2050 net zero strategy, which boosts long-term prospects for higher carbon prices.

[Insert Table 2 here]

[Insert Figure1 here]

Table 3 shows the summary statistics for the daily log returns of all the variables. The results suggest that carbon futures yield the highest daily mean return followed by green stocks, while

[6] There are also some recent papers examining carbon risk premium. Oestreich and Tsiakas (2015) present evidence of a large and significant carbon premium as the firms receiving free carbon emission allowances outperform the others, while firms with high carbon emissions are exposed to higher carbon risk raising their expected returns. In a relevant study, Bolton and Kacperczyk (2021) provide evidence of a significant positive relation between stock returns and the level of carbon emissions and suggest that investors price a carbon risk premium at the firm level.

agriculture and energy futures give daily negative returns over the sample period. Looking at the unconditional risk, measured by standard deviations, energy commodities are the riskiest, followed by carbon futures. Therefore, we can say that even though carbon credits yield high returns, they possess significant amount of risk. Higher moment measures namely, kurtosis and skewness, suggest that negative returns are more probable than positive ones, except for agriculture, and all return series display excess kurtosis, implying a high possibility of extreme returns. We also conduct further tests for unit root, autocorrelation and heteroskedasticity. Augmented Dickey-Fuller (ADF) unit root tests show the rejection of the presence of a unit root, indicating that all return series are stationary. The Ljung-Box tests applied up to 10 lags reject the null hypothesis of no autocorrelation in squared returns. Lastly, ARCH-Lagrange Multiplier (LM) tests reject the null hypothesis of homoskedasticity. In a nutshell, preliminary test results provide evidence of the suitability of all the return series for further modelling.

[Insert Table 3 here]

4. Dynamic Conditional Correlations

Given the stylized facts of serial correlation and conditional heteroskedasticity in the return series shown in the previous section, these features must be taken into account when modelling the conditional correlations. As suggested by Lee (2006), the Dynamic Conditional Correlation (DCC) model of Engle (2002) offers a simple way to estimate the time-varying processes of conditional volatilities and correlations simultaneously.[7] The DCC model includes two steps. In the first step, we estimate the conditional return and volatilities as given in equation (1) and (2), respectively below. We use the GJR-GARCH (1, 1) model of Glosten et al. (1993) to capture potential return-volatility asymmetry. If a given market does not exhibit asymmetric return-volatility relationship, we proceed with the standard GARCH specification with no asymmetry.

$$R_{m,t} = \mu_m + \psi_m R_{m,t-1} + \eta_{m,t} \tag{1}$$

$$h_{m,t} = \varphi_{m,0} + \varphi_{m,1}\eta_{m,t-1}^2 + \varphi_{m,2}h_{m,t-1} + \varphi_{m,3}I_{\{\eta_{m,t}-1<0\}}\eta_{m,t-1}^2 \tag{2}$$

where $R_{m,t}$ is the return on the market m at time t, $\eta_{m,t}$ is the model residuals, $h_{m,t}$ denotes the conditional variances and $I_{\{\eta_{m,t}-1<0\}}$ stands for the indicator function taking the value of 1 if $\eta_{m,t}$ is negative and 0 otherwise.

In the second step, we estimate the dynamic conditional correlations. The equation of the conditional covariance matrix from the DCC-GARCH model can be written as:

$$H_t = D_t K_t D_t \tag{3}$$

[7] Multivariate GARCH models, particularly DCC-GARCH, are widely used in the literature to examine cross-market interdependencies and perform portfolio analysis. However, as suggested by an anonymous referee, some recent studies also adopt various empirical techniques, including machine learning and deep learning (e.g. De Spiegeleer et al., 2018; Abdullah, 2021; García-Medina and Luu Duc Huynh, 2021) to make predictions. We are grateful to the referee to provide this insight and we will consider these models for a future study.

where, D_t represents a 2×2 diagonal matrix consisting of conditional standard deviations $\sqrt{h_{i,t}}$. The conditional correlation matrix K_t can be decomposed into:

$$K_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4}$$

where $Q_t^* = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & \dots & 0 \\ 0 & \sqrt{q_{22,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 \\ 0 & 0 & \cdots & \sqrt{q_{nn,t}} \end{bmatrix}$

Engle (2002) formulates the matrix Q_t as:

$$Q = (1 - \theta_1 - \theta_2)\overline{K} + \theta_1 \varepsilon_{t-1}\varepsilon_{t-1}' + \theta_2 Q_{t-1} \tag{5}$$

where ε_{t-1} is a 2×1 vector of standardized residuals and θ_1 and θ_2 are model coefficients to be estimated. Our primary focus is the conditional correlations which can be expressed as:

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}} \tag{6}$$

Cappiello et al. (2006) introduced a more flexible version of the DCC model to capture asymmetries in the conditional correlations. Given that financial markets are highly interconnected and might be hit by common shocks, the Asymmetric DCC (ADCC) model can be well suited to analyse market interactions. Under the ADCC model, the dynamics of Q are governed by:

$$Q = (1 - \theta_1 - \theta_2)\overline{K} - \theta_3 \bar{G} + \theta_1 \varepsilon_{t-1}\varepsilon_{t-1}' + \theta_2 Q_{t-1} + \theta_3 \zeta_{t-1}\zeta_{t-1}' \tag{7}$$

where θ_3 is the asymmetry coefficient. $\zeta_{t-1} = I[\varepsilon_t < 0] \odot \varepsilon_t$, $I[.]$ is an indicator function that takes value 1 if the errors are negative and 0 otherwise. $\odot$ represents the Hadamard product. $G = \zeta_{t-1}\zeta_{t-1}'$ is the covariance matrix of $E[\zeta_{t-1}\zeta_{t-1}']$. This asymmetric effect in the DCC setting helps us understand the correlation structure better and allows us to examine if correlations significantly change following joint shocks. We apply the asymmetric extension of the DCC model if the cross-correlations exhibit asymmetry and if not, we proceed with the standard DCC model.

Table 4 presents the results from the estimated GJR-GARCH (1,1) models. The AR (1) terms ψ in the conditional univariate mean equations are statistically significant in the case of Asia Pacific, North America, green stocks, and precious metals, implying explanatory power of past returns in predicting future returns, however, the lagged returns are not useful in forecasting for the rest of the markets. The ARCH coefficients φ_1 are statistically significant at conventional levels for carbon, North America, green stocks, and agriculture futures, suggesting that lagged shocks drive current volatility in these markets. All the GARCH parameters φ_2 are statistically significant at 1% level and high at magnitude, implying highly persistent volatility behaviour. Looking at the coefficient φ_3, volatility asymmetry is present in half of the markets (Asia Pacific, North America, green stocks, and energy futures); however, carbon credits do not exhibit leverage and volatility feedback effects. Overall, our results confirm those of Byun and Cho (2013) who suggest that carbon prices have a time varying variance, and the volatility of carbon returns has a persistent characteristic, implying that past volatility can be used to forecast the future volatility of carbon futures returns. We apply diagnostic tests to check the validity of the univariate GARCH models. More specifically, we examine if error terms display autocorrelation and remaining ARCH effects. The autocorrelation test results fail to reject the null hypothesis of no serial correlation. ARCH tests fail to reject the null hypothesis of no ARCH effects. Hence, the univariate GARCH models are well specified, and the variance-covariance matrix constructed with these models can be used for conditional correlation modelling.

[Insert Table 4 here]

Table 5 reports the results of the second stage bi-variate (A)DCC models. The sums of θ_1 and θ_2 are fairly close to one in each case, indicating that the conditional correlations are highly persistent and mean-reverting. The average values of the conditional correlations between carbon and stock markets, denoted by ρ, are low overall and range from 0.109 to 0.191, suggesting that the inclusion of carbon futures to a stock portfolio can provide diversification benefits. Among the commodity group, energy futures exhibit the highest correlations with the stock markets, while precious metals are negatively correlated with European and North American equities. The asymmetric effects in the correlations are present in almost half of the cases, indicating that joint shocks increase the co-movements between financial markets. The asymmetry coefficient θ_3 is positive for the pairs of carbon-Europe, agriculture-green stocks, precious metals-Europe and precious metals-green stocks, which shows that negative joint shocks have more impact on correlations than positive joint shocks of equal magnitude. For the pairs of carbon-North America, carbon-green stocks and precious metals-North America, the correlation asymmetry seems to be inverted since the coefficient is negative. In other words, the correlations increase following joint good news in these markets, a similar finding is also reached by Baur (2012) and Chikili (2016) for the gold market, highlighting the potential safe-haven property. All in all, the correlations between carbon/commodity futures and stock markets are dynamic, except for Asia Pacific – agriculture pair that appears to have constant conditional correlations. Moreover, the (A)DCC models do not show any evidence of statistical misspecifications as both multivariate diagnostics, Hosking and Li-McLeod, tests results suggest that we fail to reject the null hypothesis of no autocorrelations.

[Insert Table 5 here]

Figure 2 presents the dynamic correlations between stock returns and futures. Even though there seems to be specific features for each pair, some common characteristics emerge. Firstly, the dynamic correlations are highly volatile throughout the sample period which implies that assuming constant conditional correlations would not be ideal to make informed trading decisions. Secondly, stock markets exhibit stronger interlinkages with carbon, agriculture and energy futures during mid-2016 which coincides with the Brexit referendum. The Brexit has had severe impacts on financial markets by significantly increasing financial market uncertainty and damaging stability. There have been many attempts in the literature to analyse the impact of Brexit on financial markets, and most of the relevant studies suggest that financial markets, more particularly, stock markets experienced negative returns in the short run (Ramiah et al., 2017; Oehler et al., 2017; Breinlich et al., 2018; Davies and Studnicka, 2018). Our results somewhat confirm the possible detrimental effects of Brexit as the correlations become stronger and diversification benefits may diminish when needed most. Thirdly, it seems that the COVID-

19 pandemic has changed the dependence structure as the correlations reach their peak values in early 2020. Therefore, our findings confirm general results on financial asset returns, displaying higher co-dependency during periods of market downturn, which is in line with Gronwald et al. (2011).

[Insert Figure 2 here]

Looking at the dynamic correlations between carbon futures and stock returns, we see that they switch between negative and positive values; the correlations range from approximately -0.3 to 0.5 across all the markets. Green (Asia Pacific) stock markets display the highest (lowest) conditional correlations with carbon on average. Relatively stronger linkages between green equities and carbon allowances are somewhat expected as previous studies (e.g. Kumar et al, 2012; Dutta et al., 2018) argue that higher carbon prices encourage investments in clean energy companies, which would translate into higher corporate profits in the green energy sector. However, the correlation dynamics change frequently over time; for example, while European stocks have the lowest and negative correlations with carbon credits during 2015, they display the highest positive correlations in late 2020s. It is clearly evident that the correlations are strongly responsive to specific events, economic developments and market turmoil and they seem to exacerbate in certain time periods. For instance, the cross-correlations between carbon and stock returns significantly rise following the Paris Agreement adopted in December 2015 and remained at high levels during 2016. This can be linked to changing investors perception of carbon-related investments, which is also suggested by Monasterolo and De Angelis (2020) who argue that stock market investors started considering carbon as an appealing investment opportunity after the Paris Agreement. The pairwise correlations are also higher during the COVID-19 period. For example, the conditional correlations between green stocks and carbon futures surge in couple of days from around 0.15 to almost 0.45 when the WHO announced COVID-19 as a pandemic on March 11, 2020. Nevertheless, we can infer that a portfolio consisting of carbon futures and stocks might provide diversification benefits as the correlations are low in general. However, we should also note that market participants should be aware of volatile correlations while constructing their portfolios.

Comparing the stocks-carbon pairs with stocks-commodity futures pairs, we can clearly see that energy futures exhibit the strongest correlations with stock markets which are mostly positive. For example, the average correlations between carbon and European stocks are around 0.1, while those between European stocks and energy futures are approximately around 0.25, implying that carbon can be a better diversifier than energy futures. The correlations between precious metals and stock markets alter between positive and negative values; the only exception is the Asia Pacific market which always exhibits positive and low correlations with precious metals. The negative correlations may provide evidence of the safe-haven property of precious metals; however, we observe that their co-movements with stocks strengthen during the COVID-19 period, which casts doubt on their safe-haven benefits. Lastly, agricultural futures display positive correlations with stocks; even though the correlations are low overall, there are sudden increases in certain periods such as the wake of the pandemic. Our results reveal that carbon futures may share some common characteristics with commodity futures in terms of the correlation structure with equities, however, precious metals appear to be more distinct as they mostly display negative linkages with equities.

5. Hedging Analysis

The empirical results in the previous sections provide some useful insights and implications in terms of asset allocations and diversification for investors and portfolio managers. More particularly, the dynamic conditional correlations between financial assets are crucial for market participants to hedge their exposure to downside risks and price fluctuations. Theoretically, there are two different approaches for designing an optimal hedge strategy (Gagnon et al., 1998; Cotter and Hanly, 2010). The first approach focuses on risk minimization by assuming that investors are infinitely risk averse. The minimum variance hedge ratio (MVHR) is the most widely used because of its simplicity. However, as suggested by Cecchetti et al. (1988), the problem with this approach is that it ignores the expected return on the hedged portfolio. In addition, the assumption of infinitely risk averse investors might not be realistic since hedgers are heterogenous in terms of their level of risk aversion (Cotter and Hanly, 2015). The second approach is utility maximization which allows us to analyse if the hedged portfolio provides economic gains for investors. Under this approach, utility is a function of both risk and return and incorporates risk aversion preferences in the optimal hedging strategy. In this paper, we follow both approaches. First, we analyse hedge ratio and hedging dynamics in the minimum variance framework and then we compute utility gains from hedging.[8]

5.1. Hedge ratios and optimal weights

In this section, we investigate the role of the global carbon index in hedging against stock price movements based on optimal portfolio weights and hedge ratios. We further compare the hedging potential of carbon prices with that of commodity futures. In other words, using various hedging strategies, we construct different portfolios for managing the stock price risk. We also examine how hedging statistics change during the pre-COVID-19 and COVID-19 periods by splitting time-series data of hedging statistics into subsamples; pre-COVID-19 covers the period from August 1, 2014 to March 10, 2020 and the COVID-19 sample starts from the day the World Health Organization (WHO) declared COVID-19 outbreak a pandemic on March 11, 2020 and ends on July 30, 2021.

We present the methodology for hedging statistics below, building on the theory of minimum variance hedge ratio. Suppose we use asset *j* as a hedge for the stock market index *i*. Following Kroner and Ng (1998), we can write the optimal portfolio weight for asset *i* as:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}, \quad with \quad w_{ij,t} = \begin{cases} 0, \ w_{ij,t} < 0 \\ w_{ij,t}, 0 \leq w_{ij,t} \leq 1 \\ 1, \ w_{ij,t} > 1 \end{cases} \tag{8}$$

where, $h_{ij,t}$ stands for the conditional covariance between returns on assets *i* and *j*, and $h_{ii,t}$ ($h_{jj,t}$) is the conditional variance of returns on asset *i* (*j*). The weight on asset *j* is $(1 - w_{ij,t})$. The conditional variances and covariances were extracted from the (A)DCC models.

We follow Kroner and Sultan (1993)'s methodology to calculate the optimal hedge ratios (OHRs) which minimize the variance of the hedged portfolio as given in the equation (9). The

[8] It is also worth-noting that, following Kroner and Sultan (1993), Fernandez (2008) and Chen et al. (2008), we assume that future prices follow a pure martingale process (i.e. expected return on futures is zero). In this case, MVHR and utility maximization hedge ratios are equivalent.

optimal hedge ratio tells us how much a long position of one dollar in the stock market i can be hedged by a short position of λ_t dollar in asset j.

$$\lambda_t = \frac{Cov(R_{i,t}, R_{j,t} | I_{t-1})}{Var(R_{j,t} | I_{t-1})} \tag{9}$$

The statistics of optimal hedge ratio (OHR) for the entire sample, pre-COVID-19 and COVID-19 periods are presented in Table 6. The average values of the dynamic hedge ratios for carbon futures range from 0.058 to 0.116 during the entire sample period, indicating that carbon credit futures are cheap hedges overall. For example, a $1 long position in North American stocks can be hedged by shorting 9.3 cents of carbon. Comparing the hedge ratios with commodities, agriculture futures are relatively more expensive hedges; for instance, a $1 long position in green stocks can be hedged for 18.5 cents with a short position in agriculture futures. It is also worth noting that some values of optimal hedge ratios are negative suggesting that the hedge can be formed by either being long or short on both assets. Looking at the hedge ratios of precious metals, a $1 long (short) position in European and North American markets can be associated with 16.9 and 4.6 cents long (short) positions in precious metals, respectively. Furthermore, the standard deviations of the OHRs for agriculture futures are the highest followed by precious metals, demonstrating that hedge ratios of these commodities may not be stable over time, whereas the carbon futures seem to have relatively more stable hedge ratios.

[Insert Table 6 here]

The dynamic hedge ratios for the full sample are plotted in Figure 3. The figures provide some interesting insights in terms of the behaviour of OHRs. Firstly, they show that the OHRs are time varying and display considerable volatility, suggesting that hedging costs may significantly change over time. For example, a $1 long position in Asia Pacific stocks can be hedged for around 3 cents with a short position in carbon futures in early 2015, the same position must be associated with 20 cents short position in carbon futures in mid-2015. Secondly, pairwise hedge ratios significantly surge and reach a high level during the COVID-19 pandemic. As can also be seen from Table 5, the average OHR for carbon-Europe pair has increased from 0.038 in the pre-COVID period to 0.190 in the COVID-19 period. Higher hedge ratios imply an increase in hedging costs in the wake of the pandemic, due to larger number of contracts that the hedging strategy requires. This result is in line with Akhtaruzzaman et al. (2021) and Zhang et al. (2021) who document significantly higher hedge ratios after the COVID-19. Furthermore, the hedge ratios for Asia Pacific markets appear to be lower than the others, suggesting that hedging Asia Pacific stocks with carbon and commodity futures would be cheaper.

[Insert Figure 3 here]

We analyse if the increases in the OHRs are statistically significant using t-tests. The results reveal that there are significant differences between the OHRs in the pre-COVID and COVID-19 period as we reject the null hypothesis of equal hedge ratios in all the cases except for Asia Pacific-precious metals pair. We also test for a structural break in hedge ratios using Chow break point tests. More specifically, we investigate if there is a structural break on March 11, 2020, when the WHO declared the COVID-19 outbreak a global pandemic. Therefore, Chow test has a null hypothesis that there is no structural break on March 11, 2020. The F statistics presented in Table 5 provide evidence of a structural break in the OHRs for all cases, except for Asia Pacific-precious metals pair. Hence, we can note that the COVID-19 pandemic has certainly changed hedging dynamics, leading to higher hedging costs. This suggests that investors should rebalance their positions in carbon and commodity futures more frequently during the COVID-19 to hedge stocks. These results add to the existing literature on carbon markets (e.g. Philip and Shi, 2016; Ahmad et al., 2018; Wang and Guo, 2018) by analysing dynamic hedge ratios and investigating how hedging costs have changed during the COVID-19 outbreak.

Optimal portfolio weights are presented in Table 7. For the full sample, portfolio pairs with precious metals and agriculture futures carry the highest average optimal weights that range from 0.402 to 0.490, suggesting that investors should invest between 40%-50% of their capital in agriculture or precious metals futures to create well-balanced two-asset portfolios with stocks. The optimal weights for carbon futures range from 0.179 to 0.227, showing that investors should allocate about 80% of their capital for stocks and roughly 20% for carbon credits to minimize the risk without lowering the expected return of the stock-carbon portfolio. This is consistent with the findings of Dutta et al. (2018) in that investors should invest more in stocks than in carbon allowances to achieve superior risk-adjusted returns. Put it differently, including a small portion of carbon futures in a stock portfolio may reduce the overall risk for a given level of expected return. Additionally, looking at the energy-stock portfolios, we observe that energy futures have the lowest optimal weights around 10%. Therefore, we can clearly say that energy futures may not perform very well in terms of hedging which we will analyze in the next section in a greater detail.

[Insert Table 7 here]

We further examine the changes in optimal weights in pre-COVID and COVID-19 periods and conduct t-tests to see if the changes are statistically significant. The results show that optimal weights of carbon and commodity futures increase during the COVID-19 period in some cases. For example, for green stocks-carbon pair, the optimal weight is 0.163 in the pre-COVID sample, indicating that, for a $1 green stocks-carbon portfolio, 16.3 cents should be invested in carbon futures and the remaining amount in green stocks. The optimal weight of carbon futures increases to 0.283 during the COVID-19 period, which suggests that investors should increase their investment in carbon markets and decrease their investments in green stocks. This result supports the recent findings of Hanif et al. (2021) that show carbon can be a refuge asset against extreme price movement of clean energy equities. However, there are some cases where the optimal weights of carbon should be reduced in the wake of the pandemic, for instance, the optimal weights of carbon for Asia Pacific (Europe) decreases from 0.184 (0.238) in the pre-COVID to 0.158 (0.185) in the COVID-19 period. This shows that market participants investing in Asia Pacific and European markets should decrease their investment in carbon futures to achieve their optimal hedging strategy. Interestingly, our results show that the optimal weights of precious metals in Asia Pacific and Europe stock portfolios significantly decrease in the COVID-19 period, highlighting that precious metals may not act as a safe-haven for these markets. The weights of agriculture futures significantly increase after the outbreak of the Coronavirus, suggesting that market participants should hold more agriculture futures in their stock portfolios to minimize the portfolio risk. Energy futures have the lowest allocations in portfolio combinations both in pre-COVID and COVID-19 samples, confirming our previous results.

5.2.Hedging Effectiveness

Portfolio weights and hedge ratios show how an optimal hedge should be constructed to minimize risk; however, they do not help identify whether the hedge is effective. Following Ku et al. (2007) and Jin et al. (2020), we calculate the hedging effectiveness (HE) to compare the performance of different hedging strategies. Hedging effectiveness estimates the percentage of the variance eliminated from an unhedged portfolio by hedging (Hamma et al., 2021). More specifically, we quantify the variance reduction for any hedged portfolio compared to the unhedged portfolio as given below:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \tag{10}$$

Hedge effectiveness of a perfect hedge is equal to 1, while HE is 0 if hedging is not effective to reduce portfolio volatility. A higher value of HE indicates better hedging performance.

We also calculate the reductions in Value-at-Risk (VaR) and expected shortfall (ES) as alternative risk metrics. As known, these downside risk measures have been widely used by financial institutions to quantify and assess financial risks. VaR measures the maximum expected loss a portfolio can incur over some time interval with a certain confidence level. ES, also known as Conditional VaR (CVaR), represents the conditional expectation of a portfolio's losses given that the loss is beyond the VaR level (Yamai and Yoshiba, 2005). Therefore, CVaR measures the amount of tail risk a portfolio incurs (Artzner, 1997). Unlike variance, which treats all deviations from the average as the same, downside risk measures consider only losses. In other words, the standard measures of risk like variance are symmetric around the mean while downside risk measures, such as VaR and CVaR, capture the asymmetry between upside risk and downside risk (Zhou, 2016). Hence, quantifying hedging effectiveness by downside risk measures would be more realistic as financial market participants are usually more concerned with losses than gains.

Let $\{R_t,\ t=1,2,\ldots,n\}$ represent original financial return series with marginal cumulative distribution function F and probability density function f. Then, VaR of a portfolio with loss L for a given confidence level α can be expressed as:

$$VaR_\alpha(R) = \inf\{l \in \mathbb{R}: \Pr(L > l) \leq 1 - \alpha\} = \inf\{l \in \mathbb{R}: F_L(l) \leq \alpha\} \tag{11}$$

where l is the smallest number of losses. Therefore, VaR is simply a quantile of the loss distribution.

From a statistical point of view, CVaR measures how much a portfolio can lose on average beyond the VaR level and can be mathematically written as:

$$CVaR_\alpha(R) = E[R|\mathrm{R} \geq VaR_\alpha(R)] \tag{12}$$

We compute both historical and modified versions of VaR and CVaR. The non-parametric historical VaR simply sorts the return series from the lowest to the highest value, determines the probability distribution and then calculates the portfolio's losses. It is the simplest way of calculating VaR with no underlying assumption of return distributions. Using historical simulation, VaR can be estimated as:

$$\widehat{VaR}_\alpha(R) = R_{(i)} \tag{13}$$

for $\alpha \in ((i-1)/n, i/n]$.

Historical CVaR is the sample average of excessive loss exceeding historical VaR given in equation (13). Because it is the simplest way of estimating CVaR, the historical simulations method is more widely used than any other estimation methods. Following Harmantzis et al. (2006), historical ES is estimated as:

$$\widehat{CVaR}_{\alpha}(R) = E[R|\mathrm{R} \geq VaR_{\alpha}(R)] = \frac{\sum_{i=[n\alpha]}^{n} R_{n(i)}}{(n-[n\alpha])} \tag{14}$$

Even though the historical method is the easiest to apply, requiring no specific assumptions or parameters, non-parametric statistics tend to be less powerful than parametric estimations. Therefore, we also employ four moment modified downside risk measures to capture potential losses more adequately. It is a stylized empirical fact that financial time series exhibit skewness and excess kurtosis, suggesting that two moment VaR is not sufficient as a measure of downside risk (Conlon et al., 2020). The modified VaR and CVaR use the Cornish-Fisher expansion to capture higher-order moments, namely skewness and kurtosis. The modified versions of VaR and CVaR are based upon the Cornish-Fisher approximation (ZCF) of the α% quantile of the standard normal distribution:

$$Z_{CF,\alpha} = Z_{\alpha} + \frac{1}{6}(Z_{\alpha}^{2} - 1)S + \frac{1}{24}(Z_{\alpha}^{3} - 3Z_{\alpha})K - \frac{1}{36}(2Z_{\alpha}^{3} - 5Z_{\alpha})S^{2} \tag{15}$$

where S and K represent skewness and kurtosis, respectively. Accordingly, the four-moment modified VaR (MVaR) is defined as:

$$\widehat{MVaR}_{\alpha}(R) = \mu + Z_{CF,\alpha}\sigma \tag{16}$$

where μ and σ denote the mean and standard deviations of portfolio returns, respectively.

Modified CVaR (MCVaR) is computed as a function of modified VaR and captures the loss expectation, conditional on the loss beyond the MVaR:

$$\widehat{MCVaR}_{\alpha}(R) = E\left[R|\mathrm{R} \geq \widehat{MVaR}_{\alpha}(R)\right] \tag{17}$$

We set the confidence level to 95% for all downside risk measures. Our focus is downside risk reduction, which is the percentage of the VaR and CVaR reduction, estimated using both historical and parametric methods, that a hedged strategy achieves in comparison with the unhedged portfolio. Similar to the hedging effectiveness measure given in equation (10), VaR and CVaR reductions are calculated as follows:

$$(C)VaR\ Reduction = \frac{(C)VaR_{unhedged} - (C)VaR_{hedged}}{(C)VaR_{unhedged}} \tag{18}$$

Table 8 (a) reports the hedging effectiveness measures for the full sample. Hedging effectiveness of carbon measured by the variance reductions vary between 0.110 and 0.211. This indicates that carbon credit futures are cheap and effective hedges overall; for example, 21.1% of the return variance of a $1 long position in the North American stocks can be hedged by shorting 9.3 cents of the carbon index (see Table 5 for average optimal hedge ratio). Comparing the hedging performance of carbon futures with commodities, we can observe that agriculture and precious metals futures provide the most effective hedges in terms of variance reduction as the hedging effectiveness statistics range from 0.388 to 0.645. We also see that hedging stocks with energy futures is not feasible as the variance of hedged portfolio is higher than that of unhedged portfolio except for Asia Pacific stock market. Let's take green stocks as an example; variance of the hedged portfolio is 1.229 while the variance of the unhedged portfolio is 1.207. This shows that energy futures do not provide efficient hedging benefits since the variance reduction is not achieved (-0.018), validating our previous findings.

[Insert Table 8a here]

The results for the full sample indicate that adding carbon futures to stock portfolios reduces the downside risk overall. For instance, the modified CVaR of European unhedged portfolio is 0.05 while the hedged portfolio with carbon asset is 0.031, decreasing the downside risk by about 39%. Therefore, we can say that the inclusion of carbon credits into stock portfolios significantly reduces the expected maximum loss during the entire study period. The other qualitative results also remain the same; energy futures are the only assets that increase the overall portfolio downside risk for all the stock markets. Considering all the downside measures, precious metals and agriculture futures offer significant downside risk reduction, varying from 21.1% (ΔMVaR for agriculture-Asia Pacific pair) to 76% (ΔMCVaR for precious metals-Europe pair). All in all, our findings demonstrate that carbon credit futures provide consistent risk reduction effectiveness for stock portfolios during the entire study period.[9] Therefore, carbon futures are hedging instruments that can improve the downside risk performance of stock portfolios as the combinations of carbon and equities experience VaR and CVaR reductions. This result is in parallel with Reboredo and Ugando (2015) who provide evidence of significant downside risk gains for portfolios with carbon futures.

Tables 8(b) and 8(c) document hedging effectiveness for the pre-COVID and COVID-19 periods, respectively. Comparing the effectiveness of carbon futures in the pre-COVID phase with the COVID-19 period, our results show that variance reduction falls significantly during the COVID-19 pandemic. Although, hedging stocks with carbon credits leads to considerable variance reduction in the pre-COVID sample, adding carbon futures to a stock portfolio increases overall portfolio risk during the pandemic. For instance, variance reduction for European (Asia Pacific) markets falls from 35.3% (21.4%) in the pre-COVID phase to -9.4% (-9.9%) as the COVID-19 pandemic starts. The results for North America and green stocks also document weakened hedging effectiveness and show that the hedging capability of carbon futures is impaired even though the variance reduction is still positive. Taking green stocks as an example, almost 12.6% of variance reduction appears to be lost in the wake of the pandemic, as it falls from 20.5% to 7.9%. Considering the hedging effectiveness of commodity futures measured by variance reductions, it is clearly evident that agriculture futures provide the largest reduction for all the markets in the COVID-19 phase. For instance, variance reduction offered by agriculture futures for green stocks significantly increases from 39.7% in the pre-COVID to 73.9% in the COVID-19 period, which underscores the effectiveness of agriculture futures as a risk management tool during the pandemic. The hedging effectiveness of precious metals is higher for Asia Pacific and European markets and slightly lower for North America and green stocks in the pre-COVID period. Nevertheless, our results reveal that investors can reduce their overall portfolio risk by combining stocks with agriculture and precious metals and the

[9] The only exception is the ΔMCVaR for carbon-Asia Pacific pair, which shows ineffective downside risk reduction. However, considering the majority of downside risk metrics, we can say that risk reduction is efficiently achieved.

composition of the hedged portfolio can help them lower their exposure to risk. Energy futures seem to provide some variance reduction only for Asia Pacific and green stocks in the COVID-19 period, however, the percentage of variance eliminated by energy futures is quite low with a reduction of only 1.2% for Asia Pacific and 2.2% for green stocks.

[Insert Table 8b here]

[Insert Table 8c here]

The results for the pre-COVID and COVID-19 periods presented in Table 8(b) and 8(c) suggest that downside risk reduction of carbon futures falls significantly in almost all cases as consistent with the variance reductions. For example, during the COVID-19, MCVaR of carbon-Asia Pacific portfolio is -0.045 and that of the unhedged Asia Pacific portfolio is -0.030, showing that the downside risk increases by approximately 50%. Nevertheless, carbon futures seem to provide hedging benefits for some markets during the pandemic; as such, hedging North American stocks with carbon futures can reduce downside risk by 6.5% measured by historical VaR in the post-COVID sample, however, the reduction is much higher around 22% before the pandemic. Similar to the hedging benefits of carbon, precious metals also seem to have diminished hedging benefits during the COVID-19 period. The historical downside risk measures point out that the percentage of downside risk eliminated by precious metals is generally higher in the pre-COVID sample, for instance, downside risk reduction falls from 44.7% before the pandemic to 29% in the aftermath of the COVID-19 outbreak for European equities as measured by historical VaR. However, when we look at the modified statistics, we observe higher risk reduction in the COVID-19 sub-sample. To give an example, downside risk reduction measured by MCVaR increases from 54.8% in the pre-COVID-19 to 68.7% in the post-COVID-19 period for the portfolio of precious metals and North American stocks. This suggests that even though precious metals do not appear to provide downside risk gains for historical losses, they offer higher risk reduction in the COVID-19 era when we take into account skewness and kurtosis of the distribution of losses. This is in line with the findings of Pinho and Madaleno (2010) who report improved results when the leptokurtotic characteristics of the data are taken into consideration.

Regarding the hedging effectiveness of energy futures measured by downside risk reductions, we observe mixed results. Interestingly, energy futures provide better hedging effectiveness for some markets during the pandemic; for example, considering the energy-Asia pacific market portfolio, the downside risk reduction measured by MCVaR increases from -3% in the pre-COVID-19 period to 2.3% in the COVID-19 period. Nevertheless, the hedging effectiveness of energy futures is not feasible in majority of the cases as the risk reductions are still negative for the COVID-19 sample, suggesting that adding energy futures to a stock portfolio may result in increased portfolio risk during the pandemic. This is also enunciated by Mezghani et al. (2021) documenting that the oil market is the least attractive investment during COVID-19 while holding gold can be beneficial for investors. The results also demonstrate that agriculture futures have the greatest downside risk reduction potential for all the stock markets during COVID-19 pandemic. To exemplify, including agriculture futures in green stocks (European equities) portfolio produces the largest downside risk reduction by 73.2% (72.8%) as measured by MCVaR. These results confirm the recent findings of Sifat et al. (2021) who find, in contrast to energy and precious metals futures, agriculture futures attract more hedging pressure during

COVID-19 pandemic. They attribute this to higher real demand for agriculture commodities and weakening US Dollar.

In summary, our results reveal that even though carbon futures provide some hedging benefits, their hedging effectiveness is not as high as precious metals and agriculture futures. However, the hedging performance of carbon futures seems to be better than that of energy futures. This confirms the findings of Ahmad et al. (2018) indicating that carbon as an investment asset is not particularly a good hedge for stocks due to their low hedging effectiveness. However, we should also note that they use variance reductions as a measure of hedging effectiveness, which does not capture downside risks. When we consider reductions in downside risks, carbon appears to provide better hedging effectiveness; for instance, including carbon to North American stock portfolio reduces the risk of unhedged portfolio by 58.5% in the full sample period as measured by MCVaR in comparison with 21.1% variance reduction. Overall, our findings suggest that hedging strategy based on CVaR with Cornish-Fisher expansion outperforms other measures that capture variance reduction and downside risk elimination. Therefore, we can say that investors should use MCVaR as a hedging effectiveness criteria which is in line with Chai and Zhou (2018) who find that MCVaR strategy is advisable in carbon market hedging problems. Moreover, it is evident that the COVID-19 pandemic has substantially reduced the hedging effectiveness of carbon futures, however, the values of hedging effectiveness are still positive in some cases during COVID-19. The deteriorated hedging benefits provided by alternative assets during the Coronavirus crash are also found by recent studies, such as Guo and Zhou (2021).

5.3.Economic Significance Analysis of Hedging Strategy: Utility Maximization

In order to incorporate both return and risk in hedging, we now turn to examine whether there are possible economic gains from the hedging positions we established earlier. In doing so, following Narayan and Sharma (2016) and Batten et al. (2021), we assume that a hedger optimizes their utility with a mean-variance utility function. We also investigate the sensitivity of the utility results to different levels of risk aversion. As the expected utility significantly depends on the risk aversion coefficient, we consider different values of risk aversion, corresponding to less risk averse investors (Δ=3), moderate investors (Δ=6) and highly risk averse investors (Δ=12).

Following Kroner and Sultan (1993) and Batten et al. (2021), we calculate expected utility gain $\Delta E(U)$ as the difference between the utility of the hedged portfolio (P_{hedged}) and the utility of the unhedged portfolio ($P_{unhedged}$):

$$\Delta \mathrm{E(U)} = \left[E\left(U\left(P_{hedged}|\Omega_{t-1}\right)\right) - E\left(U\left(P_{unhedged}|\Omega_{t-1}\right)\right)\right] \tag{19}$$

where the expected utility of the hedged portfolio is

$$E\left(U\left(P_{hedged}|\Omega_{t-1}\right)\right) = E\left(R_{h,t}|\Omega_{t-1}\right) - \Delta Var\left(R_{h,t}|\Omega_{t-1}\right) \tag{20}$$

where Δ denotes the risk aversion parameter and *Var* represents the variance of the portfolio. Similarly, the expected utility of the unhedged portfolio is calculated as:

$$E\left(U\left(P_{unhedged}|\Omega_{t-1}\right)\right) = E\left(R_{i,t}|\Omega_{t-1}\right) - \Delta Var\left(R_{i,t}|\Omega_{t-1}\right) \tag{21}$$

The performance of the hedge strategy is simply evaluated by the utility improvement compared to the unhedged portfolio, as given in equation (19). If the difference between the utilities of hedged and unhedged portfolio is positive (negative), then the hedge strategy yields a utility gain (loss).

Table 9 presents the estimates of utility gains and losses for full sample, pre-COVID-19 and COVID-19 phases. The results demonstrate that the expected utility increases with risk aversion. This is in line with Batten et al. (2021) who find positive relation between risk aversion and expected utility, and attribute this to the variance reduction in the hedged position being larger than in the unhedged position. Overall, the empirical findings show that hedging stocks with carbon futures is always profitable for the full sample and pre-COVID-19 period. Carbon seems to provide the best hedging performance for the North American stock market for the entire sample; a less risk averse investor gets an average percentage utility gain of 0.826 while a highly risk averse investor achieves an average percentage utility gain of 3.294. As expected, precious metals and agriculture futures produce the highest economic benefits; for example, a highly risk averse investor can obtain a utility gain of 10.02% if they use North America stock index-agriculture futures hedge. Energy futures are the worst hedgers as they do not produce any utility gains in the majority of cases, except for Asia Pacific markets, which confirms our previous findings. Overall, our results show that precious metals and agriculture futures provide higher utility gains than carbon futures. Nevertheless, carbon credits seem to be better hedges against stock price movements than energy futures.

[Insert Table 9 here]

Comparing the utility gains in the pre-COVID-19 and COVID-19 samples, we see that investors in Asia Pacific and Europe markets cannot earn positive utility gains by hedging their stock positions with carbon during COVID-19 pandemic. However, hedgers using North America-carbon and green stocks-carbon pairs seem to achieve positive utility gains. We even see that the economic benefits increase for the COVID-19 sample; for instance, the utility gains increase from 2.93% in the pre-COVID to 4.73% in the post-COVID period for a highly risk averse investor if they use North America-carbon hedge. These results validate our previous findings regarding variance and downside risk reduction which in turn suggests the robustness of our analyses. During COVID-19 pandemic, since the variance reduction using carbon futures is not achieved in the case of Asia Pacific and European markets, the associated utility gains are negative irrespective of the risk aversion levels. On the contrary, hedging North American and green stocks with carbon futures can reduce overall portfolio risk while receiving positive returns and utility gains.

Our results further show that agriculture futures and precious metals offer significantly greater economic benefits for all the stock markets and any types of investors during the COVID-19 pandemic. For example, hedging North American equities with agriculture (precious metals) futures seem to provide an average utility gain of 30.65% (24.46%) for a highly risk averse investor in the COVID-19 era, while it is 4.92% (5.95%) in the pre-COVID period. This highlights that agriculture and precious metals futures can provide significant benefits for investors when they seek shelter from the COVID-19 turbulence, supporting the findings of some recent studies (e.g. Rubbaniy et al., 2021). We also observe that energy futures do not provide any utility gains for Europe and North America both in the pre-COVID and post-COVID samples, while their utility gains are always positive for Asia Pacific markets.

Regarding the utility gains of energy futures for green stocks, the economic benefits significantly increase and become positive during the pandemic. Comparing the economic benefits of carbon credits with energy futures, we observe that hedging North American and green stocks with carbon credits produce much higher utility gains in the wake of the COVID-19 pandemic.

6. Diversification Benefits

Lastly, we examine the diversification benefits of including carbon futures in an unhedged stock portfolio and compare its diversification performance with commodity futures. More specifically, we use various portfolio performance metrics, such as Sharpe, Omega and Sortino ratios, to evaluate whether the hedged portfolio outperforms the unhedged portfolio in terms of risk-adjusted return performance. We use 3-months US T-bills rate as a proxy for risk-free rate. Sharpe ratio (Sharpe, 1966) is computed as follows:

$$Sharpe = \frac{R_p - R_f}{\sigma_p} \tag{22}$$

where $R_{p,t}$ represents the portfolio returns, R_f denotes the risk-free rate and $\sigma_{p,t}$ is the standard deviations of the portfolio returns. It is well-established in the literature that Sharpe ratio has certain limitations, including an assumption that portfolio returns are normally distributed. In order to overcome this limitation, we also estimate Sortino (Sortino & van der Meer, 1991; Sortino & Price, 1994) and Omega (Keating and Shadwick, 2002) ratios.

The Sortino ratio is a variation of the Sharpe ratio and only considers downside risk. In other words, it factors in downside risk and excludes upside risk. Given that investors' attitude towards risk is asymmetric, downside risk portfolio performance measures, such as Sortino ratio, might give more accurate results. Sortino ratio is calculated as

$$Sortino = \frac{R_p - R_f}{\sigma_{p,downside}} \tag{23}$$

where $\sigma_{p,downside}$ stands for downside risk.

The final performance metric, Omega ratio, also known as gain-loss ratio, considers both downside and upside portfolio returns, as follows:

$$Omega = \frac{\frac{1}{T}\sum_{t=1}^{T} \max{(0, R_{p,t}^{+})}}{\frac{1}{T}\sum_{t=1}^{T} \max{(0, R_{p,t}^{-})}} \tag{24}$$

Table 10 presents the annualized returns, annualized standard deviations and portfolio performance analytics. We find that adding carbon futures to a stock portfolio is beneficial in all cases for the entire sample and pre-COVID period; the annualized returns increase, and the standard deviations decrease, hence the inclusion of carbon futures raises the excess returns and decreases the volatility. To illustrate, for the whole sample, the annualized return of unhedged Asia Pacific stock portfolio increases from 0.027 to 0.063 and the annualized variance declines from 0.146 to 0.138, when we include carbon futures. Therefore, our results provide evidence of diversification benefits of including carbon futures in the full sample and pre-COVID phase. The full sample portfolio analytics show that annualized Sharpe ratio for the European unhedged stock portfolio is 0.153 and it is 0.364 for carbon-European stocks portfolio, indicating that the Sharpe ratio increases more than two times. Moreover, when we consider Sortino and Omega ratios for the entire sample, we can clearly see that all the stock portfolios benefit from including carbon credit futures. To give an example, the average Sortino (Omega) ratio of green stocks unhedged portfolio is 0.061 (1.149) whereas the carbon-green stocks hedged portfolio generates a Sortino (Omega) ratio of 0.08 (1.194). Therefore, we can conclude that including carbon futures in stock portfolios enhances portfolio performance and adds value to investors in the full sample and pre-COVID periods. The sub-sample analyses demonstrate that the diversification benefits of carbon futures diminish during the Coronavirus crash; more specifically, carbon credits do not seem to provide any diversification benefit for Europe and North America. However, adding carbon futures to Asia Pacific and green stocks improves portfolio performance during the pandemic, as the performance metrics of hedged portfolios are higher than those of unhedged portfolios. In a nutshell, our results reveal deteriorated portfolio diversification benefits of carbon credits during the most recent health crisis. Nevertheless, on aggregate, we observe that hedging stocks with carbon futures increases the expected return and reduces portfolio volatility, enhancing portfolio performance.

[Insert Table 10 here]

Considering the diversification benefits of commodity futures, our results reveal that the introduction of energy and agriculture futures in a stock portfolio is not beneficial in the full sample and pre-COVID periods as it leads to significantly lower returns and deteriorated portfolio performance with much lower Sharpe, Omega and Sortino ratios. However, in the majority of the cases, our results point out increased diversification benefits when we include agriculture futures in a stock portfolio during the pandemic. Precious metals from the commodity group improves the portfolio performance in all cases, again both in the entire sample and pre-COVID phase, however, they lead to deteriorated diversification benefits in some portfolio compositions during the pandemic. When it comes to the portfolio performance of energy futures, the main findings show reduced investment benefits for Europe and North America, whereas a portfolio composed of energy futures and Asia Pacific or green stocks leads to better portfolio performance in terms of risk-adjusted return during the pandemic.

7. Conclusion

The aim of this paper is to deepen our understanding of hedging and diversification benefits provided by carbon futures. More specifically, our main research question is "what are the benefits of investing in carbon futures as an emerging asset?". This is a fundamental question to be answered in a new era of environmental responsibility and economic sustainability, contributing to the burgeoning field of energy finance. In this paper, we analyse optimal hedging strategies and diversification benefits based on the dynamic correlations between the global carbon market and equities. We also compare the portfolio performance of carbon allowances with that of commodity futures. For this purpose, we employ both symmetric and asymmetric versions of the DCC-GARCH model. More particularly, we investigate whether carbon and commodity futures can serve as efficient hedging instruments and diversifiers against equity market risk by computing first optimal hedge ratios, weights and hedging effectiveness measures and then quantifying utility gains and diversification benefits. We further use downside risk measures (VaR and CVaR) to calculate hedging effectiveness and downside portfolio metrics (e.g. Omega and Sortino) to evaluate portfolio performance.

Our main findings can be summarized as follows: First, the average correlations between commodity futures and stocks are very low; however, dynamic correlations increase strongly in periods of market turmoil, such as the Brexit referendum and the COVID-19 pandemic.

Second, carbon is a relatively cheap hedge and including roughly 20 percent of carbon allowances reduces overall portfolio risk for a given level of return. Third, the COVID-19 pandemic has brought about structural changes in hedging dynamics; the hedging costs significantly increase, and hedging effectiveness seems to have deteriorated. Fourth, analysing whether the hedged portfolios offer economic gains for investors who have different levels of risk aversion, we observe that all types of investors are able to achieve a positive utility gain in a portfolio of carbon and stocks. Regarding the effects of the COVID-19 pandemic, our findings cite mixed results; investors investing in Asia Pacific and Europe markets cannot achieve positive utility gains by hedging their stock positions with carbon while hedgers using green stocks and North America equities can do so in the wake of the COVID-19 outbreak. Fifth, adding carbon futures to a stock portfolio provides diversification benefits for all the stock markets during the entire sample and the pre-COVID period, however, including carbon futures in a stock portfolio may not be beneficial for investors in Europe and North America during the Coronavirus crash. Sixth, when we compare the performance of carbon futures with commodities, we observe that hedging and diversification performance of carbon credits is not as high as those of precious metals and agriculture futures, however, carbon allowances outperform energy futures in terms of hedging and diversification benefits. Lastly, Modified Conditional VaR (MCVaR) gives the largest downside risk reductions in most of the cases, suggesting that investors should construct their hedging strategies based on MCVaR as it outperforms other hedging effectiveness measures such as symmetric variance and historical VaR.

Our results have potential implications and provide significant insights for investors and portfolio managers. Even though carbon credits provide hedging and diversification benefits; these benefits seem to significantly change over time. Our results provide evidence of higher hedging costs and lower hedging effectiveness during the pandemic; therefore, financial market participants should be aware of changing hedging dynamics and closely monitor the markets to dynamically adjust their portfolio settings. The findings further suggest that carbon as a relatively new asset does not perform as good as precious metals and agriculture futures since its hedging effectiveness is comparatively lower, hence, it provides weaker protection against equity market risk. However, the weakest hedging instrument is energy futures, so investors would be better off if they avoid combining their stock investments with energy commodities. This suggests that carbon can be seen as a new alternative investment when hedging against the stock market risks. In other words, investors who have an exposure to equity market risk can effectively and inexpensively hedge their positions by carbon futures. Moreover, financial market participants should use the modified estimators of downside risk measures that capture skewness and kurtosis of the loss distribution as they provide the largest hedging effectiveness.

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Table 1. Summary of Literature Review

Authors	Sample Period	Variables	Method	Key Findings
Oberndorfer (2009)	2005-2007	EUA, crude oil, natural gas and electricity companies stock returns	Multiple regressions and univariate GARCH	EUA price increases (decreases) have a positive (negative) impact on stock returns of electricity corporations. The effect of carbon on electricity equities is time-varying and particularly more pronounced during the EUA market shock in 2006, showing the importance of the carbon market for equities.
Gronwald et al. (2011)	2008-2009	EUA, gas, oil, coal and electricity futures, stock market index, energy stock Index and Renewable Energy Index	Copula functions and Value at Risk (VaR)	The results show evidence of a low dependence between EUA and the composite stock market index during the first six months of 2008, however the dependence becomes stronger thereafter. Stock market indices have higher degree of interdependence with carbon futures than oil and gas futures.
Kumar et al. (2012)	2005-2008	EUA, oil futures, technology company stocks, clean energy stocks and short-term interest rates	Vector Autoregression (VAR) models	Carbon prices do not significantly explain price movements for clean energy equities, which can be attributed to relatively low carbon prices.
Luo and Wu (2016)	2008-2012	Equity markets (China, Europe, US), crude oil, EUA spot prices	Multivariate GARCH-based portfolio optimization	Carbon is positively correlated with crude oil and international stock markets. The correlations between carbon prices and stock markets in UK and US are higher and more volatile than China.
Tian et al. (2016)	2005-2012	EUA spot price and Dow Jones Euro Stoxx Utilities Index	Multivariate GARCH	The correlations between carbon and stock returns on electricity companies are insignificant (significant) during Phase I (Phase II), which shows increased integration between carbon and stock markets.
Zhang et al. (2017)	2013-2016	EU-ETS market, global oil markets, and global stock markets (China, Germany, France, UK, US)	Multivariate GARCH-based portfolio optimization	Even though including carbon in a portfolio does not generate higher returns, it reduces the overall portfolio volatility. Therefore, carbon can provide diversification benefits.
Afonin et al. (2018)	Phase I: 2005-2007	EUA futures, stocks, government bonds, crude oil, natural gas, non-energy	Portfolio optimization	The results provide evidence of portfolio diversification from adding carbon to a portfolio consisting of equities, bonds, crude oil, natural gas and non-energy

	Phase II: 2008-2012 Phase III: 2013-2015	commodities, Euribor 1-month rate		commodities, only for short sales and Phase I. During Phase II and III, there are no portfolio improvements.
Ahmad et al. (2018)	2008-2017	The WilderHill Clean Energy Index, gold prices, the VIX, carbon prices, oil prices, oil volatility and bond prices.	Multivariate GARCH	Carbon is not the best hedge for clean energy stocks as its hedging effectiveness is relatively low. Only 1.7% of the return variance of clean energy stocks can be hedged by carbon.
Dutta et al. (2018)	2009-2017	EUA and clean energy stock indices	Multivariate GARCH	The results show insignificant price linkages between EUA and clean energy stocks. Investors allocating roughly 18% of their capital in EUA and the remaining in clean energy equities can achieve superior risk-adjusted returns.
Jiménez-Rodríguez (2019)	2005-2015	EUA and stock market indices for France, Germany, Italy, Spain and the UK	Granger causality and cointegration	The Granger causality runs from stocks markets to carbon prices. The results also suggest that the linkages between carbon and stock prices significantly change over time.
Xia et al. (2019)	2008-2019	EUA, renewable energy stocks, oil, natural gas, electricity and coal	Diebold and Yilmaz (2014) connectedness measure	The empirical findings show weak bi-directional interactions between carbon and renewable energy stocks. Renewable energy stocks display higher linkages with crude oil.
Ji et al. (2019)	2005-2018	EUAs and electricity companies' stocks	Diebold and Yilmaz (2014) connectedness measure	EUAs are the largest information recipient from all electricity companies. Therefore, electricity companies' behaviour should be incorporated in the process of carbon pricing.
Tan et al. (2020)	2008-2018	EUA futures, crude oil, natural gas, coal, non-energy commodity index, corporate bond spread, T-bills, stock returns and electricity futures	Diebold and Yilmaz (2012, 2014) spillover index	Carbon displays higher linkages with energy assets than financial assets. As a result, carbon may provide diversification benefits for a non-energy portfolio.

Wen et al. (2020)	2013-2019	Shenzhen carbon emission trading market and stocks in China	Nonlinear ARDL model	An increase in carbon prices has a greater effect on stock markets than a decrease in carbon prices. Some sectors, including energy, industrial, utilities and financials, are significantly sensitive to carbon price changes.
Hanif et al. (2021)	2011-2020	EUA and six clean energy indices	Diebold and Yilmaz (2012, 2014), Baruník, and Křehlík (2018) and copula functions	The paper gives evidence of larger spillovers between EUA and green stocks in the short-term than in the long-term. Traders in carbon markets should hedge against price risks in clean energy stocks. Investors can reap diversification benefits of adding carbon to green stock portfolios.
Jiang and Ma (2022)	2013-2018	EUA, Brent oil and The WilderHill clean energy index	Wavelet decompositions and Multivariate GARCH	In a $1 portfolio, investors should invest 40% in carbon and 60% in clean energy stocks. $1 long position in clean energy stocks can be hedged by shorting approximately 50 cents in carbon markets.

Notes. This table provides a summary of papers that analyse the links between carbon and stock markets and/or hedging/diversification benefits of carbon allowances.

Table 2. Index details

Segment	Index	Coverage
Carbon	IHS Markit Global Carbon Index	The index is the first benchmark and liquid index that is investable and tracks global carbon credit markets including futures contracts on European Union Allowances (EUA), California Carbon Allowances (CCA) and the Regional Greenhouse Gas Initiative (RGGI). The index uses pricing data from OPIS by IHS Markit Pricing (North American Pricing) and ICE Futures Pricing (European Pricing).
Stock Market	MSCI Asia Pacific Index	The index includes large and mid cap companies across five developed (Australia, Hong Kong, Japan, New Zealand and Singapore) and nine emerging market countries (China, India, Indonesia, Korea,Malaysia, Pakistan, the Philippines, Taiwan and Thailand) in the Asia Pacific region.
Stock Market	MSCI Europe Index	This index tracks the stock market performance of large and mid cap companies across fifteen countries (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK) in Europe.
Stock Market	MSCI North America Index	This index tracks the performance of large and mid cap US and Canada stock markets.
Stock Market	NASDAQ OMX Green economy Index	The index is a global index designed to track the stock performance of companies operating the following sectors: advanced materials; biofuels; energy efficiency; financial; green building; healthy living; natural resources; pollution mitigation; recycling; renewable energy generation; transportation and water.
Commodity	S&P GSCI Agriculture Index	This index is a benchmark for investments in agricultural commodity futures. It includes Chicago Wheat, Kansas Wheat, corn, soybeans, coffee, sugar, cocoa and cotton.
Commodity	S&P GSCI Precious metals Index	The index is a benchmark for a basket of gold and silver futures.
Commodity	S&P GSCI Energy Index	The index tracks the performance of energy commodity futures, including WTI crude oil, Brent crude oil, RBOB gasoline, heating oil, gasoil and natural gas

Note. This table lists the variables used in the research.

Table 3. Descriptive statistics and initial tests

	CARBON	ASIA PACIFIC	EUROPE	NORTH AMERICA	NADSAQ GREEN	AGRICULTURE	ENERGY	PRECIOUS METALS
Mean	0.095	0.015	0.019	0.046	0.049	-0.014	-0.017	0.020
Median	0.085	0.045	0.079	0.068	0.102	-0.057	0.092	0.019
Maximum	10.427	5.432	8.180	9.127	9.253	5.588	17.376	5.715
Minimum	-15.643	-5.753	-12.314	-12.811	-12.237	-5.252	-30.173	-5.426
Std. Dev.	1.999	0.921	1.128	1.139	1.099	1.061	2.482	0.995
Skewness	-0.363	-0.234	-1.209	-1.177	-1.221	0.122	-1.222	-0.170
Kurtosis	8.192	7.622	16.542	24.811	22.161	5.271	25.578	7.659
ADF	-19.652[a]	-20.167[a]	-15.056[a]	-13.043[a]	-9.482[a]	-14.074[a]	-7.127[a]	-19.613[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(10)$	249.971[a]	683.022[a]	612.416[a]	2304.94[a]	158.406[a]	133.792[a]	421.076[a]	186.265[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH (10)	16.055[a]	31.696[a]	41.36[a]	120.85[a]	80.306[a]	8.8068[a]	29.019[a]	10.628[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note. This table documents descriptive statistics and initial test (ADF, Q and ARCH) results for returns of stock markers, carbon credits, and commodity futures. t. Returns of asset k are computed as the difference in the natural logarithm of prices in percentage, i.e. $R_{k,t} = (\ln P_{k,t} - \ln P_{k,t-1}) \cdot 100$. The sample period runs from August 1, 2014 to July 30, 2021. Q and ARCH represent Ljung–Box Q test and ARCH Lagrange Multiplier tests, respectively. 10 lags are used in both tests. We have employed ADF test with automated lag selection, where the optimal laglength is determined using AIC. a, b and c denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4. Univariate GARCH estimates

	CARBON	ASIA PACIFIC	EUROPE	NORTH AMERICA	NADSAQ GREEN	AGRICULTURE	ENERGY	PRECIOUS METALS
μ	0.115[a]	0.011	0.021	0.059[a]	0.039[b]	-0.012	0.000	0.012
	(0.040)	(0.020)	(0.020)	(0.015)	(0.019)	(0.023)	(0.044)	(0.021)
ψ	-0.035	0.084[a]	0.034	-0.075[b]	0.056[b]	0.012	-0.034	-0.038[b]
	(0.027)	(0.027)	(0.034)	(0.031)	(0.028)	(0.025)	(0.028)	(0.015)
φ_0	0.141[b]	0.030[b]	0.035	0.043[a]	0.030[a]	0.023[b]	0.131[a]	0.009
	(0.070)	(0.012)	(0.010)	(0.011)	(0.009)	(0.009)	(0.046)	(0.015)
φ_1	0.114[a]	0.011	0.013	0.122[b]	0.098[a]	0.074[a]	0.021	0.041
	(0.028)	(0.013)	(0.029)	(0.054)	(0.033)	(0.018)	(0.014)	(0.038)
φ_2	0.857[a]	0.867[a]	0.843[a]	0.719[a]	0.818[a]	0.914[a]	0.886[a]	0.961[a]
	(0.038)	(0.032)	(0.026)	(0.037)	(0.030)	(0.017)	(0.027)	(0.039)
φ_3	-	0.170[a]	-	0.272[a]	0.117[a]	-	0.132[a]	-
		(0.048)		(0.080)	(0.045)		(0.037)	
$Q^2(10)$	5.948	5.554	11.981	6.268	6.905	4.495	8.847	4.825
	[0.819]	[0.851]	[0.286]	[0.792]	[0.734]	[0.922]	[0.546]	[0.902]
ARCH(10)	0.705	0.599	1.384	0.643	0.942	0.364	0.927	0.537
	[0.720]	[0.816]	[0.181]	[0.7778]	[0.492]	[0.962]	[0.507]	[0.865]

Notes. This table reports parameter estimates from the univariate GARCH model. Values in parentheses (brackets) represent standard errors (p-values). The sample period runs from August 1, 2014 to July 30, 2021.Q and ARCH represent Ljung–Box Q test and ARCH Lagrange Multiplier tests, respectively. 10 lags are used in both tests a, b and c denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5. (A)DCC estimates

	θ_1		θ_2		θ_3		ρ	Hosking		Li-McLeod	
Carbon-Asia Pacific	0.092[a]	(0.026)	0.988[a]	(0.005)	-		0.109	66.016	[0.831]	66.159	[0.828]
Carbon-Europe	0.102[a]	(0.035)	0.980[a]	(0.010)	0.176[b]	(0.072)	0.115	84.926	[0.276]	84.917	[0.277]
Carbon-North America	0.083[c]	(0.048)	0.909[a]	(0.008)	-0.174[a]	(0.041)	0.140	79.221	[0.471]	79.225	[0.470]
Carbon-Green stocks	0.081[c]	(0.045)	0.910[a]	(0.007)	-0.161[a]	(0.047)	0.191	90.087	[0.185]	90.069	[0.179]
Agriculture-Asia Pacific	0.025	(0.079)	0.831	(0.516)	-		0.115	47.813	[0.997]	47.990	[0.992]
Agriculture-Europe	0.014	(0.019)	0.961[a]	(0.034)	-		0.093	77.417	[0.497]	77.447	[0.496]
Agriculture-North America	0.017[b]	(0.008)	0.937[a]	(0.030)	-		0.142	60.203	[0.932]	60.319	[0.931]
Agriculture-Green stocks	0.001	(0.000)	0.977[a]	(0.017)	0.133[a]	(0.041)	0.173	73.112	[0.665]	73.275	[0.630]
Energy-Asia Pacific	0.020[c]	(0.012)	0.928[a]	(0.063)	-		0.175	62.558	[0.898]	62.704	[0.896]
Energy-Europe	0.035[a]	(0.012)	0.948[a]	(0.023)	-		0.241	91.301	[0.143]	91.245	[0.144]
Energy-North America	0.042[a]	(0.015)	0.768[a]	(0.101)	-		0.310	59.556	[0.940]	59.657	[0.939]
Energy-Green stocks	0.027[a]	(0.008)	0.955[a]	(0.016)	-		0.291	73.538	[0.621]	73.620	[0.619]
Precious Metals-Asia Pacific	0.008	(0.010)	0.934[a]	(0.072)	-		0.119	77.058	[0.508]	77.100	[0.507]
Precious Metals-Europe	0.152[a]	(0.034)	0.838[a]	(0.014)	0.162[a]	(0.057)	-0.157	79.921	[0.449]	79.934	[0.449]
Precious Metals-North America	0.165[a]	(0.039)	0.813[a]	(0.016)	-0.208[a]	(0.052)	-0.041	86.690	[0.234]	86.725	[0.233]
Precious Metals-Green stocks	0.159[a]	(0.037)	0.844[a]	(0.011)	0.233[a]	(0.050)	0.022	79.121	[0.474]	79.166	[0.473]

Notes. This table reports parameter estimates from the second stage (A)DCC model. Values in parentheses (brackets) represent standard errors (p-values). The sample period runs from August 1, 2014 to July 30, 2021.a, b and c denote statistical significance at the 1%, 5% and 10% levels, respectively. Hosking and Li-McLeod are multivariate diagnostic tests. 10 lags are used in both tests.

Table 6. Optimal hedge ratios

	Full sample				Pre-COVID-19	COVID-19		
	Mean	Max.	Min.	S.Dev.	Mean	Mean	t-statistics	Chow test
Asia Pacific								
Carbon	0.058	0.372	-0.018	0.048	0.048	0.098	-16.308[a]	358.597[a]
Agriculture	0.101	0.331	0.029	0.051	0.098	0.113	-4.254[a]	24.345[a]
Energy	0.077	0.449	0.007	0.047	0.073	0.093	-6.390[a]	50.682[a]
Precious Metals	0.109	0.443	-0.043	0.05	0.109	0.109	-0.188	0.051
Europe								
Carbon	0.068	1.41	-0.533	0.15	0.038	0.19	-16.262[a]	332.623[a]
Agriculture	0.127	2.165	-0.124	0.203	0.101	0.232	-6.529[a]	119.324[a]
Energy	0.125	0.787	-0.069	0.101	0.115	0.164	-8.750[a]	63.721[a]
Precious Metals	-0.169	0.427	-1.463	0.193	-0.204	-0.027	-22.039[a]	263.164[a]
North America								
Carbon	0.093	1.881	-0.172	0.147	0.071	0.182	-8.917[a]	168.797[a]
Agriculture	0.167	3.061	-0.017	0.24	0.138	0.282	-5.932[a]	104.133[a]
Energy	0.146	1.266	0.015	0.099	0.144	0.157	-2.776[a]	5.180[b]
Precious Metals	-0.046	0.575	-1.221	0.174	-0.067	0.038	-12.128[a]	104.025[a]
Green stocks								
Carbon	0.116	1.364	-0.005	0.118	0.091	0.216	-13.397[a]	364.261[a]
Agriculture	0.185	2.038	0.025	0.202	0.145	0.347	-9.942[a]	323.560[a]
Energy	0.135	0.58	-0.026	0.092	0.123	0.187	-9.355[a]	142.822[a]
Precious Metals	0.016	0.856	-1.007	0.159	-0.005	0.103	-10.639[a]	132.996[a]

Notes. This table documents descriptive statistics of hedge ratios. Full sample covers the period from August 1, 2014 to July 30, 2021 while Pre-COVID-19 and COVID-19 periods are from August 1, 2014 to March 10, 2020 and from March 11, 2020 to July 30, 2021. T-tests test the null hypothesis of equal hedge ratios before and after the COVID-19 pandemic. Chow-test test for a structural break in hedge ratios on March 11, 2020, when the WHO declared the COVID-19 outbreak a global pandemic. It has a null hypothesis that there is no structural break on March 11, 2020. a, b and c denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7. Optimal weights

	Full sample				Pre-COVID-19	COVID-19	
	Mean	Max.	Min.	S. Dev.	Mean	Mean	t-statistics
Asia Pacific							
Carbon	0.179	0.831	0.004	0.166	0.184	0.158	3.229[a]
Agriculture	0.402	0.927	0.038	0.211	0.391	0.445	-3.827[a]
Energy	0.119	0.657	0.000	0.098	0.117	0.123	-0.758
Precious Metals	0.429	0.892	0.111	0.178	0.443	0.370	7.228[a]
Europe							
Carbon	0.227	1.000	0.000	0.213	0.238	0.185	4.957[a]
Agriculture	0.456	1.000	0.040	0.237	0.444	0.509	-3.768[a]
Energy	0.126	0.816	0.000	0.110	0.133	0.098	5.608[a]
Precious Metals	0.490	0.977	0.113	0.160	0.502	0.445	5.393[a]
North America							
Carbon	0.205	1.000	0.000	0.219	0.200	0.225	-1.948[b]
Agriculture	0.409	1.000	0.015	0.279	0.385	0.504	-6.446[a]
Energy	0.107	1.000	0.000	0.165	0.101	0.131	-3.091[a]
Precious Metals	0.443	0.981	0.031	0.221	0.444	0.439	0.379
Green stocks							
Carbon	0.187	1.000	0.000	0.187	0.163	0.283	-10.634[a]
Agriculture	0.411	1.000	0.025	0.249	0.365	0.598	-14.135[a]
Energy	0.098	0.758	0.000	0.133	0.075	0.189	-10.481[a]
Precious Metals	0.449	0.994	0.076	0.181	0.429	0.531	-9.414[a]

Notes. Notes. This table documents descriptive statistics of optimal weights. Full sample covers the period from August 1, 2014 to July 30, 2021 while Pre-COVID-19 and COVID-19 periods are from August 1, 2014 to March 10, 2020 and from March 11, 2020 to July 30, 2021. T-tests test the null hypothesis of equal hedge ratios before and after the COVID-19 pandemic. a, b and c denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8 (a). Hedging effectiveness- Full sample (August 1, 2014- July 30, 2021)

	Var.	ΔVar.(%)	H. VaR	ΔH.VaR (%)	H. CVaR	ΔH.CVaR (%)	M.VaR	ΔM.VaR (%)	M. CVaR	ΔM. CVaR (%)
Asia Pacific										
Unhedged Portfolio	0.848		-0.014		-0.022		-0.015		-0.025	
Carbon	0.755	0.11	-0.013	0.098	-0.021	0.077	-0.014	0.054	-0.03	-0.199
Agriculture	0.463	0.454	-0.011	0.217	-0.016	0.297	-0.012	0.211	-0.017	0.335
Energy	0.824	0.029	-0.015	-0.014	-0.022	0.000	-0.015	-0.007	-0.026	-0.028
Precious Metals	0.519	0.388	-0.011	0.259	-0.016	0.275	-0.011	0.272	-0.016	0.347
Europe										
Unhedged Portfolio	1.273		-0.017		-0.029		-0.019		-0.05	
Carbon	1.018	0.200	-0.014	0.163	-0.025	0.14	-0.015	0.197	-0.031	0.389
Agriculture	0.524	0.588	-0.012	0.326	-0.017	0.395	-0.012	0.346	-0.019	0.623
Energy	1.3	-0.022	-0.018	-0.052	-0.03	-0.031	-0.019	-0.021	-0.051	-0.008
Precious Metals	0.48	0.622	-0.01	0.407	-0.016	0.441	-0.01	0.484	-0.012	0.760
North America										
Unhedged Portfolio	1.298		-0.017		-0.029		-0.017		-0.033	
Carbon	1.023	0.211	-0.014	0.17	-0.025	0.132	-0.014	0.19	-0.014	0.585
Agriculture	0.46	0.645	-0.011	0.315	-0.016	0.443	-0.011	0.333	-0.017	0.476
Energy	1.407	-0.084	-0.018	-0.067	-0.031	-0.087	-0.02	-0.185	-0.063	-0.933
Precious Metals	0.494	0.619	-0.01	0.412	-0.016	0.436	-0.01	0.423	-0.012	0.625
Green stocks										
Unhedged Portfolio	1.207		-0.016		-0.027		-0.017		-0.042	
Carbon	1.042	0.137	-0.015	0.045	-0.024	0.093	-0.014	0.179	-0.014	0.667
Agriculture	0.505	0.582	-0.012	0.258	-0.016	0.39	-0.012	0.304	-0.018	0.571
Energy	1.229	-0.018	-0.016	-0.058	-0.028	-0.045	-0.018	-0.083	-0.056	-0.345
Precious Metals	0.538	0.555	-0.01	0.342	-0.017	0.379	-0.01	0.393	-0.013	0.687

Notes. This table reports the values of variance and downside risk measures and their changes for hedged and unhedged portfolios for the full sample from August 1, 2014 to July 30, 2021. Var stands for variance. HVaR, HCVaR, MVaR and MCVaR represent historical Value-at-Risk (VaR), historical Conditional VaR, Modified VaR and Modified Conditional VaR, respectively.

Table 8 (b). Hedging effectiveness- Pre-COVID-19 sample (August 1, 2014- March 10, 2020)

	Var.	ΔVar.(%)	H. VaR	ΔH.VaR (%)	H. CVaR	ΔH.CVaR (%)	M. VaR	ΔM.VaR (%)	M. CVaR	ΔM. CVaR (%)
Asia Pacific										
Unhedged Portfolio	0.708		-0.013		-0.020		-0.014		-0.023	
Carbon	0.557	0.214	-0.012	0.112	-0.018	0.123	-0.013	0.079	-0.021	0.098
Agriculture	0.412	0.418	-0.011	0.201	-0.015	0.270	-0.011	0.207	-0.016	0.333
Energy	0.681	0.039	-0.014	-0.037	-0.021	-0.015	-0.014	-0.021	-0.024	-0.030
Precious Metals	0.394	0.444	-0.010	0.269	-0.014	0.304	-0.010	0.279	-0.016	0.303
Europe										
Unhedged Portfolio	1.041		-0.016		-0.026		-0.018		-0.038	
Carbon	0.673	0.353	-0.013	0.205	-0.020	0.230	-0.014	0.211	-0.031	0.165
Agriculture	0.491	0.529	-0.011	0.292	-0.017	0.356	-0.012	0.333	-0.019	0.500
Energy	1.063	-0.021	-0.017	-0.050	-0.027	-0.031	-0.018	-0.006	-0.040	-0.053
Precious Metals	0.335	0.678	-0.009	0.447	-0.013	0.494	-0.009	0.478	-0.016	0.564
North America										
Unhedged Portfolio	0.815		-0.015		-0.024		-0.016		-0.036	
Carbon	0.571	0.299	-0.012	0.221	-0.019	0.198	-0.013	0.168	-0.022	0.390
Agriculture	0.403	0.506	-0.010	0.325	-0.015	0.380	-0.010	0.329	-0.016	0.553
Energy	0.944	-0.159	-0.016	-0.039	-0.026	-0.084	-0.016	-0.032	-0.047	-0.315
Precious Metals	0.318	0.610	-0.009	0.435	-0.013	0.464	-0.009	0.419	-0.016	0.548
Green stocks										
Unhedged Portfolio	0.690		-0.014		-0.021		-0.015		-0.034	
Carbon	0.549	0.205	-0.012	0.135	-0.018	0.132	-0.013	0.129	-0.023	0.301
Agriculture	0.416	0.397	-0.011	0.227	-0.015	0.288	-0.011	0.259	-0.017	0.484
Energy	0.734	-0.064	-0.015	-0.050	-0.023	-0.061	-0.015	-0.048	-0.041	-0.215
Precious Metals	0.335	0.514	-0.009	0.369	-0.013	0.392	-0.009	0.367	-0.016	0.531

Notes. This table reports the values of variance and downside risk measures and their changes for hedged and unhedged portfolios for the pre-COVID-19 sample from August 1, 2014 to March 10, 2020. Var stands for variance. HVaR, HCVaR, MVaR and MCVaR represent historical Value-at-Risk (VaR), historical Conditional VaR, Modified VaR and Modified Conditional VaR, respectively.

Table 8 (c). Hedging effectiveness- COVID-19 sample (March 11, 2020- July 30, 2021)

	Var.	ΔVar.(%)	H. VaR	ΔH.VaR (%)	H. CVaR	ΔH.CVaR (%)	M. VaR	ΔM.VaR (%)	M. CVaR	ΔM. CVaR (%)
Asia Pacific										
Unhedged Portfolio	1.411		-0.018		-0.027		-0.018		-0.030	
Carbon	1.551	-0.099	-0.016	0.125	-0.030	-0.081	-0.020	-0.077	-0.045	-0.464
Agriculture	0.665	0.529	-0.012	0.332	-0.018	0.337	-0.014	0.257	-0.020	0.355
Energy	1.394	0.012	-0.018	0.049	-0.027	-0.004	-0.018	0.016	-0.030	0.023
Precious Metals	1.022	0.276	-0.013	0.272	-0.022	0.190	-0.014	0.213	-0.022	0.283
Europe										
Unhedged Portfolio	2.203		-0.022		-0.037		-0.024		-0.072	
Carbon	2.409	-0.094	-0.021	0.014	-0.039	-0.043	-0.024	0.008	-0.056	0.229
Agriculture	0.652	0.704	-0.013	0.396	-0.019	0.497	-0.013	0.449	-0.020	0.728
Energy	2.251	-0.022	-0.022	-0.009	-0.039	-0.043	-0.025	-0.025	-0.075	-0.030
Precious Metals	1.067	0.516	-0.015	0.290	-0.024	0.348	-0.014	0.412	-0.018	0.746
North America										
Unhedged Portfolio	3.247		-0.025		-0.046		-0.028		-0.075	
Carbon	2.852	0.122	-0.023	0.065	-0.043	0.071	-0.026	0.099	-0.058	0.227
Agriculture	0.688	0.788	-0.014	0.435	-0.020	0.565	-0.014	0.512	-0.021	0.726
Energy	3.278	-0.009	-0.024	0.041	-0.051	-0.097	-0.033	-0.166	-0.095	-0.269
Precious Metals	1.205	0.629	-0.015	0.394	-0.028	0.403	-0.016	0.449	-0.023	0.687
Green stocks										
Unhedged Portfolio	3.288		-0.025		-0.045		-0.030		-0.075	
Carbon	3.029	0.079	-0.024	0.060	-0.042	0.054	-0.026	0.112	-0.057	0.240
Agriculture	0.859	0.739	-0.016	0.377	-0.021	0.533	-0.015	0.502	-0.020	0.732
Energy	3.214	0.022	-0.023	0.095	-0.048	-0.078	-0.031	-0.051	-0.086	-0.145
Precious Metals	1.352	0.589	-0.017	0.337	-0.027	0.388	-0.017	0.437	-0.025	0.672

Notes. This table reports the values of variance and downside risk measures and their changes for hedged and unhedged portfolios for the COVID-19 sample from March 11, 2020 to July 30, 2021. Var stands for variance. HVaR, HCVaR, MVaR and MCVaR represent historical Value-at-Risk (VaR), historical Conditional VaR, Modified VaR and Modified Conditional VaR, respectively.

Table 9. Utility gains

	Full sample			Pre-COVID-19			COVID-19		
	Δ=3	Δ=6	Δ=12	Δ=3	Δ=6	Δ=12	Δ=3	Δ=6	Δ=12
Carbon									
Asia Pacific	0.294	0.575	1.136	0.465	0.920	1.828	-0.396	-0.816	-1.655
Europe	0.775	1.539	3.068	1.118	2.221	4.427	-0.629	-1.248	-2.487
North America	0.826	1.649	3.294	0.738	1.469	2.932	1.177	2.364	4.738
Green Stocks	0.504	0.998	1.987	0.435	0.859	1.706	0.777	1.552	3.102
Agriculture									
Asia Pacific	1.137	2.291	4.600	0.871	1.758	3.532	2.216	4.454	8.930
Europe	2.227	4.473	8.963	1.636	3.288	6.590	4.623	9.274	18.578
North America	2.486	4.997	10.020	1.218	2.454	4.925	7.621	15.298	30.652
Green Stocks	2.076	4.181	8.392	0.803	1.626	3.270	7.210	14.496	29.067
Energy									
Asia Pacific	0.067	0.142	0.290	0.072	0.154	0.319	0.055	0.104	0.202
Europe	-0.107	-0.191	-0.358	-0.094	-0.160	-0.293	-0.152	-0.297	-0.585
North America	-0.362	-0.690	-1.346	-0.419	-0.807	-1.582	-0.141	-0.233	-0.416
Green Stocks	-0.081	-0.147	-0.280	-0.152	-0.284	-0.548	0.225	0.445	0.885
Precious Metals									
Asia Pacific	0.997	1.984	3.958	1.347	1.895	3.780	1.177	2.344	4.679
Europe	2.380	4.755	9.504	2.130	4.248	8.483	3.380	6.788	13.603
North America	2.400	4.809	9.628	1.489	2.979	5.959	6.085	12.212	24.464
Green Stocks	1.996	4.003	8.018	1.064	2.127	4.252	5.747	11.555	23.171

Note. This table documents the estimated average percentage utility gain from Eq. (14) for different levels of risk aversion, corresponding to less risk averse investors (Δ=3), moderate investors (Δ=6) and highly risk averse investors (Δ=12). Positive values indicate a situation where hedging is economically efficient. Full sample covers the period from August 1, 2014 to July 30, 2021 while Pre-COVID-19 and COVID-19 periods are from August 1, 2014 to March 10, 2020 and from March 11, 2020 to July 30, 2021, respectively.

Table 10. Portfolio analytics

	Full sample					Pre-COVID-19					COVID-19				
	Return	S.Dev	Sharpe	Omega	Sortino	Return	S.Dev	Sharpe	Omega	Sortino	Return	S.Dev	Sharpe	Omega	Sortino
Asia Pacific															
Unhedged	0.027	0.146	0.144	1.046	0.022	-0.012	0.134	-0.125	0.996	-0.002	0.200	0.189	1.028	1.206	0.096
Carbon	0.063	0.138	0.417	1.097	0.045	0.018	0.119	0.110	1.036	0.018	0.270	0.198	1.333	1.279	0.116
Agriculture	-0.012	0.108	-0.162	0.991	-0.005	-0.047	0.102	-0.509	0.933	-0.036	0.146	0.130	1.081	1.200	0.101
Energy	0.009	0.144	0.027	1.024	0.011	-0.037	0.131	-0.319	0.962	-0.019	0.219	0.188	1.133	1.225	0.105
Precious Metals	0.058	0.114	0.463	1.103	0.050	0.018	0.100	0.134	1.041	0.021	0.236	0.161	1.433	1.286	0.132
Europe															
Unhedged	0.033	0.179	0.153	1.053	0.023	-0.008	0.162	-0.079	1.006	0.003	0.219	0.236	0.904	1.210	0.081
Carbon	0.064	0.160	0.364	1.094	0.040	0.036	0.130	0.235	1.061	0.028	0.188	0.247	0.740	1.180	0.071
Agriculture	-0.003	0.115	-0.071	1.006	0.003	-0.038	0.111	-0.383	0.951	-0.025	0.156	0.128	1.168	1.221	0.106
Energy	-0.026	0.181	-0.172	0.989	-0.005	-0.074	0.164	-0.481	0.931	-0.032	0.194	0.239	0.791	1.188	0.072
Precious Metals	0.056	0.110	0.464	1.107	0.050	0.033	0.092	0.306	1.072	0.036	0.155	0.164	0.911	1.199	0.089
North America															
Unhedged	0.105	0.181	0.549	1.142	0.055	0.055	0.143	0.351	1.088	0.038	0.334	0.287	1.143	1.275	0.099
Carbon	0.118	0.161	0.694	1.166	0.067	0.075	0.120	0.582	1.124	0.057	0.309	0.269	1.129	1.260	0.099
Agriculture	0.048	0.108	0.395	1.088	0.044	0.015	0.101	0.099	1.034	0.017	0.196	0.132	1.443	1.271	0.127
Energy	0.012	0.188	0.038	1.034	0.013	-0.025	0.154	-0.193	0.983	-0.007	0.178	0.288	0.599	1.162	0.057
Precious Metals	0.092	0.112	0.781	1.173	0.077	0.060	0.090	0.611	1.128	0.062	0.236	0.175	1.316	1.279	0.120
Green Stocks															
Unhedged	0.115	0.174	0.622	1.149	0.061	0.042	0.132	0.277	1.069	0.031	0.469	0.288	1.602	1.331	0.130
Carbon	0.145	0.162	0.853	1.194	0.080	0.074	0.118	0.585	1.121	0.057	0.483	0.277	1.719	1.351	0.140
Agriculture	0.043	0.113	0.333	1.077	0.038	-0.003	0.102	-0.072	1.004	0.002	0.253	0.147	1.677	1.302	0.151
Energy	0.073	0.176	0.387	1.103	0.040	-0.010	0.136	-0.106	1.000	0.000	0.488	0.285	1.686	1.356	0.129
Precious Metals	0.094	0.116	0.764	1.165	0.077	0.051	0.092	0.496	1.105	0.052	0.291	0.185	1.538	1.306	0.139

Note. This table documents portfolio metrics for hedged and unhedged portfolios. Full sample covers the period from August 1, 2014 to July 30, 2021 while Pre-COVID-19 and COVID-19 periods are from August 1, 2014 to March 10, 2020 and from March 11, 2020 to July 30, 2021, respectively.

Figure 1. IHS Markit global carbon index daily prices

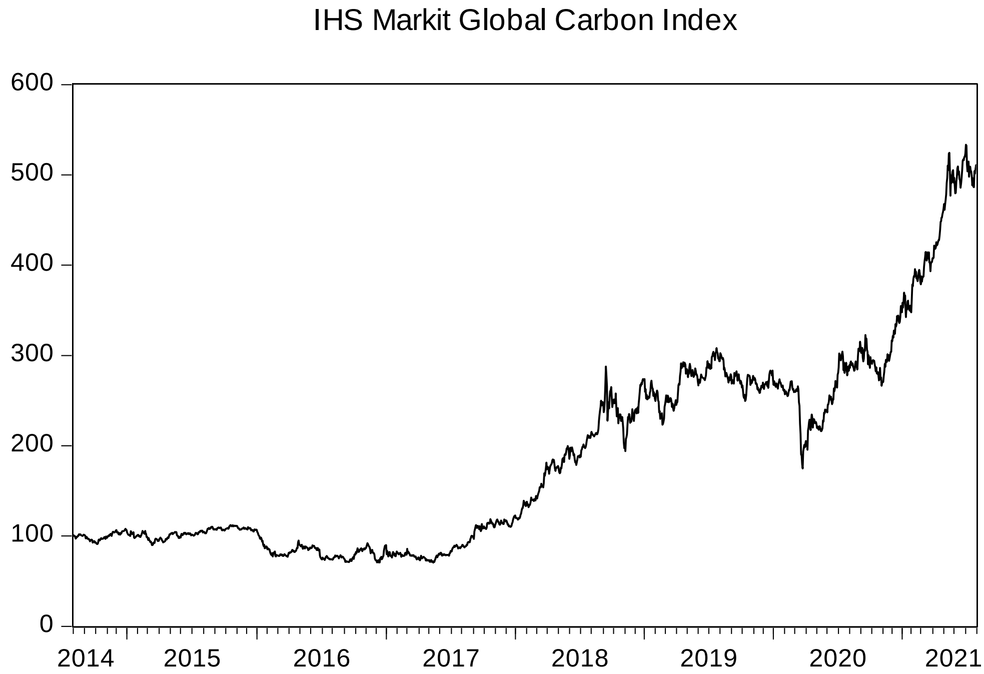

Figure 2. Dynamic correlations

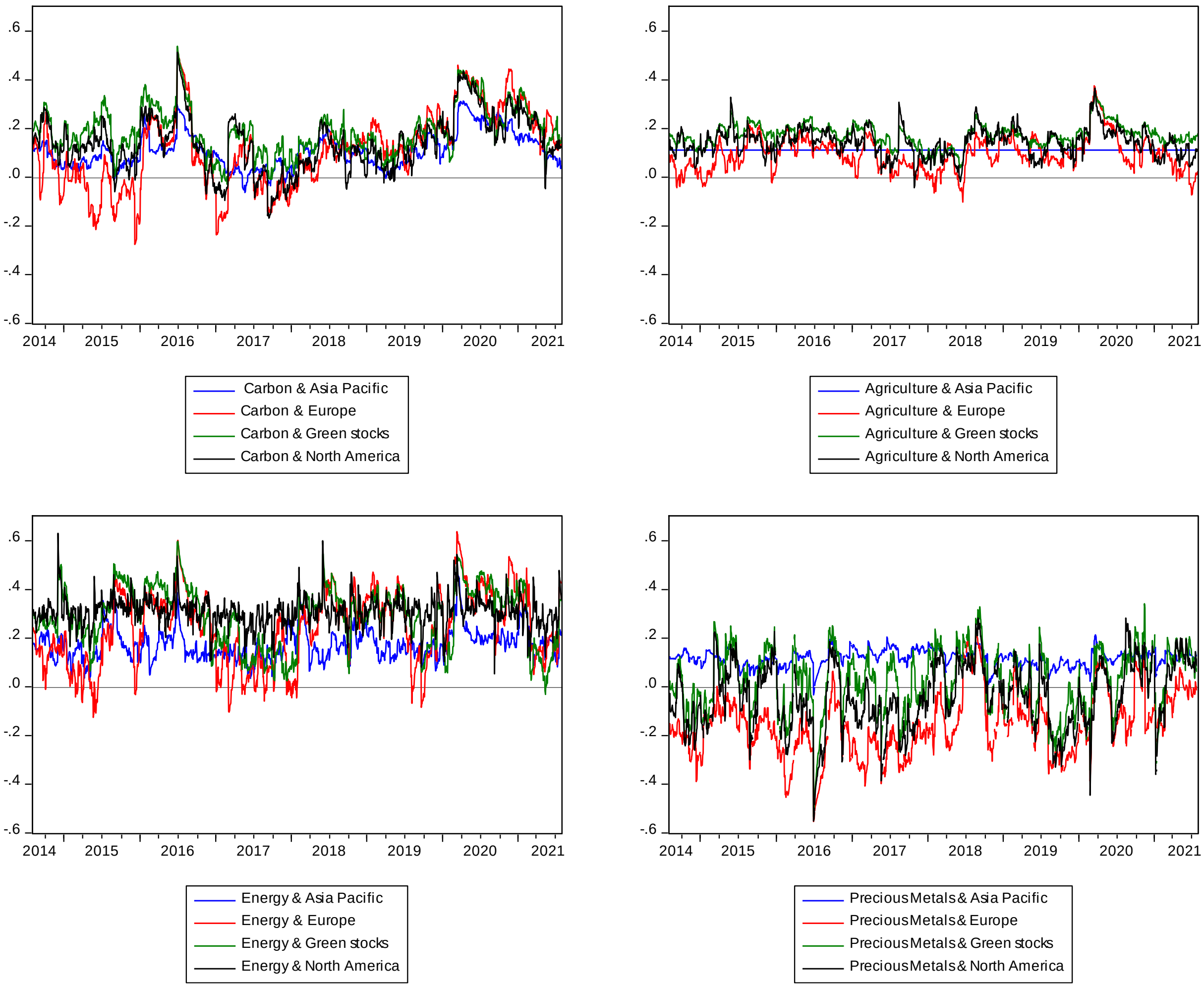

Figure 3. Optimal hedge ratios