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Climate risk and sustainable investing: New evidence from Chinese renewable energy firms

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Abstract

While numerous empirical papers have investigated the volatility dynamics of Chinese clean energy equity markets, this is among the first studies to assess the impact of climate uncertainty on the risk levels of such assets. Given that China is extensively investing in green projects to achieve carbon neutrality, this strand of research offers important implications

to investors and policymakers. Methodologically, we employ the GARCH-MIDAS model to examine the effect of the climate policy uncertainty (CPU) index on the volatility levels of the Chinese clean energy exchange-traded fund (ETF). We compare the effects of the CPU index with leading uncertainty indicators, including the crude oil volatility index (OVX), geopolitical risk (GPR), and technology sector volatility. The in-sample and out-of-sample analyses show that CPU has significant predictive contents for forecasting the volatility of renewable energy ETF and that the GARCH-MIDAS-CPU process outperforms other approaches. These results offer key implications to policymakers and socially responsible investors.

Keywords: Climate policy uncertainty; Clean energy ETF; Volatility, GARCH-MIDAS; Renewable energy

JEL Classification: D8, G11, E37, C32, Q42

1. Introduction

Global temperature has increased significantly over the last few decades. The 2000s, for example, has been the warmest decade since 1850, and consequently, we witness major weather anomalies including the 2013 European heatwave and the droughts in Russia and the United States in 2010 and 2012, respectively (Makkonen et al., 2021). Due to such extreme weather events, the demand for alternative energy sources, which emit fewer pollutants into the air than traditional energies, is also climbing substantially.

Because of its tremendous economic growth in recent years, China has become a leading consumer of conventional energies. Accordingly, its total CO_2 emission rate has also reached a new height. To deal with increasing climate risk and energy scarcity, the Chinese government has initiated an energy transition in order to replace the fossil fuel-based economy with an efficient low-carbon system (Janda et al., 2022). In fact, the country has already achieved an incredible success in lifting the level of clean energy usage and curtailing the cost of generating alternative energies during the past two decades. According to the 14th five-year plan, for instance, China aims to reduce 27% CO_2 emissions by incorporating 20% of clean energy to the primary energy mix.

The main objective of this study is to investigate the effect of environmental uncertainty on the stock prices of Chinese renewable energy companies. Our main purpose is to examine whether the prices of such assets react to increasing climate risk positively. Hence, we explore if an increase in environmental risk causes an upsurge in equity prices for Chinese clean energy companies. With the increase in climate risk, one would expect a shift towards renewable energies. This would cause an increment in the demand levels for such energies, reflected on the clean energy asset prices.

Furthermore, given the inverse association between asset return and its volatility, we might expect a decrease in the risk levels for renewable energy assets with the upsurge in climate risk estimate. The above arguments lead to the formulation of the following hypothesis.

H_1: The volatility of Chinese renewable energy assets react negatively to increasing climate risk.

While testing for this hypothesis, we make a number of contributions to the standing literature. First, although several recent studies (Wen et al., 2014; Reboredo and Wen, 2015; Zhang and Du, 2017; Janda et al., 2022) examine different features of Chinese clean energy equities, this is among the first studies to assess the effect of climate uncertainty on such equities. This strand of research offers important implications for ethical investors, who take part in new energy businesses with a view to keeping a low-carbon portfolio. Due to the fact that socially responsible investing has key environmental impacts that guarantee a certain degree of sustainability (Yahya et al., 2021), our study could receive special attention from eco-friendly investors who require precise information on how to hedge the potential risk linked to climate change. Engle et al. (2020) also argue that during the phases of extreme climate events, investors should adjust their portfolio to hedge environmental risk as such adjustments might offer long-term benefits through compensating the losses due to weather anomalies.

Second, we measure the climate risk using the recently published climate policy uncertainty (CPU) index, which is developed by Gavriilidis (2021). Employing this index, which is a text-based indicator of environmental uncertainty, could be advantageous for assessing the aforesaid linkage given that it is created using several relevant keywords including "uncertainty", "uncertain", "carbon dioxide", "climate", "climate risk", "greenhouse gas emissions", "greenhouse", "CO2", "emissions", "global warming", "climate change", "green energy", "renewable energy", "environmental", "regulation", "legislation", "law", "policy" etc.

Third, we consider the application of GARCH-MIDAS model proposed by Engle et al. (2013). The advantage of this process is two-fold. Firstly, while the GARCH type models are extensively used in prior studies, these approaches consider the variables at the same frequency. Engle et al. (2013) remedy this limitation by combining the mixed data sampling (MIDAS) technique (Ghysels et al., 2006) with the GARCH process, introducing the GARCH-MIDAS approach. This process allows the prediction of stock market volatility by employing the monthly or weekly observations of influential macroeconomic variables (e.g., Asgharian et al., 2013; Wei et al., 2010). Secondly, the GARCH-MIDAS process has recently received enormous attention among the academics as it performs better than the GARCH-type models and stochastic volatility approaches. For instance, when comparing various GARCH and realized volatility (RV) models, Ghysels et al. (2019) provide empirical evidence that the MIDAS-based model offers the best predictions for both in-sample and out-of-sample volatilities. Hence, employing the GARCH-MIDAS process would be useful for understanding how the time-varying volatility of Chinese new energy companies behaves with the fluctuations in climate uncertainty.

In brief, our results demonstrate that CPU has significant predictive contents for forecasting the volatility of renewable energy ETF. Both the in-sample and out-of-sample analyses confirm this finding. Moreover, we also compare the effects of CPU index with leading uncertainty indicators including crude oil volatility index, geopolitical risk and technology sector volatility. The findings suggest that the GARCH-MIDAS process that incorporates CPU outperforms other approaches. Given that proper knowledge on the time-varying linkage between climate uncertainty and the volatility of green investments is crucial for diversify the portfolio risk during the periods of weather anomalies, our findings have key implications to ethical investors and policymakers. In particular, our investigation would be useful for socially responsible investors who aim to hedge climate risk and form risk-adjusted portfolios. Moreover, policymakers should pay special attention to global oil price variations as oil market uncertainty has emerged as one of the key drivers of clean energy volatility. To combat oil price risk, the Chinese government should lift the levels of oil reserve and monitor the oil futures market more precisely. Besides, the development of carbon allowance market is also necessary to mitigate the oil price risk and promote clean energy investments in China.

2. Overview of renewable energy investments in China

China has been the leading country globally since 2005 in renewable energy power capacity, including total electricity generation, though its relative share is only 28.8% in 2021 in electricity production from renewable sources (Enerdata, 2022). Nevertheless, in 2020, the renewable energy generation capacity in China was remarkably more than the combined capacities of the USA, Brazil, India, and Germany, the following four big producers of renewable energies worldwide (IRENA, 2022). China's meteoric rise to the ranking of clean energy generation has led to Asia's continued dominance in the global renewable energy capacity chart in recent times. Until 2021 the installed capacity of renewable energies in Asia was 15,27,528 MW, almost equal to the combined capacities of the rest of the world, 1612437 MW (IRENA, 2022). A huge strand of recent empirical works (Magazzino et al., 2021; Ji and Zhang, 2019; Balakrishnan et al., 2020; Zhao et al., 2022; Liu et al., 2022) highlighted the potentials and pitfalls of renewable energy in China.

Notably, clean energy technologies originate from natural sources: bioenergy, direct solar energy, geothermal energy, hydropower, wind, and ocean energy (Owusu and Asumadu-Sarkodie, 2016), albeit wind, wave, solar, and biomass currently run ahead with high potentials (Østergaard et al., 2022). China is blessed with unlimited clean energy sources, with the potential to build the world's most powerful renewable energy system (Mathiesen et al., 2011).

Fig. 1 shows China's three significant technologies for renewable energy generation: hydropower, onshore wind energy, and solar photovoltaic, with insignificant contributions from solid biofuels, renewable municipal waste, offshore wind energy, biogas, and geothermal energy. One more notable characteristic of the Chinese renewable energy technologies scenario, like the global trend, is its continuously decreasing dependency on renewable hydropower and increasing usage of onshore wind energy and solar. Interestingly, solar energy and wind energy have a broader presence now, not only in the clean energy production of China but also in other major clean energy producers: the USA, Brazil, and Germany. According to IRENA (2022), the primary renewable energy production in China in 2020 is 13,217,328TJ, of which local consumption is 13,207,713TJ, considering 13,936TJ and 23,551TJ imports and exports to and from China, respectively. Major consumers of renewable energies in China are residential, industry, commercial, and transport, mainly using renewable energy for electricity generation and direct usage, with an insignificant amount going for heat generation. However, in the transformation and distribution process, a significant amount of renewable energy still turns into losses in China. Therefore, for a sustainable future, China can also pay more attention to the less explored clean energy sources, geothermal energy (Hou et al., 2018); algal biofuel (Musa et al., 2018); bioenergy (Qin et al., 2018).

Figure 1 goes here

Investment in renewable energy is a tricky issue concentrated primarily on specific regions. Total investments in renewable energy have reached the highest level and have become almost flat recently worldwide. However, East Asia and the Pacific are attracting the highest investment commitments in renewable energy globally because of China over 2013-2018, followed by OECD

Americas and Western Europe. In 2013-2018, East Asia and the Pacific region received a whopping amount of 508.72 billion dollars in renewable energy investments (IRENA, 2022). With increasing pressure to reduce carbon emissions into the air, the Chinese government declared to achieve peak carbon emissions by 2030 and carbon neutrality by 2060 (Zhang et al., 2021). While China's renewable energy system has developed significantly over time, it is still the highest emitter of CO_2 in the world (Zhang and Du, 2017). With the rapid development of clean energy, investment and financing issues in the power sector of China are getting more complicated and challenging. The initial struggles of China in developing renewable energies were policy and technology risks that came down heavily; however, they still need to work hard to address the market risk (Ming et al., 2014).

Fig. 2 presents renewable energy capacity investment in China quarterly since 2011. The statistics show that till 2017, China made a steady investment growth in the capacity built-up of clean energy. From January-June of 2022, China invested 41 billion USD and 58 billion USD into large-scale solar and wind projects, respectively. Hopefully, the country is on the right track to strike the pre-set goal of 1,200-gigawatt wind and solar capacity by 2030 (Asia Fund Managers, 2022). Most renewable energy financing comes through four financial instruments: balance sheet financing equity, balance sheet financing debt, project level market rate debt, and project level equity. The private sector is the major contributor of funds to renewable energy. In 2013-2108, the private sector's investment in renewable energy was 1338.00 billion US dollars. In contrast, public sector investment in clean energy stood at 261.73 billion US dollars in the same period. From 2000 to 2020, Brazil, the highest recipient, received 46.8 billion dollars, China received 4.5 billion US dollars, whereas USA and Germany received 0.2 and 3.2 billion US dollars sequentially (IRENA, 2022). However, public sector financing though small in amount, has a critical role in the early stage of renewable project development and private sector capital attraction. Yang et al. (2019) found that government subsidies strongly impact renewable energy investment in China. In addition, tax incentives encourage clean energy firms, especially medium, small and micro-sized, to invest more in China. Furthermore, research & Development (R&D) subsidies can help promote renewable energy investment in China, which may attract Venture Capitalist (VC) firms as well to accelerate investment growth (Wu et al., 2020).

Figure 2 goes here

Renewable electricity generation has become a default policy from the beginning of the 2020 to 2030 decade due to the advancement in solar and wind energy technology, thereby reducing the costs of clean energy generation. For example, the global weighted average installation cost per kilowatt of solar photovoltaic energy was 4731 US dollars in 2010, reaching 883 US dollars in 2020. This reduction in installation costs and higher capacity usage over time has reduced the global weighted average Levelized Cost of Equity (LCOE) cost of solar photovoltaic to 0.057 per kilowatt-hour in 2020. Similarly, the global weighted average installation cost per kilowatt of onshore and offshore wind was 1971 and 4706 US dollars sequentially in 2010, which turned into 1355 and 3185 US dollars in 2020. In addition, the capacity usage of wind energy firms also increased over that period. Thus, the global weighted average Levelized Cost of Equity (LCOE) cost of onshore and offshore wind energy became 0.039 and 0.084 per kilowatt-hour in 2020. However, the amount of installation costs and capacity factors usage remains volatile for bioenergy and geothermal sources of clean energy. So, the global average LCOE for bioenergy and geothermal are still having a zigzag trend.

China and India are the two most prosperous countries producing solar photovoltaic energy. The average per kilowatt-hour solar cost was 0.0447 US dollars in India in 2019, which is 0.0541 in

China, well below the global average of 0.061 per kilowatt-hour in 2019. Sweden is the most cost-effective producer of onshore wind energy, with 0.0460 per kilowatt-hour in 2019. In contrast, China and India incurred 0.0470 and 0.0490 US dollars per kilowatt-hour in the same period. However, the global average LCOE for onshore wind power in 2019 was 0.045 US dollars per kilowatt-hour. Renewable energy, on the one side, provides clean energy for a sustainable future; on the other side, it creates sustainable employment opportunities for people across the globe. About 12.67 million direct jobs were globally available in 2021 across various renewable energy segments. China is the largest provider of employment in the renewable energy sector. About 5.3 million were working in 2021 in the Chinese renewable energy sector. Of these jobs, about 2.6 million people are directly working in solar photovoltaic, about .87 million people in hydropower, about .65 million in wind energy, about .63 million in solar heating, about .2 million in solid biomass, about .15 million in biogas and remaining people in geothermal energy, CSP and liquid biofuels.

Globally, the renewable energy sector is considered a vibrant field of innovation. Until 2021, 943987 patents have been submitted on various renewable energy segments worldwide. Solar energy, followed by wind energy, has received the highest patent application among the various clean energy sources. China submitted the highest number of patent applications globally, and the number of Chinese submissions till 2021 is 409934. China made around 50,000 new patent submissions solely in 2021. China's recent patent applications mainly involve solar energy (PV-thermal hybrid, solar photovoltaic, solar thermal). Likewise, China is also leading the rest of the world in enabling technologies. About 1,50,000 new patents application for enabling technologies were in rooster in 2019, of which China solely made about 1 00,000 applications. In case of enabling technologies, Chinese patent applications mainly fall into the areas of batteries, charging stations, energy storage, machine related technologies, and fuel cells. China is replacing non-renewable fuels with renewable energies in producing electricity. This replacement policy reduces vast amounts of carbon dioxide emission into the air. In 2020, China avoided 1,922 million tonnes of carbon dioxide emissions from the air, using clean energy sources in place of an assumed mix of non-renewable energy sources (83% coal, 5% natural gas, 6% oil, and 7% nuclear) for producing electricity.

3. Literature review

Clean energy's role in protecting the environment is well documented (khan et al., 2021). Environmental protection can trigger the growth of green investment and thus lead firms to stable financial performance (Chen and Ma, 2021). Cortez, Andrade, and Silva (2022) showed that the clean energy portfolios outperformed their non-clean counterparts in recent times in Europe, reinstating the investors' confidence in clean energy stock market assets. Moreover, the clean energy stock market is in a parallel state regarding price fairness and information discovery that supports using clean energy stock as a monitoring tool for any change in climate policy to various stakeholders (Choi et al., 2023). Furthemore, environmentally friendly securities emerge as the savior of the financial market due to their crucial role in restoring investors' confidence in the market after the financial crisis of 2008 (Tiwari et al., 2023), and they can be treated as a risk diversifier against fossil fuel investment shocks (Santi, 2023).

Climate policy aims to reduce the uncertainty associated with climate risks; thus, relevant solid climate policies can assist in coping with climate change (Gao and Zhang, 2023). In addition, green policies are strengthening the relationship between clean energy financing and investment (Li et al., 2022) and reducing CO2 emissions from BRICS countries (Mngumi et al., 2022). Recently, climate policy uncertainty emerged as a significant factor in analyzing the performance of clean energy stocks relative to brown stocks. Its effect is beneficial and steered by crisis times (Bouri et al., 2022). Climate policy uncertainty is now an indicator of climate risk and assists in estimating the range of climate change, disclosing the uncertainty attached to government-backed policies devoted to addressing meteorological and environmental issues (Zhang and Razzaq, 2022). Gavriilidis (2021) stated that climate policy uncertainty has a powerful and adverse effect on CO2 emissions through encouraging green growth investment and research and development. Even from a firm perspective, managers play an active role in price discovery and organizational resource distribution. So a manager's perception of climate risk provides vital information to the market movement. Jung and Song (2023) stated that a manager's viewpoint on climate change is inversely related to the likelihood of future stock price crash risk. A positive association exists between climate risk disclosures and the likelihood of a stock price crash. The more a company discloses its climate risk perspective, the safer it is to face stock price crash (Lin and Wu, 2023).

Growing climate risk positively influences clean energy investment, thus raising the price level of clean energy assets and stabilizing their returns. At the high level of climate risk, the correlation between crude oil and green energy returns decreases. Even clean energy assets are better than gold in hedging oil market risk (Dutta et al., 2023). Environment, Social, and Governance (ESG) portfolios are better as a diversification tool for physical climate uncertainty. The disturbances transmission between the traditional and ESG portfolios are significantly lower during severe climate uncertainty periods (Cepni et al., 2023). Climate policy uncertainty has the predictive information capability to unearth the price dynamics between green and brown energy stocks and mostly lead investors to prefer green energy stocks over brown energy stocks (Bouri et al., 2022). However, climate policy uncertainty also has its limitations. Ren et al. (2023) opined that climate policy uncertainty depresses corporate financialization and negatively impacts energy-intensive firms. In case of inconsistency in climate policy, significant damage may exert upon energy-intensive firms.

The geopolitical risk strongly influences renewable energy investment (Abbas et al., 2023), leading to lowered investment and more significant financial instability (Li et al., 2022). Alternatively, Yang et al. (2021) found that significant risk spillover exists between geopolitical risk and renewable energy stock prices; however, that spillover has no exact positive or negative pattern. Interestingly, Kassouri et al. (2021) pointed out that high technology stock price variations have zero effect on investors' expectations of green energy stock returns. However, price fluctuations in the fintech markets accord the susceptibility of prices in green energy stocks, bonds, and equities, thus, sustainable development (Tiwari et al., 2023). In addition, Le (2023) found a connection between cryptocurrency volatility and the energy business transition from non-renewable to renewable, especially during the COVID-19 crisis, as energy consumption drops then. The relationship between crude oil and clean energy indices is not linear but varies with a sectorial variation. Wind and crude oil have a weaker connection than wind and geothermal energy or bioenergy; even the relationship is evolutionary with time (Bouoiyour et al., 2023). The correlated movement of crude oil and alternative energy prices is negative (Li et al., 2022). The clean energy index is a safe financial instrument with limited volatility spillover and a one-way effect on future crude oil prices.

In an empirical study, Hoque et al. (2023) said that global energy stocks and carbon emissions futures are related to the US climate policy uncertainty. With uncertainty in US climate policy, global energy stocks act as information transmitters in return spillover, whereas global clean energy stocks act as shock receivers. On volatility transmissions, brown energy stocks, climate policy uncertainty, and carbon emissions future play role as shock transmitters, where clean energy stocks are the recipients. Hu et al. (2023) conducted a survey study in the Zhejiang Province of China. They found that environmental policy uncertainty has two components: policy content uncertainty (PCU) and policy enforcement uncertainty (PEU), which can substantially inhibit corporate green investments. They stressed that executives have a minimum role in increasing clean energy investment; rather government should maintain a stable, clean energy policy to reduce PEU. Chen et al. (2023) assert that climate policy uncertainty strongly affects stock price volatility, and it can predict future stock price movement effectively in China. However, they did not show how climate policy uncertainty can affect clean energy stock prices compared to other volatility indices and risks in China. Clean energy stocks are the main character of the future global energy landscape, and the authorities must ensure solid and stable green policies for a sustainable future.

4. Data

A number of recent studies show that renewable energy equities are often influenced by the variations in technology sector asset prices, crude oil volatility index (OVX) and geopolitical risk (GPR). For example, Janda et al. (2022) argue that since investors often consider high-tech and new energy companies as the similar assets, the stock prices of clean energy firms are significantly affected by the fluctuations in equity prices of high-tech companies. In addition, Dutta et al. (2020a) find that as oil and clean energy are substitutes, increasing volatility in crude oil prices causes a growth in the volatility levels of renewable energy assets. We, therefore, compare the effects of these variables with that of CPU in our empirical analysis. We collect the information on climate policy uncertainty and geopolitical risk from http://www.policyuncertainty.com. In addition, the observations on KraneShares MSCI China clean energy ETF (KGRN) and Invesco China technology ETF (CQQQ) are collected from the Thomson Reuter's DataStream database. The crude oil volatility index (OVX) is freely available from the website of Chicago Board Options Exchange (CBOE).

The sample period ranges from October 13, 2017 to March 31, 2022, yielding a total of 1124 daily observations. The beginning of our sample period is dictated by the availability of the KGRN index. Table 1 reports the descriptive statistics of different ETFs under study. We observe that the clean energy ETF is less volatile than the technology sector ETF. Besides, the Jarque-Bera test shows that normality assumption is violate in each case. Moreover, the unit root tests (ADF and PP), presented in Table 2, further document that the ETF returns appear to be stationary. Next, Fig. 3 plots the clean energy ETFs and climate risk index. This graph reveals that the KGRN ETF experiences a decline amid the COVID-19 pandemic. While looking at the CPU data, we also observe a number of spikes during the pandemic times.

Table 1 goes here

Table 2 goes here

Figure 3 goes here

5. Methodology

5.1. GARCH-MIDAS process

Methodologically, we employ the GARCH-MIDAS approach proposed by Engle et al. (2013). This model has received ample attention in prior literature (Su et al., 2017; Liu et al., 2019; Wang et al, 2020; Fang et al., 2020) due to the fact that it allows us to handle the data frequency mismatch between the daily ETF observations and the monthly CPU data. Note that in the GARCH-MIDAS process the conditional volatility of asset returns consists of two components: long- and short-term risk components. We frame this model as follows:

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

where, $R_{i,t}$ refers to the return on day i of period t (month), μ indicates the daily expected return and $\epsilon_{i,t}|I_{i-1,t} \sim N(0,1)$ with $I_{i-1,t}$ representing the information setup to day $i-1$ of month *t*. In addition, $g_{i,t}$ and τ_t are short- and long-term volatility components, where $g_{i,t}$ is modeled as a mean-reverting asymmetric GARCH(1,1) process:

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

where α, β are assumed to take positive values only and $\alpha+\beta+\gamma/2<1.$ If $\gamma \neq 0$, then asymmetry occurs. Next, the long-term component is given as:

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

where, X_{t-k} denotes the low-frequency CPU index with *K* being the maximum lag and $\varphi_k(\omega_1,\omega_2)$ refers to the Beta weighting function defined as:

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

5.2. Forecast evaluation

5.2.1. Root mean square error

The forecasting performance of different models used in this study is evaluated using the heteroskedasticity adjusted root mean square error (HRMSE) proposed by Bollerslev and Ghysels (1996). We define this statistic as:

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

with T indicating the number of data points to be forecasted, while RV_t and $\widehat{RV}_t$ specify the true and estimated volatility for day t, respectively.

5.2.2. Mincer–Zarnowitz regression

The out-of-sample predictions are also compared applying the Mincer–Zarnowitz (MZ, 1969) regression approach. This technique is beneficial as it examines if the proposed models provide incremental information relative to the baseline GARCH-MIDAS model. We define the MZ regression approach as follows:

(6) $$RV_t = \varphi_0 + \varphi_1 \widehat{RV}_t + \epsilon_t$$

where, RV_t and $\widehat{RV}_t$ are the true and estimated volatility for day t, respectively. We then compare the proposed models on the basis of R^2 (coefficient of determination) statistics. Note that we employ the range-based volatility measures, proposed by Parkinson (1980) and Rogers and Satchell (1991), as a proxy for true volatility. Parkinson introduces the following measure:

(7) $$RV_t = \frac{1}{4log2}[\log(H_t) - \log(L_t)]^2$$

Here, H_t and L_t are respecively the high and low values for the ETF index on day t.

Rogers and Satchell (1991), on the other hand, proposes the following measure:

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

where O_t and C_t indicate the opening and closing values for an asset on day t. The advantage of applying the Rogers and Satchell (1991) measure is that it considers the extreme observations of a particular asset, which allows us to detect potential jumps throughout the non-trading hours.

6. Empirical findings

6.1. Estimates of GARCH-MIDAS models

Table 3 shows the results of our GARCH-MIDAS specifications. In total, we have estimated 4 different GARCH-MIDAS models, which are denoted by GARCH-MIDAS-OVX, GARCH-MIDAS-GPR, GARCH-MIDAS-TECH and GARCH-MIDAS-CPU. As mentioned earlier, the idea is to compare the forecast power of CPU index with other important uncertainty indicators such as OVX and GPR. Note that the GARCH-MIDAS-TECH process measures the impact of the volatility of Invesco China technology ETF (CQQQ) on the Chinese clean energy ETF.

Table 3 goes here

These findings reveal that the estimates of the GARCH-MIDAS parameters are all positive and significant across the models. Hence, the GARCH-MIDAS process is appropriate for modeling the asset returns and might be employed for predicting the risk linked to ETF investments. The asymmetry parameter γ has a significant negative impact on the stock volatility. Therefore, bad news, when compared to good news, would exert a higher short-term effect on the volatility of ETF returns. The value of $\alpha + \beta$ further indicates the high degree of volatility persistence in the Chinese ETF index.

Next, the parameter θ, which measures the impact of CPU, appears to be negative and significant. This result supports our hypothesis indicating that there would be a drop in the volatility levels of

Chinese renewable energy assets with the increase in climate uncertainty. This finding simply suggests that higher climate risk seems to encourage market participants to shift towards green investing. Finally, the R^2 statistics, obtained from the in-sample Mincer–Zarnowitz (MZ, 1969) regression model, reveal that MIDAS-GARCH-CPU specification outperforms other approaches.

We also notice other interesting findings. For instance, OVX, which measure the uncertainties related to crude oil market, seems to affect the volatility of renewable energy asset in a positive way. This finding is consistent with earlier studies which argue that as oil and clean energy are substitutes, an upsurge in oil market uncertainty causes a substantial growth in the volatility levels of renewable energy assets (see Dutta, 2017; Ahmad, 2017; Ahmad et al., 2018; Xia et al., 2019; Dutta, 2019; Pham, 2019; Uddin et al., 2019; Dutta et al., 2020b; Dutta et al., 2020c; Dawar et al., 2021; Dutta et al., 2021; Yahya et al., 2021). Next, we find a similar impact of geopolitical uncertainty on the risk levels of green asset, which is also in line with prior studies including Yang et al. (2021) and Dutta and Dutta (2022). The authors of the above-mentioned articles identify several channels through which GPR impacts the volatility levels of green investments. Finally, we find a significant linkage between Chinese clean energy and technology sector ETFs. This correlation could be attributed to the fact that financial market participants often consider high-tech and new energy companies as the identical assets. Similar findings are also documented in prior empirical works (see Henriques and Sadorsky, 2008; Broadstock et al., 2012; Kumar et al., 2012; Sadorsky, 2012a; Sadorsky, 2012b; Managi and Okimoto, 2013; Nasreen et al., 2020; Tiwari et al., 2021; Pradhan and Tiwari, 2021; Chatziantoniou et al., 2022; Tiwari et al., 2022).

Given that proper knowledge on the time-varying linkage between climate uncertainty and the volatility of green investments is crucial for diversify the portfolio risk during the periods of weather anomalies, our findings have key implications to ethical investors and policymakers. In particular, our investigation would be useful for socially responsible investors who aim to hedge climate risk and form risk-adjusted portfolios. It is also worth noting that portfolio optimization might be substantially influenced by the high and low values of climate risk index. Therefore, choice of hedging instruments would depend on the levels of uncertainty. Moreover, policymakers should pay special attention to global oil price variations as well, since oil market uncertainty has emerged as one of the key drivers of clean energy volatility. To combat such oil price risk, the Chinese government should lift the levels of oil reserve and monitor the oil futures market more precisely (Wen et al., 2014).

Our findings also recommend that the Chinese government should develop its carbon market more precisely. Recent literature suggests that while China has taken a number of important steps to achieve the net zero goals, its emission trading market is still underdeveloped and hence highly volatile (Weng and Xu, 2018). Since efficient carbon allowance market is essential for minimizing the environmental risk in this region, the government should launch a unified, efficient, regulated, and supervised emission trading scheme. Besides, an improved and efficient emission trading market is also crucial for reducing crude oil usage which has been the main source of carbon emission over the last few decades.

6.2. Forecast evaluation

We now aim to obtain the out-of-sample volatility forecasts for the clean energy ETF. Specifically, our sample is separated into two sub-groups: (1) In-sample observations for the estimation of our GARCH-MIDAS models: from October 2017 to December 2020 and (2) Out-of-sample observations for assessing the performance of these models: from January 2021 to March 2022. The findings of volatility forecasts are presented in Tables 4 and 5. Table 4 includes the results of

HRMSE statistics and Diebold and Mariano (DM, 1995) test, while Table 5 reports the R^2 statistics from MZ regression models. The results of Table 4 indicate that the GARCH-MIDAS-CPU model produces lower HRMSE statistics compared to other approaches. The DM also rejects the null hypothesis of equal forecast accuracy.

Next, the out-of-sample forecast analysis based on MZ regression process further shows that CPU offers further information which is not provided by OVX/GPR/TECH. For instance, the R^2 statistics (when using the Rogers and Satchell (1991) measure) amount to 26.01, 29.52, 32.61, 38.98 and 40.34 for the baseline GARCH-MIDAS, GARCH-MIDAS-TECH, GARCH-MIDAS-GPR, GARCH-MIDAS-OVX and GARCH-MIDAS-CPU models, respectively (see Table 5).

Overall, we find that CPU has significant predictive contents for the volatility of sustainable investments and that the application of CPU improves the MIDAS-GARCH volatility forecasts.

Table 4 goes here

Table 5 goes here

7. Conclusions and policy implications

The aim of this study is to assess the impact of climate uncertainty on the volatility levels of Chinese clean energy ETF. To serve this purpose, we employ the GARCH-MIDAS model and compare the effects of CPU index with leading uncertainty indicators including crude oil volatility index, geopolitical risk and technology sector volatility. Both the in-sample and out-of-sample analyses show that CPU has significant predictive contents for forecasting the volatility of renewable energy ETF and that GARCH-MIDAS-CPU process outperforms other approaches.

This strand of research has important implications to socially responsible investors and policymakers. For example, understanding the varied impacts of climate uncertainty on the risk levels of green finance is crucial for making proper asset allocation decisions during the periods of weather anomalies. As eco-friendly investors not only focus on the environmental performance of a firm but also track its financial performance, our investigation would be useful for them to hedge climate risk and form risk-adjusted portfolios. Moreover, investors should also pay special attention to technology equities and global oil price variations as these factors are the key drivers of clean energy stock prices.

For policymakers, on the other hand, precise knowledge on the financial performance of renewable energy companies is essential given that such technologies play a major role in developing alternative energies in China. Although the country has attained a considerable success in lifting the level of renewable energy usage, the lack of development in renewable energy technologies may cause difficulties for China's domestic suppliers when increasing energy conversion efficiency and producing clean energies. To overcome such hurdles, the renewable energy firms in China should receive more flexible financial support mechanisms through financial intermediaries such as banks, funds, and stocks. Moreover, food price stability and food security are also major concerns for China since generating clean energies (such as biofuel) often competes for land with agricultural production. To deal with this issue, advanced agricultural management and landscape planning is required. Otherwise, food prices would increase which hamper the growth in clean energy production. To sum up, the Chinese government needs to adopt effective strategies to avoid the adverse effect of environmental risk. One such strategy could be a significant reduction in fossil fuel usage by investing more in developing clean energy technologies. To this end, fiscal or economic incentives could be introduced to promote energy transition.

Moreover, the development of carbon allowance market is also necessary to mitigate crude oil usage and promote clean energy investments in China. In fact, an improved and efficient emission trading market is crucial for accelerating the deployment of CCUS (carbon capture, utilization and storage) projects in China. Therefore, it is important for the Chinese government to launch a unified, efficient, regulated, and supervised emission trading scheme which can be successfully integrated into the global market. While China has successfully implemented the initial phases of pilots and designing an emission trading system, now the target is to link these pilot markets to the national carbon market in order to significantly curtail the rate of emission. Besides, the government should pay special attention to market supervision, information transparency and the development of relevant legislation. Doing so will also help China reach the net zero goals and achieve green development eventually.

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Table 1: Summary statistics

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera test
Clean energy ETF	0.000326	0.020932	0.2798	9.49	1989.34***
Technology ETF	-0.000217	0.021249	0.8008	15.84	7839.23***

Notes: *** indicates statistical significance at 1% levels.

Table 2: Results of unit root tests

Index →	Clean energy ETF		Technology ETF	
	Level	Return	Level	Return
ADF	-0.9559	-33.99***	-1.3758	-34.00***
PP	-0.8581	-34.02***	-1.3875	-34.06***

Notes: *** indicates statistical significance at 1% level.

Table 3: Estimates of GARCH- MIDAS models

Models →	GARCH- MIDAS - OVX	GARCH- MIDAS - GPR	GARCH- MIDAS - TECH	GARCH- MIDAS - CPU
μ	0.0067	0.0069	0.0064	0.0059
α	0.1239***	0.1452***	0.1526***	0.1391***
β	0.8701***	0.8437***	0.8348***	0.8276***
ω	0.1413***	0.1973***	0.1774***	0.1413***
γ	-0.0544***	-0.0441***	-0.0431**	-0.0401***
θ	0.0034**	0.0027**	0.0388***	-0.0057**
m	0.3456***	0.2986***	0.3001***	0.3183***
R^2 statistic	0.24	0.21	0.26	0.31

Notes: This table presents the findings of the different GARCH-MIDAS models for the renewable energy ETF. θ measures the effect of OVX/GPR/TECH/CPU. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 4: Error statistics and DM test results

Models	HRMSE	DM test statistic
Panel A: RV is based on Parkinson's measure		
GARCH-MIDAS	0.000564	4.32***
GARCH-MIDAS-OVX	0.000301	2.26**
GARCH-MIDAS-GPR	0.000422	3.98***
GARCH-MIDAS-TECH	0.000489	4.02***
GARCH-MIDAS-CPU	0.000267	
Panel B: RV is based on Rogers and Satchell's measure		
GARCH-MIDAS	0.000561	4.19***
GARCH-MIDAS-OVX	0.000300	2.11**
GARCH-MIDAS-GPR	0.000419	3.91***
GARCH-MIDAS-TECH	0.000478	3.88***
GARCH-MIDAS-CPU	0.000264	

Notes: The true realized volatility is proxied by two different range-based measures: Parkinson (1980) and Rogers & Satchell (1991). The in-sample data range from October 2017 to December 2020, while the out-of-sample data span from January 2021 to March 2022. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 5: R^2 statistics from MZ regressions

Models	R^2 statistics (%) (RV is based on Parkinson's measure)	R^2 statistics (%) (RV is based on Rogers and Satchell's measure)
GARCH-MIDAS	25.69	26.01
GARCH-MIDAS-OVX	38.71	38.98
GARCH-MIDAS-GPR	32.86	32.61
GARCH-MIDAS-TECH	29.01	29.52
GARCH-MIDAS-CPU	39.16	40.34

Notes: This table reports the R2 statistics obtained from the MZ regression approach. The in-sample data range from October 2017 to December 2020, while the out-of-sample data span from January 2021 to March 2022.