# Risk-Return Profile of Environmentally Friendly Assets: Evidence from the NASDAQ OMX Green Economy Index Family


## Abstract

The COVID-19 pandemic, geopolitical risks and net-zero targets have created not only pressures but incentives for energy investors. The renewable energy has become the largest energy sector and provided significant investment opportunities. However, companies operating in this sector are highly risky due to economic and political barriers. Therefore, it is of crucial importance for investors to properly assess the risk-return dynamics of these investments. This paper examines the risk-return characteristics of clean energy equities at a disaggregate level using a battery of performance metrics. The main results provide evidence of significant heterogeneity across clean energy sub-sectors; for instance, fuel cell and solar stocks display higher downside risks than the others, while the developer/operator equities are the least risky. The findings further provide evidence of higher risk-adjusted returns during the coronavirus pandemic; as an example, energy management companies appear to provide the highest risk-adjusted returns in the wake of the COVID-19. Comparing the performance with traditional sectors, clean energy stocks outperform certain sectors, including dirty assets. These findings offer important implications for investors, portfolio managers, and policy makers.



**Keywords: Clean energy equities; sustainable investments; COVID-19 pandemic**


## 1. Introduction

Climate change and global heating have been seriously threatening the ecosystem and all living organisms. Climatic risks, such as deforestation, even played a notable role in the emergence of COVID-19 pandemic, leading to the transmission of various deranged viruses from animals to humankind (Ford et al., 2022). Given the acceleration of climate change over the recent years and its devastating consequences, it has been imperative to take immediate actions to reduce greenhouse gas emissions before any irreversible repercussions on the ecosystem. In this respect, countries have massively started investing in green energy to lessen greenhouse gases, especially aligned with the 2015 Paris Agreement.[1] Accordingly, green finance has become the key to channel capital investments in environmentally friendly projects that can lead the path to build a net zero economy, providing superior benefits in environmental management (Alkathery et al., 2022; Zhang et al., 2023). In view of a recent report of the International Energy Agency (IEA) (2022), the global energy investment is expected to increase by 8% in 2022, reaching to USD 2.4 trillion in total of which USD 1.4 trillion makes up investments in clean energy (CE, henceforth). The IEA report (2022) further indicates that renewable energy investments have also been growing at a rate of 12% since the coronavirus pandemic, accounting for two-thirds of the growth in the energy sector.[2] In addition, as shown in Figure 1, it is worth noting that the total installed power capacity for alternative energy in 2019 is

[1] The Paris Agreement signed in 2015 by 196 countries adopted the first-ever legally binding global climate treaty which aimed to limit global warming well below the threshold of 2 °C (above pre-industrial level) – in fact, the treaty set a goal to reduce the global warming increase to 1.5 °C to avoid dangerous climate change.

[2] For more details, see the IEA's report of "World Energy Outlook 2022" which is available at: https://iea.blob.core.windows.net/assets/830fe099-5530-48f2-a7c1-11f35d510983/WorldEnergyOutlook2022.pdf

estimated to be tripled by 2050 (Bloomberg N. E. F., 2020). Consequently, the substantial amounts of capital flow in green investing, along with the positive outlook for CE, have attracted investors allocating significant resources to sustainable assets[3], creating an "investment enthusiasm" which contributed to the investment resiliency in the sector even during the pandemic (Tan et al., 2021).

[Insert Figure 1 about here]

CE is an alternative to fossil fuel-based energy and plays a central role in mitigating climate change. Investments in CE help to meet climate and sustainability goals set by the 2015 Paris Climate Agreement and the United Nations (UN) Sustainable Development Goals. In 2022, the global oil and gas sector income is expected to jump to USD 4 trillion which is more than double of the last five-years average and the total global energy bill is anticipated to hit USD 10 trillion (IEA, 2022) as a consequence of the ongoing Russian invasion of Ukraine. The exorbitant prices severely damage economies, forcing governments to intervene to cushion the blow of higher energy costs. At this point, expediting the transition to CE and diversifying the sources of energy supply become eminent for the global welfare as well as the climate protection which can amplify environmental benefits. Therefore, sustainable finance has become of focus as it can effectively promote the channeling of required capital to CE production which is the only enduring solution for carbon reduction. On these grounds, institutional investors play a key role in mobilizing the capital flow and are already in control of some major investments in the field of solar and wind power generation. In addition, fossil fuel market risk also adversely affects industrial productivity[4] and CE investments as an alternate source can significantly reduce the energy market risk for governments, businesses, and portfolio investors. However, green investments are exposed to both idiosyncratic and systematic risks that may hamper the capital flows to this sector. Hence, an in-depth analysis of their risk-return profile would be useful for market participants and helpful to remove any potential obstacles in front of sustainable development and environmental management.

In light of the above discussion, it is apparent that relevant and timely information on the performance of CE assets is very important to investors in optimizing the risk-return performance of their climate protective portfolios.[5] In fact, the requisite increase in climate protective investments impels both the authorities and investors to take effective decisions to promote the efficiency in green energy markets. However, as stated by Pham (2019) and Kuang (2021a), the CE sector displays heterogeneity which insinuates that its performance depends significantly on the sub-sectors, signifying the importance of active portfolio management at a

[3] Green investments – particularly CE investments, are environmentally friendly and sustainable. Hence, they are also considered as a part of sustainable assets (Cunha et al., 2020; Daugaard, 2020).

[4] Cunha et al. (2021) and Hong et al. (2022) state that natural disasters and geopolitical issues might have adverse shocks to energy markets, generating energy price volatility, which in turn lead to many negative impacts on industrial productivity. This situation consequently influences the level of investment risk in climate protective portfolios as well.

[5] Although sustainable investments have grown steadily in the recent years, yet global achievements are far from satisfying the goals set by the 2015 Paris Agreement or the UN Agenda of 2030. As indicated by Cunha et al. (2020), one of the main obstacles against the acceleration of sustainable investments is the lack of sufficient and efficacious information on the performance of these investments.

disaggregate level. The majority of previous studies examine CE investments at an aggregate level which may disregard the unique properties of their sub-sectors. Therefore, a detailed analysis of CE assets at the disaggregate level may enhance the construction of optimal investment strategies which can help energy investors to make informed decisions. This motivates us to study risk-return dynamics of CE at the sub-sector level. Consequently, in this paper, we attempt to explore the risk-return characteristics of CE stocks at a disaggregate level, using a variety of portfolio metrics. We compare the performance of CE stocks to that of traditional sectors and investigate whether the risk-return dynamics changed during the pandemic. Relatedly, we ask two specific research questions: i) Do clean energy equities provide higher risk-adjusted returns than other sectors? ii) How has the COVID-19 pandemic altered the risk-return characteristics of these environmentally friendly investments? In order to address these questions, we focus on the NASDAX OMX Green Economy Index Family, which consists of companies in a spectrum of industries that are closely associated with sustainable development.

This study makes several contributions to the existing literature. First, as stated earlier, most of the prior studies analyze the dynamics of CE equities at an aggregate level and do not distinguish between various CE sources. Even though there are a few recent studies focusing on the disaggregated CE stocks, these studies largely explore the connection between oil prices and CE sub-sectors (Pham, 2019; Tan et al., 2021; Usman, 2023). To the best of our knowledge, there is no study that comprehensively examines the univariate risk-return performance of CE equities at a disaggregated level. Therefore, our study fills this gap and adds to the body of knowledge by assessing the performance of individual CE sub-sectors. Second, we analyze whether the risk-return dynamics have altered during the pandemic. As known, the COVID-19 pandemic has severely affected the demand and supply dynamics in the energy sector; however, its impact varies across the sector. While the demand for fossil fuels has fallen, the demand for clean energy has risen (Wan et al., 2021). As noted by scholars, “green development” is seen as the primary path to sustainability in the post-COVID era (Zhang et al., 2023; Madaleno et al., 2022). Accordingly, global clean energy investments have significantly grown and are expected to grow further in line with the net-zero pathway. Therefore, we contribute to the existing literature by exploring how the occurrence of one of the most severe pandemics in history changed the risk-return characteristics of sustainable assets.

Third, unlike previous studies that compare the performance of CE stocks to a benchmark index and oil & gas companies, we compare the risk-return performance not only to the overall market and dirty stocks but also to a wide range of sectoral indexes. As suggested by Cunha et al. (2021), this can provide additional insights for a variety of stakeholders. Fourth, investigating the dynamics of CE equities at a disaggregate level provides us a broader picture which would be useful not only to investors who allocate capital in clean energy sectors but also to decision-makers in terms of policy design. Net-zero requires substantial amount of clean energy investments and many countries have adapted policies to promote green investments. However, CE sectors are in various stages of development since the amount of invested capital greatly varies across them. Therefore, comprehending the risk-return characteristics of a diverse set of CE sectors can be useful for decision-makers to build an effective policy framework to support the growth of sustainable finance for a greener economy. Furthermore, deciphering the risk-return relations of CE sectors can be eminent in ensuring the stability in clean energy market which can safeguard the long-lasting flow of capital to environmentally friendly projects. Hence, our findings can provide eminent benefits to policy makers in their efforts to develop an effective environmental management roadmap, accelerating the transition to clean energy sources along with insuring energy security.

Our main findings underscore the heterogeneity across the green stocks in terms of risk-return characteristics. More specifically, certain sub-sectors, such as fuel cell and solar, possess higher risk than the others, whereas developer/operator index exhibits the lowest risk among the sustainable investments. Accordingly, our results emphasize that neglecting the sectoral properties may mask valuable information as CE sectors differ significantly in terms of risk-return characteristics. In other words, examining CE stocks at a disaggregated sub-sector level can provide valuable insights for market participants about the performance of these green equities. In addition, by utilizing sub-sector analyses, clean energy investments can be prioritized for an efficient diversification of energy resources which can enhance the economic significance of the CE sector. In the context of the pandemic, the most recent research shows an increasing trend in investments in climate friendly projects; focusing on promoting green energy sources and technologies as well as improving clean energy efficiency (Madaleno et al., 2022; Ye et al., 2022; Chen and Ma, 2022; Yearsley, 2020). In this regard, we further show that none of the CE equities outperform the benchmark index both during the full sample or pre-COVID-19 periods, but they all significantly outperform the dirty assets. However, the COVID-19 pandemic has changed the dynamics since the CE stocks provide much higher risk-adjusted returns in the wake of the pandemic. Particularly, energy management companies stand out as the best performing asset among all the sectors considered as they offer the highest risk-adjusted returns.

The remainder of the paper is as follows. The next section summarizes the related literature. Section 3 explains the data and descriptive statistics. The adopted methodologies and related empirical results using various portfolio metrics, downside risk measures and CAPM-based metrics are presented in sections 4, 5 and 6 respectively. The final section concludes the paper.

## 2. Literature Review

The existing literature on CE can be divided into several strands. The first strand of the literature mostly focuses on the interactions between oil and green energy markets. More specifically, previous research puts the relationship between aggregate CE indexes and oil prices in the center and measures both return and volatility dynamics by utilizing various quantitative techniques (see among others, Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012a; Managi and Okimoto, 2013; Reboredo, 2015; Ahmad et al., 2018; Ferrer et al., 2018; Maghyereh et al., 2019; Alkathery and Chaudhuri, 2021). These studies document significant return and volatility connectedness between oil prices and CE indexes. It is also worth noting that the aforementioned studies mainly use an aggregate CE index, particularly the WilderHill Clean Energy Index (ECO), and overlook unique characteristics within the CE investment universe. Apart from the oil-CE linkages, some recent studies also focus on the co-movements between CE stocks and other financial securities, including cryptocurrencies, non-ferrous metals and bonds (e.g., Nguyen et al., 2021a; Chen et al, 2022; Khalfaoui et al., 2022).

The second strand of the literature examines the risk-return performance of CE stocks from the asset pricing perspective. For instance, using a variable beta model, Sadorsky (2012b) shows that higher sales growth (oil price returns) reduces (increases) systematic risk for renewable energy companies. In another research, Bohl et al. (2013) focus on the performance of German renewable energy stocks and find evidence of substantial systematic risk implied by a beta value of nearly two. They further report that these assets deliver significantly negative Carhart four-factor alphas, suggesting that market participants should be wary of poor risk-return performance of German CE stocks. In a more recent study, Inchauspe et al. (2015) investigate the determinants and risk-return performance of the WilderHill New Energy Global Innovation Index (NEX), using a state-space asset pricing model. They show that the performance significantly depends on the time period; the index offers excess returns over risk-adjusted premium from 2003 to 2007, while it yielded negative active returns during the 2009–2013 period. This strand of the literature also includes studies that focus on broader sustainability indexes. For example, Cunha et al. (2020) investigate the performance of regional Dow Jones Sustainability Indexes (DJSIs) and market benchmarks from 2013 to 2018. Their findings indicate superior risk-adjusted returns in certain regions and investors can reap the benefits of investing in those indexes. In another study, Cunha and Samanez (2013) analyze the performance of the Corporate Sustainability Index (ISE) of the Brazilian Mercantile, Futures and Stock Exchange (BM&FBOVESPA) from 2005 to 2010 and find that these investments did not achieve satisfactory performance during the sample period, even though they displayed some interesting features, such as increasing liquidity and low unsystematic risk. Overall, there is no consensus in the extant literature examining the risk-return performance of environmentally friendly investments since such studies report mixed results which could perhaps be attributed to the usage of different sample periods, indexes or research methodologies.

Third strand of the literature is relatively new and investigates the dynamics of CE equities at a disaggregate level. Our paper mainly relates to this stream of the existing literature. There are relatively limited number of studies that consider heterogeneity within sustainable investments. Table 1 reports a summary of empirical studies that focus on CE stocks at disaggregate level. As can be seen, these studies mainly investigate the interlinkages between oil prices and CE equities using a battery of statistical methods. For example, Pham (2019) examines the linkages between CE sub-sector indexes and oil prices for the period from 2010 to 2018. The findings support stronger connectedness of biofuel and energy management equities with oil prices, whereas the connectedness is weaker for wind, geothermal and fuel cell stocks. In another study, Pham (2021) analyzes the dependence between green bonds and green equity sub-sectors, including CE, green building, green transportation, and water. The findings imply that a portfolio of green bonds and green equities can provide diversification benefits for energy investors. Comparing the portfolio performance of CE sub-sectors to those of equity market benchmark index and dirty energy stocks for the period between 2010 and 2021, Kuang (2021a) shows that CE equities underperform the benchmark market index but outperform dirty energy stocks. The findings also show evidence of significant variations within the CE sub-sectors. More specifically, investing in the developer/operator index might be more suitable for moderate risk-averse investors, whereas the fuel cells, wind, and solar indexes might be more attractive to investors with higher risk tolerance. Consequently, these studies highlight the diversity of the CE market as its sub-sectors display heterogeneity in terms of risk-return performance.

[Insert Table 1 about here]

The most recent strand of the relevant literature involves the impact of COVID-19 pandemic on green stocks. Wan et al. (2021) report improved returns for CE firms in comparison to fossil fuel companies during the coronavirus outbreak which they attribute to the increased investor attention in sustainable investments. In a more recent study, Roy et al. (2022) find a positive relationship between idiosyncratic volatility (IVOL) and the excess returns of CE stocks from 2011 to 2021. During the COVID-19 period, they fail to report any significant return-IVOL relation and show that the renewable energy equities display high-tech stocks-like features which they attribute to higher information asymmetry. Kuang et al. (2021b) suggest that the prices of CE stocks experience more substantial falls than global equity markets during the pandemic and adding these assets to an international equity portfolio might increase the downside risks. Liu et al. (2022) analyze the effects of uncertainties caused by the COVID-19 pandemic on renewable energy stock returns and volatilities. They find that the impact of the pandemic on renewable energy stocks is more pronounced compared to the 2007–2009 global financial crisis.

Overall, the literature review shows a lack of research on the risk-return profile of clean energy stocks as an investment vehicle. Prior studies mostly explore the relationship between various assets, predominantly crude oil, and renewable energy equities. The survey of the literature in Table 1 shows that, similar to our paper, Kuang (2021a) analyzes the risk-return characteristics of clean energy stocks at sub-sector level, however it examines their performance from a different angle by constructing hypothetical portfolios and comparing the performance of CE stocks only to oil & gas companies. Our paper is different from Kuang (2021a) in that we investigate risk-return profile of individual CE sub-sectors and compare their performance to a wide range of sectoral indexes. In addition, our sample covers the COVID-19 period, which allows us to explore how the performance changed during the pandemic. The COVID-19 as a health crisis has also reflected its catastrophic ramifications in the global economic activity, intensifying the systemic risk in financial markets. The most recent literature on the effects of the coronavirus crash accentuates its aggrandizing impact on the systematic risk of global financial markets (Abuzayed et al., 2021; Akhtaruzzaman et al., 2021; Bouri et al., 2020; Nguyen et al., 2021b; Rizwan et al., 2020). Therefore, we extend the relevant literature by assessing the wide range of CE and traditional sectors and updating the evidence regarding the impacts of the COVID-19 on environmentally friendly assets.

## 3. Data and Descriptive Statistics

We use the NASDAQ OMX Green Economy Index Family to investigate the risk-return characteristics of CE stocks.[6] Following Cunha et al. (2021), we compare their performance to that of sector stock returns and benchmark equity index. As stated by Pham (2019), the NASDAQ OMX Green Economy Index Family is the most comprehensive renewable energy index since it tracks the performance of CE sub-sectors. Table 2 provides a detailed explanation of each stock index we used in our analyses. We retrieved the daily data are from the Refinitiv Datastream and the data period spans from 13 October 2010 to 31 December 2021.[7]

[Insert Table 2 about here]

[6] The data and estimation codes are available upon request.

[7] NASDAQ OMX's Green Economy Sector indexes were launched on October 13, 2010.

Table 3 illustrates the descriptive statistics of the returns on each index for the full sample period, and pre-COVID-19 and COVID-19 period sub-samples.[8] The pre-COVID-19 and COVID-19 periods span from 13 October 2010 to 10 March 2020 and from 11 March 2020 to 31 December 2021, respectively. Among the CE group, FLC (BCL) have the highest (lowest) average return in the full sample, whereas TECH offers the highest mean return in the conventional sector group. OLG is the only sector that has negative returns, suggesting that green stocks may outperform fossil fuel stocks which is consistent with Wen et al. (2014). In terms of unconditional risk represented by standard deviations, FLC, followed by SLR, is the riskiest index.

[Insert Table 3 about here]

Comparing the summary statistics during the pre-COVID-19 and COVID-19 period, we observe that the average returns have significantly increased during the COVID-19, regardless of the market considered. FLC, followed by SLR, experienced the highest return increase in times of the global pandemic. This can be attributed to additional energy demand from hospitals during the COVID-19, particularly, solid oxide fuel cells played a key role in meeting the extra energy needs (Afroze et al., 2021) which explains the higher earnings for companies operating in this sector. However, we should also note that all the markets are riskier during the pandemic as evidenced by the higher standard deviations. Therefore, despite greater returns, portfolio diversification with green stocks might be harder requiring more information, which we will explore further in the following sections.

Figure 2 plots the daily closing prices of the sub-sector CE indexes. It is clearly evident that green stocks are heterogenous in terms of their evolution over time, which is consistent with Pham (2019). While some indexes (e.g., DEV, GIT and EMN) tend to move together, some others (e.g., AMT, FLC and STR) display more distinct movements. The summary statistics presented in Table 3 also provide evidence of heterogeneity across CE stocks as they exhibit distinct features in terms of return, risk and distributional characteristics.

[Insert Figure 2 about here]

Figure 3 displays the cumulative returns and drawdown risk of both CE and other sector indexes throughout the full sample period.[9] We included the NASDAQ Composite index in both graphs for comparison. Panel A shows that none of the CE indexes can outperform the composite index. The cumulative returns significantly increase after the pandemic even though all the indexes experienced short-lived declines when the World Health Organization (WHO) declared the COVID-19 a global pandemic in March 2020. FLC appears to be the most vulnerable index to drawdown risk. Panel B plots the time-varying risk-return dynamics of traditional sector indexes and reveals that TECH and HLT have the potential to outperform the composite index. OLG has the highest drawdown risk among all the indexes, particularly after the oil plunge in 2014.

[8] We calculated the returns as $R_{i,t} = (lnP_{i,t} - lnP_{i,t-1})$, where $R_{i,t}$ denotes the return of index $i$ on day $t$ and $P_{i,t}$ stands for the closing price of index $i$ on day $t$.

[9] A drawdown simply refers to the largest loss potential an investor could experience and can be calculated as the difference between the highest peak and the subsequent lowest trough.

[Insert Figure 3 about here]

## 4. Portfolio Metrics

We assess the performance in terms of risk-adjusted returns by using portfolio metrics. Sharpe's measure is one of the most commonly used metrics by investors and portfolio managers and quantifies risk-adjusted returns as follows (Sharpe, 1966):

$$Sharpe = \frac{R_i - R_f}{\sigma_i} \quad (1)$$

where $R_i$ stands for the annualized returns on the index $i$, $R_f$ is the risk-free rate of return (1-month US Treasury rate) and $\sigma_i$ represents the annualized standard deviation. Although the Sharpe ratio is a useful metric, it has been highly criticized in the literature (e.g., Eling, 2008; Demiralay et al., 2022) because it assumes that asset returns are normally distributed. However, it is a stylized fact that asset returns do not follow a normal distribution. Besides, the Sharpe ratio treats all the volatility the same and does not allow us to distinguish between upside and downside volatility. To overcome these limitations, we also employ Omega (Keating and Shadwick, 2002) and Sortino (Sortino and van der Meer, 1991; Sortino and Price, 1994) metrics.

Omega ratio is a relatively new portfolio ratio and does not require any distributional assumptions. It is defined as the ratio of probability weighted gains and losses:

$$Omega = \frac{\frac{1}{T}\sum_{t=1}^{T} \max\left(0, R_{i,t}^{+}\right)}{\frac{1}{T}\sum_{t=1}^{T} \max\left(0, R_{i,t}^{-}\right)} \quad (2)$$

Sortino ratio is similar to Sharpe ratio and it measures the performance of an asset compared to a risk-free asset – the difference is that the Sortino ratio uses downside risk instead of standard deviations. Given that investors have a disproportionately large aversion to losses and the Sortino ratio only considers downside risk, it is viewed as a realistic measure in the literature (e.g., Benartzi and Thaler, 1995; Barberis et al., 2001).

$$Sortino = \frac{R_i - R_f}{\sigma_{i,downside}} \quad (3)$$

where $\sigma_{i,downside}$ represents the downside risk.

The results from the portfolio metrics for the full sample period are presented in Panel A of Table 4. Sharpe, Omega and Sortino ratios are the highest for COM, TECH and IND, while some CE sectors, e.g., DEV and GIT, offer relatively modest risk-adjusted returns. Overall, the findings underscore our previous argument that CE sectors are heterogenous in terms of return performance. Although some green indexes, such as SLR, WND, DEV and GIT, outperform certain sector indexes, including BANK, TEL and OLG, they do not display high performance to beat the composite index.

[Insert Table 4 about here]

Panel B and C of Table 4 report the findings from the portfolio metrics for the pre-COVID-19 and COVID-19 periods, respectively. The results indicate that the risk-adjusted returns substantially increase in the wake of the pandemic. For example, the Sharpe ratio of SLR is negative (-0.011) in the pre-COVID-19 period, while it is much higher (1.067) in the COVID-19 period – it even outperforms all the traditional sectors, except for TECH and IND. Another interesting observation is that, considering the risk-adjusted return metrics, EMN outperforms all the sectors during the pandemic, which can be linked to increasing efforts for greener and sustainable economies. The pandemic has prompted individuals and businesses to mitigate the detrimental impacts of climate change. Energy management plays an important role in the path to a more sustainable future as the companies operating in this sector help reduce energy consumption by providing solutions that can be applied to multiple energy sources. The technologies developed in this sector, such as microturbines and appliances, can be utilized by many other energy sectors, including renewables, energy efficiency and even fossil fuels (Pham, 2019).

Overall, our results show evidence of substantial risk-return variability across alternative energy sub-sectors, supporting the findings of Pham (2019) and Pham (2021). Therefore, benefits of investing in CE stocks vary depending on the sub-sector and such variations should not be overlooked by market participants who wish to add these assets to their portfolios. The results also indicate that although CE stocks underperform the composite index and several sectors in the full sample and pre-COVID-19 periods, they outperform dirty assets (OLG), which is in line with Kuang (2021a). As for the COVID-19 period, the portfolio metrics for all the indexes, except for HLT, significantly increase which can be linked to increased investor attention. However, we should also note that adding these sub-sectors to a portfolio may increase overall portfolio risk, as evidenced by higher standard deviations in the previous section. This corroborates the findings of Kuang (2021b) who reports that CE stocks are not safe-havens and may lead to higher portfolio risk in the wake of the pandemic.

## 5. Downside Risk Measures

Many techniques have been proposed to measure the risk of financial assets in the existing literature. The simplest risk measure is variance; however, there has been strong criticism against the use of variance as a risk metric because it penalizes upside risk as much as downside risk (Jin et al., 2006). Therefore, variance is not a realistic risk measure as financial market participants associate the risk only to losses (negative returns) or the returns below their target rate (Mamoghli and Daboussi, 2009). As stated by Estrada (2006) and Ang et al. (2006), there has been relatively little empirical work into downside risk even though the asymmetric treatment of risk has long been recognized by researchers (e.g., Roy, 1952). In this section, we analyze the downside risks of CE securities using various metrics, such as semi-variance, downside deviation and Value-at-Risk (VaR) models.

One of the early downside risk measures, known as semi-deviation, was introduced by Markowitz (1959). It is calculated as the average squared deviation below the average returns and hence it factors in downside risk rather than upside risk when designing risk management strategies. It can be expressed as:

$$\sigma_{SD} = \sqrt{\frac{1}{n}\sum_{for\ all\ R_i \le \bar{R}}^{n}(R_i - \bar{R})^2} \tag{4}$$

where $\bar{R}$ represents the average returns, *n* is the total number of observations and $\sigma_{SD}$ stand for semi-deviation.

Sortino and van der Meer (1991) and Sortino and Forsey (1996) argue that investors strive to achieve a minimum rate of return on their investments. They further state that the minimum return should be taken into account while calculating downside risk even if it is uncertain. In this regard, we also compute the downside risk metrics that consider the minimum target return as follows:

$$\sigma_D = \sqrt{\frac{1}{n}\sum_{i=1}^{n} min[(R_i - r_T), 0]^2} \tag{5}$$

where $\sigma_D$ represents downside deviation and $r_T$ is the target return.[10] In a similar way, we can also calculate gain and loss deviations to better capture the asymmetry between upside and downside risk as given below:

$$\sigma_G = \sqrt{\frac{1}{n_u}\sum_{i=1}^{n} max[(R_i - r_T)]^2} \tag{6}$$

$$\sigma_L = \sqrt{\frac{1}{n_d}\sum_{i=1}^{n} min[(R_i - r_T)]^2} \tag{7}$$

where $\sigma_G$ and $\sigma_L$ stand for gain deviation and loss deviation, respectively. $n_u$ ($n_d$) represents the number of returns greater (less) than minimum acceptable return.

Value-at-Risk (VaR), invented by JPMorgan in the 1980s, is the most widely used metric when measuring downside risks associated with financial assets. VaR quantifies the worst potential loss at a given confidence level. More specifically, 95% (99%) VaR represents the loss that is likely to be exceeded 5% (1%) of the time. In other words, it describes the quantile of the distribution of gains and losses – if *p* is the probability level, VaR corresponds to the *c*=1-*p* tail level (Jorion, 2001). Financial institutions are also required to use VaR as the market risk measure under Basel II and Basel III frameworks. However, VaR has been subjected to heavy criticisms although it has been widely used by portfolio managers and regulators. First and foremost, VaR completely ignores any loss beyond the confidence level (Yamai and Yoshiba, 2005). In addition, it is not sub-additive, hence it penalizes diversification and does not consider risk reduction when forming portfolios (Harmantzis et al, 2006). Artzner (1997) introduced expected shortfall (ES), also known as conditional VaR (CVaR) or tail VaR, to overcome the limitations associated with VaR. ES can be defined as the conditional expectation of losses beyond the confidence level; specifically, it captures the losses beyond the VaR level. It is also shown to be sub-additive, which makes it a coherent risk measure.

There are several methods of calculating VaR and ES, including non-parametric and parametric techniques. The first and simplest method is the historical VaR (HVaR, henceforth), which is a non-parametric method and calculates the losses by sorting the returns from the lowest to the highest value (Demiralay et al., 2022). It can be simply shown as:

$$HVaR = q_{0.95} \tag{8}$$

[10] Following Riddles (2001), we calculated all the downside risk statistics that require target return by assuming the minimum acceptable rate is zero. In other words, any negative return is considered as undesirable.

where $q_{0.95}$ is the 95% empirical quantile of the negative returns. In a similar way, the historical ES (HES) can be computed by the negative value of the average returns below the quantile.

As stated earlier, the historical risk measures defined above are non-parametric and do not require any specific distributional assumptions. However, parametric measures tend to be more powerful than non-parametric ones when estimating risks. Therefore, we also use two-moment and four-moment parametric VaR and ES measures to adequately compute downside risks. These measures allow us to estimate the shape of the distribution tails of the risk quantile. Two-moment VaR, also called Gaussian VaR, can be written as:

$$GVaR = -\bar{R} - z_c \times \sigma \qquad (9)$$

where $\bar{R}$ is the average returns, $z_c$ is the $c$-quantile of the standard normal distribution and $\sigma$ denotes the standard deviations of the returns. Similarly, two-moment parametric ES can be computed as:

$$GES = -\bar{R} - \frac{1}{c}\varphi(z_c) \times \sigma \qquad (10)$$

where $\varphi$ represents the Gaussian density function.

The limitations of the two-moment risk measures have been well established in the existing literature. These measures assume that financial returns are normally distributed; however, the return distributions may exhibit fat tails and be leptokurtic (Bredin et al., 2017). For this reason, four-moment downside risk metrics can enable us to capture downside risks more accurately. Four-moment VaR (also known as Modified VaR) introduced by Favre and Galeano (2002), corrects two-moment VaR for excess kurtosis and skewness by using the Cornish–Fisher expansion (Cornish and Fisher, 1938). The Cornish-Fisher expansion approximates the quantile of the distribution as follows:

$$z_{cf} = z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2 \qquad (11)$$

where $S$ and $K$ denote skewness and kurtosis, respectively. Accordingly, the four-moment modified VaR (MVaR) can be written as:

$$MVaR = -\bar{R} - z_{cf} \times \sigma \qquad (12)$$

Similarly, modified ES (MES) can be defined as the expected value of all returns below the Cornish-Fisher quantile (Boudt et al., 2008). If the return series are normally distributed, then modified VaR (ES) collapses to Gaussian VaR (ES).

Panel A of Table 5 presents downside risk measures for the full-sample period. The results suggest that FLC has the highest downside risk, regardless of the measure considered, except for the modified ES, which is in line with the findings of Pham (2019) and Zhou et al. (2021). When we focus on the modified ES, the riskiest asset is BCL followed by OLG. All the measures indicate that DEV has the lowest risk, making it a suitable asset for investors to consider downside protection. The findings also provide evidence of variation across the CE sub-sectors in terms of downside risks. For instance, the modified ES of BCL is -0.077, while that of DEV is only -0.015, which shows that the downside risk of BCL is at least five times larger than DEV. As DEV involves with developing renewable investment projects, the substitution effect may play a role in investor sentiment, placing DEV equities as less risky green assets. The development and initialization of green energy production projects may induce a reduction in fossil fuel demand by providing a cost advantage and rise in market shares. We also observe that the ES metrics are generally higher than any other downside risk measures; therefore, using other metrics than ES tend to underestimate the risks. This is because simple downside risk measures, such as semi-deviation and downside deviation, only consider average returns or minimum acceptable returns. In addition, even though historical and modified VaR estimate the maximum risk of an asset with a degree of confidence, they discard the losses beyond the confidence level. Therefore, VaR does not fully capture the tail risk. This supports the findings of Chai and Zhou (2018) that the information provided by VaR may mislead investors and ES is a better risk management tool than VaR.

[Insert Table 5 about here]

Panel B and C in Table 5 report the downside risks for the pre-COVID-19 and COVID-19 samples, respectively. At first glance, the results show that most of the risk statistics heighten during the COVID-19 period which is in line with previous research (e.g. Akhtaruzzaman et al., 2021; Bouri et al., 2020). Taking a closer look, we see that some CE sub-sectors have significantly higher downside risks in the aftermath of the global pandemic. For example, the modified ES of SLR (BCL) increases from 0.045 (0.057) during the pre-COVID-19 period to 0.102 (0.115) after the pandemic in absolute terms. Even DEV that possesses the minimum risk experiences substantial surges in its downside risks; for instance, its semi deviation increases from 0.007 to 0.012. There are few exceptions though, taking GIT as an example, the modified ES of the index is lower in the COVID-19 sub-sample. Considering the other sectors, the results demonstrate that BANK and OLG appear to be the riskiest in both sub-samples. When we compare the riskiness of CE sub-sectors to other sectors, we notice that some CE sectors are riskier than the conventional sectors. Especially after the pandemic, downside risks of some CE sectors increase more than those of the other sectors. For instance, the modified risk metrics of BCL, SLR and FLC are higher than OLG and BANK during the COVID-19 pandemic, compared to the pre-COVID-19 period. This shows that certain CE sub-sectors have become riskier than traditional sectors after the pandemic.

Overall, our results suggest that there is significant variation across CE stocks in terms of downside risk, which is consistent with our previous findings. We find that some green sub-sectors, including BCL, SLR and FLC, are riskier than most of the traditional sectors, while some other CE stocks (e.g., DEV) exhibit lower downside risks. In addition, our results provide evidence of heightened risks for all the indexes during the pandemic; however, the increases in downside risk metrics of CE assets are generally higher than those of the conventional sectors. Our results are in parallel with Roy et al. (2022) who report higher volatility in CE markets after the pandemic. They link this to the substitution effect, as substantial volatility in the crude oil markets due to distorted supply chains create higher uncertainty for renewables, which in turn leads to higher risk premiums. Higher risks during the pandemic can also be attributed to investor attention. As stated by Wan et al. (2021), CE has gained a new momentum as a result of green recovery plans in times of the COVID-19, which directs financial market participants' attention to these equities. This is consistent with the notion that investors' decisions are attention-driven (Barber and Odean, 2008) and they can adapt to changing market conditions (Lo, 2012).

## 6. CAPM-Based Metrics

In this section, we compare the performance of CE and other sector indexes against the benchmark portfolio (i.e., NASDAQ Composite index). To do this, we use a single-factor model, also known as the Capital Asset Pricing Model (CAPM), which allows us to have a set of useful measures related to excess returns and systematic risk. Although the CAPM has been widely criticized, it provides simple, yet powerful, predictions about how to estimate systematic risk (Fama and French, 2004). The CAPM was developed in the 1960s by Sharpe (1964), Treynor (1961), Lintner (1965a, b) and Mossin (1966). It is still commonly utilized in financial applications – e.g., measuring the systematic risk of individual stocks or portfolios, estimating the cost of capital and assessing the portfolio performance.

We use the following regression equation to estimate the parameters in the CAPM:

$$R_i - R_f = \alpha + \beta \times (R_m - R_f) \qquad (13)$$

where

$$\alpha = R_i - R_f - \beta \times (R_m - R_f)$$

$$\beta = \frac{Cov(R_i,R_m)}{var(R_m)}$$

In the above equations; $R_i$ represents the asset returns, $R_f$ is the risk-free rate of return and $R_m$ denotes the return on the market portfolio. $\alpha$ is the intercept of the regression equation and estimates the excess return and $\beta$ measures the systematic risk. $Cov(R_i, R_m)$ stands for the covariance between the index and the market portfolio, whereas $var(R_m)$ denotes the variance of the market portfolio.

The assumption of symmetric beta is restrictive and may not fully capture the relationship between the risk and return. Ang et al. (2006) state that the regular beta does not reflect all risks, because investors treat downside risks and upside risks differently. In this study, we relax this assumption and compute asymmetric beta. Following Ang et al. (2006), we compute the upside beta ($\beta^+$) and downside beta ($\beta^-$) as follows:

$$\beta^+ = \frac{Cov(R_i,R_m|R_m>\bar{R}_m)}{var(R_m|R_m>\bar{R}_m)} \qquad (14)$$

$$\beta^- = \frac{Cov(R_i,R_m|R_m<\bar{R}_m)}{var(R_m|R_m<\bar{R}_m)} \qquad (15)$$

where $\bar{R}_m$ is the average market return. The upside and downside beta are also called “bull beta” and “bear beta”, respectively.

We also use other metrics derived from the single-factor model, including Treynor ratio and information ratio. Treynor ratio, also known as the “reward-to-volatility ratio”, is similar to the Sharpe ratio – however, it measures the performance using the systematic risk estimated by beta instead of using standard deviation of the asset. It is defined as follows:

$$Treynor = \frac{R_i - R_f}{\beta_i} \qquad (16)$$

Information ratio is another performance metric that compares returns of an asset or a portfolio to a benchmark. However, it considers active returns and tracking error while evaluating the performance. It can be written as:

$$Information = \frac{R_i - R_m}{\sigma_{(R_i - R_m)}} \qquad (17)$$

where $R_i - R_m$ is the active premium and $\sigma_{(R_i - R_m)}$ represents the tracking error (standard deviation of the active premium).

Table 6 presents the CAPM-based statistics. Panel A documents the results for the full sample period and shows that the beta of FLC and SLR are higher than one; therefore, they are more volatile than the market portfolio. Another asset that is riskier than the benchmark is TECH with a beta value of 1.119. The systematic risk parameters of all the other indexes are lower than unity, suggesting that they are less volatile than the benchmark index. Considering the asymmetric beta, we observe that upside beta is lower than the downside beta in the majority of the cases. This shows that systematic risk mostly increases under bear market conditions. The downside beta of BCL and FLC are greater than one, whereas the upside beta of these two indexes are less than one, which recommend that the two sub-sectors become even riskier than the benchmark portfolio when the market conditions are adverse. On the other hand, the upside beta of SLR, GIT and TECH are greater than one, showing that these indexes covariate more with the market when the market is high. Therefore, they may also have a larger payoff when the return on the benchmark is high. Looking at the risk-adjusted statistics, DEV has the highest Treynor ratio among all the indexes studied; thus, it provides the highest return for given systematic risk. Comparing this with the traditional sectors, TECH and HLT have a lower Treynor ratio than DEV does; however, they outperform all the other indexes in terms of systematic risk-adjusted returns. Information ratio is all negative for CE indexes, highlighting that they cannot produce any excess return over the market portfolio. Hence, they significantly underperform the benchmark index.

[Insert Table 6 about here]

Panel B and C of Table 6 report the results for the pre-COVID-19 and COVID-19 periods, respectively. The sub-sample analysis shows that systematic risk of half of the CE indexes (i.e., BCL, SLR, GEO, FLC and DEV) increased during the pandemic. The other half of the green indexes (i.e., WND, STR, GIT, EMN and AMT) have lower systemic risks in the same period. As for the asymmetric beta, the results show that the majority of the CE indexes exhibit higher upside betas during the COVID-19, compared to the pre-pandemic period. Another interesting observation is that the variations in the systematic risk of green indexes are generally larger than those of the other sectors in the two sub-samples. For instance, the downside beta of BCL increases from 0.799 in the pre-pandemic period to 1.353 during the pandemic, while the highest increase in the downside beta in the other sector group is observed for FIN, increasing from 0.938 to only 0.993. This indicates that the COVID-19 has more pronounced impacts on renewable energy sectors than any other sector in terms of riskiness, which supports our previous findings. Focusing on the risk-adjusted returns, Treynor ratio analysis shows higher excess returns per unit of systematic risk in times of the COVID-19, except for DEV among all the sectors considered. Therefore, we can conclude that although green stocks are exposed to higher systematic risk compared to the pre-pandemic period, investors holding these assets earn at least higher than the risk-free rate during the pandemic. However, looking at the information ratio analysis, most of the indexes still cannot outperform the benchmark as only SLR, FLC, EMN and TECH can produce positive ratio in the COVID-19 sub-sample. Furthermore, considering Treynor ratio, EMN outperforms all the other indexes in the wake of the pandemic, which is consistent with our previous findings. The results also show that SLR displays an exceptional performance during the pandemic as its information ratio is the highest, implying that it generates the highest excess return over the benchmark. In short, investing in EMN, FLC and SLR companies during the COVID-19 could produce excess returns over the risk-free rate and the market portfolio.

Overall, the results show that the CE indexes have an intermediate risk-return performance since most of them had an unsatisfactory performance in the pre-COVID-19 sub-sample. Nevertheless, some green sub-sectors, such as WND, DEV, GIT and EMN, could produce excess returns over the risk-free rate before the pandemic. When we focus on the COVID-19 period, we observe that all the renewable energy indexes outperform the risk-free rate and some of these indexes even generate higher returns than the market portfolio. Moreover, the risk-return performance significantly depends on the sub-sector – for instance, the full-sample results suggest that the upside (downside) beta ranges from 0.468 (0.562) to 1.082 (1.308) among the green sector group. This underscores the importance of sector-specific information; thus, the use of a broad CE index might mask this valuable information. Therefore, financial market participants should carefully consider the heterogeneity across the green sectors when designing portfolio strategies, as their risk-return performance is considerably sector-dependent. Our results support those of Roy et al. (2022) who find evidence of significant variability in terms of CE stock betas. Interestingly, our findings contradict the results of Sadorsky (2012b) and Bohl et al. (2013) who report that CE stocks are twice as risky as the benchmark. In contrast, we find that the highest beta in the full (COVID-19) sample is 1.20 (1.451) which belongs to FLC. This finding suggests that FLC (the riskiest CE sub-sector) is only approximately 20% (45%) riskier than the benchmark index in the full (COVID-19) sample period. The difference between our findings and the aforementioned studies, however, might be due to different time span and sectoral focus.

## 7. Concluding Remarks

Policy actions on climate change, increasing pressure from stakeholders to transition to a low-carbon economy and deployment of new renewable energy technologies have led to exponential growth of CE sector. Concomitantly, the developments in the alternative energy have sparked investors' interests in environmentally friendly financial instruments. Investors, traders and fund managers alike increasingly seek to align their values with their portfolio holdings. Therefore, green finance can convey the necessary means to attain a new world order with climate friendly practices. Green financial instruments can channel collective efforts to climate protective projects ensuring the development of an environmentally sustainable global economy. Hence, alternative energy investments are essential for implementing effective environmental management practices to achieve the goal of environmental sustainability. In this context, CE equities help investors reduce their exposure to dirty assets and provide investment opportunities to diversify their portfolios. Relatedly, we aim to investigate the risk-return characteristics of CE stock indexes and compare their performance with more conventional sector indexes. Following Pham (2019) and Kuang (2021a), we hypothesize that CE sector is too broad to be considered as a single sector and a one-size-fits-all strategy may mislead market participants when making investment decisions and designing risk management strategies. Therefore, our study offers a more comprehensive understanding about the CE sub-sectors in terms of risk-return performance beyond the generic information provided by most previous studies that only focus on aggregate CE indexes.

The results have important implications for investors, portfolio managers and policy makers. Particularly, our findings shed light on the risk-return nexus of CE sub-sectors, conveying relevant and timely information to environmental management decisions for an efficient allocation of green finance flows. First, comprehending the heterogeneity of CE sub-sectors can help investors and fund managers choose the asset that meet their expectations. For example, the EMN index can provide high risk-adjusted returns for investors who seek to protect their investments from the COVID-19 turbulence, whereas the DEV index could be more attractive to investors with moderate risk tolerance in general. Second, our results show that certain CE indexes, such as DEV and EMN can outperform fossil fuel investments, suggesting that a de-carbonization strategy using these assets can generate higher risk-adjusted returns. Finally, authorities should consider the distinctive features of CE sub-sectors when making policy decisions. For instance, some sub-sectors, such as SLR and FLC, have higher downside risk than other CE sub-sectors. Therefore, specific sub-sector attributes should be taken into account while designing policy interventions for the CE sector which would ensure the resiliency in reaching the goal of environmentally sustainable development.

Although we use a broad range of performance metrics and analyze CE sub-sectors comprehensively, our research still has some limitations. First, we only evaluate the performance of the CE indexes listed in the NASDAQ Green Economy index family. Future studies could focus on a different dataset of CE indexes, such as MSCI Alternative energy indexes and compare the performance of these indexes. Second, we do not construct portfolios that consist of green equities and traditional benchmarks and/or sectors; however, a mixed portfolio analysis could provide valuable insights into the portfolio performance of sustainable investments. Third, although sector-level studies can provide useful information, future studies could also consider analyzing firm-level data. Lastly, the CAPM-based metrics could be extended by adding additional asset pricing factors in the regression, which could offer further implications in terms of risks and excess returns.

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**Table 1. Summary of studies that focus on clean energy equities at disaggregated level**

| Authors | Purpose | Sample period | CE sub-sectors considered | Method | Key results |
|---|---|---|---|---|---|
| Pham (2019) | Analysing the connectedness between sub-sector CE stocks and oil prices. | 13 October 2010-21 August 2018 | NASDAQ OMX Green Economy indexes: Bio/Clean Fuel, Solar, Wind, Geothermal, Fuel cell, Developer/Operator, Energy storage, Smart grid, Green IT, Energy management, Advanced materials. | Diebold and Yilmaz (2012, 2014) spillover index, Dynamic Conditional Correlations (DCC) model. | The linkages between CE stocks and oil prices vary significantly across the sub-sectors. Biofuel and energy management stocks (wind, geothermal and fuel cell) are the most (least) connected to oil price. |
| Kuang (2021) | Optimal allocation within the clean energy stock market. | 15 October 2010–07 May 2021 | NASDAQ OMX Green Economy indexes: Bio/Clean Fuel, Solar, Wind, Geothermal, Fuel cell, Developer/Operator, Energy storage, Smart grid, Green IT, Energy management, Advanced materials. | Mean-variance and Mean-Conditional Value-at-Risk Optimizations. | CE equities underperform the market index but outperform dirty stocks. The results provide evidence of heterogenous diversification benefits. The developers/ operators index offers the highest risk-adjusted returns for investors with moderate risk tolerance while the wind and energy storage indexes help reduce the tail risks of dirty stocks. |
| Pham (2021) | Examining the dependence structure between green bonds and CE stocks. | August 2014–August 2020 | Green building, Green transportation and Global water indexes. | The connectedness framework of Diebold and Yılmaz (2014) and Baruník and Křehlík (2018). Cross-quantilogram dependence. | Green bonds and green equity are less (more) connected during normal (extreme) market conditions. The spillover effect between the two markets is generally short-lived and intensified during the pandemic. |
| Tan et al. (2021) | Quantifying risk spillovers between oil and CE equities. | 13 October 2010–28 August 2020 | NASDAQ OMX Green Economy indexes: Bio/Clean Fuel, Solar, Wind, Geothermal, Fuel cell, Developer/Operator, Energy storage, Smart grid, Green IT, Energy management, Advanced materials. | Diebold and Yilmaz (2012, 2014) spillover index model and VAR for VaR model. | Risk spillovers are time-varying and moderate overall; however, the patterns of spillovers significantly depend on the sub-sector. CE equities transmit extreme downside risk to oil at higher magnitudes than the opposite impact. |
| Hammoudeh et al. (2021) | Investigating the causal relationships between the returns and volatility of oil | 13 October 2010–8 September 2020 | NASDAQ OMX Green Economy indexes: Solar, Wind, Geothermal, Fuel cell, Developer/Operator. | Causality-in-quantiles. | In terms of causality in returns, oil has a prediction power of the CE stocks in normal times, but not in extreme market conditions. The volatility analysis provides evidence of significant bi-directional causality in the low |

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| | prices and five clean energy stock indexes. | | | | volatility regime. No bi-directional causality is detected during the COVID-19 pandemic. |
| Zhou et al. (2021) | Analysing volatility spillovers and risk spreads in renewable energy markets. | 18 October 2010–31 December 2019 | NASDAQ OMX Green Economy indexes: Bio/Clean Fuels, Solar, Wind, Geothermal, Fuel Cell. | Multivariate GARCH models and multidimensional analysis method. | The fuel cell and solar indexes dominate the other indexes in the risk spread paths. A multidimensional perspective is useful for analysing the interactions in renewable energy markets because the spillover effects are more clearly evident when considering multiple markets. |
| Sharma (2022) | Examining risk spillovers between conventional and green finance. | August 2011–June 2021 | NASDAQ OMX Green Economy indexes: Solar, Wind, Global water, the NASDAQ Clean Edge Green Energy Index (CELS)/ | The connectedness framework by Diebold and Yılmaz (2012) and Baruník and Křehlík (2018). | There is bi-directional causality between conventional and green indexes in the long-run. During the COVID-19 pandemic, the linkages between the two sets of markets intensified. Going green can provide investors reasonably good risk-adjusted returns. |
| Ren and Lucey (2022) | Exploring whether clean energy is a safe haven for cryptocurrencies. | 1 January 2018–17 September 2021 | NASDAQ OMX Green Economy indexes: Bio/Clean Fuels, Fuel Cell, Renewable Energy, Geothermal, Solar, Wind. | Multivariate GARCH models and the connectedness framework by Diebold and Yılmaz (2014). | Although clean energy is not a direct hedge for cryptocurrencies, it is a weak safe haven for cryptocurrencies in extreme bearish markets. The connectedness is weak between clean energy and cryptocurrencies which suggests that clean energy can serve as a hedge and diversification tool for cryptocurrencies. |
| Chen et al. (2022) | Investigating the asymmetric impacts of non-ferrous metal price shocks on clean energy equities. | 13 October 2010–23 June 2021 | NASDAQ OMX Green Economy indexes: Bio/Clean Fuel, Solar, Wind, Geothermal, Fuel cell, Developer/Operator, Energy storage, Smart grid, Green IT, Energy management, Advanced materials. | Quantile-on-quantile regression and causality-in-quantiles. | There is significant heterogeneity across CE sub-sectors in terms of reaction to shocks in non-ferrous metal prices. Nonferrous metals cannot act as safe havens for clean energy stock markets during turbulent times. |
| Usman (2023) | Testing the relationship between oil prices and CE stocks. | 13 October 2010–30 June 2022 | NASDAQ OMX Green Economy indexes: Bio/Clean Fuel, Solar, Wind, Geothermal, Fuel cell, Developer/Operator, Energy storage, Smart grid, Energy management, Advanced materials. | Stochastic dominance tests. | The decoupling hypothesis of clean energy stocks is supported as the correlation between clean energy stocks is lower when the oil market returns are extremely high. Overall, conventional energy stocks tend to co-move with oil shocks more than clean energy stocks. |

**Notes:** This table presents a summary of studies that focus on clean energy stocks at sub-sector level.

**Table 2. Index Details**

| Group | Index | Symbol | Description |
|---|---|---|---|
| Bio/clean fuels | NASDAQ OMX Bio/Clean Fuels Index | BCL | This index is designed to track companies that produce fuels from plant-based material for transportation |
| Renewable energy | NASDAQ OMX Solar Index | SLR | This index is designed to track companies that produce energy through solar power. |
| | NASDAQ OMX Wind Index | WND | This index is designed to track companies that produce energy through wind power. |
| | NASDAQ OMX Geothermal Index | GEO | This index is designed to track companies that produce energy through geothermal power. |
| | NASDAQ OMX Fuel Cell Index | FLC | This index is designed to track companies that produce energy through fuel cells. |
| | NASDAQ OMX Developer/Operator Index | DEV | This index is designed to track companies that develop and operate renewable energy projects such as solar and wind farms. |
| Energy Efficiency | NASDAQ OMX Energy Storage Index | STR | This index is designed to track companies that provide solutions to increase the ability of energy storage, such as batteries. |
| | NASDAQ OMX Green IT Index | GIT | This index tracks companies that provide solutions that decrease energy consumption via IT solutions such as online collaboration, efficient data centers, computer networks, and virtualization software. |
| | NASDAQ OMX Energy Management Index | EMN | This index tracks companies that provide solutions that decreases energy consumption with better energy management systems such as efficient motors, micro turbines, process controls, and appliances. |
| Advanced material | NASDAQ OMX Advanced Material Index | AMT | This index is designed to track companies that produce materials that enable renewable technologies or reduce dependencies for petroleum-based products. |
| Benchmark | NASDAQ Composite Index | COM | This index is a broad-based capitalization-weighted index of stocks listed on the NASDAQ stock exchange. |
| Technology | NASDAQ-100 Technology Sector Index | TECH | This index is designed to track the performance technology companies listed on the NASDAQ stock exchange. |
| Financials | NASDAQ Financial-100 Index | FIN | This index is designed to track the largest financial organizations listed on the NASDAQ stock exchange. |
| Industrials | NASDAQ Industrials Index | IND | This index contains securities of NASDAQ-listed companies not classified in one of the NASDAQ sector indexes, such as general industrials, aerospace/defense, food producers and chemicals. |
| Banks | NASDAQ Bank Index | BANK | This index contains common stocks of banks listed on the NASDAQ stock exchange. |
| Healthcare | NASDAQ Health Care Index | HLT | This index measures the performance of health care companies including health care providers, medical equipment, medical supplies, biotechnology, and pharmaceuticals. |
| Telecommunications | NASDAQ Telecommunications Index | TEL | This index is designed to track the performance of telecommunications companies listed on the NASDAQ stock exchange, including providers of fixed-line and |

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|---|---|---|---|
| | | | mobile telephone services, and makers and distributors of high-technology communication products. |
| Transportation | NASDAQ Transportation Index | TSP | This index is designed to track the performance of transportation companies listed on the NASDAQ stock exchange, including delivery services, marine transportation, railroads, transportation services, trucking, and airlines. |
| Oil & Gas | NASDAQ US Smart Oil & Gas Index | OLG | This index is designed to provide exposure to US companies within the Oil & Gas sector. |

Source: NASDAQ and Pham (2019).

**Notes**: This table presents the details of the indexes used in this research.

**Table 3. Descriptive Statistics**

| | BCL | SLR | WND | GEO | FLC | DEV | STR | GIT | EMN | AMT | COM | TECH | FIN | IND | BANK | HLT | TEL | TSP | OLG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A. Full Sample Results* | | | | | | | | | | | | | | | | | | | |
| Mean | 0.007 | 0.050 | 0.039 | 0.012 | 0.051 | 0.037 | 0.009 | 0.037 | 0.036 | 0.023 | 0.064 | 0.071 | 0.039 | 0.060 | 0.035 | 0.051 | 0.025 | 0.033 | -0.001 |
| Median | 0.059 | 0.092 | 0.069 | 0.080 | -0.047 | 0.067 | 0.059 | 0.079 | 0.059 | 0.069 | 0.115 | 0.129 | 0.092 | 0.121 | 0.063 | 0.136 | 0.082 | 0.091 | 0.026 |
| Std. Dev. | 1.816 | 2.085 | 1.658 | 1.664 | 3.334 | 1.027 | 1.479 | 1.465 | 1.489 | 1.492 | 1.224 | 1.447 | 1.335 | 1.184 | 1.640 | 1.385 | 1.299 | 1.411 | 1.914 |
| Skewness | -1.067 | -0.456 | -0.501 | 0.383 | 0.375 | -1.603 | -0.270 | -0.413 | -0.425 | -0.539 | -0.811 | -0.578 | -0.808 | -0.842 | -0.313 | -0.524 | -0.518 | -0.472 | -0.684 |
| Kurtosis | 16.366 | 9.108 | 7.622 | 16.411 | 8.273 | 32.967 | 6.639 | 12.458 | 13.562 | 9.414 | 13.953 | 11.002 | 17.462 | 11.561 | 12.301 | 7.230 | 10.779 | 11.267 | 12.635 |
| *Panel B. Pre-COVID-19 Sample Results* | | | | | | | | | | | | | | | | | | | |
| Mean | -0.005 | 0.016 | 0.035 | 0.004 | 0.010 | 0.033 | -0.009 | 0.025 | 0.013 | 0.005 | 0.049 | 0.056 | 0.030 | 0.046 | 0.018 | 0.049 | 0.015 | 0.021 | -0.030 |
| Median | 0.055 | 0.067 | 0.075 | 0.072 | -0.075 | 0.067 | 0.043 | 0.079 | 0.051 | 0.070 | 0.093 | 0.116 | 0.090 | 0.100 | 0.067 | 0.137 | 0.080 | 0.084 | 0.032 |
| Std. Dev. | 1.516 | 1.788 | 1.552 | 1.345 | 2.938 | 0.872 | 1.332 | 1.375 | 1.376 | 1.396 | 1.093 | 1.284 | 1.148 | 1.064 | 1.321 | 1.305 | 1.225 | 1.286 | 1.606 |
| Skewness | -0.788 | -0.210 | -0.475 | 0.427 | 0.338 | -0.596 | -0.268 | -0.605 | -0.450 | -0.388 | -0.596 | -0.480 | -0.743 | -0.647 | -0.886 | -0.450 | -0.456 | -0.515 | -1.331 |
| Kurtosis | 12.406 | 5.287 | 7.136 | 22.666 | 9.608 | 7.177 | 6.211 | 10.335 | 8.316 | 7.811 | 7.491 | 5.834 | 10.815 | 7.866 | 11.805 | 5.224 | 7.288 | 5.899 | 16.648 |
| *Panel C. COVID-19 Sample Results* | | | | | | | | | | | | | | | | | | | |
| Mean | 0.068 | 0.225 | 0.064 | 0.051 | 0.262 | 0.060 | 0.100 | 0.100 | 0.154 | 0.118 | 0.138 | 0.146 | 0.089 | 0.127 | 0.122 | 0.064 | 0.077 | 0.094 | 0.152 |
| Median | 0.103 | 0.205 | 0.046 | 0.204 | 0.105 | 0.057 | 0.178 | 0.077 | 0.217 | 0.065 | 0.252 | 0.227 | 0.100 | 0.249 | 0.038 | 0.124 | 0.091 | 0.125 | 0.013 |
| Std. Dev. | 2.911 | 3.205 | 2.127 | 2.780 | 4.894 | 1.608 | 2.078 | 1.861 | 1.969 | 1.910 | 1.752 | 2.095 | 2.045 | 1.673 | 2.753 | 1.742 | 1.629 | 1.931 | 3.044 |
| Skewness | -1.071 | -0.701 | -0.529 | 0.225 | 0.273 | -2.122 | -0.313 | -0.026 | -0.433 | -0.874 | -1.039 | -0.672 | -0.758 | -1.056 | 0.023 | -0.659 | -0.662 | -0.403 | -0.149 |
| Kurtosis | 10.690 | 7.563 | 6.962 | 6.570 | 4.515 | 30.895 | 5.130 | 13.579 | 17.188 | 10.242 | 14.836 | 11.287 | 14.108 | 11.415 | 6.327 | 9.358 | 14.943 | 13.863 | 5.523 |

**Notes**: This table reports the summary statistics of the indexes. The full sample spans from 13 October 2010 to 31 December 2021. Pre-COVID-19 and COVID-19 periods are from 13 October 2010 to 10 March 2020 and from 11 March 2020 to 31 December 2021, respectively.

**Table 4. Portfolio Metrics**

| | BCL | SLR | WND | GEO | FLC | DEV | STR | GIT | EMN | AMT | COM | TECH | FIN | IND | BANK | HLT | TEL | TSP | OLG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A. Full Sample Results* | | | | | | | | | | | | | | | | | | | |
| Sharpe | -0.095 | 0.212 | 0.241 | -0.032 | -0.027 | 0.497 | -0.032 | 0.286 | 0.261 | 0.120 | 0.764 | 0.698 | 0.361 | 0.735 | 0.197 | 0.491 | 0.193 | 0.252 | -0.165 |
| Omega | 1.011 | 1.070 | 1.068 | 1.021 | 1.045 | 1.113 | 1.017 | 1.079 | 1.073 | 1.046 | 1.166 | 1.150 | 1.094 | 1.158 | 1.065 | 1.107 | 1.058 | 1.068 | 0.999 |
| Sortino | 0.005 | 0.033 | 0.033 | 0.010 | 0.023 | 0.049 | 0.008 | 0.035 | 0.034 | 0.022 | 0.071 | 0.068 | 0.040 | 0.068 | 0.029 | 0.051 | 0.026 | 0.032 | -0.001 |
| *Panel B. Pre-COVID-19 Sample Results* | | | | | | | | | | | | | | | | | | | |
| Sharpe | -0.181 | -0.011 | 0.225 | -0.072 | -0.177 | 0.532 | -0.216 | 0.173 | 0.029 | -0.065 | 0.643 | 0.611 | 0.313 | 0.622 | 0.093 | 0.504 | 0.082 | 0.145 | -0.417 |
| Omega | 0.991 | 1.024 | 1.063 | 1.009 | 1.010 | 1.110 | 0.983 | 1.055 | 1.027 | 1.011 | 1.137 | 1.128 | 1.077 | 1.132 | 1.038 | 1.107 | 1.035 | 1.045 | 0.948 |
| Sortino | -0.004 | 0.012 | 0.031 | 0.004 | 0.005 | 0.052 | -0.009 | 0.025 | 0.013 | 0.005 | 0.061 | 0.060 | 0.035 | 0.060 | 0.018 | 0.052 | 0.017 | 0.022 | -0.025 |
| *Panel C. COVID-19 Sample Results* | | | | | | | | | | | | | | | | | | | |
| Sharpe | 0.131 | 1.067 | 0.315 | 0.066 | 0.554 | 0.473 | 0.652 | 0.773 | 1.277 | 0.927 | 1.291 | 1.093 | 0.564 | 1.225 | 0.534 | 0.457 | 0.662 | 0.674 | 0.621 |
| Omega | 1.070 | 1.219 | 1.087 | 1.052 | 1.155 | 1.126 | 1.139 | 1.185 | 1.285 | 1.195 | 1.273 | 1.228 | 1.148 | 1.249 | 1.137 | 1.108 | 1.159 | 1.161 | 1.144 |
| Sortino | 0.031 | 0.099 | 0.042 | 0.027 | 0.082 | 0.049 | 0.069 | 0.078 | 0.112 | 0.087 | 0.109 | 0.098 | 0.060 | 0.103 | 0.065 | 0.051 | 0.066 | 0.069 | 0.073 |

**Note**s: This table reports the portfolio metrics, including annualized returns and standard deviations, Sharpe, Omega and Sortino portfolio measures. The full sample spans from 13 October 2010 to 31 December 2021. Pre-COVID-19 and COVID-19 periods are from 13 October 2010 to 10 March 2020 and from 11 March 2020 to 31 December 2021, respectively.

**Table 5. Downside Risk Measures**

| | BCL | SLR | WND | GEO | FLC | DEV | STR | GIT | EMN | AMT | COM | TECH | FIN | IND | BANK | HLT | TEL | TSP | OLG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A. Full Sample Results* | | | | | | | | | | | | | | | | | | | |
| Semi Dev. | 0.014 | 0.015 | 0.012 | 0.012 | 0.023 | 0.008 | 0.011 | 0.011 | 0.011 | 0.011 | 0.009 | 0.011 | 0.010 | 0.009 | 0.012 | 0.010 | 0.010 | 0.010 | 0.014 |
| Gain Dev. | 0.012 | 0.014 | 0.011 | 0.012 | 0.026 | 0.007 | 0.010 | 0.010 | 0.010 | 0.010 | 0.008 | 0.009 | 0.009 | 0.007 | 0.012 | 0.009 | 0.009 | 0.009 | 0.013 |
| Loss Dev. | 0.015 | 0.016 | 0.012 | 0.013 | 0.022 | 0.009 | 0.011 | 0.012 | 0.012 | 0.012 | 0.010 | 0.012 | 0.011 | 0.010 | 0.013 | 0.011 | 0.010 | 0.011 | 0.015 |
| Downside | 0.014 | 0.015 | 0.012 | 0.012 | 0.022 | 0.008 | 0.011 | 0.011 | 0.011 | 0.011 | 0.009 | 0.010 | 0.010 | 0.009 | 0.012 | 0.010 | 0.010 | 0.010 | 0.014 |
| HVaR | -0.027 | -0.034 | -0.026 | -0.025 | -0.050 | -0.015 | -0.023 | -0.022 | -0.022 | -0.023 | -0.020 | -0.023 | -0.019 | -0.019 | -0.024 | -0.023 | -0.021 | -0.022 | -0.030 |
| HES | -0.043 | -0.049 | -0.039 | -0.040 | -0.074 | -0.024 | -0.035 | -0.036 | -0.035 | -0.036 | -0.031 | -0.035 | -0.033 | -0.030 | -0.040 | -0.033 | -0.032 | -0.034 | -0.046 |
| GVaR | -0.030 | -0.034 | -0.027 | -0.027 | -0.054 | -0.017 | -0.024 | -0.024 | -0.024 | -0.024 | -0.019 | -0.023 | -0.022 | -0.019 | -0.027 | -0.022 | -0.021 | -0.023 | -0.031 |
| GES | -0.037 | -0.042 | -0.034 | -0.034 | -0.068 | -0.021 | -0.030 | -0.030 | -0.030 | -0.031 | -0.025 | -0.029 | -0.027 | -0.024 | -0.033 | -0.028 | -0.027 | -0.029 | -0.039 |
| MVaR | -0.030 | -0.034 | -0.028 | -0.021 | -0.047 | -0.015 | -0.024 | -0.023 | -0.023 | -0.025 | -0.020 | -0.023 | -0.021 | -0.020 | -0.025 | -0.023 | -0.021 | -0.022 | -0.031 |
| MES | -0.077 | -0.065 | -0.051 | -0.021 | -0.057 | -0.015 | -0.040 | -0.043 | -0.043 | -0.049 | -0.046 | -0.048 | -0.046 | -0.045 | -0.045 | -0.042 | -0.042 | -0.045 | -0.068 |
| *Panel B. Pre-COVID-19 Sample Results* | | | | | | | | | | | | | | | | | | | |
| Semi Dev. | 0.011 | 0.013 | 0.011 | 0.010 | 0.020 | 0.007 | 0.010 | 0.010 | 0.010 | 0.010 | 0.008 | 0.010 | 0.009 | 0.008 | 0.010 | 0.010 | 0.009 | 0.010 | 0.012 |
| Gain Dev. | 0.009 | 0.011 | 0.010 | 0.010 | 0.023 | 0.005 | 0.009 | 0.009 | 0.009 | 0.009 | 0.007 | 0.008 | 0.007 | 0.007 | 0.008 | 0.008 | 0.008 | 0.008 | 0.010 |
| Loss Dev. | 0.012 | 0.013 | 0.012 | 0.010 | 0.020 | 0.007 | 0.010 | 0.011 | 0.010 | 0.011 | 0.009 | 0.010 | 0.009 | 0.009 | 0.010 | 0.010 | 0.010 | 0.010 | 0.013 |
| Downside | 0.011 | 0.013 | 0.011 | 0.010 | 0.020 | 0.006 | 0.010 | 0.010 | 0.010 | 0.010 | 0.008 | 0.009 | 0.008 | 0.008 | 0.010 | 0.010 | 0.009 | 0.010 | 0.012 |
| HVaR | -0.024 | -0.031 | -0.025 | -0.020 | -0.042 | -0.014 | -0.022 | -0.022 | -0.022 | -0.022 | -0.018 | -0.022 | -0.017 | -0.018 | -0.021 | -0.022 | -0.020 | -0.021 | -0.026 |
| HES | -0.036 | -0.042 | -0.036 | -0.032 | -0.065 | -0.021 | -0.031 | -0.034 | -0.033 | -0.034 | -0.028 | -0.031 | -0.029 | -0.027 | -0.032 | -0.031 | -0.031 | -0.031 | -0.040 |
| GVaR | -0.025 | -0.029 | -0.025 | -0.022 | -0.048 | -0.014 | -0.022 | -0.022 | -0.022 | -0.023 | -0.017 | -0.021 | -0.019 | -0.017 | -0.022 | -0.021 | -0.020 | -0.021 | -0.027 |
| GES | -0.031 | -0.037 | -0.032 | -0.028 | -0.060 | -0.018 | -0.028 | -0.028 | -0.028 | -0.029 | -0.022 | -0.026 | -0.023 | -0.021 | -0.027 | -0.026 | -0.025 | -0.026 | -0.033 |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MVaR | -0.025 | -0.030 | -0.026 | -0.015 | -0.041 | -0.015 | -0.022 | -0.023 | -0.023 | -0.023 | -0.018 | -0.022 | -0.019 | -0.018 | -0.022 | -0.022 | -0.021 | -0.022 | -0.028 |
| MES | -0.057 | -0.045 | -0.046 | -0.015 | -0.048 | -0.027 | -0.036 | -0.047 | -0.042 | -0.041 | -0.034 | -0.036 | -0.042 | -0.034 | -0.051 | -0.035 | -0.037 | -0.037 | -0.076 |
| *Panel C. COVID-19 Sample Results* | | | | | | | | | | | | | | | | | | | |
| Semi Dev. | 0.022 | 0.024 | 0.016 | 0.019 | 0.033 | 0.012 | 0.015 | 0.013 | 0.014 | 0.014 | 0.013 | 0.016 | 0.015 | 0.013 | 0.019 | 0.013 | 0.012 | 0.014 | 0.022 |
| Gain Dev. | 0.018 | 0.020 | 0.014 | 0.020 | 0.035 | 0.011 | 0.013 | 0.014 | 0.014 | 0.013 | 0.011 | 0.014 | 0.015 | 0.010 | 0.020 | 0.011 | 0.011 | 0.014 | 0.020 |
| Loss Dev. | 0.024 | 0.025 | 0.016 | 0.019 | 0.030 | 0.014 | 0.015 | 0.015 | 0.016 | 0.015 | 0.016 | 0.017 | 0.017 | 0.015 | 0.020 | 0.013 | 0.014 | 0.016 | 0.021 |
| Downside | 0.022 | 0.023 | 0.015 | 0.019 | 0.032 | 0.012 | 0.015 | 0.013 | 0.014 | 0.014 | 0.013 | 0.015 | 0.015 | 0.012 | 0.019 | 0.013 | 0.012 | 0.014 | 0.021 |
| HVaR | -0.037 | -0.050 | -0.032 | -0.044 | -0.071 | -0.020 | -0.030 | -0.022 | -0.023 | -0.026 | -0.025 | -0.034 | -0.026 | -0.025 | -0.043 | -0.026 | -0.023 | -0.024 | -0.044 |
| HES | -0.071 | -0.075 | -0.049 | -0.061 | -0.101 | -0.038 | -0.049 | -0.045 | -0.047 | -0.045 | -0.043 | -0.052 | -0.049 | -0.042 | -0.064 | -0.039 | -0.040 | -0.046 | -0.067 |
| GVaR | -0.047 | -0.050 | -0.034 | -0.045 | -0.078 | -0.026 | -0.033 | -0.030 | -0.031 | -0.030 | -0.027 | -0.033 | -0.033 | -0.026 | -0.044 | -0.028 | -0.026 | -0.031 | -0.048 |
| GES | -0.059 | -0.064 | -0.043 | -0.057 | -0.098 | -0.033 | -0.042 | -0.037 | -0.039 | -0.038 | -0.035 | -0.042 | -0.041 | -0.033 | -0.056 | -0.035 | -0.033 | -0.039 | -0.061 |
| MVaR | -0.051 | -0.054 | -0.036 | -0.041 | -0.072 | -0.025 | -0.034 | -0.026 | -0.028 | -0.032 | -0.028 | -0.033 | -0.032 | -0.028 | -0.042 | -0.029 | -0.025 | -0.029 | -0.048 |
| MES | -0.115 | -0.102 | -0.064 | -0.057 | -0.095 | -0.069 | -0.053 | -0.033 | -0.044 | -0.070 | -0.072 | -0.073 | -0.074 | -0.067 | -0.063 | -0.059 | -0.054 | -0.053 | -0.074 |

**Notes**: This table shows downside risk measures. The full sample spans from 13 October 2010 to 31 December 2021. Pre-COVID-19 and COVID-19 periods are from 13 October 2010 to 10 March 2020 and from 11 March 2020 to 31 December 2021, respectively.

**Table 6. CAPM-Based Metrics**

| | BCL | SLR | WND | GEO | FLC | DEV | STR | GIT | EMN | AMT | TECH | FIN | IND | BANK | HLT | TEL | TSP | OLG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A. Full Sample Results* | | | | | | | | | | | | | | | | | | |
| Alpha | -0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.001 |
| Beta | 0.815 | 1.188 | 0.516 | 0.617 | 1.200 | 0.452 | 0.758 | 0.960 | 0.885 | 0.819 | 1.119 | 0.874 | 0.934 | 0.864 | 0.944 | 0.885 | 0.874 | 0.966 |
| Beta+ | 0.747 | 1.082 | 0.476 | 0.686 | 0.930 | 0.468 | 0.686 | 1.045 | 0.920 | 0.791 | 1.127 | 0.911 | 0.912 | 0.887 | 0.898 | 0.930 | 0.844 | 0.980 |
| Beta⁻ | 1.009 | 1.254 | 0.568 | 0.667 | 1.308 | 0.562 | 0.774 | 0.932 | 0.882 | 0.861 | 1.091 | 0.949 | 0.949 | 0.960 | 0.917 | 0.881 | 0.928 | 1.095 |
| R-squared | 0.301 | 0.487 | 0.145 | 0.206 | 0.194 | 0.290 | 0.394 | 0.643 | 0.530 | 0.452 | 0.897 | 0.642 | 0.932 | 0.415 | 0.695 | 0.695 | 0.576 | 0.381 |
| A. Alpha | -0.108 | -0.062 | 0.015 | -0.068 | -0.062 | 0.021 | -0.095 | -0.058 | -0.050 | -0.070 | -0.001 | -0.040 | 0.000 | -0.051 | -0.022 | -0.076 | -0.056 | -0.145 |
| Correlation | 0.549 | 0.698 | 0.381 | 0.454 | 0.441 | 0.538 | 0.628 | 0.802 | 0.728 | 0.672 | 0.947 | 0.802 | 0.966 | 0.645 | 0.834 | 0.834 | 0.759 | 0.617 |
| Information | -0.723 | -0.328 | -0.327 | -0.637 | -0.342 | -0.388 | -0.829 | -0.591 | -0.532 | -0.673 | 0.152 | -0.559 | -0.205 | -0.484 | -0.333 | -0.939 | -0.623 | -0.833 |
| Treynor | -0.034 | 0.059 | 0.123 | -0.014 | -0.012 | 0.180 | -0.010 | 0.069 | 0.070 | 0.035 | 0.143 | 0.088 | 0.148 | 0.060 | 0.115 | 0.045 | 0.065 | -0.052 |
| *Panel B. Pre-COVID-19 Sample Results* | | | | | | | | | | | | | | | | | | |
| Alpha | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.001 |
| Beta | 0.677 | 1.121 | 0.534 | 0.536 | 1.074 | 0.365 | 0.806 | 1.002 | 0.946 | 0.859 | 1.105 | 0.872 | 0.938 | 0.890 | 0.991 | 0.945 | 0.911 | 1.010 |
| Beta+ | 0.564 | 0.972 | 0.436 | 0.550 | 0.790 | 0.340 | 0.758 | 1.047 | 0.976 | 0.838 | 1.094 | 0.891 | 0.928 | 0.885 | 0.952 | 0.992 | 0.851 | 1.017 |
| Beta⁻ | 0.799 | 1.146 | 0.634 | 0.615 | 1.192 | 0.447 | 0.835 | 1.012 | 0.957 | 0.898 | 1.081 | 0.938 | 0.955 | 0.990 | 0.970 | 0.952 | 0.966 | 1.138 |
| R-squared | 0.238 | 0.470 | 0.141 | 0.189 | 0.160 | 0.210 | 0.438 | 0.633 | 0.565 | 0.452 | 0.884 | 0.688 | 0.928 | 0.542 | 0.689 | 0.710 | 0.600 | 0.472 |
| A. Alpha | -0.093 | -0.094 | 0.020 | -0.056 | -0.102 | 0.037 | -0.115 | -0.058 | -0.081 | -0.089 | 0.005 | -0.033 | 0.001 | -0.064 | 0.001 | -0.076 | -0.058 | -0.183 |
| Correlation | 0.488 | 0.686 | 0.376 | 0.435 | 0.399 | 0.458 | 0.662 | 0.796 | 0.752 | 0.672 | 0.940 | 0.829 | 0.963 | 0.736 | 0.830 | 0.843 | 0.774 | 0.687 |
| Information | -0.715 | -0.554 | -0.233 | -0.611 | -0.455 | -0.231 | -0.973 | -0.561 | -0.731 | -0.761 | 0.180 | -0.524 | -0.141 | -0.646 | -0.062 | -0.912 | -0.631 | -1.180 |
| Treynor | -0.064 | -0.003 | 0.104 | -0.029 | -0.077 | 0.202 | -0.057 | 0.038 | 0.007 | -0.017 | 0.113 | 0.066 | 0.112 | 0.022 | 0.105 | 0.017 | 0.033 | -0.105 |

*Panel C. COVID-19 Sample Results*

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Alpha | -0.001 | 0.000 | 0.000 | -0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.001 | 0.000 | 0.000 | 0.000 |
| Beta | 1.091 | 1.320 | 0.479 | 0.780 | 1.451 | 0.626 | 0.661 | 0.876 | 0.761 | 0.738 | 1.148 | 0.880 | 0.927 | 0.810 | 0.849 | 0.764 | 0.800 | 0.874 |
| Beta+ | 1.022 | 1.225 | 0.568 | 0.883 | 0.992 | 0.673 | 0.564 | 1.092 | 0.863 | 0.734 | 1.177 | 0.978 | 0.878 | 0.936 | 0.845 | 0.881 | 0.882 | 0.956 |
| Beta$^{-}$ | 1.353 | 1.444 | 0.468 | 0.713 | 1.425 | 0.745 | 0.692 | 0.820 | 0.805 | 0.836 | 1.095 | 0.993 | 0.935 | 0.963 | 0.837 | 0.798 | 0.907 | 1.096 |
| R-squared | 0.432 | 0.521 | 0.156 | 0.242 | 0.270 | 0.465 | 0.310 | 0.680 | 0.458 | 0.458 | 0.923 | 0.569 | 0.942 | 0.266 | 0.730 | 0.676 | 0.527 | 0.253 |
| A. Alpha | -0.190 | 0.114 | -0.007 | -0.135 | 0.168 | -0.067 | 0.021 | -0.052 | 0.130 | 0.040 | -0.031 | -0.080 | -0.003 | 0.025 | -0.128 | -0.070 | -0.041 | 0.080 |
| Correlation | 0.657 | 0.722 | 0.394 | 0.492 | 0.520 | 0.682 | 0.557 | 0.825 | 0.677 | 0.677 | 0.961 | 0.754 | 0.971 | 0.515 | 0.854 | 0.822 | 0.726 | 0.503 |
| Information | -0.858 | 0.507 | -0.740 | -0.851 | 0.106 | -1.119 | -0.498 | -0.768 | 0.168 | -0.334 | 0.043 | -0.818 | -0.503 | -0.333 | -1.559 | -1.169 | -0.700 | -0.142 |
| Treynor | 0.055 | 0.411 | 0.222 | 0.037 | 0.297 | 0.193 | 0.326 | 0.261 | 0.525 | 0.381 | 0.317 | 0.208 | 0.351 | 0.289 | 0.149 | 0.224 | 0.259 | 0.343 |

**Notes**: This table reports CAPM-based metrics. The full sample spans from 13 October 2010 to 31 December 2021. Pre-COVID-19 and COVID-19 periods are from 13 October 2010 to 10 March 2020 and from 11 March 2020 to 31 December 2021, respectively.

**Figure 1. Total Installed Power Capacity**

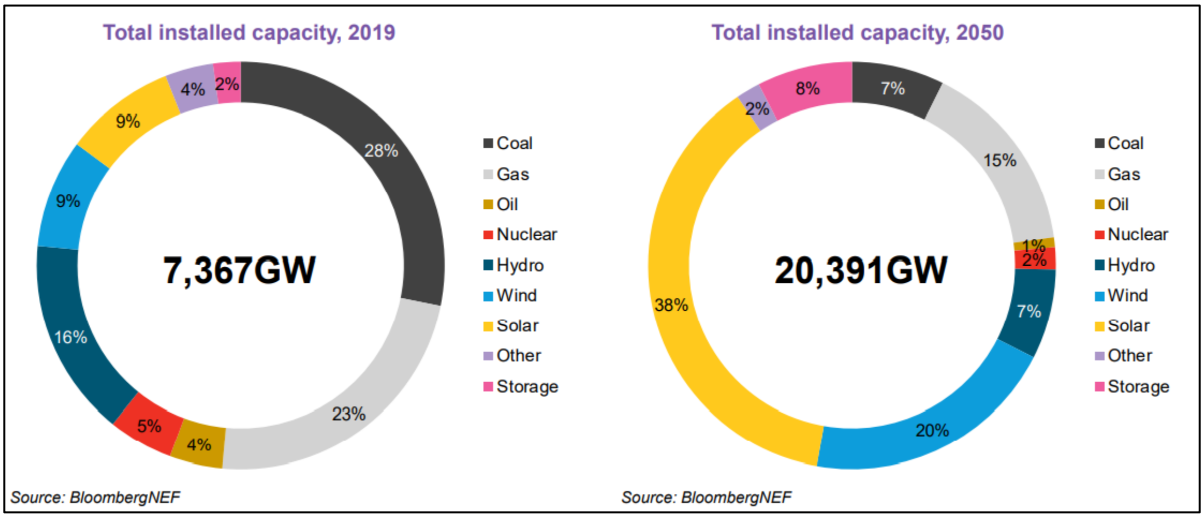


**Figure 2. Closing Prices of the Clean Energy Indexes**

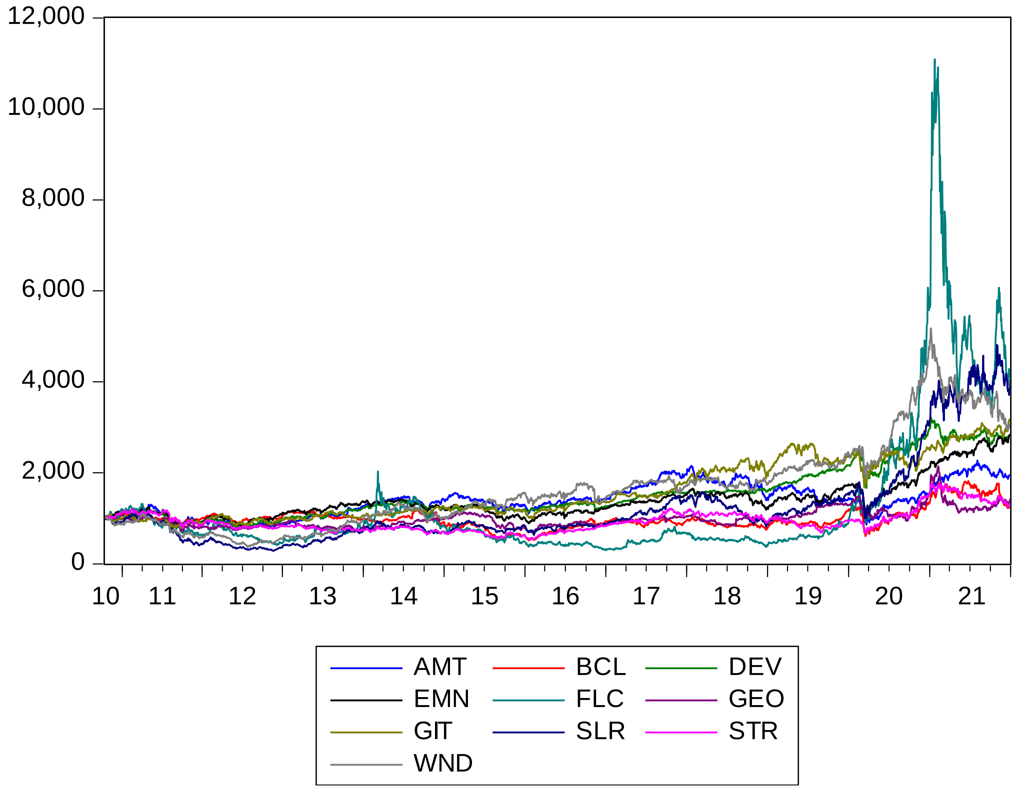
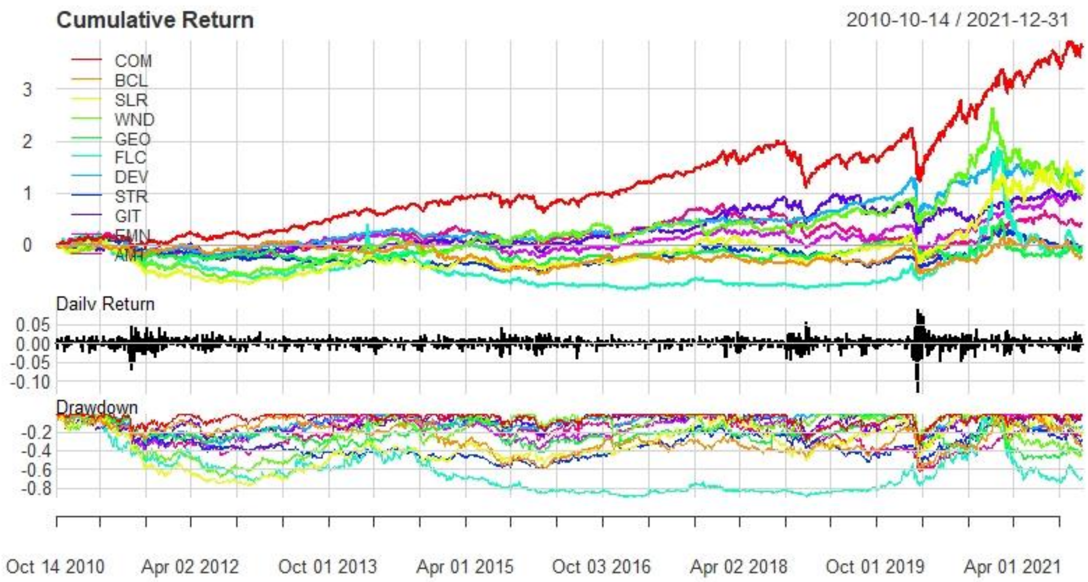


**Figure 3. Index Performance**

Panel a. Performance summary of clean energy indexes




Panel b. Performance summary of other indexes