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Environmentally clean and dirty energy equities during extraordinary global conditions

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ABSTRACT

I examine which extraordinary international events coincide with pronounced changes in the equity markets for some of the world's largest publicly traded suppliers on opposite sides of the global energy mix — oil and environmentally clean energy companies. First, I adapt an intuitively appealing non-parametric filter to empirically timestamp unexpected and prominent increases and decreases in a wide range of global indicators relevant to the international energy market. Then, I use such extraordinary conditions to characterise the performance of oil and environmentally clean energy equities, and their relationships. My findings suggest that jumps in the global stock market, international crude oil market shocks, and the US dollar real effective exchange rate, are the indicators that define the financial landscape during which considerable gains, losses, and instability across both types of energy markets materialise. In contrast, major elevated uncertainties related to geo-political risk and climate policy reflect relative stability in the equities of both oil and environmentally clean energy companies. Although these results imply that both energy assets are potentially lucrative hedging strategies for investors to exploit during heightened geo-political and climate policy uncertainties, clean energy equities offer market participants the option to combine profit maximising and sustainability objectives while minimising global energy security risks.

1. Introduction

Energy plays a vital role in powering the global economy. As such, energy market developments remain at the centre of attention for economists, households, investors, and policymakers alike. In fact the performance of the energy market, including renewable or green energy, serve as a leading predictor of macroeconomic performance (Ha, 2023) and has far reaching implications for politics, society, and culture (see Le et al., 2021, and references within). At the same time, there is monumental growth in environmentally clean energy[1] investment opportunities and sustainable stock indices in response to the contemporary climate change debate (Sadorsky, 2012; Demiralay et al., 2024). Within this discourse the pressures to rebalance the global energy mix by reducing the dependence of the world economy on energy sources derived from fossil fuels, in favour of environmentally cleaner alternatives, is ever-increasing (Song et al., 2019). Indeed, stable energy and climate policies are vital for achieving sustainability (Shahbaz et al., 2024). In particular, the Sustainable Development Goal (SDG) target 7.2 specifically underscores the aim to substantially increase the share of renewable energy in the global energy mix by the year 2030.[2]

Environmentally clean energy investments provide opportunities for market participants to combine their profit maximising incentives with climate related objectives (Farid et al., 2023). Interestingly, Henriques and Sadorsky (2018) show that portfolios divesting from dirty energy and into environmentally clean energy perform better than those with just dirty assets, and risk-averse investors would be willing to pay for this switch, even when accounting for trading costs. In financial markets, these two sources of energy are viewed as competing assets (Wen et al., 2014), where rising oil prices are beneficial to clean energy firms (Henriques and Sadorsky, 2008). This gain occurs through a substitution effect in portfolio holdings, which favours environmentally cleaner energy sources, as investors perceive that the demand for alternatives will increase relative to dirty energy (Kassouri and Altıntaş, 2021).

Although clean energy stocks and green bonds are attractive investment alternatives to the environmentally conscious investor (Saeed et al., 2021), there are still many hurdles that the clean energy market has yet to overcome. For instance, investing in clean energy tends to be more speculative and riskier than investing in traditional dirty

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[1] In this paper, *clean energy* is an umbrella term that incorporates green and renewable energy, while *dirty energy* primarily refers to oil and gas.

[2] See https://sdgs.un.org/goals/goal7.

[3] This annual flagship report of the International Energy Agency is available at https://www.iea.org/reports/world-energy-outlook-2021.

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energy (Wen et al., 2014). Another issue is that companies reporting environmental information obtain negative investor responses compared to those containing traditional annual financial reports (Meng and Zhang, 2022). What is more, the World Energy Outlook 2021 report suggests that the realities of an energy transition scenario to net zero emissions by 2050, after several decades of a reliance on fossil fuels for over 80% of the energy supply, has the potential to create energy security risks alongside the rise of clean energy that result from energy demand and investment mismatches.[3] To scrutinise the risks associated with the energy transition, a financial market lens can be useful to evaluate developments in the global energy mix. Just as stock market activity is an important leading indicator for the state of the economy, as markets react in real-time to news and shocks, the performance of stock indices for specific types of companies can provide key insights into the conditions unfolding within those sectors and their ability to raise equity finance for their operations.

Against this background, Saeed et al. (2021) points to a gap in the environmentally clean and dirty energy finance literature concerning the potential drivers of extreme behaviours in these assets. Their study addresses that deficit by using quantile-based estimators to investigate the connectedness at tails of the conditional distribution of return shocks. They find that macroeconomic conditions and crude oil market uncertainty explain connectedness at lower quantiles, while the US dollar affects all quantiles. My work complements theirs. In particular, my study is the first to identify extreme conditions in a wide range of drivers that the literature suggests influence energy markets and, using these episodes, I characterise and compare the performance and relationship between clean and dirty energy equities. My testable research question is: what extraordinary global events coincide with remarkable changes in the standardised asset return moments and relationships of environmentally clean and dirty energy equities? Indeed, answering this question informs our understanding of the pertinent sources of energy market risks in the 21st century.

To answer the above-mentioned research question, two related issues need to be addressed: (i) which international indicators are most relevant to the equities of multinational energy companies? and (ii) how to systematically locate extraordinary events in these indicators? To address the first issue, I consolidate a set of theoretically and empirically important factors documented in the literature. Beyond demand and supply market dynamics, other factors affect energy stock prices and agitate their volatilities, such as exogenous shocks related to geo-political risk in oil producing and exporting countries, financial recessions like the sub-prime mortgage crisis of the late 2000s, uncertainties, and other extreme events like the coronavirus pandemic in 2020 (Alshater et al., 2022; Ftiti et al., 2022). I include ten indicators drawn from the spheres of the international crude oil market; global uncertainties; and the international economics and finance environment. In the subsequent section of the paper (literature review), I provide extensive justifications for the determinants included in my analysis.

To address the second issue, on an appropriate empirical strategy to identify extraordinary events in global indicators, I again turn to the literature for an appropriate solution. A distinct line of research focuses on models that include censored regressors to assess whether the economy or financial markets have exaggerated responses to specific oil price movements such as increases (Mork, 1989; Lee et al., 1995), large surprise increases (Hamilton, 1996), and very large surprise increases (Hamilton, 2003). In this paper, to date extraordinary changes in global factors affecting energy markets, I adapt the censoring measure introduced in Hamilton (2003) to identify very large surprise increases in a time series. There are three important reasons for my approach. First, the censoring filter in Hamilton (2003) is an already established off-the-shelf technique to detect abrupt and substantial price changes in the empirical oil economics literature. Recent studies continue to use this non-linear price transformation in their empirical work on oil and the macroeconomy (see, e.g., Karaki, 2017 and Charfeddine et al., 2020).

Secondly, this time series censor resonates with studies on the identification of jumps and black swan events in financial markets. *Jumps* refer to sudden and very large changes when compared to the current market state (Hanousek et al., 2014), whereas *black swans* refer to rare outlier events that have extreme adverse impacts and are predictable only retrospectively (Bogle, 2008). Hanousek et al. (2014) explain that an advantage of this operational definition of jumps is model-independent, without the need to model the underlying data generating process of a time series, while a disadvantage is that this view of jumps is broad and ambiguous. The non-linear oil price measure introduced in Hamilton (2003) can be viewed as a non-parametric approach to jump detection in monthly data — which is the highest frequency available for many of the leading indicators of energy market performance considered in this paper.

The third reason I adopt the non-linear filter in Hamilton (2003) relates to the attributes of the measure — it is simple to compute, model-free, and flexible. Many other strategies, borrowed from finance research, have been successfully introduced into the energy economics literature for dating different price conditions in energy assets. For example, Ntantamis and Zhou (2015) and Mahadeo et al. (2019) employ non-parametric rule-based algorithms used to detect bull and bear market phases in stock prices that follow the approaches of Pagan and Sossounov (2003) and Lunde and Timmermann (2004), to date increasing and decreasing states in benchmark oil prices. Others like Caspi et al. (2018) and Figuerola-Ferretti et al. (2020) have considered timestamping explosions in oil prices that relate to the rapid growth and bursts associated with asset bubbles, with the application of the *psymonitor* approach put forward in Phillips et al. (2015). However, when compared to the data filtering strategy proposed in Hamilton (2003), it is far less straightforward to apply bull/bear rule-based algorithms and the bubble formation/flash crash detectors to time series data outside the remit of asset prices. In fact, the time series filter used in Hamilton (2003) can be easily adopted by portfolio managers, with only a rudimentary knowledge of quantitative finance, to identify extreme conditions in various leading global indicators of international energy markets.

Once the extraordinary events are dated, I characterise the standardised returns behaviour, volatilities, and relationships between the equity indices of companies involved in environmentally clean and dirty energy in times of sudden and abrupt changes in global conditions. These are compared to a universal state of stability, where no jumps in any of the global indicators are observed. A reasonable assumption about the equity markets of the world's largest multinational energy companies are that they are liquid and efficient. Such markets are expected to absorb information about global events instantaneously. Hence, I focus on a contemporaneous perspective in this paper. This view fits with the literature on contagion analysis, which describes an increase in market linkages in the wake of a shock to one market (Forbes and Rigobon, 2002). Contagion effects tend to appear and vanish rather abruptly, when compared to cointegrating relationships which are inclined to endure into the long run (see, *inter alia*, Reboredo et al., 2014; Mahadeo et al., 2019). These relatively sudden jumps have the potential to disrupt energy markets, providing investment opportunities and threats, which I aim to shed light on in this study. Such extraordinary conditions can create tangible repercussions for energy security and the real economy if they affect how multinational energy firms fund their operations via equity financing on the stock market.

My central findings indicate that both types of energy firms tend to perform similarly under extraordinary global conditions. I document that the largest gains and losses recorded in the standardised returns in clean and dirty energy markets relate to positive and negative jumps, respectively, in the global stock market. Furthermore, the most remarkable turbulent volatility in both energy markets occur when there are major downturns in global economic activity. In addition, the highest negative skewness, which are a feature of crises that indicate recurrent small gains and occasional large losses, happen when there are extraordinary drops in oil consumption demand. Leptokurtosis, which is another feature of financial market distress as it increases the likelihood that extreme values reside in the tails of an asset returns distribution, is highest for the clean energy equity market when there are depreciation jumps in the US dollar real effective exchange rate and appreciation jumps in the case of oil equities. Interestingly, I find comparatively less synchronous changes in the equities of clean energy and oil companies under states of major elevated uncertainties related to geo-political risk and climate policy. Instead, both types of energy firms exhibit positive returns accompanied by low volatility and kurtosis levels during such turmoil. These results imply that both energy assets are potentially lucrative hedging strategies for investors in times of extreme geo-political risk and climate uncertainty. Yet, clean energy equities provide traders with an option to combine profit maximising and sustainability objectives while minimising the risks to global energy security.

The rest of the paper is organised as follows. Section 2 provides a literature review under three subsections, which lay the foundation for my research. The first part briefly covers the origins of the energy equity finance literature. The second part synthesises related work on the impact that various global indicators have on energy markets, with an emphasis on the findings as they relate to environmentally clean and dirty energy equities. This is followed by a concise coverage of the various off-the-shelf non-linear oil price transformations and the econometric problems associated with their use in regression models. Section 3 continues with the approach that I adopt to date extraordinary conditions in global factors affecting energy markets and its fit-for-purpose characteristics in the context of my study. I then document the measures I use to consider the performance of (and relationship between) clean and dirty energy equities. Subsequently, I define the data and explain my sample coverage. In Section 4, I present my results and discussion related to the time series behaviour of energy equities, volatilities, and relationships. Thereafter, I proceed to describe the extraordinary conditions identified by my dating filter. I then bring it all together to understand how energy equities and their relationship measures perform under jumps in global indicators. Finally, Section 5 concludes with a summary and a feasible direction for future research.

2. Literature review

In this section, I concisely cover three strands of related literature from which my paper departs. The first is on the growth of the energy economics and finance literature that has led to focus on clean and dirty energy companies. The second strand of literature covers the leading global factors affecting international energy markets. The third strand is on non-linear oil price measures.

2.1. Genesis of the energy equity finance research genre

Since the seminal work of Hamilton (1983), research on the impact of oil price fluctuations on the macroeconomy continues to grow (see, *inter alia*, Burbidge and Harrison, 1984; Hooker, 1996; Barsky and Kilian, 2004; Narayan et al., 2014; Bjørnland et al., 2018; Herrera et al., 2019). A companion literature on the impact of oil price changes on the stock market has sprouted and expanded alongside it (see, *inter alia*, Huang et al., 1996; Jones and Kaul, 1996; Sadorsky, 1999; Basher and Sadorsky, 2006; Park and Ratti, 2008; Basher et al., 2018; Heinlein et al., 2021). A subset of the literature in the oil finance genre emphasises the stocks of either environmentally clean energy companies (see, *inter alia*, Henriques and Sadorsky, 2008; Sadorsky, 2012; Reboredo, 2015; Inchauspe et al., 2015; Reboredo et al., 2017; Ahmad et al., 2018; Uddin et al., 2019; Sadorsky, 2021; Kocaarslan and Soytas, 2021; Tian et al., 2022) or dirty energy companies (see, *inter alia*, Sadorsky, 2001; Boyer and Filion, 2007; Sadorsky, 2008; Kang et al., 2017). More recently, there is also an increasingly relevant hybrid line of work that explicitly covers both environmentally clean and dirty energy firms in their investigations (see, *inter alia*, Wen et al., 2014; Henriques and Sadorsky, 2018; Song et al., 2019; Naeem et al., 2020; Kassouri and Altıntaş, 2021; Saeed et al., 2021; Bouri et al., 2022; Naeem et al., 2022; Ren and Lucey, 2022; Farid et al., 2023). It is within that last group, which offers a comparative perspective, where my paper aims to contribute.

2.2. Global factors affecting energy markets

Here, I succinctly synthesise the related literature on the main factors affecting the world's largest publicly traded clean and dirty energy firms. These factors can be sorted into three categories: international crude oil market shocks, global uncertainties, and international economic and financial variables.

2.2.1. International crude oil market shocks

Accounting for the effects of supply and demand side shocks in the crude oil market has been popularised by the work of Kilian (2009). That seminal study uses a structural vector autoregressive (SVAR) framework with three variables: world crude oil supply, a novel measure of global real economic activity based on dry cargo bulk freight rates, and real oil prices. The SVAR has a simple recursively identified contemporaneous matrix, motivated by delay restrictions based on economic theory to disentangle three structural shocks: oil supply, global aggregate demand, and oil-specific demand. Importantly, Kilian (2009) demonstrates that the economy responds differently, depending on whether the innovation is derived from the supply or demand side forces of the crude oil market.

Over time, the literature has matured with many oil market SVAR model extensions. These include, but are not limited to, the impact of oil price shocks on the US stock market (Kilian and Park, 2009); the identification of oil price shocks in SVARs by embedding prior distributions for the demand and supply elasticities (Kilian and Murphy, 2012; Baumeister and Hamilton, 2019); the inclusion of policy uncertainty (Kang and Ratti, 2013); the explicit identification of speculative demand shocks (Kilian and Murphy, 2014); a statistical identification approach to decompose crude oil demand and supply shocks in VARs (Herwartz and Plödt, 2016); an alternative SVAR identification of crude oil demand and supply shocks with asset price information (Ready, 2018); the detection by Hamilton (2021) of an accidental double log transformation coding error in the Kilian (2009) measure of global real economic activity and the subsequent correction of this mistake in Kilian (2019); and the development of alternative measures of global economic activity (Baumeister and Hamilton, 2019; Baumeister et al., 2022).

Overall, empirical studies suggests that demand forces play a principal role in the stock market performance of energy companies. Broadly speaking, energy sector equity returns have a heightened vulnerability to spillover effects from falling oil-specific demand, when compared to other shocks from the oil and stock market (Heinlein and Mahadeo, 2023). In the context of oil and gas companies, an increase in an oil demand side shock positively affects returns (Kang et al., 2017). For environmentally clean energy companies, there is robust information transmission among clean energy stocks and oil demand shocks (Naeem et al., 2020).

2.2.2. Global uncertainties

Beyond oil market shocks, research on the impact of various types of uncertainties on energy markets is another common theme in the empirical literature. Many of these studies employ novel indices that follow the work of Baker et al. (2016), which measures policy uncertainty based on the frequency that keywords and phrases on a specific topic appear in major newspaper outlets. Three flavours of uncertainties are particularly relevant for international energy markets: global economic policy, geo-political, and climate risks. Research finds that the effects of economic policy uncertainty (EPU) on dirty energy returns is negative (Kang et al., 2017), while EPU mediates the link between reserve currency and the volatility of clean energy stocks (Kocaarslan and Soytas, 2021).

Additionally, major geo-political events can induce emotional responses in energy markets, causing considerable fluctuations in energy prices and affect the valuations of energy stocks (see Yang et al., 2024, and references therein), and repeat events can particularly jeopardise renewable energy investment (see Husain et al., 2024, and references therein). This is because a heightened geo-politically risky environment can influence the expectations of investors about future circumstances related to crude oil supply and demand, consequentially shaping their views on the alternative energy investments (Demiralay et al., 2024). Caldara and Iacoviello (2022) builds on the methodology of Baker et al. (2016) to produce a news-based measure of geo-political events and risks, using international newspapers coverage of such material. Recent applications involving this index in energy markets convey that: (i) geo-political risks (GPR) transmit a positive spillover to the clean equity and bond markets through the substitution channel, as investors may have a preference for clean over dirty investments or other geo-politically exposed assets (Sohag et al., 2022); and (ii) GPR triggers a negative effect on oil returns and volatility (Antonakakis et al., 2017).

Furthermore, Gavriilidis (2021) introduces a climate policy uncertainty (CPU) index, which once again builds on the work of Baker et al. (2016), based on news from major US newspapers. The CPU captures landmark legislations, political announcements, and protests related to the topic of climate change, and the index has a strong negative effect on CO_2 emissions. In empirical work, the CPU index is found to be an important factor affecting the performance of clean energy stocks compared to their dirty counterparts (Bouri et al., 2022).

2.2.3. International economic and financial variables

Financial market indices and economic conditions are also typical determinants of energy market performance. Chief among such factors are fluctuations in the US dollar exchange rate, given that oil contracts are globally traded in this currency. Oil price increases depreciate the US dollar against oil exporter currencies, whereas the exchange rate of oil importers depreciate relative to the US dollar (Lizardo and Mollick, 2010). Recent evidence suggests that oil prices Granger-cause the US exchange rate in the booming periods of the 2000s and, yet, the converse is true in the 2008 Global Financial Crisis (GFC) (Albulescu and Ajmi, 2021). With specific reference to dirty firms, rather than benchmark oil prices, depreciations of an oil-exporting country's currency against the US dollar has been found to reduce oil and gas stock returns (see, e.g., the results of Sadorsky, 2001, for Canadian oil and gas companies). In terms of clean energy firms, the volatility of clean energy stocks is only influenced by US dollar fluctuations when uncertainties are appropriately accounted for (Kocaarslan and Soytas, 2021).

On the coverage of the connection between energy and stock markets, the literature on headline stock indices and benchmark oil prices is well-developed. A comprehensive review of theoretical and empirical research on oil prices and stock markets is covered in Degiannakis et al. (2018). This relationship has been unstable over time but, more recently, it has been positive in the post-GFC era (Mohaddes and Pesaran, 2017) — an attribute that is commonly linked to the increasing financialisation of oil and other commodities (Creti et al., 2013). However, research on overall stock market indices and energy companies is comparatively sparse. In the case of dirty equities and the aggregate stock market, Boyer and Filion (2007) show a positive association between the Canadian equity market returns and Canadian oil and gas company stock returns. For clean equities, Uddin et al. (2019) find that S&P 500 returns have a strong positive influence on global renewable energy stock returns.

In addition to the aforementioned conditions that affect energy markets, new research by Baumeister et al. (2022) produces a catch-all index of global economic conditions which are useful to assess energy market prospects. Their index is based on 16 indicators from eight categories — real economic activity, commodity prices, financial indicators, transportation, uncertainty, expectations, weather, and energy-related measures. They find that their novel index help to provide the most accurate model for forecasting the real Brent oil price and fuel consumption jointly. As the use of their global economic conditions index remain unexplored in analyses involving clean and dirty energy stocks, my paper aims to contribute in this direction.

2.3. Non-linear oil price measures

Non-linear oil price measures have arisen in the empirical oil economics literature, not only due to economists fascination with testing for asymmetric responses of one variable to increases and decreases in another variable, but also in an effort to maintain the statistical significance of the oil price/macroeconomy relationship in US data. The most prominent of these measures in the literature are Mork (1989), who separates oil prices into increases and decreases; Lee et al. (1995), who scale oil price changes using its conditional volatility to obtain unexpected increases and decreases that arise from a stable environment; Hamilton (1996), who censors all oil price changes other than the largest increase over the preceding year; Hamilton (2003), who extends the previous filter to identify the largest oil price increase over the preceding three years; and Akram (2004), who censors oil prices that fluctuate within a typical band and retains the outliers outside this range. Examples of studies that adopt some of these non-linear oil price measures in their analyses include Hooker (2002), Jiménez-Rodríguez and Sánchez (2005), Bjørnland (2009), and Jimenez-Rodriguez (2009).

However, despite their widespread adoption in the empirical literature, Kilian and Vigfusson (2011) show that censored regressor models, involving non-linear measures that force observations to zero, lead to invalid estimates of the intercept and slope (the regressor coefficient), even in the simplest possible (bivariate) case. They propose a structural model, which encompasses both symmetric and asymmetric models as special cases, to correctly compute impulse responses functions. Taking into account such developments, there has since been a recurrent interest in modelling the impact of oil prices on the economy using the non-linear measures with more recent data, such as Karaki (2017) and Charfeddine et al. (2020). Yet, a lack of convergence in the results of these two studies remain — the former study finds no evidence against the null of a symmetric impact of oil price changes on economic growth, while the latter study finds contrasting results that oil price increases matter more than decreases.

My study builds on an emerging line of work that combines the literatures on demand and supply shocks in the crude oil market with non-linear oil price measures. These include Mahadeo et al. (2022b) and Heinlein and Mahadeo (2023) who analyse the contemporaneous effects of extreme positive and negative oil market shocks on financial asset market relationships in oil exporting countries, using the earlier mentioned measures introduced in Hamilton (1996) and Akram (2004). In particular, such studies use these non-linear measures to sort the time series of a source market into subsamples of stable and extreme states, and evaluate how the relationship between a source and recipient market changes in these different states. As the non-linear measures are used for dating and subsampling of various market states, and not as censored regressors in regression models, the previously mentioned estimation pitfalls identified in Kilian and Vigfusson (2011) are avoided.

3. Methods and data

This section is dedicated to how I determine which extraordinary international conditions coincide with pronounced changes in the equity markets, for some of the world's largest publicly traded suppliers on the opposite sides of the global energy mix, and the data I use for this purpose. It consists of four parts. In the first part, I explain my procedure to date extraordinary global conditions and highlight its appealing advantages in the context of my study. Next, in the second part, I describe the various measures used to gauge the performance of, and relationship between, clean and dirty energy equities. Subsequently, the third part covers data definitions and the fourth part describes the sample period of the study.

3.1. Global indicators: a simple approach to date extraordinary conditions

My paper uses the non-linear measure introduced in Hamilton (2003), which captures the largest increase in oil prices over the preceding three years, as a technique to date extraordinary conditions in global indicators. A reasonable assumption is that movements in key indicators of such a magnitude should "surprise" the energy market. This data filter is particularly useful in the context of my study, for the following reasons. First, it is straightforward to extend the specification to other major global factors affecting energy markets beyond oil prices, as Eq. (1) shows:

$$I^{net+}_{i,t} = \begin{cases} 1, & \text{if } I_{i,t} > \max(0, I_{i,t-1}, I_{i,t-2}, \ldots, I_{i,t-36}) \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where I^{net+} is an indicator variable, which takes the value of 1 if the current value at time t is greater than the values observed over the preceding three years[4] and 0 elsewhere. i denotes the various factors affecting energy markets that are outlined in the next section — the demand and supply side shocks in the crude oil market; global uncertainties related to economic policy, geo-political risk, and climate policy; and international economic and financial variables such as the real effective exchange rate of the US dollar, global stock market behaviour, and global economic conditions.

Second, where relevant, I am also able to easily consider a companion indicator variable to Eq. (1), which captures extraordinary decreases ($I^{net-}_{i,t}$) as Eq. (2) conveys:

$$I^{net-}_{i,t} = \begin{cases} 1, & \text{if } I_{i,t} < \min(0, I_{i,t-1}, I_{i,t-2}, \ldots, I_{i,t-36}) \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

In the mainstream literature, it is oil price increases which tends to be the focus. This is related to the stylised fact illustrated in Hamilton (1983, 1985) that many US recessions in the post-WWII period were preceded by oil price increases. However, as the focus of my paper is on clean and dirty energy companies, extraordinary decreases are equally important to assess. These include: remarkable reductions in oil demand and supply; momentous depreciations in the US real effective exchange rate; and black swan events such as unexpected and notable negative global stock returns and drastic declines in global economic conditions.

Third, I avoid the estimation pitfalls described in Kilian and Vigfusson (2011) that are mentioned in the previous section. This is because I do not use the resulting censored series on extraordinary increases and decreases in conditions affecting clean and dirty equities in a regression model. Instead, I use these censored variables as a data driven approach to date extraordinary periods (months) in the global indicators. As dating crises and remarkable events is an empirical problem in the literature (see Fry-McKibbin et al., 2014, and references therein), my adoption of the filter suggested in Hamilton (2003) offers an appealing measure to detect extraordinary events that arise from a stable environment that can be consistently applied across global indicators relevant to the clean and dirty energy equities.

Fourth, the well-established non-linear price measure of Hamilton (2003) from the empirical oil economics literature integrates well with the concept of jump detection from the finance literature. Indeed, the premises from both strands of research are identical: the former literature suggests that net price increases (i.e., the largest price increase over the preceding three years) from a stable environment are those which are consequential to the economy; while, in the latter literature, a jump is defined as sudden and sharp price movement compared to the current market situation (see, e.g., Hanousek et al., 2014). Eqs. (1) and (2) describe a model-independent measure to locate *extraordinary events* or *jumps* in monthly data for global factors affecting energy markets.

Fifth, related to the previous point, this model-free feature implies that the net increase and decrease filters are suitable for consistent application across the various categories of leading global indicators of energy markets when compared to alternative algorithms to date bull and bear market phases (see, e.g., Pagan and Sossounov, 2003; Lunde and Timmermann, 2004) or bubbles and flash crashes (see, e.g., Phillips et al., 2015) that are designed for stock price data. Indeed, it is more complicated and computationally expensive to apply such algorithms to a wide range of time series data with very different data generating processes.

Finally, it is simple to derive a series to reflect periods of global stability defined as time periods that are mutually classified as zero in Eqs. (1) and (2), across all global factors affecting energy markets. A consolidated global stability series can be a useful indicator variable for identifying a reference subsample, to evaluate how energy equities perform in stable conditions, compared to periods where extraordinary events occur.

3.2. Energy equities: performance and relationship measures

In this subsection, I describe the measures used to gauge the performance of clean and dirty energy equities and their relationships during extraordinary global events. I first compare the various moments (mean, standard deviation, skewness, and kurtosis) of the standardised returns distributions for both types of energy equities under the various extraordinary global conditions. Here, returns are calculated in the typical way as the log-difference of the asset price index times 100. Then, the energy asset returns are standardised to scale the series (with an approximate mean of zero and a unit standard deviation) to allow comparisons between the series. Subsequently, the summary statistics of the standardised energy returns are classified under the various net three-year increases and decreases in the global indicators, and the global stability reference subsample.

As asset returns volatility is a commonly used proxy for uncertainty (see, e.g., Bloom et al., 2007), I also consider volatility in the clean and dirty energy equity indices as another performance measure in these markets during extraordinary international events. For this purpose, I use squared standardised returns. The squared returns is the most popular approximation of unobserved volatility in financial markets, it is easy to compute, and it is readily shown that the squared returns (r_t^2) is an unbiased estimator for the variance of that series (σ_t^2) (see Giles, 2008, and references within).

I also investigate the relationship between clean and dirty energy equities in extraordinary global conditions. As both types of energies are considered to be alternative energy sources, the interdependence of the equities between these two energy markets have important implications for the future developments of the global energy sector (Farid et al., 2023). To measure relationships, I use two different approaches to evaluate the joint asset behaviour between clean and dirty energy equities: the dynamic equity ratio and rolling correlations. The former relationship measure follows Bouri et al. (2022), who use the dynamic

[4] As the data for the global indicators are in monthly frequency, a three-year look-back window implies 36 months.

price ratio between clean and dirty energy stocks as a measure of the relationship between these two markets. This is an established time-varying ratio to analyse the evolution of joint asset price behaviour in hard commodity markets (see, e.g., Huang and Kilic, 2019). In addition, a dynamic price ratio series has an intuitive appeal in the context of my study — falling (rising) values indicate that the clean energy stock price index is declining (increasing) relative to the dirty energy stock price index. Indeed, an understanding of the dynamic price relationship between competing energy sources is a crucial issue for investors for portfolio risk management and hedging (see, e.g., Ftiti et al., 2022), and for policymakers wanting insights into the evolution of the global energy mix. The dynamic equity ratio ($r_t^{c/o}$) is computed as the log of the clean energy equity index ($\ln CEI_t$) divided by the log of the oil companies equity index ($\ln OEI_t$), as shown in Eq. (3):

$$r_t^{c/o} = \ln CEI_t / \ln OEI_t \tag{3}$$

For the other measure of the relationship between clean and dirty energy equities, I use the monthly sum of rolling correlation coefficients based on daily data to indicate the strength of the association between the two markets during extraordinary conditions. Rolling correlation analysis is another common measure of association in the oil finance genre (see, e.g., Giri, 2022). I first estimate a bivariate VAR(p) model with daily data on clean and dirty energy equity returns, to control for lead–lag effects in the two markets. Here, p is the lag order of the process for which Bayesian information criterion suggests an optimal lag length of one trading day. The two residual series estimated in the VAR(1) system of equations for clean and dirty energy equities, also called return shocks in the literature (see, e.g., Samarakoon, 2011; Mahadeo et al., 2022a), are then used for computing the rolling correlations. To determine the size of the moving window for the main results, I follow Giri (2022) and use 60 observations (i.e., about three trading months).[5]

3.3. Data definitions

For environmentally clean energy equities, I follow Farid et al. (2023) and use the S&P Global Clean Energy Index, which traditionally constitutes the stocks of companies that produce energy from renewable sources (e.g., solar, wind, hydro, nuclear). This index has been recently revised and expanded to track the performance of companies involved in clean energy related business in developed and emerging markets from around the world, with a target of 100 constituents. For inclusion in the index, such activities include either the production of clean energy or the provision of clean energy technology and equipment. Stocks included must also be a member of the S&P Global BMI (Broad Market Index) and is excluded if the carbon footprint of the company exceeds specific emission thresholds.[6] I use the S&P Global Oil Index to represent dirty energy equities, which tracks the performance of 120 of the largest publicly listed oil and gas companies from around the world involved in exploration, extraction, and production activities, which are also a subset of the Energy Sector constituents of the S&P Global BMI.[7]

Data on the global factors affecting energy markets include ten of the most relevant variables to these markets drawn from the international crude oil market (four indicators); global uncertainties (three indicators); and international economic and financial variables (three indicators). The four international crude oil market series are the oil supply, economic activity, oil consumption demand, and oil inventory demand shocks estimated in Baumeister and Hamilton (2019),[8] who explain that their Bayesian inference approach has clear advantages over the traditional oil market SVAR models popularised in the literature. In particular, their approach relaxes the rigid identifying assumptions in traditional SVAR modelling and, at the same time, makes use of a richer information set beyond the oil market data.

The three global uncertainty variables I use are precisely those uncertainties covered in the literature review section. These include the *global* economic policy uncertainty index, which is a global new-based variant of the US economic policy uncertainty index developed in Baker et al. (2016); the geo-political risk index of Caldara and Iacoviello (2022); and the climate policy uncertainty index of Gavriilidis (2021). All of these indices are constructed using the text-based analysing methodologies consistent with the seminal work conducted by Baker et al. (2016).[9]

Also discussed in the literature review are the three international economic and financial variables relevant to energy markets: US dollar exchange rates, global stock market returns, and global economic conditions. For the US dollar exchange rate indicator, I use the US real broad effective exchange rate (REER).[10] This index is computed as weighted averages of bilateral exchange rates adjusted by relative consumer prices and it has a straightforward interpretation — increases (decreases) in this index implies real appreciations (depreciations) of the US dollar against other currencies. Data for global stock market returns are computed as the returns of the S&P Global 1200 Index.[11] This is a composite index that constitutes the S&P flagship indices of the US (S&P 500), Canada (S&P TSX 60), Europe (S&P Europe 350), Japan (S&P Japan 150), Australia (S&P ASX 50), Asia (S&P Asia 50), and Latin America (S&P Latin America 40). Finally, I include the novel index introduced in Baumeister et al. (2022) to capture global economic conditions.[12] As mentioned earlier, it is a single index that consolidates data spanning multiple dimensions, all of which are expected to be influential to energy markets.

3.4. Sample

The period under investigation runs from 2003M12 to 2021M12, where the start date is dictated by the availability of the clean energy equity series and the end date is based on the consistent availability of the ten global factors affecting energy company equities.[13] To prime the non-linear net three-year increase and decrease data filters, outlined in Eqs. (1) and (2), requires three additional years of earlier data for all of the global factors. The data are in monthly frequency, which is the highest frequency available for the majority of the global factors affecting energy equities. However, the one exception are the data used for one of measures on the relationship between clean and dirty energy equities — the rolling correlations, for which I use the monthly sum of

[5] I also estimate the rolling correlation coefficients between clean energy and oil equities with various moving window sizes: 30, 90, and 120 trading days. I find that smaller window sizes exhibit more fluctuations, while longer window sizes yield a smoother series. However, the overall pattern of the trend in the correlation remains similar. As such, for the main results, I follow Giri (2022) and report the findings with the rolling correlation coefficients using 60 trading days. Instructions and codes for the inspecting the sensitivity of the rolling correlation window sizes are included in the supplemental data files that accompany this paper.

[6] See https://www.spglobal.com/spdji/en/indices/sustainability/sp-global-clean-energy-index.

[7] Both energy equity series are extracted from the Bloomberg Terminal.

[8] The data are obtained from Christiane Bausmeister's website, available at https://sites.google.com/site/cjsbaumeister/datasets?authuser=0.

[9] All uncertainty data are available from the website of Baker, Bloom, and Davis at https://www.policyuncertainty.com/.

[10] The US broad REER index is available from the Federal Reserve Economic Data (FRED) website: https://fred.stlouisfed.org/series/RBUSBIS.

[11] The S&P Global 1200 index data are extracted from the Bloomberg Terminal.

[12] The data are obtained from Christiane Bausmeister's website, available at https://sites.google.com/site/cjsbaumeister/datasets?authuser=0.

[13] One additional observation, 2003M11, is lost in the computation of returns.

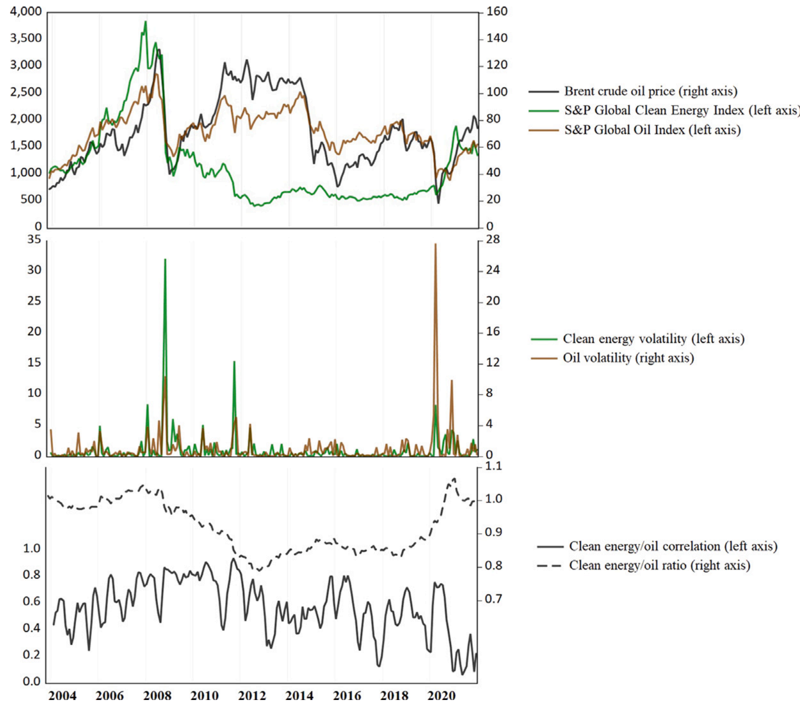

Fig. 1. Equity indices, volatilities, and relationships for clean energy and oil companies. In the top graph, the S&P Global Clean Energy and Oil equity indices share the left axis. The Brent crude oil prices are in US dollars per barrel and measured on the right axis — this series is included for reference purposes. The centre graph shows the squared standardised returns for the S&P Global Clean Energy Index (left axis) and Oil Index (right axis) to proxy volatilities in these markets. In the bottom graph, the two relationships measures between these two types of energy markets are shown: the left axis displays the monthly averages of the 60 trading day rolling correlation coefficients between the return shocks of the S&P Global Clean Energy and Oil indices; while the right axis shows the dynamic equity ratio between the log of the S&P Global Clean Energy and Oil indices. Refer to the main text for further explanations.

energy market return shocks based on daily data, as described earlier in the methodology. As this correlation measure is also primed with 60 trading days (approximately three months) of energy equity data, the series starts from 2004M02, again due to the availability of the clean energy equity index. All data were retrieved between June and August of 2022.

4. Results and discussion

This section consists of four parts. I plot and describe the clean and dirty energy equity indices, their standardised return volatilities, and relationship measures in the first part. In the second part, I illustrate and explain the results obtained from the net three-year increase and decrease filters applied to the ten global factors affecting energy markets. In the third part, I address the main aim of the paper by consolidating the efforts made in the previous parts, and discuss the performance of the clean and dirty energy equities and their relationships during extraordinary global conditions.

4.1. Energy equities, volatilities, and relationships

In Fig. 1, the top graph shows three series: the S&P Global Clean Energy Index (in green); the S&P Global Oil Index (in brown); and the Brent crude oil price index (in black) for reference, which is closely mirrored by the oil companies' equity index. All three indices convey upward trends in the booming period of the 2000s (i.e.,2003–2007) and experience pronounced crashes in the 2008 GFC. The indices for oil prices and companies recover by 2011 but tumble again in the oil crash of 2014, and again in the COVID-19 pandemic. The clean energy equity index, however, remains subdued in the GFC aftermath and stays this way until the very end of my sample, where upticks are seen after the initial impacts of the pandemic on global stock markets begin to wane.

The centre graph of Fig. 1 illustrates the equity index volatilities for clean (green line) and dirty (brown line) energy companies, as measured by the squared standardised returns of the indices presented in the top graph. The most striking spikes in volatility in both energy equity markets occur in the 2008 GFC, in 2011, and in COVID-19; whereas the pre-GFC booming period of the 2000s and the oil market crash of 2014/2015 generate comparatively much less volatility for energy firms.

From the bottom graph in Fig. 1, the two relationships measures can be observed — the rolling correlation between clean and dirty energy equities (solid black line), as well as the dynamic equity ratio between the clean energy and oil equity indices (broken black line). Based on the rolling correlations, these coefficients fluctuate around an increasing trend in the 2000s, followed by a decreasing trend up to the mid-2010s, then large swings in correlations thereafter, with a relatively weaker association in the final year of the sample. The dynamic equity ratio appears relatively stable in the booming 2000s but enters into a steady decline in the aftermath of the 2008 GFC, which continues until the end of 2012, indicating a decline in clean energy equities relative to oil company equities. A plausible cause of the decline from 2008 in clean energy equities to that of oil companies is the shale oil revolution. In fact, in 2008, the shale oil revolution reversed the long-standing decline in crude oil production in the US (Kilian, 2016), making the boom experienced by the oil and gas companies appear as a lucrative investment strategy on the stock market. This dynamic price ratio becomes somewhat stagnant after 2012 but begins to increase from 2019 onwards, indicating a more recent improvement in the equity index of clean energy relative to the index for oil companies.

4.2. Extraordinary conditions in global energy market indicators

Fig. 2 depicts the ten global factors affecting environmentally clean and dirty energy markets. In the spirit of Fabozzi et al. (2022), I also

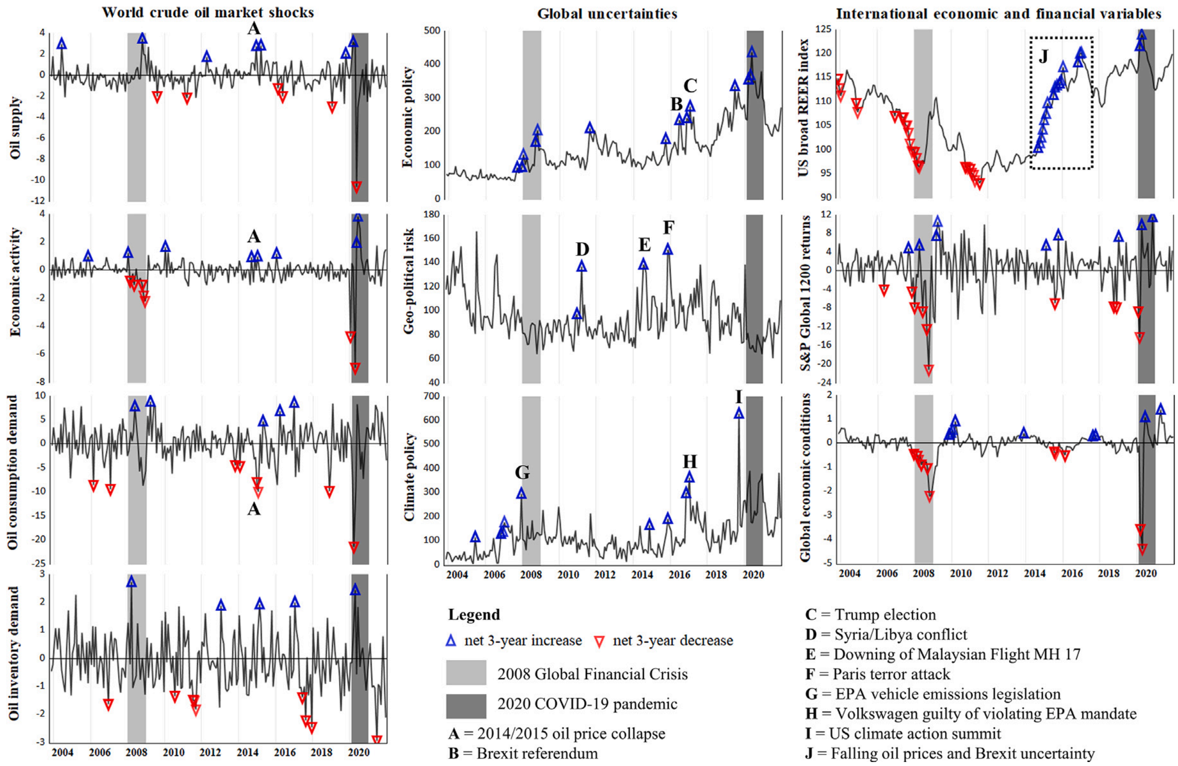

Fig. 2. Extraordinary conditions in the global leading indicators of international energy markets. The left column illustrates the four crude oil market shocks identified in Baumeister and Hamilton (2019). The middle column displays the three global uncertainties affecting energy markets: global economic policy following the methodology of Baker et al. (2016); geo-political risk measure of Caldara and Iacoviello (2022); and the climate policy related uncertainty index of Gavriilidis (2021). The right column shows three international economic and financial variables that are relevant to the global energy markets: US dollar real broad effective exchange rate index; the S&P Global 1200 returns; and the global economic conditions index of Baumeister et al. (2022). All blue upward (red downward) pointing triangles annotated to the series are the positive (negative) jumps in the series that are identified by the net three-year increases (decreases) rule-based specification defined in Eq. (1) (Eq. (2)). On all graphs in this figure, grey vertical shaded bars indicate the 2008 GFC (light grey) and 2020 COVID-19 pandemic (dark grey). There are no net three-year decreases for the three uncertainty series, as only positive jumps that indicate a heightened uncertainty environment are of concern for monitoring global energy equity markets. Refer to the main text for further explanations.

advocate for the use of graphical depictions — they are directly interpretable and are a valuable tool to financial economists for understanding the performance of indices of interest under extreme international macro-financial and policy events. As such, all graphs in this figure have blue upward (red downward) pointing triangles to indicate where an extraordinary rise (fall) is located in a particular variable, which is identified by the net three-year increase (decrease) filter suggested in Eq. (1) (Eq. (2)). On all graphs in this figure, grey vertical shaded bars indicate the 2008 GFC (light grey) and 2020 COVID-19 pandemic (dark grey). The first column plots the four international crude oil market shocks. Unsurprisingly, most extraordinary oil market shocks occur around the 2008 GFC and COVID-19, highlighting the strong connection between the international crude oil market and global crises. Outside of these two significant events, the oil price collapse of 2014/2015 also creates extraordinary shocks (see A in Fig. 2). The magnitude of the negative extraordinary shocks in oil supply, economic activity, and oil consumption demand at the time of the pandemic are especially unprecedented in the sample.

In the second column of Fig. 2, the three policy uncertainties are displayed, along with the extraordinary increases in these indices.[14] The top graph plots the global economic policy uncertainty index, which has a tendency to trend upwards in my sample. There are 14 periods of extraordinary increases in this index, clustering around momentous global events such as the 2008 GFC; the Brexit referendum in June 2016 (see B in Fig. 2); the Trump election win and inauguration in late 2016 into early 2017 (see C in Fig. 2); and the COVID-19 pandemic (2020). The geo-political risk index of Caldara and Iacoviello (2022) in the centre graph has just 4 periods of extraordinary uncertainty in my sample, captured by the net three-year increase filter, which includes conflicts in Syria and Libya in March 2011 (see D in Fig. 2); the downing of Malaysian Flight 17 over eastern Ukraine in July 2014 (see E in Fig. 2); and the Paris terror attacks in November 2015 (see F in Fig. 2). The bottom graph in the global uncertainties column shows the climate policy uncertainty index of Gavriilidis (2021), with ten episodes of extraordinary increases in uncertainty levels. These dates coincide with many landmark events in climate related news annotated by Gavriilidis (2021): the failure of the Climate Stewardship and Innovation Act in June 2005; Western Governors' Association Clean and Diversified Energy Advisory Committee recommendations in January 2007; Environmental Protection Agency (EPA) vehicle emissions legislation in December 2007 (see G in Fig. 2); US-China climate change deal in November 2014; Keystone XL pipeline permit rejection in November 2015; Volkswagen AG guilty plea to violating the EPA mandate in January 2017 (see H in Fig. 2); and the US Climate Action Summit in September 2019 (see I in Fig. 2).

The final column of Fig. 2 illustrates the three international economic and financial variables. In the top series, the US broad REER has a declining trend in the pre-GFC period, with a number of extraordinary depreciations. Yet, the appreciations during the GFC are not captured by the net three-year increase measure, as much of this period is classified as "corrections" for the previously observed depreciations. Much of the later part of 2010 and the early part of 2011 heralds another period of unprecedented depreciations in the REER index, associated with a second round of quantitative easing (known as QE2) by the Fed. The latter half of 2014 until the start of 2017 is largely

[14] Extraordinary decreases are not applicable for the three uncertainty policy indices, as this would locate periods of falling uncertainty. Such periods of stability are not expected to be sources of disruption in energy markets.

characterised by extraordinary appreciations in the US broad REER index, in part due to falling oil prices as well as rising uncertainties related to other major currencies such as the euro and the pound sterling over Brexit (see J in Fig. 2). Two further episodes of extraordinary US REER appreciations are noted in the pandemic. From the middle and bottom graphs, which respectively show the S&P Global 1200 Index returns and global economic conditions index of Baumeister et al. (2022), it is unsurprising that much of the extraordinary decreases in these variables are during the 2008 GFC and COVID-19 crises, with extraordinary increases characterising the recoveries in the post-crisis periods.

For the net three-year increases and decreases suggested in Eqs. (1) and (2), adapted from the non-linear oil price measure of Hamilton (2003), I also consider longer and shorter look-back periods of four and two years (48 and 24 months), respectively, to detect jumps in the global indicators. These results are qualitatively consistent to the main findings. However, the shorter look-back window yields additional conditions which cannot always be tied to extraordinary historical events, whereas the longer lags date too few observation months in the subsamples. Hence, the net-three year period optimally reflects unexpected and landmark global historical episodes, as outlined in Fig. 2, for the ten indicators.[15]

4.3. Energy equities during extraordinary global conditions

Table 1 shows the first, second, third, and fourth central moments of the standardised equity returns for clean and dirty energy equities during extraordinary conditions in the ten global indicators relevant to energy markets. In the last two columns, I report how the joint asset relationships between these energy markets change under such periods using the dynamic equity ratio and rolling correlation measures. For reference, in the first two rows, I include the performance of the standardised energy market equity returns and relationships for both the overall sample and the period of global stability. The latter state of the world is defined as that time period where no extraordinary global events take place and comprises 56% of the overall sample (i.e., 121 months of 217 months). From the overall sample, the mean standardised equity returns for both types of energy companies are near zero and standard deviations are approximately one. Comparing the overall sample to the global stability subsample, the latter has a relatively higher positive returns and the volatilities, as measured by the standard deviations, are less than unity to indicate lower market risks in stable conditions for both types of energy companies. The dynamic price ratio is 0.92 in both periods and the rolling correlations convey a relatively strong positive relationship ($\rho > 0.5$).

The subsamples defined by extraordinary conditions account for the remaining 44% of the overall sample (i.e., 217 subtract 121 months).[16] Explaining which jumps in the global indicators characterise the extreme values in the moments of the two energy asset returns distributions provide an insightful and simplistic point of departure for analysing the results. To support this, Figs. 3, 4, and 5 are the companion illustrations that show the volatilities of the S&P Global Clean Energy and Oil Indices (measured by the squared standardised equity returns in the left column), as well as the two relationship measures between these assets (in the right column). Superimposed onto these three figures are the jumps in Fig. 2, to show the extraordinary conditions in the international crude oil market shocks (Figs. 3), global uncertainties (Figs. 4), and international economic and financial variables (Figs. 5). I jointly use these results to address my research question — which extraordinary global events coincide with the pronounced changes in the standardised asset return moments and relationships of clean and dirty energy equities?

Across both clean energy and oil companies, the biggest gains and losses in mean standardised returns are noted in periods of extraordinary increases and decreases in the S&P Global 1200 returns, respectively. These findings resonate with previous studies that report strong positive associations between the returns of headline stock market indices with the stock returns of clean energy (see, e.g., Uddin et al., 2019) and oil and gas companies (see, e.g., Boyer and Filion, 2007). Also noteworthy, for both types of energy markets, the period with the second largest losses in standardised returns are during conditions of extraordinary positive oil supply shocks. This suggests that a glut in the crude oil market is unfavourable to investors in either types of energy firms. Such logic is consistent with basic demand and supply analysis: excess supply will bring down the equilibrium price of oil; and, as clean energy and oil are thought to be substitutes, the demand for clean energy is expected to fall due to the availability of a cheaper alternative, also bringing down clean energy asset prices. While the literature suggests that the impact of oil supply shocks on the economy and stock market appears to have diminished (see Broadstock and Filis, 2014, and references within), my findings serve as an important reminder that extraordinary oil supply conditions remain relevant to energy markets.

The most turbulent volatility, across all global factors, occur in the environmentally clean energy market during times of extraordinary negative shocks in economic activity using data based on the estimation approach suggested in Baumeister and Hamilton (2019), whereas the same is experienced for oil companies in negative extraordinary events using the global economic conditions index proposed in Baumeister et al. (2022). These findings highlight just how sensitive both energy markets are to downturns in global economic activity. In addition, the volatilities of clean and dirty energy companies in the bottom left graphs of Fig. 5 display some of their highest levels during the extraordinary negative episodes in global economic conditions related to the 2008 GFC and COVID-19.

Moments beyond the first and second are often overlooked and, yet, contain important information about the distribution of financial asset returns, particularly in the presence of black swan events (see, e.g., Fabozzi et al., 2021). Both energy asset returns show the largest negative skewness values in extraordinary negative oil consumption demand conditions, whereas their largest positive skewness values are recorded under extraordinary buoyancy in the S&P Global 1200 market returns. When asset returns exhibit negative (positive) skewness, this implies recurrent small gains (losses) and occasional large losses (gains). Negative skewness has a tendency to be related to crisis conditions, characterising the infrequent and abrupt negative values associated with such times (Ranciere et al., 2008).

Considering the fourth moment, the highest kurtosis values for the equity returns of clean energy and oil companies are documented under extraordinary depreciation and appreciations in the US broad REER index, respectively. Elevated fourth moments in the distribution of standardised asset returns are a stylised fact of financial market stress, as leptokurtosis in asset returns increase the probability of extreme values in the tails of the distribution function (Fry-McKibbin and Hsiao, 2018; Fry-McKibbin et al., 2018). Juxtaposing the kurtosis results and the standardised return volatilities in Fig. 5 (top left pair of graphs), the depreciation jumps in the US broad REER index occur in the former half of the sample, which clusters around the uncertainties in energy market (implied by their volatilities) associated with the run up to the 2008 GFC and the effects of quantitative easing in its wake. Moreover, REER appreciation jumps in the US dollar characterise the latter half of the sample, which includes the uncertainties in energy markets associated with the oil price crash of 2014/2015, Brexit uncertainties, as well as the COVID-19 pandemic.

[15] Instructions and codes for the robustness exercises are included in the supplemental data files that accompany this paper.

[16] As there are months where more than one global indicator can be characterised as extraordinary, the observations under the various global condition samples do not equate to the overall observation of 217 months.

Table 1
Summary performance statistics of the standardised equity returns and relationships for S&P Global Clean Energy and Oil indices during extraordinary global conditions.

Conditions	Obs.	Standardised equity returns								Clean energy/oil relationship	
		S&P Global Clean Energy Index				S&P Global Oil Index					
		Mean	SD	Skew.	Kurt.	Mean	SD	Skew.	Kurt.	$r^{c/o}$	ρ^{w}
Overall sample	217	0.006	1.000	-1.517	8.855	-0.004	0.993	-0.831	6.555	0.921	0.573
Global stability	121	0.050	0.807	-0.200	4.011	0.058	0.805	-0.200	3.619	0.916	0.540
Oil market shocks											
Oil supply											
Net 3-year +	7	-1.305	2.244	-1.152	3.030	-1.347	2.097	-1.086	2.646	0.908	0.615
Net 3-year –	6	0.260	1.059	-0.070	1.302	0.205	0.685	0.897	3.104	0.902	0.680
Economic activity											
Net 3-year +	8	-0.598	1.323	-0.432	2.149	-0.631	0.737	-0.527	2.323	0.931	0.658
Net 3-year –	7	-0.608	2.403	-1.531	3.932	-0.232	1.779	-0.374	2.319	0.974	0.729
Oil consumption demand											
Net 3-year +	5	0.698	0.584	0.344	1.943	0.992	0.392	0.066	1.486	0.914	0.620
Net 3-year –	8	-0.003	1.265	-1.654	4.599	-1.209	1.721	-1.806	5.184	0.904	0.534
Oil inventory demand											
Net 3-year +	5	0.627	0.452	0.405	1.438	0.578	1.073	0.435	1.963	0.915	0.620
Net 3-year –	9	-0.458	1.495	-1.469	4.355	-0.263	1.034	-0.493	2.350	0.904	0.591
Uncertainties											
Global economic policy											
Net 3-year +	14	-0.900	2.119	-0.913	2.744	-0.712	2.029	-0.738	2.828	0.935	0.690
Geo-political risk											
Net 3-year +	4	0.160	0.842	0.031	1.042	0.137	0.899	0.636	1.973	0.881	0.605
US climate policy											
Net 3-year +	10	0.176	0.664	-0.610	2.200	0.096	0.810	-0.669	2.585	0.935	0.550
International economic/finance											
US broad REER index											
Net 3-year +	18	-0.347	1.008	-0.571	3.432	-0.700	1.475	-1.227	6.701	0.870	0.558
Net 3-year –	23	0.090	0.934	-1.553	6.104	0.291	0.827	-0.515	3.810	0.986	0.668
S&P Global 1200 returns											
Net 3-year +	9	1.331	0.450	0.504	1.833	1.513	0.740	1.280	3.728	0.954	0.708
Net 3-year –	11	-1.784	1.781	-0.945	2.946	-1.898	1.442	-1.081	3.689	0.957	0.681
Global economic conditions index											
Net 3-year +	9	0.064	0.654	-1.464	4.080	-0.038	0.444	-0.403	2.382	0.924	0.581
Net 3-year –	11	-1.070	2.133	-1.015	2.917	-0.818	2.161	-0.682	2.700	0.965	0.719

Notes: the period of global stability is derived as those periods mutually dated as zero in Eqs. (1) and (2) across all ten global indicator variables. Net 3-year + (-) are the extraordinary increases (decreases) detected by in Eq. (1) (Eq. (2)). As there are months where more than one global indicator can be characterised as extraordinary, the observations under the various global condition samples do not equate to the overall observation of 217 months. $r_t^{c/o}$ is the dynamic equity ratio between the natural logs of S&P Global Clean Energy and Oil equity indices, while ρ^{w} is the rolling correlations between the return shocks for these two energy assets based on a window of 60 trading days. Abbreviations are obs. for observations, SD for standard deviation, Skew. for skewness, and Kurt. for Kurtosis. Refer to the main text for further explanations.

On relationship measures between environmentally clean and dirty energy equities, the dynamic equity ratio deviates away from its sample average of 0.92 to record a minimum of 0.87 and maximum of 0.99 under extraordinary US broad REER index appreciations and depreciations, respectively. This implies that a fall (rise) in the clean energy equity index relative to the equity index of oil companies coincides with currency market jumps that strengthen (weaken) the US dollar relative to other currencies. From the rolling correlation coefficients between the equity return shocks of clean energy and oil companies, against a sample average of 0.57, I document the relatively weakest (0.53) and strongest (0.73) correlations in months of extraordinary negative oil consumption demand and economic activity shocks, respectively. On one hand, taking the former result when the correlation weakens together with the standardised returns, volatilities, skewness, kurtosis values, and the dynamic equity ratio all collectively show that periods of extreme drops in oil consumption demand affects oil companies much more adversely than clean energy companies. On the other hand, the latter finding about when correlations are strongest suggests that cross market correlations increase when global economic activity abruptly slows down, as less of either types of energy are needed in such times.

Prima facie, somewhat unusual findings are the negative returns on both energy assets in the presence of positive jumps in the global economic activity shocks of Baumeister and Hamilton (2019), shown in Table 1. This impression is further supported by the negative returns on oil company equities under positive jumps in the global economic activity index of Baumeister et al. (2022). On closer inspection, Fig. 2 shows that some of the extraordinary positive conditions detected in these two measures of global economic activity are associated with growth corrections for the COVID-19 pandemic. Therefore, the negative oil company returns associated with jumps in global economic growth can be supported by the notion that investors have a tendency to be more pessimistic about oil compared to stocks (see, e.g., Xu et al., 2019). Furthermore, while global stock markets and economies began to recover from the initial February and March downturns of COVID-19 as early as April of 2020, the effects would endure in the energy markets – particularly oil – for some time longer. Farid et al. (2023, and references within) explain that the drop in clean energy associated with the COVID-19 pandemic was less than the crude oil market. For instance, the storage scarcity related to the physical delivery of oil led to an incredible collapse of the Brent and WTI benchmark oil prices in April 2020, coupled with the travel restrictions, lockdowns, and work

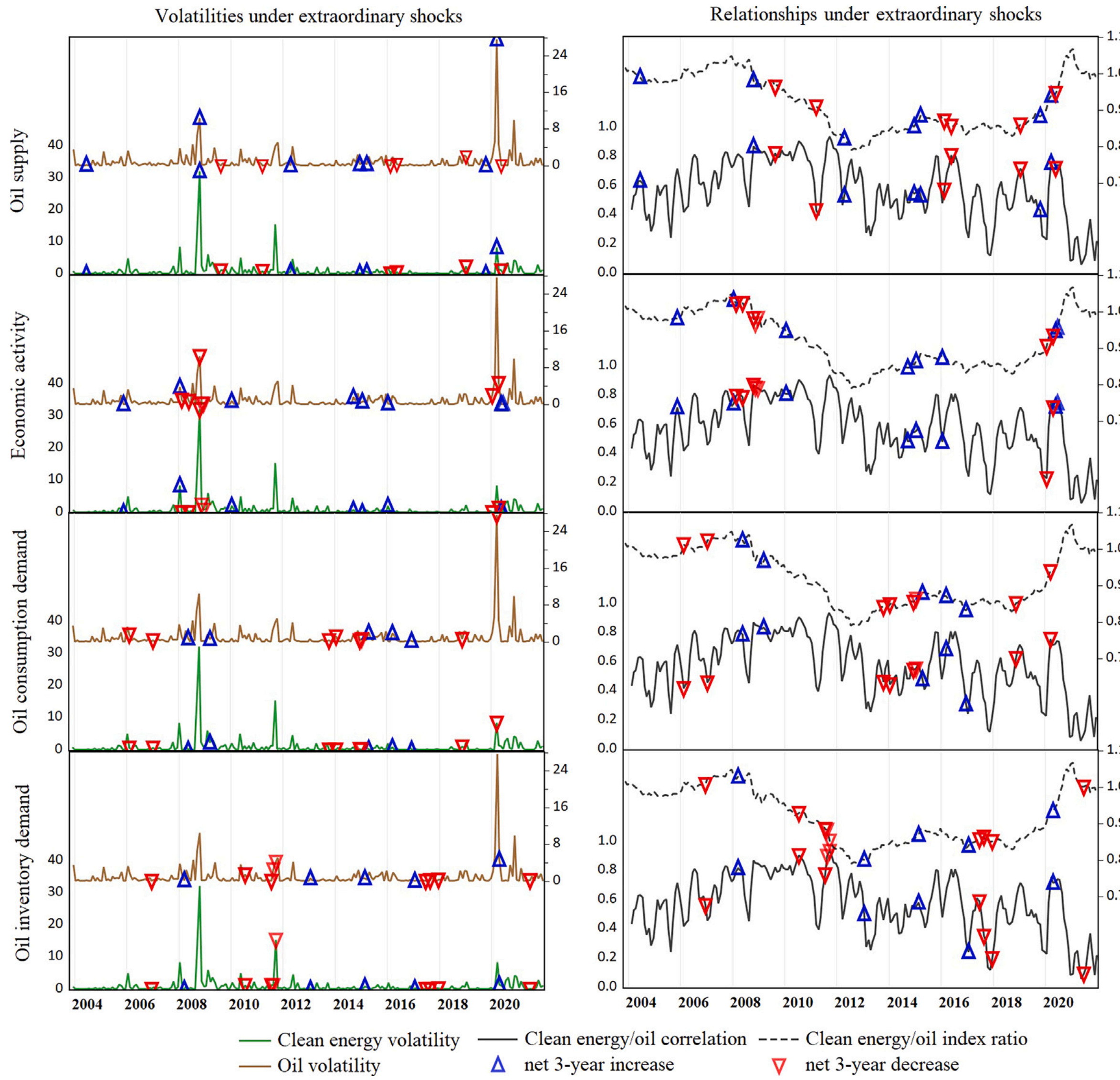

Fig. 3. Clean energy and oil volatilities and relationships under extraordinary crude oil market supply and demand shocks. The left column are the volatilities of the S&P Global Clean Energy Index (green line, left axis) and Oil Index (brown line, right axis). The right column shows the two relationship measures between clean energy and oil equities: the rolling correlation coefficients of their return shocks (left axis) and the dynamic equity ratio (right axis). Each row of graphs in the figure can be read as the energy market volatilities and relationships during net three-year increases, indicated by blue upward triangles, and decreases, indicated by red downward triangles, in oil supply shocks (first row); economic activity shocks (second row); oil consumption demand shocks (third row); and oil inventory demand shocks (fourth row). For further details, see the centre and bottom graphs and notes of Fig. 1, as well as the left column graphs on world crude oil market shocks and notes of Fig. 2. Refer to the main text for further explanations.

from home policies that kept energy markets in a more prolonged state of uncertainty.

Additionally, on one hand, I find that extremely high levels of global economic policy uncertainty characterises negative returns and abnormal increases in volatility for both energy assets. This is consistent with the earlier findings of Kang et al. (2017) who show that economic policy uncertainty has adverse effects on oil returns. On the other hand, during major uncertainties related to geo-political risks and climate policies, both standardised energy assets display positive returns, tranquil volatility, and low kurtosis values. This, however, contradicts Antonakakis et al. (2017) who argue that geo-political risk elicit negative effects on oil returns and volatility. Nevertheless, with specific reference to geo-political risk and oil companies, as many countries involved in key global political uncertainties are often oil producers and exporters, my findings fits well with fundamental economic theory: supply disruptions in a market will drive up the prices of that commodity. In fact, Heinlein et al. (2021) explain that in the start of 2020, while there was a dip in stock indices around the world for a stint when financial markets absorbed negative information about rising geo-political tensions associated with the assassination of the Iranian general Qasem Soleimani in Iraq, there was a simultaneous uptick in benchmark crude oil prices. They suggest that investors likely saw oil as a hedging strategy for falling headline stock price indices, along with the perceived oil supply disruptions in the OPEC market. Moreover, the dynamic equity ratio falls to a relatively low value (0.88) in the sample of heightened geo-political risks, which indicates a fall in the equity index of clean energy relative to that of oil companies. While my findings are in line with Sohag et al. (2022) who find a positive spillover from the GPR index to clean energy equities, the falling dynamic equity ratio is at odds with their inference that there is a substitution effect between clean energy and geo-politically risky assets such as dirty investments like oil.

Overall, there is a general consistency in the performance of clean and dirty energy equities during extraordinary conditions. Both standardised energy asset display similar signs on mean returns for most of the subsamples. Furthermore, the similar periods where volatilities

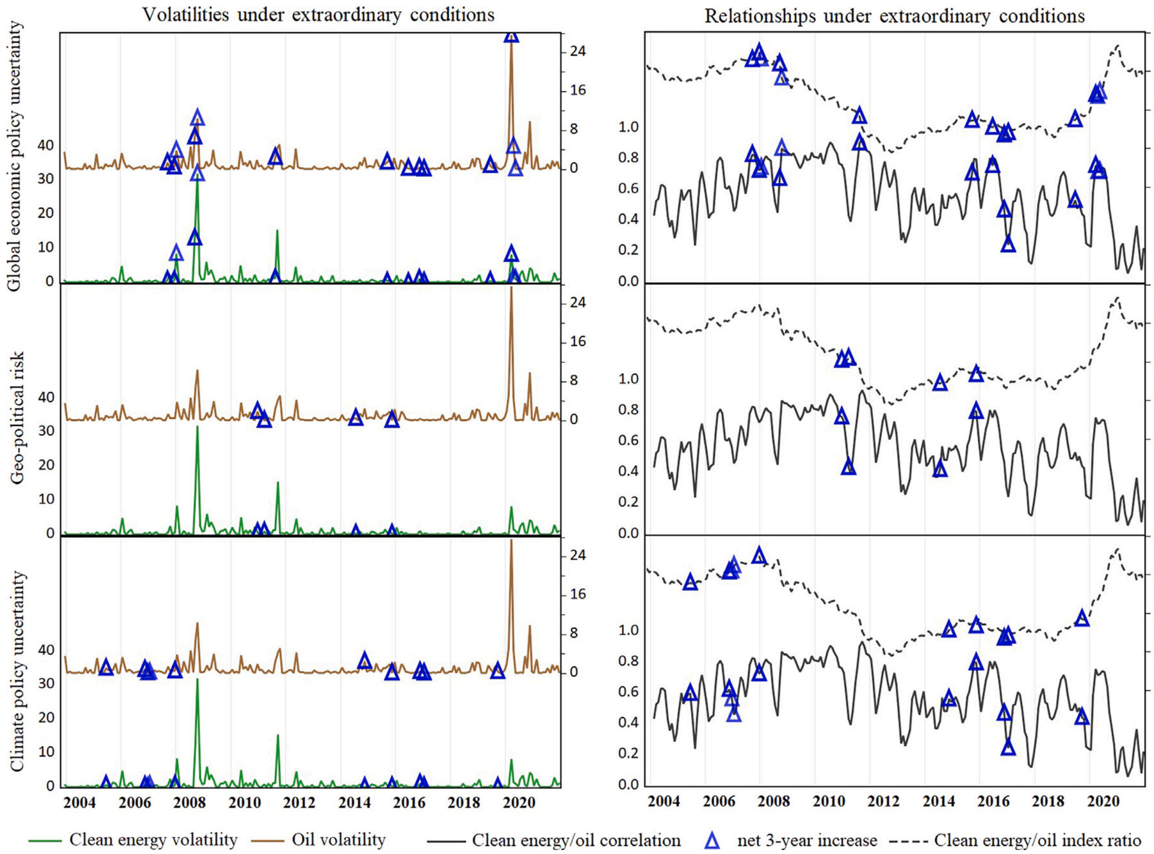

Fig. 4. Clean energy and oil volatilities and relationships under extraordinary global economic policy uncertainty, geo-political risk, and climate policy uncertainty. See notes for Fig. 3. Each row of graphs in the figure can be read as the energy market volatilities and relationships during net three-year increases (indicated by blue upward triangles) in global economic policy uncertainty (first row); geo-political risk (second row); and climate policy related uncertainty (third row). For further details, see the centre and bottom graphs and notes of Fig. 1, as well as the centre column graphs on global uncertainties and notes of Fig. 2. Refer to the main text for further explanations.

spike in both markets and the relatively strong rolling correlations across the various subsamples reinforce this view, which contradicts the conjecture that clean energy and oil are competing asset classes (see, e.g., Wen et al., 2014). Instead, the relatively comparable performance of clean and dirty energy equities under the various extraordinary subsample conditions would favour an argument that the equities of these alternative energy sources behave as a market of one. Yet, although both energy assets appear to be potentially lucrative hedging strategies in the presence of unexpected geo-political and climate policy related events, an environmentally conscious investor can opt to invest in the clean energy equity market to combine their profit maximising incentives with sustainability objectives (see, e.g., Farid et al., 2023). Indeed, a trade-off of oil and gas stocks in favour of clean energy stocks can increase the flow of investment into the latter, while minimising energy security and climate risks.

5. Conclusion

I compare the equity market performance between clean and dirty (oil and gas) multinational companies, under extraordinary conditions in leading energy market indicators. This line of research is important, given the climate change discourse and the need to rebalance the global energy mix away from dirty fuels and move towards environmentally cleaner energy sources. It is also vital because these large energy suppliers, regardless of their carbon footprint, play a crucial part in meeting the energy demands around the world. As equity financing via the stock market is a key way in which such firms fund their operations, monitoring the financial stability of energy markets has critical implications for global energy security and growth.

I contribute to the clean and dirty energy finance literature by proposing a filter to locate prominent increases and decreases in a wide range of global factors affecting energy markets. I also discuss several advantages of this technique for detecting jumps in time series data beyond asset prices, which makes it appealing over alternative algorithms in the literature. I then calculate various performance measures of clean and dirty energy equities (namely standardised returns statistics, volatilities, and market relationship measures) and classify these under the various extraordinary subsample conditions timestamped with my data filter.

My results show that the equities of environmentally clean and dirty energy firms have similar performances during extraordinary global conditions. I observe the largest gains (losses) in the standardised asset returns of both types of energy firms occur when there are positive (negative) jumps in the global stock market. These findings are a testament to the intimate financial connection between energy markets and the global stock market in unprecedented times. Related to this, I also find that the most turbulent volatility in both energy markets take place when there are significant downturns in global economy. Other financial instability indicators, such as periods of the highest negative skewness and excess kurtosis in energy asset returns, are respectively seen when oil consumption demand falls drastically and when there are jumps in the US dollar real effective exchange rate (leptokurtosis is noted during appreciations for the standardised equity returns of oil and depreciations in the case of clean energy). However, jumps in uncertainties related to geo-political risk and climate policy reflect relative stability in the standardised returns behaviour for the equities of clean energy and oil companies, exhibiting positive returns accompanied by low volatility and kurtosis levels. This stability suggests that both types of energy assets are potentially profitable

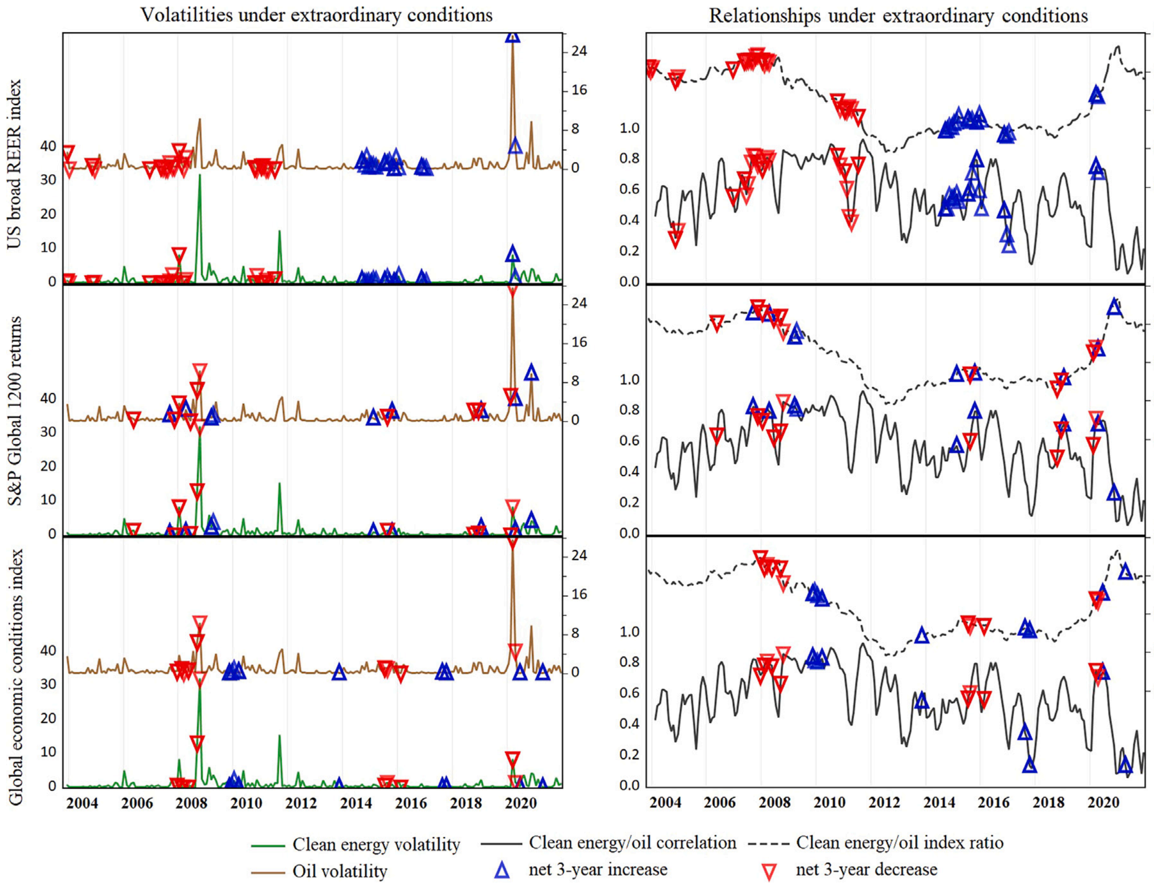

Fig. 5. Clean energy and oil volatilities and relationships under extraordinary international economic and financial conditions. See notes for Fig. 3. Each row of graphs in the figure can be read as the energy market volatilities and relationships during net three-year increases, indicated by blue upward triangles, and decreases, indicated by red downward triangles, in the US broad REER index (first row); S&P Global 1200 returns (second row); and the global economics condition index (third row). For further details, see the centre and bottom graphs and notes of Fig. 1, as well as the right column graphs on international economic and financial variables and notes of Fig. 2. Refer to the main text for further explanations.

hedging investments against other assets that are affected during geopolitical risk and climate policy crises. However, during such turmoil, opting to invest in clean energy equities instead of oil offer traders the ability to combine profit maximising and sustainability objectives, while minimising global energy security risks.

Ultimately, my analysis provides a contemporaneous perspective of how environmentally clean and dirty energy companies perform under extraordinary conditions in the major factors affecting global energy markets. This is based on the reasonable assumption of liquid and efficient international energy markets. To complement my analysis, a promising direction for future research is to examine the more long lasting and delayed effects that jumps in the leading global indicators have for clean energy and oil equities. Together, both immediate and long term outlooks are helpful for the development of a comprehensive early warning system for financial instability in energy markets.

CRediT authorship contribution statement

Scott Mark Romeo Mahadeo: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.122227.

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