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Do dirty and clean energy investments react to infectious disease-induced uncertainty?

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A R T I C L E I N F O

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A B S T R A C T

Following the outbreak of novel coronavirus, numerous studies have assessed the effect on global financial markets. However, investigations into whether, and to what extent, dirty and clean energy asset classes are sensitive to contagious diseases are rare. This study aims to fill this gap in the literature. We measured the effects of contagious viruses using the recently introduced infectious disease-related uncertainty index (EMVID). Our data include the iShares Global Energy ETF and clean energy stock indices from leading economies such as the United States, the European Union, Japan, and China. Employing the GARCH-MIDAS model, we find that the uncertainty associated with infectious diseases has a significant positive (negative) effect on the realized volatility (RV) of dirty (green) assets. This finding is novel given that it indicates the potential for "green recovery" in the post-pandemic era. Our findings further document that EMVID has significant predictive content for the volatility of these assets and that inserting the EMVID index into the GARCH-MIDAS process produces better volatility predictions than other uncertainty measures, including the crude oil volatility (OVX), geopolitical risk (GPR), and economic policy uncertainty (EPU) indices. Hence, the EMVID provides additional information not contained in the OVX, GPR, or EPU during the pandemic period. Our findings will be useful for energy market participants to make appropriate asset allocation decisions during pandemics.

1. Introduction

Global energy markets have experienced several depressions over the last two decades. For instance, the 2007–2009 recession introduced a sharp drop in crude oil prices. During these financial crises, energy prices plummeted from over $100 per barrel to $32. Later, the 2010s' oil glut caused another significant downturn in international oil markets, which commenced in December 2014 and peaked in early 2016 when oil prices fell below $30 per barrel. The oversupply of crude oil, declining demand for various commodities, and geopolitical tensions among oil-exporting countries are plausible reasons for these oil market crashes (Dutta, 2018).

The most recent depression in the energy markets emerged in the aftermath of the COVID-19 pandemic. The per-barrel price for the Brent market dropped to $22.58 during March 2020, hitting its lowest level since November 2002. In the interim period, we observe a similar decrease in the WTI oil price index, which has been the largest collapse over the last two decades. Additionally, the crude oil volatility index (OVX), shown in Fig. 1, indicates that although oil volatility has experienced several jumps since its inception in 2007, the most prominent spike is seen during the COVID-19 pandemic phase.

Although the pandemic has had negative consequences for international crude oil markets, the demand for clean energy has increased dramatically (Wan et al., 2021). The increasing demand for renewable energy can be attributed to the introduction of a "green recovery" strategy in many countries to accelerate the transition towards a low-carbon economy. The goal of this strategy is that, although COVID-19 has caused a global economic crisis, the transition to a green economy remains a priority. While the effects of the pandemic may be felt in the economy and climate for decades, introducing this "green recovery"

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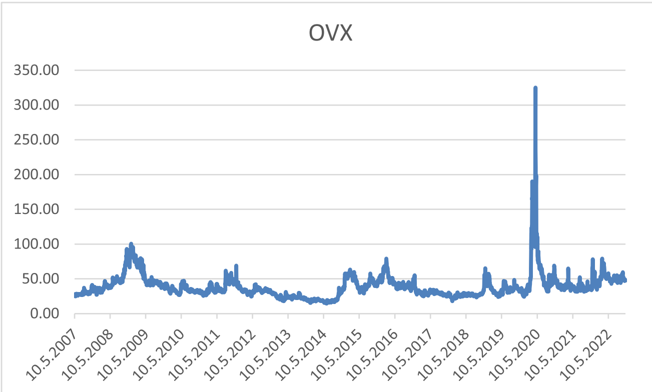

Fig. 1. Time series plot of crude oil volatility index (OVX).

strategy would certainly prevent one crisis leading to another. In addition, it would also boost the economy during the post-pandemic period. In summary, the effect of infectious disease-induced uncertainty on clean energy firms is somewhat positive; therefore, investors have paid more attention to green stocks during the pandemic. Notably, investor attention theory (Barber and Odean, 2008; Zhang and Wang, 2015) and the adaptive market hypothesis (Lo, 2005, 2012) support this reasoning. These two theories propose that investors are information-intensive and seem to pay more attention to event-related assets, adapting their investment strategies to new market patterns when unexpected events occur (Wan et al., 2021). Earlier studies (Gupta et al., 2021; Bouri et al., 2021a, 2021b) also find that investor attention plays a key role in making investment decisions during the pandemic. Overall, the adverse effect of the COVID-19 pandemic has shifted public attention towards the potential for green recovery; thus, green equity has received considerable attention from socially responsible investors.[1] This discussion leads to the formulation of the following hypothesis.

H1. Infectious disease-induced uncertainty increases (decreases) the volatility of dirty (green) assets.

Testing this hypothesis has key implications for investors and policymakers. For instance, if our empirical findings support this hypothesis, it indicates the probability of green recovery during the post-pandemic period as clean energy assets receive significant attention from investors. Policymakers, by contrast, could use the results to develop appropriate strategies for the global renewable energy market. If the sample countries or regions react differently to various uncertainty measures, country-specific policies should be adopted. If the responses do not differ significantly, governments and policymakers should introduce unified policies to address the adverse effects of these uncertainties on the clean energy sector.

Overall, our study extends the existing literature in several ways. First, we measured the effects of contagious viruses using the infectious disease-related uncertainty index (EMVID) recently developed by Baker et al. (2020a, 2020b). This newspaper-based equity market volatility tracker is particularly of interest as it is constructed using keywords such as economic, economy, financial, stock market, equity, equities, Standard and Poors, volatility, volatile, uncertain, uncertainty, risk, risky, epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1 and H1N1. However, although several studies argue that the EMVID contains predictive content for financial market uncertainty (Wang et al., 2021; Bouri et al., 2021a, 2021b; Gupta et al., 2021; Karamti and Belhassine, 2021), empirical evidence on the ability of this index to forecast the realized volatility of energy sector asset classes is lacking. This is quite surprising, given that global crude oil markets have performed aberrantly following the COVID-19 outbreak, which might be reflected in the stock prices of energy companies. Our study aimed to fill this gap in the literature. Second, we compared the effects of EMVID across diverse energy sector asset classes. In particular, we investigated whether it exerts similar effects on clean and dirty energy investments. Given that these two types of energy sector assets act as substitutes, news or events that influence dirty energy assets have associated shocks that may also be transmitted to clean energy assets (Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012a; Sadorsky, 2012b; Managi and Okimoto, 2013; Kocaarslan and Soytas, 2019; Saeed et al., 2020). Hence, our investigation has important implications for socially responsible investors who intend to maintain low-carbon portfolios. Therefore, this strand of research is essential for achieving the sustainable development goals. Third, we examined whether EMVID affects clean energy investments globally or in specific regions. To serve this purpose, our sample comprises clean energy stocks from several countries including the United States, the European Union (EU), China, and Japan. We chose these countries because they are among the leading economies. Over the last decade, renewable energy investments have increased substantially in these regions. This strand of research provides crucial information for market participants when developing appropriate hedging strategies during pandemics. Fourth, we explore whether the effect of the EMVID index on the volatility of energy-sector asset returns differs from that of other important uncertainty measures, including the OVX, GPR, and EPU. Several studies have documented significant linkages between these indicators and energy sector asset classes (Ahmad et al., 2018; Pham, 2019; Dutta et al., 2020a; Yang et al., 2021; Saeed et al., 2020). Hence, our objective is to examine whether the effect of infectious-disease-related risk on the energy sector asset class is greater than that of these key uncertainty measures. Doing so would confirm the robustness of our findings. In addition, such analyses are crucial for more precisely predicting the volatility of both green and dirty assets.

Methodologically, we apply the GARCH-MIDAS process and extend it by inserting the EMVID index as the main explanatory variable. Our in-sample estimation shows that the R^2 value increases substantially once the baseline GARCH-MIDAS process is adjusted to include EMVID information content. We also find that the uncertainty associated with infectious diseases has a significant positive (negative) effect on the realized volatility (RV) of dirty (green) assets and that the GARCH-MIDAS-EMVID specification outperforms other approaches across assets and geographical regions. Furthermore, the out-of-sample analysis reveals that EMVID has significant predictive content for the volatility of these assets, which the OVX, GPR, and EPU do not. These results offer important implications for energy market participants who wish to maintain an optimal portfolio of dirty and clean energy assets.

2. Review of literature

2.1. Impact of COVID-19 on energy investments

Following the effect of COVID-19 on the world economy, a strand of literature has examined how global energy markets reacted to the outbreak. For example, Atri et al. (2021) showed that news related to the COVID-19 pandemic caused a substantial drop in crude oil prices. Employing the log periodic power-law singularity process, Gharib et al.

[1] Note that infectious disease-induced risk may affect energy investments through financial market integration as well. For instance, recent studies (Zhang et al., 2020; Goodell, 2020) document that financial markets are severely affected by the COVID-19 pandemic and because of market integration, there is a risk spillover effect among the major financial sectors. Bouri et al. (2021a) also argue that COVID-19 has caused chaos in international financial markets, jeopardizing global financial stability. The authors further conclude that because of the high correlations among the financial assets, shocks emanating from COVID-19 transmit from one asset to another. A recent study by Chen et al. (2022a) shows that the outbreak exerts a substantial effect on crude oil and relevant commodity markets, which in turn influence the clean energy asset class, since all these markets are highly correlated.

(2021) document that the WTI and Brent markets experienced negative financial bubbles because of the pandemic. In addition, Chen et al. (2021) find that COVID-19 shocks negatively affect the equity prices of oil exploration and production companies. Using the computable general equilibrium model, Jia et al. (2021) document that the outbreak led to a declining demand for crude oil, which in turn reduced its prices sharply. Adedeji et al. (2021) also find that the COVID-19 pandemic has had an abrupt and unprecedented effect on world oil prices as WTI is traded at a negative price for the first time in oil market history. In addition, Le et al. (2021) demonstrate that the increasing number of cases of COVID-19 was responsible for the significant drop in WTI crude oil prices. Ahundjanov et al. (2021) also reached the same conclusion. Bourghelle et al. (2021) argue that COVID-19 generated both demand and supply shocks, which introduced a recession in international crude oil markets. A recent study by Wang et al. (2022) reveals that oil consumption rates in the United States during the pandemic were nearly 18 % lower than those during COVID-free periods. In addition, Z. Chen et al. (2022) and L. Chen et al. (2022) show that the outbreak increased the volatility of the Chinese crude oil futures market, which created anxiety among participants in commodity markets.

Numerous studies have examined the evolution of the relationship between crude oil and other financial markets during the pandemic. Important contributions include Sharif et al. (2020), Dutta et al. (2020a), Mensi et al. (2021), Francisco Jareño et al. (2021), Hung (2021), Dutta et al. (2021), Hammoudeh et al. (2021), Zhu et al. (2021), Heinlein et al. (2021), Zhang and Hamori (2021), Cao and Cheng (2021), Abduzayed and Al-Fayoumi (2021) and others. Sharif et al. (2020), for instance, find that the oil slump had a robust effect on US stock markets during the COVID-19 outbreak. Francisco Jareño et al. (2021) show that the link between the oil and cryptocurrency markets appears to be stronger during the turbulent period than during the pre-COVID era. Additionally, Cao and Cheng (2021) find that the oil market was significantly affected by corn price volatility during the COVID-19 pandemic. Applying causality in the mean and in-variance models, Hammoudeh et al. (2021) document an insignificant association between the oil and clean energy stock markets. A recent study by Dutta et al. (2021) shows that climate bonds have nearly zero correlation with the WTI oil index, implying that green bonds can hedge oil market risk during health crisis periods. Zhang and Hamori (2021) report that the effect of coronavirus on the relationship between oil and stock markets remains uncertain in both the short and long run.

2.2. Literature on the EMVID index

A number of recent studies have used the information on EMVID index to investigate the impact of infectious-disease induced uncertainty on the return and volatility of various financial markets. Bouri et al. (2021a, 2021b), for instance, employ the heterogeneous autoregressive realized variance (HAR-RV) process to forecast the volatility of gold returns. The study reports that the EMVID index plays a crucial role in predicting the short- and long-term volatility of this precious metal amid the pandemic periods. In addition, Gupta et al. (2021) explore the effects of EMVID on the level, slope and curvature factors derived from the term structure of interest rates of the US covering maturities from 1 year to 30 years. Applying a multivariate DCC-GARCH model, the authors find significant predictability of the three latent factors from the EMVID index at each point of the entire sample, and show the presence of instantaneous spillover from uncertainty to level, slope and curvature. Employing a series of univariate GARCH models, Wang et al. (2022) inspect the impact of EMVID on the risk levels of Bitcoin market and provide evidence that the volatility of this leading cryptocurrency increases during the pandemic time. Additionally, Akyildirim et al. (2022) examine whether the time-varying linkage between various agricultural commodity futures markets and the corresponding sentiment indices is influenced by EMVID during the pandemic times. The study finds that the effect of COVID-19, measured by EMVID, appears to be significant around the first cycle of the pandemic in 2020. Moreover, Chen et al. (2022b) examine the impact of various commodities and infectious disease-induced uncertainties on the US and Chinese equity markets. The authors show that although the EMVID index does not affect the financial markets of these two leading economies before the COVID-19 outbreak, such effects become highly significant when the pandemic hits in 2020. In addition, Karamti and Belhassine (2021) consider the application of a wavelet approach in order to explore the time-frequency connectedness between the COVID-19 outbreak and the major financial markets. The wavelet coherency analysis finds strong evidence of contagion effects between EMVID index and various assets including stocks, commodities, cryptocurrencies etc. during the first and second waves of the pandemic. Hasan (2022) also concludes that the uncertainties linked to COVID-19 pandemic, which are measured by EMVID and other news-based indexes, exert a significant negative impact on the US equity market returns. More recently, Lesame et al. (2024) examine whether investors in international real estate investment trusts (REITs) markets reveal herding behavior due to the uncertainty caused by the global health crisis in early 2020. In doing so, the authors estimate the cross-sectional absolute deviation (CSAD) measure and find that both the static and time-varying results support the herding in international REITs amid the COVID-19 pandemic. The findings further suggest that the impact of EMVID on herding is asymmetric.

Unlike the existing literature, this study investigates how the volatility of green and dirty assets respond to the infectious disease-induced uncertainty. Doing so is crucial given that the estimates of such effects help us understand if the transition to a green economy will remain a priority amid the post-pandemic period.

In addition, the cross-country comparative studies are also important given that the clean energy firms operating in USA, Europe and Asia do not have the same level of technological innovations.[2] Besides, the degree of government support policies also differs from one country to another. For instance, contrary to the European policies supporting the clean energy deployment, which begin in 1997 (Jo et al., 2016), and China's clean energy policies since 2005 (Liu et al., 2021), policy support in USA has been relatively weak (Usman et al., 2020). Therefore, the findings of such cross-border analyses would shed further light on whether investing in the clean energy sector has received considerable attention globally following the COVID-19 pandemic regardless of this heterogeneity of government support policies.

3. Data

Our data include daily observations of stock indices and monthly observations of uncertainty indicators. Although we use clean energy stock prices at the country level, the iShares Global Energy ETF (IXC) is employed to represent dirty assets. The IXC tracks the investment results of an index comprising global equities in the oil and gas sectors. Our sample period spans June 2017 to October 2022, and the beginning of this period relies on renewable energy equity prices. Information on the IXC index and country-level renewable energy stock prices were collected from the Bloomberg Terminal.

Next, we obtained information on the EMVID index from http://policyuncertainty.com/infectious_EMV.html. Note that EMVID is a newspaper-based index which tracks the equity market volatility (EMV) owing to infectious diseases. To construct this index, Baker et al. (2020a, 2020b) first specified four sets of terms namely, E: economic, economy,

[2] Based on the Bloomberg database, the total R&D investment of Chinese clean energy enterprises is 5 times higher than that of USA with the number of patents being 24 times that of USA. In addition, the total R&D investment of European clean energy enterprises is 2 times higher than that of USA with the number of patents being 4 times that of USA. Qiao et al. (2023) also argue that USA has lagged-behind across all the renewable energy innovation indicators due to the lack of government support policies.

financial; M: "stock market," equity, equities, "Standard and Poors"; V: volatility, volatile, uncertain, uncertainty, risk, risky; ID: epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1. The authors then obtained daily counts of newspaper articles that contained at least one term in each of the sets across approximately 3000 US newspapers. The raw EMVID counts were scaled by the count of all articles on the same day, and the authors then multiplicatively rescaled the resulting series to match the level of the VIX using the overall EMV index and scaling the EMVID index to reflect the ratio of the EMVID articles to the total EMV articles. Overall, EMVID considers the key role of public media and investor attention during the pandemic, making it a suitable proxy for pandemics (Wang et al., 2022; Lesame et al., 2024).

Regarding other uncertainty indices, the EPU and GPR indices are publicly available at https://www.policyuncertainty.com/. Notably, we used country-specific GPR indices for the United States, China, and Japan, whereas the global GPR index was used for the EU region. OVX data were obtained from the Chicago Board Options Exchange (CBOE).

Note that the renewable energy stock market data of the United States, the EU, China, and Japan were considered in our analysis because these countries/regions have emerged as leading economies of clean energy investments. For instance, China has currently the largest solar power capacity amounting to approximately 418-terawatt hours. Owing to its rapid industrial development, China's ecosystem has degraded markedly over the past few years. Thus, green financing has become increasingly popular. China has the largest green finance market worldwide, followed by the United States. Notably, the United States has also increased its investment in CCUS (carbon capture, utilization and storage) projects and is presently leading the way in CCUS investments (26 %), with Japan close behind at 14 % and the EU at 11 %. In recent years, unprecedented advances in CCUS technologies, which are crucial for meeting global climate targets, have been observed in these regions. Moreover, based on a recent report from the European Commission, the EU, the United States, and Japan have developed the highest number of climate-neutral solutions during the last decade. Altogether, the dynamics of clean energy assets in these countries/regions are worthy of investigation, given their significant investments in reaching net-zero goals.

Table 1 presents the summary statistics for the stock returns. We find that the IXC is more volatile than all clean energy stock indices, and that Chinese green equities have a higher standard deviation than other countries. Furthermore, the normality assumption was violated in each case, as suggested by the Jarque-Bera tests. In addition, the results of the different unit root tests (ADF and PP) indicate that all return indices are stationary.

Next, Fig. 2 presents the stock indices. This graph shows the effect of the COVID-19 pandemic on these assets. For instance, dirty stocks witnessed a significant drop during the COVID-19 period, whereas clean energy stocks grew after the COVID-19 outbreak. Fig. 3, which plots the EMVID index, shows that the infectious disease-induced risk increased substantially during the pandemic period.

4. Methodology

4.1. GARCH-MIDAS process

The GARCH-MIDAS approach, proposed by Engle et al. (2013), has received considerable attention in recent literature (Liu et al., 2019; Wang et al., 2020; Fang et al., 2020; Li et al., 2024) as employing this approach has several benefits. First, the GARCH-MIDAS process allows data sampled at different frequencies to be used in the same regression. Second, it appears in a distributed lag form, given that the dependent variable in one period is explained by more than one lag in the (higher frequency) independent variable. Third, it includes multiple regressors at different frequencies. Fourth, the GARCH-MIDAS process splits total volatility into short- and long-term components, which provides volatility forecasts superior to traditional GARCH models (Ghani et al., 2023). Finally, the recent literature demonstrates that considering exogenous variables in the long-term volatility component can significantly improve its predictive power (Ma et al., 2021). Hence, this model has emerged as an efficient econometric tool for handling mixed-frequency data directly, without frequency conversion. Therefore, this study applies the GARCH-MIDAS process to manage the data frequency mismatch between daily stock prices and monthly EMVID data.

Note that the main objective of this approach is to combine the GARCH model with the MIDAS process for introducing the short-term and long-term volatility components into the volatility equation of the traditional GARCH model. Thus, the conditional volatility has two components. The short-term volatility component follows the conventional GARCH process, whereas the MIDAS regression allows us to use the lower frequency data (e.g., monthly EMVID index and other uncertainty indicators in this case) to describe the long-term fluctuations in the volatility equation (Li et al., 2024). In sum, the short-term component accounts for daily fluctuations that are assumed short-lived, while the long-term component verifies if the uncertainty measures considered in our analysis exert a long-term impact on the stock market volatility.

Now, we define the GARCH-MIDAS process as follows:

$$R_{i,t} = \mu + \sqrt{g_{i,t}\tau_t}\epsilon_{i,t}, \tag{1}$$

where, $R_{i,t}$ refers to the logarithmic return on day i of period t (month) and μ indicates the daily expected return. In addition, $\epsilon_{i,t}|I_{i-1,t} \sim N(0,1)$ with $I_{i-1,t}$ representing the information setup to day $i-1$ of month t. Besides, $g_{i,t}$ and τ_t refer to short- and long-term volatility components, respectively. Hence, the total conditional variance (i.e., $\sigma^2_{i,t}$) is defined as

$$\sigma^2_{i,t} = g_{i,t}\tau_t \tag{2}$$

where $g_{i,t}$ is modeled as a mean-reverting asymmetric GARCH(1,1) process:

$$g_{i,t} = (1-\alpha-\beta-\gamma/2) + \left(\alpha+\gamma \bullet 1_{\{r_{i-1,t}-\mu<0\}}\right) \times \frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t} + \beta g_{i-1,t}, \tag{3}$$

with $\alpha, \beta > 0$ and $\alpha+\beta+\gamma/2 < 1$. If $\gamma \neq 0$, then asymmetry occurs.

Next, the long-term volatility component, τ_t, is given as

Table 1
Summary statistics.

	Global energy (IXC)	USA	EU	Japan	China
Mean	0.0002	0.0005	0.0005	0.0004	0.0006
Std. dev.	0.0202	0.0124	0.0111	0.0136	0.0172
Skewness	−1.2551	−0.3871	−0.1676	−0.2855	−0.2558
Kurtosis	22.63	7.26	4.48	5.408	4.906
Jarque-Bera	22,253.25	245.33	223.89	336.89***	229.02***
ADF	−11.88***	−23.51***	−35.90***	−35.43***	−37.55***
PP	−38.06***	−36.89***	−35.92***	−35.44***	−37.54***

*** Statistical significance at 1 % level.

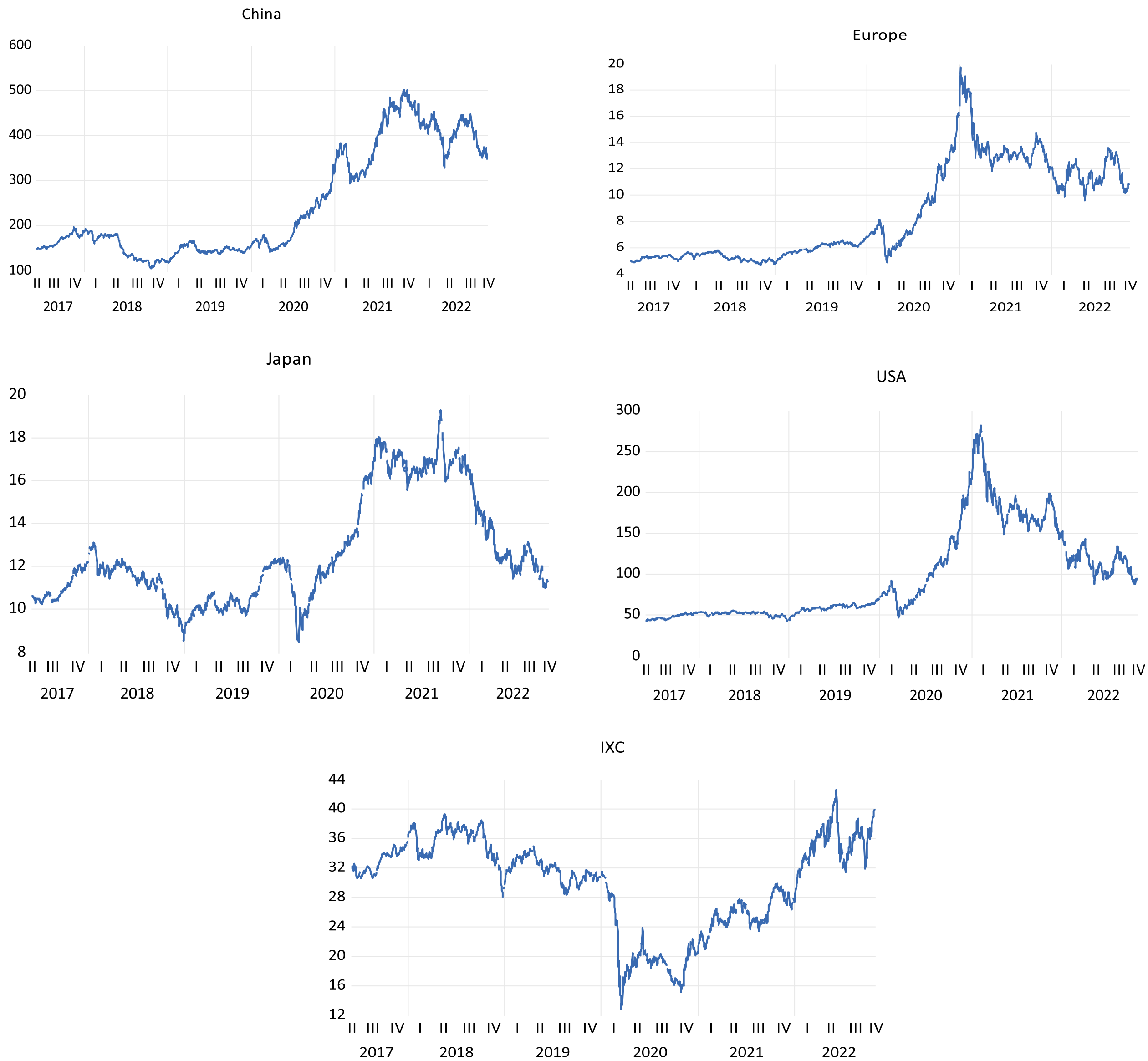

Fig. 2. Time series plots of the stock indexes.

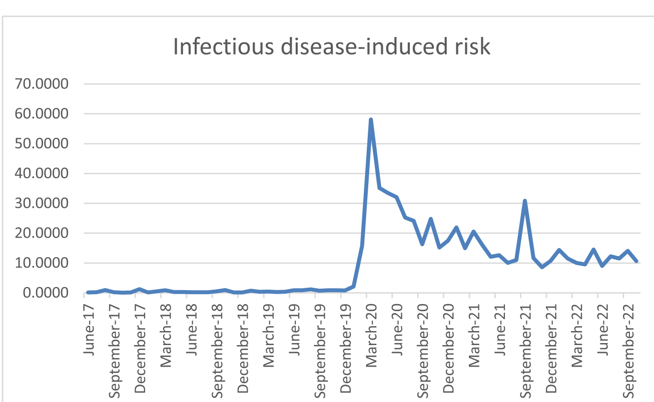

Fig. 3. Time series plot of EMVID index.

$$log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) EMVID_{t-k}, \tag{4}$$

where K is the number of periods over which volatility is smoothed. We replace EMVID with EPU, GPR, and OVX to examine the effects of these uncertainty indicators on the long-term volatilities of different assets. Finally, $\varphi_k(\omega_1, \omega_2)$ refers to the Beta weighting function defined as:

$$\varphi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1 - 1} \bullet (1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K} (j/K)^{\omega_1 - 1} . (1 - j/K)^{\omega_2 - 1}} \tag{5}$$

Note that $\varphi_k(\omega_1, \omega_2) \geq 0, k = 1, 2, \cdots K$. In line with Fang et al. (2018), we set $\omega_1 = 1$, implying that the weight decreases monotonically. Although Engle et al. (2013) propose both beta-and exponentially weighted lag structures, Ghysels et al. (2007) show that the beta polynomial is more flexible and is employed more frequently to accommodate various lag structures. Therefore, we use a beta-weighting function in our analysis.

4.2. Forecast evaluation

To compare the out-of-sample forecasting performance of the different models, we evaluated the heteroskedasticity-adjusted root mean square error (HRMSE) proposed by Bollerslev and Ghysels (1996). This statistic is defined as

$$HRMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{RV_t - \widehat{RV_t}}{RV_t}\right)^2} \tag{6}$$

where T indicates the number of observations to be forecasted, and RV_t and $\widehat{RV_t}$ specify the actual and estimated volatility for day t, respectively.

Additionally, we employed the Diebold and Mariano (1995) (DM) test to examine the null hypothesis of no difference in the accuracy associated with the different approaches. To do so, let $e_{it} = RV_t - \widehat{RV_t}$ $(i = 1, 2)$ denote the prediction errors. Now, suppose that $d_t = f(e_{1t}) - f(e_{2t})$. We then wish to test:

$$H_0 : E(d_t) = 0$$

DM (1995) computes the approximate asymptotic variance of $\overline{d}$ as follows:

$$Var(\overline{d}) \approx k^{-1}\left[\eta_0 + 2\sum_{l=1}^{p-1}\eta_l\right] \tag{7}$$

where η_l implies the l-th autocovariance of d_t estimated as:

$$\widehat{\eta} = k^{-1}\sum_{t=l+1}^{k}(d_t - \overline{d})(d_{t-l} - \overline{d}) \tag{8}$$

We then define the DM test statistic as:

$$\mathbf{DM} = \left(\widehat{\boldsymbol{Var}(\overline{\boldsymbol{d}})}\right)^{-\mathbf{1/2}}\overline{\boldsymbol{d}} \tag{9}$$

Assuming that $\boldsymbol{H_0}$ is true, the DM statistic is normally (asymptotically) distributed.

It is worth mentioning that we use the range-based volatility measure, proposed by Parkinson (1980), for computing the RV for different stock indexes. This estimator is given as

$$RV_t = \frac{1}{4ln2}(lnH_t - lnL_t)^2 \tag{10}$$

where H_t and L_t refer to the highest and lowest prices on trading day t.

5. Findings

5.1. Estimates of GARCH-MIDAS models

Tables 2–5 demonstrate the results of our GARCH-MIDAS specifications. In Table 2, we estimate the effect of infectious-disease-induced risks on different asset classes. In Tables 3–5, we do the same for the OVX, GPR, and EPU indices. As discussed earlier, our objective was to compare the forecast power of the EMVID index with other key uncertainty measures for both clean and dirty energy investments. In addition, our results focus on country-level data to examine whether EMVID affects clean energy investments globally or in specific regions.

The outcomes in Table 2 indicate that the coefficients of the GARCH-MIDAS models appear to be significant for each asset under investigation. Thus, the process adopted fits the equity returns and can be used to predict the volatility of the assets under study. The asymmetry parameter γ has a significant negative influence on the return volatility. Therefore, bad news would have a bigger short-term effect on the volatility levels than good news would. We also document a high degree of volatility persistence in these markets, given the high values of the GARCH parameters.

We now focus on the parameter θ, which measures the long-term effects of EMVID. The results show that θ is significant for both clean and dirty energy investments implying that infectious disease-induced risk exerts a long-term effect on the volatility levels of these assets. One interesting finding is that the long-term effect is negative for clean energy stock indices and positive for dirty assets. This finding indicates that an increase in the risk of infectious diseases leads to a decline in the volatility of clean energy investments, thereby supporting our hypothesis.

One would expect that the outbreak of novel viruses (e.g., COVID-19) would exert a substantial effect on several important industries, including the automotive, aviation, high-tech, retail, travel, and tourism sectors, which might cause enormous disruption to the international business front. In particular, the need for medical isolation and travel bans substantially influences traditional energy markets. For instance, the international oil markets witnessed a significant downturn following the COVID-19 pandemic (Dutta et al., 2020b). Thus, we conclude that an upsurge in the EMVID index encourages participants in traditional energy markets to shift towards sustainable investment. Consequently, the risk associated with clean (dirty) energy investments tends to decrease (increase).

Furthermore, among the countries studied, the Chinese clean energy stock market appears to be more sensitive to changes in the EMVID index. This result could be attributed to China being significantly invested in renewables in recent years and its clean energy market is therefore more volatile than the US, EU, and Japanese markets amid health crises.

Note that while a number of recent studies have investigated whether the EMVID index has predictive contents for various financial and commodity markets, our findings differ from those in several aspects. Firstly, earlier literature finds that EMVID exerts a positive effect on the volatility levels of different asset classes, implying that investing in these assets might be risky following the pandemic. Bouri et al. (2021a, 2021b), for instance, show that the volatility of gold prices reacts positively to EMVID and thereby, increases following the outbreak of COVID-19. Wang et al. (2022) also report a similar result for the Bitcoin market. In addition, Chen et al. (2022b) show that although the EMVID index does not affect the Chinese and US equity markets before the COVID-19 outbreak, these assets become highly volatile when the pandemic hits in 2020. Hasan (2022) also documents that an increase in the EMVID index leads to an upsurge in the US stock market volatility. In sum, all these papers report a positive association between EMVID and the volatility of different asset classes, whereas the present study finds that the volatility of clean energy assets reacts negatively to this uncertainty index. Hence, unlike the other asset classes, the volatility of green equites decreases during the pandemic time. This result simply indicates that the pandemic has shifted investors' attention towards green investments. Such reactions to the global health crisis also suggest the possibility of a green recovery. This is a novel finding given that although the outbreak of COVID-19 leads to a global economic crisis, the demand for clean energy grows. In summary, we find that clean energy assets receive considerable attention from the international investors during the COVID-19 crisis, which indicates that the transition to a green economy still remains a priority. This piece of information will certainly create more attention towards green investments during the post-pandemic period. Secondly, we show that while there exist significant differences in government support policies and the level of renewable energy deployment in USA, Europe, China and Japan, the EMVID index exerts similar effects on the volatility of green assets in these regions. Hence, irrespective of this heterogeneity of government support, we observe uniformity in the response to the infectious disease-induced uncertainties.[3] This finding implies that the outbreak of COVID-19 has drawn increased global attention towards sustainable investments. In sum, our study extends the prior literature by documenting several new findings, which have not been reported in earlier works. These results

[3] In Appendix A, we report the result of a statistical test which confirms that the effects of EMVID on the country-level clean energy assets do not vary.

Table 2
Impact of EMVID.

Index →	IXC	USA	EU	Japan	China
μ	0.0001	0.0008	0.0002	0.0005	0.0009***
α	0.1501***	0.1098***	0.1060***	0.0941***	0.0751***
β	0.7198***	0.8557***	0.8201***	0.8397***	0.8984***
ω	0.0003***	0.0004***	0.0003***	0.0005***	0.0001***
γ	−0.0845***	−0.0557***	−0.0332**	−0.1001***	−0.0404***
θ	0.0068**	−0.0087**	−0.0091***	−0.0098**	−0.0119**
m	0.3174***	0.3349***	0.2279***	0.2976***	0.2457***
Log-likelihood	3345.15	3676.98	3777.56	3877.11	3676.71

Notes: This table presents the effects of EMVID index on green and dirty investments. IXC refers to the iShares global energy ETF renewable energy ETF, representing the dirty asset. The remaining columns indicate the clean energy stocks from different countries. θ measures the effect of EMVID.
*** Statistical significance at 1 % level.
** Statistical significance at 5 % level.

Table 3
Impact of OVX.

Index →	IXC	USA	EU	Japan	China
μ	0.0004	0.0007	0.0002	0.0006	0.0008**
α	0.1296***	0.1109***	0.1049***	0.0640***	0.0713***
β	0.7701***	0.8472***	0.7923***	0.8738***	0.9035***
ω	0.0001***	0.0004***	0.0003***	0.0006***	0.0001***
γ	−0.0819***	−0.0542***	−0.0334**	−0.0991***	−0.0384***
θ	0.0076**	−0.0032**	−0.0038***	−0.0209**	−0.0238**
m	0.3001***	0.3349***	0.2306***	0.2878***	0.2543***
Log-likelihood	3385.81	3661.72	3760.85	3822.02	3630.54

Notes: This table presents the effects of OVX index on green and dirty investments. IXC refers to the iShares global energy ETF renewable energy ETF, representing the dirty asset. The remaining columns indicate the clean energy stocks from different countries. θ measures the effect of OVX.
*** Statistical significance at 1 % level.
** Statistical significance at 5 % level.

Table 4
Impact of GPR.

Index →	IXC	USA	EU	Japan	China
μ	0.0006	0.0008	0.0002	0.0006	0.0009**
α	0.1332***	0.1126***	0.0741***	0.994***	0.0732***
β	0.7607***	0.8491***	0.8891***	0.8335***	0.8819***
ω	0.0003***	0.0001***	0.0003***	0.0007***	0.0001***
γ	−0.0789***	−0.0493***	−0.0299**	−0.1009***	−0.0391***
θ	0.0064**	−0.0087**	−0.0081***	−0.0090**	−0.0097**
m	0.3128***	0.3349***	0.2456***	0.2791***	0.2333***
Log-likelihood	3321.26	3608.42	3736.64	3818.84	3602.56

Notes: This table presents the effects of GPR index on green and dirty investments. IXC refers to the iShares global energy ETF renewable energy ETF, representing the dirty asset. The remaining columns indicate the clean energy stocks from different countries. θ measures the effect of GPR.
*** Statistical significance at 1 % level.
** Statistical significance at 5 % level.

Table 5
Impact of EPU.

Index →	IXC	USA	EU	Japan	China
μ	0.0005	0.0007	0.0004	0.0004	0.0008***
α	0.1248***	0.1151***	0.0662***	0.1000***	0.0746***
β	0.8105***	0.8349***	0.8897***	0.7619***	0.8790***
ω	0.0004***	0.0003***	0.0002***	0.0006***	0.0002***
γ	−0.0802***	−0.0501***	−0.0330**	−0.1016***	−0.0396***
θ	0.0061**	−0.0087**	−0.0080***	−0.0088**	−0.0095**
m	0.3024***	0.3349***	0.1990***	0.2385***	0.2181***
Log-likelihood	3318.04	3601.65	3711.54	3791.22	3579.09

Notes: This table presents the effects of EPU index on green and dirty investments. IXC refers to the iShares global energy ETF renewable energy ETF, representing the dirty asset. The remaining columns indicate the clean energy stocks from different countries. θ measures the effect of EPU.
*** Statistical significance at 1 % level.
** Statistical significance at 5 % level.

could open a new avenue of research as they offer key implications to both policymakers and socially responsible investors.

Next, Tables 3–5 also document several notable findings. In Table 3, for instance, crude oil volatility is found to have a positive effect on the volatility of renewable energy stocks. This outcome is in line with the prior literature arguing that as traditional and renewable energies are substitutes, higher crude oil volatility causes an increase in the risk levels of renewable energy stocks (see Dutta, 2017, 2019; Ahmad, 2017; Ahmad et al., 2018; Xia et al., 2019; Pham, 2019; Uddin et al., 2019; Dutta et al., 2020b, 2020c, 2021; Dawar et al., 2021; Yahya et al., 2021). Next, our analysis reports a robust connection between geopolitical uncertainty and the risk linked to green and dirty assets. This finding is consistent with that of Yang et al. (2021) and Dutta and Dutta (2022). For example, Dutta and Dutta (2022) claim that as shifting towards alternative energy promotes better energy self-sufficiency and curtails geopolitical conflicts, rising geopolitical uncertainty would boost market participants to invest in renewable energy sectors.

Our results demonstrate that both clean and dirty energy investments are sensitive to economic policy uncertainties. Several studies (Aysan et al., 2019; Lee, 2019; Park and Park, 2019) argue that rising EPU causes immediate disturbances in financial markets such as equities and commodities. Given that clean and dirty assets are significantly connected to these financial markets, they are influenced by the rise and fall in the EPU index. Notably, we document similar findings for all countries under investigation. Hence, it appears that clean energy assets in all these countries share common features.

Next, we assess whether the EMVID index exerts a greater effect on the volatility of clean and dirty asset returns than the OVX, GPR, or EPU indices. We report the R^2 statistics provided by the in-sample Mincer–Zarnowitz (1969) MZ regression approach in Table 6. These numbers reveal that the GARCH-MIDAS-EMVID specification outperforms other approaches across assets and geographical regions.

Given that precise knowledge of the time-dependent association between infectious-disease-induced uncertainties and the volatility of green (dirty) assets is vital for diversifying portfolio risk during pandemic periods, our findings have key implications for ethical investors and policymakers. In particular, this strand of research would be useful for eco-friendly investors who aim to hedge against infectious-disease-induced risk to form risk-adjusted portfolios. For policymakers, conversely, it is important to understand the importance of developing efficient carbon markets in Asian countries, as our results suggest that the Chinese and Japanese stock indices are highly sensitive to oil price risk. The inception of unified and efficient carbon markets would reduce the dependence on crude oil and promote clean energy.

5.2. Out-of-sample volatility forecasts

Table 7 presents the out-of-sample forecast results based on the HMSE statistics and DM tests. The in-sample estimation period is from June 2017 to December 2020, whereas the out-of-sample data span January 2021 to October 2022. Our analysis indicates that for both green and dirty investments, the GARCH-MIDAS-EMVID specification produces the lowest HRMSE statistics. For example, when examining the results for the Japanese clean energy equity index, the HRMSE statistics

Table 6
In-sample R^2 statistics from MZ regressions.

Models	IXC	USA	EU	Japan	China
GARCH-MIDAS	0.18	0.16	0.15	0.15	0.16
GARCH-MIDAS-OVX	0.23	0.22	0.22	0.21	0.24
GARCH-MIDAS-GPR	0.21	0.20	0.19	0.17	0.23
GARCH-MIDAS-EPU	0.21	0.19	0.19	0.18	0.20
GARCH-MIDAS-EMVID	0.25	0.23	0.24	0.22	0.25

Notes: This table presents the R^2 statistics obtained from the in-sample MZ regression approach.

are 0.000171, 0.000129, 0.000132, 0.000134, and 0.000122 for the GARCH-MIDAS, GARCH-MIDAS-OVX, GARCH-GPR, GARCH-MIDAS-EPU, and GARCH-MIDAS-EMVID models, respectively. The DM test results further confirm the superiority of the GARCH-MIDAS-EMVID model by rejecting the null hypothesis of equal forecast accuracy.

Thus, our findings suggest that the EMVID index offers additional information not contained in the OVX, GPR, and EPU indices. In summary, the out-of-sample forecast analysis suggests that using the information on infectious-disease-induced uncertainty increases the precision of the GARCH-MIDAS model.

6. Discussion

The empirical literature on energy market investments has expanded extensively over the past few years. In particular, the drivers of clean energy asset volatility have received enormous academic attention. To this end, the literature identifies different uncertainty measures that significantly affect the volatility levels of renewable energy equity markets. For instance, several studies (Dutta, 2017; Ahmad et al., 2018; Pham, 2019; Dutta et al., 2020a; Dutta et al., 2020b; Saeed et al., 2020) document that oil price uncertainty, as measured by the OVX, appears to be a key driver of green stock volatility. More importantly, these studies show that the volatility of green stocks is more sensitive to the OVX than oil price shocks, demonstrating the role of oil market uncertainty in understanding the risk linked to green investments. This finding is not unexpected, as increasing oil market uncertainty encourages investors and policymakers to shift towards new energy investments, thereby driving the volatility of green assets. Another strand of research reveals that the volatility of green stocks is highly susceptible to geopolitical risk (GPR). Recent contributions include those by Yang et al. (2021), Dutta and Dutta (2022), and Coskun et al. (2023). These authors claim that increasing geopolitical uncertainty tends to affect green asset volatility through investor sentiment. Additionally, EPU has emerged as a major driver of green investment. For instance, Cui et al. (2023) argue that variations in EPU may give rise to policy uncertainty for clean energy investments, which would cause energy companies to curtail their investments in producing alternative energies. This could make the green sector highly volatile.

Unlike the aforementioned studies, we find that inserting the EMVID index into the GARCH-MIDAS process produces better volatility predictions than other uncertainty measures, including OVX, GPR, and EPU. Hence, the findings of our analysis are novel because we show that the EMVID index provides additional information that is not contained in the OVX, GPR, or EPU indices. The finding that the EMVID information content outperforms that of the OVX merits further explanation because numerous studies have documented that the OVX is the main driver of green asset volatility (Saeed et al., 2020; Dutta and Dutta, 2022). One plausible explanation lies in the choice of the sample period. Specifically, the out-of-sample forecast period covers the pandemic period, during which EMVID seems to explain the variation in green stocks better than the OVX. Unlike EMVID, the OVX disregards the key role of investor attention, which plays a pivotal role in investment decisions during a pandemic (Bouri et al., 2021a; Wan et al., 2021). Hence, the EMVID index appears to have more predictive value than the OVX during the sample period.

These findings have practical implications for socially responsible investors, policymakers, and researchers. For instance, our analysis documents that geopolitical uncertainty affects the clean energy business in both advanced (e.g., the US) and emerging economies (e.g., China). Thus, we witness more deviations towards global clean energy deployment with a rise in geopolitical risk. Hence, growing uncertainty owing to geopolitics encourages the future evolution of green innovation, thereby reducing the need for fossil fuels. Therefore, geopolitical conflicts tend to decrease the adverse effects of fossil fuels on the global environment as well as the different economic activities. The shift towards green energy owing to geopolitical uncertainty also stimulates

Table 7
HRMSE statistics and DM test results.

Models ↓	IXC		USA		EU		Japan		China	
	HRMSE	DM	HRMSE	DM	HRMSE	DM	HRMSE	DM	HRMSE	DM
GARCH-MIDAS	0.000143	6.98***	0.000168	6.14***	0.000162	6.81***	0.000171	7.19***	0.000170	7.23***
GARCH-MIDAS-OVX	0.000102	2.13**	0.000121	2.18**	0.000122	2.19**	0.000129	2.26**	0.000127	2.28**
GARCH-MIDAS-GPR	0.000110	3.01***	0.000128	3.08***	0.000124	2.97***	0.000132	3.16***	0.000131	3.08***
GARCH-MIDAS-EPU	0.000109	2.99***	0.000129	3.11***	0.000123	2.95***	0.000134	3.31***	0.000130	3.02***
GARCH-MIDAS-EMVID	0.000098		0.000116		0.000117		0.000122		0.000121	

Notes: This Table reports the HRMSE statistics and DM test results. The true realized volatility is proxied by the range-based measure proposed by Parkinson (1980). The in-sample data range from June 2017 to December 2020, while the out-of-sample data span from January 2021 to October 2022.
*** Statistical significance at 1 % level.
** Statistical significance at 5 % level.

different economies to become self-reliant. For example, Saudi Arabia and the United Arab Emirates recently launched nuclear energy technologies that generate electricity and produce desalination, leading to greater energy self-sufficiency (Sweidan, 2021). Thus, eco-friendly investors and policymakers should pay more attention to important geopolitical events (e.g., the Russian invasion of Ukraine or the Israeli–Palestinian conflict) to gain proper knowledge of clean energy deployment.

Moreover, our analysis indicates that crude oil volatility plays a pivotal role in energy investment. Specifically, we find that rising oil market uncertainty encourages governments to invest more in green innovation. It is also worth noting that geopolitical risk affects the clean energy sector by creating chaos in crude oil markets (Qian et al., 2022). For instance, China is investing significantly in purchasing cheap oil from Russia amid the ongoing Russo-Ukrainian war, which has cut its investments in green innovation.[4] Overall, investors and policymakers should observe the effect of geopolitical oil price risk on green investments closely. Otherwise, the energy transition process would be sluggish, which would increase the opposing effects of environmental change.

Finally, investigating how dirty and green stocks react to the EMVID index is timely, and has key implications. For instance, the finding that infectious disease-related uncertainty increases (decreases) the volatility of dirty (green) assets suggests that the pandemic has shifted investors' attention towards sustainable investments. Such positive reactions to the global health crisis indicate the possibility of a green recovery. Our findings are thus important for global renewable energy planning. Given that all sample countries or regions react similarly to various uncertainty measures, governments and policymakers should develop unique policies to deal with the adverse effects of such uncertainties on the clean energy sector.

6.1. *Robustness check*

In our earlier analysis, we used Parkinson's range-based volatility measure to evaluate the actual volatility of both green and dirty assets. For the robustness check, we now use the volatility measure proposed by Rogers and Satchell (1991), which is given as:

$$RV_t = ln\left(\frac{H_t}{O_t}\right)ln\left(\frac{H_t}{C_t}\right) + ln\left(\frac{L_t}{O_t}\right)ln\left(\frac{L_t}{C_t}\right) \tag{11}$$

with O_t and C_t implying the opening and closing prices on trading day t. The benefit of this estimator is that it uses opening and closing prices, in addition to high and low prices, to capture jumps during non-trading times.

Table 8 displays the findings of our robustness test based on the RV measure of Rogers and Satchell (1991) and shows the R^2 (%) statistics provided by the MZ regression models. These results are consistent with those reported in Table 6 confirming that the GARCH-MIDAS-EMVID specification outperforms other approaches irrespective of the asset classes and geographical regions. For instance, when considering the Chinese renewable energy equity index, the R^2 statistics are equal to 0.14, 0.20, 0.15, 0.17 and 0.22 for the GARCH-MIDAS, GARCH-MIDAS-OVX, GARCH-MIDAS-GPR, GARCH-MIDAS-EPU and GARCH-MIDAS-EMVID models, respectively.

Table 8
In-sample R^2 statistics from MZ regressions based on the Rogers and Satchell RV measure.

Models	IXC	USA	EU	Japan	China
GARCH-MIDAS	0.17	0.12	0.17	0.16	0.14
GARCH-MIDAS-OVX	0.25	0.19	0.21	0.22	0.20
GARCH-MIDAS-GPR	0.22	0.16	0.18	0.19	0.15
GARCH-MIDAS-EPU	0.23	0.16	0.20	0.17	0.17
GARCH-MIDAS-EMVID	0.28	0.21	0.23	0.23	0.22

Notes: This table presents the R^2 statistics obtained from the in-sample MZ regression approach based on the Rogers and Satchell RV measure.

Next, Table 9 exhibits the out-of-sample forecast results based on the Rogers and Satchell (1991) RV measure. We found that the HMSE statistics and DM test results are also consistent with those reported in Table 7. In summary, inserting the EMVID index into the GARCH-MIDAS process produces better volatility predictions than other uncertainty measures.

7. Conclusions and policy implications

Following the outbreak of novel coronavirus, Numerous studies have assessed the effect on global financial markets. However, investigations into whether, and to what extent, dirty and clean energy asset classes are sensitive to contagious diseases are rare. This study aims to fill this gap in the literature. We measured the effects of contagious viruses using the recently introduced infectious disease-related uncertainty index (EMVID). Our data include the iShares Global Energy ETF and clean energy stock indices from leading economies such as the United States, the EU, Japan, and China. Employing the GARCH-MIDAS model, we find that the uncertainty associated with infectious diseases exerts significant effects on the realized volatility of both dirty and clean energy sector assets. We further document that EMVID has significant predictive content for the volatility of these assets, which is usually not contained in key uncertainty measures, including the OVX, GPR, and EPU. For example, when examining the results for the EU clean energy equity index, the HRMSE statistics, based on the Parkinson's (1980) realized volatility measure, are found to be 0.000162, 0.000122, 0.000124, 0.000123, and 0.000117 for the GARCH-MIDAS, GARCH-MIDAS-OVX, GARCH-GPR, GARCH-MIDAS-EPU, and GARCH-MIDAS-EMVID models, respectively. Hence, our analysis suggests that using the information on infectious-disease-induced uncertainty increases the precision of the GARCH-MIDAS model.

[4] In May 2023, China's oil imports from Russia hit an all-time high because of the discounted prices of Russian oil.

Table 9
HRMSE statistics and DM test results based on the Rogers and Satchell RV measure.

Models ↓	IXC		USA		EU		Japan		China	
	HRMSE	DM	HRMSE	DM	HRMSE	DM	HRMSE	DM	HRMSE	DM
GARCH-MIDAS	0.000129	6.01***	0.000161	5.78***	0.000158	6.04***	0.000166	7.32***	0.000171	7.04***
GARCH-MIDAS-OVX	0.000104	1.97**	0.000119	2.24**	0.000123	2.21**	0.000126	1.98**	0.000126	1.87*
GARCH-MIDAS-GPR	0.000112	3.09***	0.000126	2.81***	0.000126	2.89***	0.000133	3.18***	0.000129	2.76***
GARCH-MIDAS-EPU	0.000113	3.13***	0.000127	2.88***	0.000128	2.94***	0.000133	3.19***	0.000131	2.98***
GARCH-MIDAS-EMVID	0.000096		0.000111		0.000116		0.000119		0.000120	

Notes: This table reports the HRMSE statistics and DM test results. The true realized volatility is proxied by the range-based measure proposed by Rogers and Satchell (1991) RV measure. The in-sample data range from June 2017 to December 2020, while the out-of-sample data span from January 2021 to October 2022.
*** Statistical significance at 1 % level.
** Statistical significance at 5 % level.
* Statistical significance at 10 % level.

Given that proper investment decisions depend mainly on a precise estimate of the time-varying volatility of financial assets, our investigation offers key implications for energy market investors. For example, investors and policymakers may use our findings to identify the potential factors that influence the risk linked to dirty and clean energy asset classes. Because all uncertainty measures used in this study have significant effects on the assets under study, information on each of these indicators should receive careful attention from market participants. As our sample includes observations from the pandemic period (i.e., COVID-19), the EMVID index seems to have emerged as the most important factor. However, one exception is that dirty assets appear to be more sensitive to the OVX than to the EMVID, EPU, and GPR. The results reveal that crude oil volatility remains the major determinant of the risk levels for traditional energy stocks. This finding is useful for energy market participants in making appropriate asset allocation decisions during a pandemic.

Moreover, while looking at the effect of EMVID across the countries, we notice that Chinese stocks are more sensitive to infectious disease-induced uncertainty than those in other countries. Specifically, the estimates of the effects of EMVID are found to be −0.0087, −0.0091, −0.0098 and − 0.0119 for USA, EU, Japan and China, respectively. In addition, both Japan and China are heavily influenced by changes in the OVX. To alleviate the adverse effects of oil price volatility, governments in these Asian countries should take major steps such as increasing oil reserves and elevating carbon taxes. Moreover, the development of a carbon allowance market is necessary to moderate crude oil use and promote clean energy investments in South and East Asian states. Hence, it is important for policymakers to develop a unified, efficient, regulated, and supervised emission trading scheme that is obligatory for clean energy development. Governments in both developed and developing economies should support clean energy deployment by providing incentives, subsidies, and endowments. Doing so promotes green financing, which is crucial for avoiding the opposing effects of various uncertainties on sustainable investments. Promoting green financing also leads to greater energy self-sufficiency, thus decreasing the influence of geopolitical oil price risk on clean energy development. Such technological innovations are key to achieving climate neutrality and contribute to both industrial development and environmental sustainability.

This study has some limitations. For instance, we estimate the true volatility of dirty and green assets using range-based volatility measures, although the realized variance computed from intraday trading data provides a more efficient estimate of true volatility. Because of the lack of high-frequency data, we could not compute the realized variance from intraday returns. Given that modelling volatility plays a key role in risk management and portfolio optimization, precise estimates of actual volatility are of utmost importance to market participants. Future studies should consider using intraday data to obtain superior volatility forecasts. Furthermore, investigating how infectious disease-induced uncertainty affects the time-varying correlations between the energy sector and other asset classes is crucial for making appropriate asset allocation decisions. This exercise is left for future research.

CRediT authorship contribution statement

Anupam Dutta: Writing – original draft, Validation, Formal analysis, Conceptualization. **Donghyun Park:** Writing – review & editing, Writing – original draft, Project administration, Formal analysis. **Gazi Salah Uddin:** Writing – review & editing, Writing – original draft, Supervision, Formal analysis. **Kakali Kanjilal:** Writing – review & editing, Writing – original draft, Supervision. **Sajal Ghosh:** Writing – review & editing, Writing – original draft, Supervision.

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.

Appendix A

Table A1
Comparing the effects of EMVID across country-level clean energy assets.

Pair →	USA-EU	USA-China	USA-Japan	EU-China	EU-Japan	China-Japan
p-Values	0.131	0.229	0.148	0.542	0.337	0.501

Notes: This table shows the *p*-values of the test for comparing the effects of EMVID across country-level clean energy assets. The *t*-statistic for testing of equality is given by $t = \dfrac{\widehat{\theta}_1 - \widehat{\theta}_2}{s.e(\widehat{\theta}_1 - \widehat{\theta}_2)}$, where $\widehat{\theta}_1$ and $\widehat{\theta}_2$ refer to the estimated effects of EMVID for country 1 and country 2, respectively.

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