The Dynamic Impact of Covid-19 Pandemic on Environment-friendly Energy Industry

Wen Zhou*

Department of Economics, Trinity College, Hartford, 06103, USA

*Corresponding author: wen.zhou@trincoll.edu

Abstract. Most of the current research on green energy and the pandemic focuses on how green investments changed after the epidemic and how the pandemic affected the local economy. The correlation between the rate of return on green energy and the number of confirmed cases in China and the rest of the globe is the main topic of this research. The daily cumulative confirmed Covid-19 cases in China and the rest of the world, and daily price of green energy are used as time series variables. They are daily data from the end of January 2020 to the end of July 2022. The study's findings largely show how the price of green energy has changed in relation to the pandemic's progression. A VAR (12) model makes a forecast on how the pandemic, which is expected to become stationary after the tenth period, would affect the price of green energy. The ARMA-GARCH model's findings demonstrate a statistically significant negative correlation between the price of green energy and the number of verified cases. In other words, compared to the pandemic, the price of green energy is lower. The pandemic has had no impact on the rate of return of green energy throughout the specified period, though.

Keywords: time series; green energy price; Covid-19; rate of return; ARMA-GARCH Model.

1. Introduction

Green energy, or environmental-friendly energy, is defined as any type of energy generated from natural resources. The range of green energy includes wind power, solar power, geothermal energy, and other renewable energy. In recent decades, environmental problems have become increasingly pressing. More and more individuals and organizations started to dedicate themselves to the cause of environmental protection. According to EARTH.ORG, global warming is the top environmental issue in 2022 confronting all mankind. In 2022, there are 418 parts per million carbon dioxides in total in the atmosphere [1]. As a primary source of carbon dioxide emission, fossil fuels should be considered responsible for some environmental problems. With high attention to the green energy industry, renewable energy was valued to be more than \$880 billion in 2020 globally. Its value is expected to exceed \$1900 billion by 2030 [2].

Since 2019, COVID-19 pandemic has swept the globe–countries all over the world sacrificed their economic development to get through the pandemic. According to the International Monetary Fund, the global median GDP had dropped 3.9% within a year since 2019 [3]. After popularization of COVID-19 vaccines in major countries in the world, the world economy gradually recovers from the pandemic. A part of the current literatures investigated the correlation between the pandemic and comprehensive economic changes in one or more regions. Oum, Kates, and Wexler's study shows that despite the projections that the world economy will recover fully by 2021, recovery has been unequal, and inequalities in vaccination coverage and availability may put much of the world's progress in jeopardy [4]. During the pandemic, demand for energy and green energy prices continued to drop.

Given the background of economic recovery, this study senses the need to investigate whether the green energy industry was affected by the pandemic, and if so, to what extent. Existing literatures are distributed in several areas: whether the green energy industry is affected in terms of production, transportation, etc.; whether green investment is affected.

Hosseini pointed out that the COVID-19 pandemic has impacted businesses that produce renewable energy as well as supply networks and industrial facilities, hampering the shift to a sustainable energy economy, but it was too early to conclude how large the impact the pandemic has on the green energy industry [5]. Yosino, Taghuzadeh-Hesary, and Otsuka theoretically demonstrated how investors' present allocation decisions, which take into account SDGs and are based on the recommendations of numerous consulting firms, would result in investment portfolio distortion [6]. By analyzing time series data from 1990 to 2020, Li, Hamawandy, Wahid, Rjoub, and Bao found the correlation between economic and financial variables from China, such as renewable energy investment (IRE) and green finance (GFi), and GDP [7]. Anser, Godil, Khan, and others tested linear causation between the pandemic and green energy consumption crossing 65 countries. With a variation of 17.127% across a time horizon, the intertemporal relationship from the study demonstrates that green energy sources would probably have an impact on the number of coronavirus cases [8].

There are a very small number of studies specifically focusing on the correlation between confirmed cases and green energy prices. This paper-built models among the time series variables including logarithmic cumulative confirmed cases in China, logarithmic cumulative confirmed cases overseas, and logarithmic rate of return of green energy. The paper first unit root test to testify the stationary of three variables. Once the stationary is confirmed, a VAR (12) model containing the three variables was built to forecast the variables. With a further impulse response graph drawn, it virtually illustrates the changes of variables based on a VAR (12) model. The volatility of green energy prices was also tested in this paper with related risks presented. An ARMA-GARCH model was built to get relatively accurate estimates of parameters. The research gives the outcome of the GARCH portion significant weight and develops conclusions based on the GARCH model performance in light of the conditional heteroscedasticity seen in the stock price series.

The paper is arranged in the following structure. Part 2 introduces research design. Sources of data are explained in the first section of part 2. After that, methodology of the root test is fully explained. This paper introduces VAR model and ARMA-GARCH model in the rest of the second part, including theory and functions related to both models. According to the structure of ARMA-GARCH model, specifications of AR, MA, ARCH, and GARCH models are also explained in part 2. The third part includes the empirical results and discussion based on them. The testing results of VAR (12) with order selection process and impulse response graphs are presented. The paper gives the result of ARMA model order selection by the ACF and PACF first. And then, AR (10), MA (10), ARCH (1), and GARCH (1) model results are listed in Table 3 as the result of the ARMA-GARCH model. In discussion section, potential explanations of the results and suggestions to investors and policy makers are provided.

2. Research Design

2.1 Data source

The Chinese cumulative quantity of Covid-19 infected people is collected from the National Health Commission of the People’s Republic of China.[9] It is a national government website releasing officially collected health-related data from China. Because of the website’s officiality, the accuracy and authenticity of data sources could be guaranteed. The data contains daily cumulative numbers from January 21st of 2020 to July 30th of 2022.

The cumulative quantity of COVID-19 infected people is obtained from the Choice Financial Platform, which is launched by East Money Information Co., Ltd [10]. This comprehensive platform provides financial statistics, industry information, and portfolio analysis to professional financial users. The provided information covers all kinds of financial derivatives, CSI 100 Index, Hong Kong stocks, American stocks, new three boards, funds, bonds, currencies, and futures. For this study, the data from January 20th of 2020 to July 29th of 2022 was exported from the platform.

The daily friendly energy price was exported from the Choice Financial Platform, too. Data from Feb 3rd of 2020 to July 29th of 2022 was exported.

The collected data were matched to each other according to their date. To keep the database unified, the date that all three variables’ prices are available was filtered out and sorted by date. For further analysis, data for each day was numbered from the oldest to the newest. The further analysis uses logarithmic data. To get the logarithmic sequence of case data in later analysis, the study adds one to the initial sequence if no additional confirmed cases are found within a certain period. This will not affect the study's outcome. All the data analysis of this study was finished by Stata. It provides results of unit root test, VAR model, and ARMA-GARCH model.

2.2 Unit Root Test (ADF Test)

The unit root test, as known as ADF test, tests whether a time series variable is stationary by testing whether the variable processes a unit root. The further analysis needs the time series variable to be stationary, hence it is important to make sure every time series variable in this paper process has no unit root.

The standard unit root test assumes the time series to be written as:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta x_{t-i} + \mathcal{E}_t \tag{1}$$

The coefficient $\beta = 1$, showing the series has a unit root and is not stationary, is the null hypothesis of the test. The alternative hypothesis is that $\beta < 1$, which indicates that the series is stationary.

Table 1 is the result of the ADF test among logarithmic data. It shows that all t-scores of three time series variables are significant. In this case, that implies that green energy, cumulative infected number in China, and cumulative infected number overseas do not process unit root, and they are stationary under 1 percent significance level. According to the ADF test result, the VAR model and ARMA-GARCH model could be built.

Table 1. ADF-test result

Variables	t-statistic	p-value
	Friendly energy	
Yield	-17.370	0.000^{***}
	Covid-19 pandemic: newly confirmed cases	
China	-15.885	0.0000^{***}
Overseas	-6.314	0.0000^{***}

Note: **, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

2.3 VAR Model Specification

2.3.1 VAR Model Budling

A multivariate time series model called the vector autoregressive (VAR) model connects the present observations of a variable to its historical observations as well as historical data of other variables in the system. On the premise of correlation between dependent variables, the VAR model provides a way to analyze various variables in one model, estimating the multivariable time series as one piece.

In this case, the VAR(p) model containing three variables is written as:

$$y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \varepsilon_t \tag{2}$$

where $y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix}$, $\Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix}$, $\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$, $\Gamma_1 = \begin{bmatrix} \beta_{11} & \gamma_{11} & \lambda_{11} \\ \beta_{21} & \gamma_{21} & \lambda_{21} \\ \beta_{31} & \gamma_{31} & \lambda_{31} \end{bmatrix}$,…,$\Gamma_p = \begin{bmatrix} \beta_{1p} & \gamma_{1p} & \lambda_{1p} \\ \beta_{2p} & \gamma_{2p} & \lambda_{2p} \\ \beta_{3p} & \gamma_{3p} & \lambda_{3p} \end{bmatrix}$.

where y_t =dependent variables in the system, Γ_p =coefficient matrix for corresponding terms, $\varepsilon_t =$ error term matrix in period t.

2.3.2 VAR Model – Impulse Response Graph

The impulse graph displays the current measurement's impulse reaction over time. It provides an overview of interaction within or between variables, which is difficult to analyze among a large number of estimates from a VAR (3) model.

The response effect can be calculated by:

$$\psi_s = \frac{\partial y_{t+s}}{\partial \varepsilon_t} \tag{3}$$

The change in $y_{i,t+s}$, the value of variable I in the timestamp t + s, should equal the reaction impact when variable j increases by one unit in the disturbance term jt at the timestamp t. By interpreting equation (3) as a function of time interval s, the equation transformed into the impulse response function (IRF).

Graphs are capable to show all impulse responses from a VAR system. They are examples of the virtualized result of VAR system.

2.4 ARMA-GARCH Model Specification

ARMA-GARCH model is a time series model that combines ARMA and GARCH models. An ARMA model among China infected cumulative number, overseas infected cumulative number, and environmental-friendly energy price need to be built first, and then the GARCH model is built based on ARMA model’s residual term to make the model less complicated and more precise. The outcome of the GARCH model gives the conclusion of the green energy market risk based on effectiveness of the pandemic.

2.4.1 ARMA Model Building

Autoregressive moving average (ARMA) model is usually used to trace and analyze long-term data in market studies. It is an important time series investigation tool based on autoregression (AR) model and moving average (MA) model. The AR index decides the number of historical data points needed for predicting current or future estimates. And the MA index decides the methodology for forecasting current or future estimates by using average difference of historical data. ARMA model as a combination of two models has more complicated estimates but higher estimates’ accuracy than AR and MA models alone.

2.4.2 ARCH Model Building

The ARCH model, which uses autoregressive logic to forecast variance in the future, assumes that if a time series variance of the most recent period is high, it is possible that the variance of the next period would also be high.

A standard ARCH(p) model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \tag{4}$$

where σ_t^2= estimated variance in given period, ε_t= actual variance in given period t, and α_0 = constant.

The ARCH model is limited by its autocorrelation procedure. It fits heteroscedastic autocorrelated functions in short term; however, the residual series of most financial data are autocorrelated in high order. To improve ARMA model, a low-order GARCH model can be built with fewer estimated coefficients needed.

2.4.3 GARCH Model Building

The generalized autoregressive conditional heteroskedasticity (GARCH) model is a financial regression model used for modeling residuals. This kind of model can better predict and analyze fluctuation than other models. In this case, the GARCH model was used to test residual terms of the ARCH model and correct the ARCH error term.

A standard GARCH (p, q) model is in form of:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_t\varepsilon_{t-p}^2 + \beta_1\varepsilon_{t-1}^2 + \cdots + \beta_q\varepsilon_{t-q}^2 + \gamma x_t \quad (5)$$

where σ_t^2 = estimated variance in given period t, ε_t^2= actual variance in given period t, x_t = newly confirmed cases, α_0 = constant.

In this paper, both Chinese newly confirmed cases and that from the rest of the world are used in the model respectively as an independent variable γ explaining external effect.

3. Empirical Results and Analysis

3.1 VAR Order Selection

Normally, the order of the VAR model is expected to be high enough that it can better embody the model's dynamic characteristics. In other words, if the order is small, autocorrelation among random errors occurs, which is not expected. The higher the order, the more coefficients need to be estimated, and the lower degree of freedom. That causes the imprecision of parameter estimation if the sample is not large enough.

In order to find the best order, the likelihood ratio (LR) test was applied in this paper. LR is a composite index reflecting both sensitivity and specificity. In this case, the Stata command VARSOC order-selection criteria were applied to obtain the proper order p of the VAR (p) model based on the LR test. Table 2 is the results from order selection. It shows that a VAR (12) model is required for further procedure.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1376.64				2.0e-06	-4.62506	-4.61643	-4.6029
1	5172.99	7592.7	9	0.0000	.7e-12	-17.3771	-17.3425	-17.2884
2	5758.47	1171	9	0.0000	8.2e-13	-19.3181	-19.2577	-19.163
3	5783.6	50.253	9	0.0000	7.7e-13	-19.3724	-19.2861	-19.1508
4	5820.85	74.506	9	0.0000	7.0e-13	-19.4675	-19.3553	-19.1795
5	5870.53	99.37	9	0.0000	6.1e-13	-19.6045	-19.4664	-19.25
6	5939.54	138.01	9	0.0000	5.0e-13	-19.8065	-19.6426	-19.3856
7	6056.45	223.81	9	0.0000	3.5e-13	-20.1699	-19.98	-19.6824
8	6201.78	290.66	9	0.0000	2.2e-13	-20.6289	-20.4132	-20.075
9	6343.67	283.79	9	0.0000	1.4e-13	-21.0763	-20.8347	-20.456
10	6364.27	41.199	9	0.0000	1.4e-13	-21.1154	-20.8479	-20.4286
11	6478.38	228.22	9	0.0000	9.5e-14	21.4693	-21.1759	-20.716
12	6635.98	315.2*	9	0.0000	5.8e-14*	-21.9696*	-21.6504*	-21.1499*

Once the VAR (12) model is established, the VAR (12) stability can be tested by Stata. The Stata tested the eigenvalue stability criterion after estimating the vector autoregression's parameters, using a unit circle to show the outcome. Stable VAR estimates will output dots inside the unit circle. As figure 1 illustrates, all the dots lie in the unit circle, which implies that the VAR (12) model established based on the LR order-selection criteria is stable. So, the VAR (12) model outcomes are certified for further analysis.

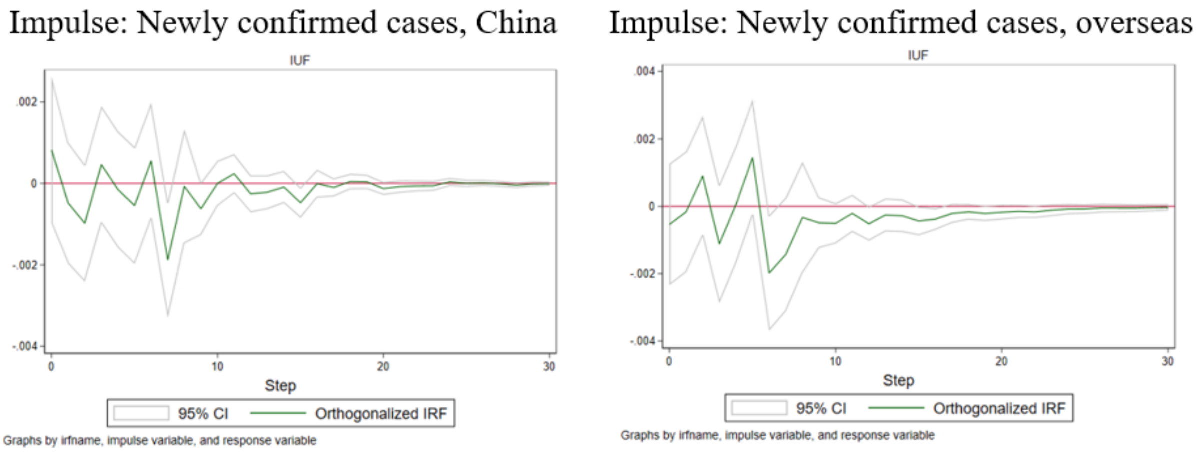

Figure 1. Impulse and response

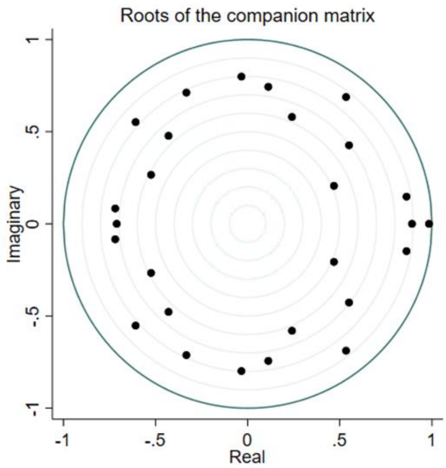

Figure 2. VAR stability

3.2 VAR Model Impulse Response Graph

In the VAR model, the impulse response analysis contributes to assessing the effect of one variable on another in terms of time and extent of the effect. It provides a view of how the change of one variable would impact the rest of variables in the system. However, because of the large number of parameters used in a VAR (12) model, the impact of change in one certain variable is limited.

According to the impulse response result illustrated in Figure 2, when t = 0, 1 percent of the increase in infected cumulative number in China leads to the logarithmic rate of return of green energy fluctuating around zero. The highest positive effect happened in period number zero, which is less than 0.1%, and the lowest negative effect will occur in period number seven, which is approximate -0.2%. In general, the net effect of the pandemic is negative in the first ten periods. In terms of the effect of time, the impact of the current period on the green energy market decreases to zero alone with time from t = 10 to future periods.

Similar to the effect of newly confirmed cases in China on the green energy market, the impulse response graph of newly confirmed cases overseas tends to be stable after period number 10. However, the highest positive effect (t=5) will occur earlier than the lowest negative effect (t=6). After the highest positive effect that the overseas newly confirmed cases bring to the given market, the effect drops immediately to the lowest negative effect point. Based on this observation, it is reasonable to consider that the impact of the overseas pandemic on the green energy market is instantaneous and enormous.

3.3 ARMA Order Selection

ARMA model follows the same order-selection criteria as AR and MA models. In this case, Stata was applied to draw autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs among three variables. The former is about the correlation between historical data and current data of one time series, and the latter is about the correlation between historical residual and current residual of one time series. On the graphs, the rate of return point lying out of the benchmark value should be a statistically significant term for ARMA model. In Figure 3, the rate of return exceeds the black square for the first time for both PACF and ACF at lag orders 10 and 24. So, an ARMA (10) and ARMA (24) model were tested. After testing both models, the ARMA (10) was found statistically stationary.

PACF ACF

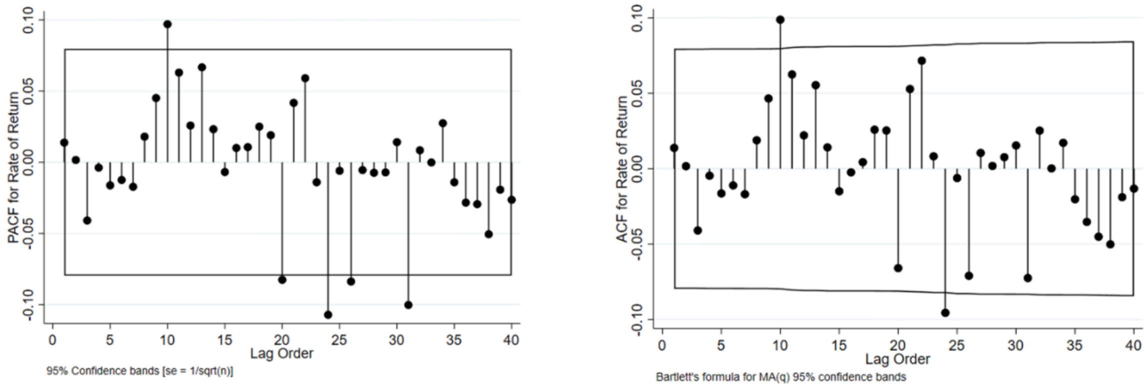

Figure 3. PACF and ACF

3.4 ARMA-GARCH Model Results

Table 3 gives the result of ARMA-GARCH model estimation with AR and MA models with lag order of and ARCH and GARCH models with lag order of 1. According to the table, the ARCH outputs of columns (1) and (2) show significance at 1%. This indicates that at the latest period, the squared error term could be used to estimate current rate of fluctuation. In other words, the conditional heteroscedasticity of logarithmic rate of return of green energy is statistically significant, and the logarithmic rate of return of green energy meets satisfaction of ARCH modeling. However, the coefficients of newly confirmed cases in China and overseas are not significant, so it is not sufficient to claim that the change of profit in the green energy industry is affected under a normalized epidemic environment.

Table 3. ARMA-GARCH estimation results

	(1)		(2)	
	Coefficient	Std. err	Coefficient	Std. err
	Mean equation			
AR (-10)	-0.4062	0.2793	-0.4164	0.2816
MA (-10)	0.5164^{**}	0.2624	0.5249^{**}	0.2641
Constant	0.0016	0.0009	0.0017^{**}	0.0009
	Variance equation			
Newly confirmed cases, China	-0.4811	0.6306		
Newly confirmed cases, overseas			-0.0179	0.0178
ARCH (-1)	-0.0904^{***}	0.0220	-0.0908^{***}	-0.0216
GARCH (-1)	-0.3359	0.2488	-0.3374	0.2439
Constant	-1.7375	7.1901	-6.8956^{***}	0.3599

Note: ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

4. Discussion

According to the results of ARMA-GARCH model, the price of green energy is lower over the pandemic. There are two explanations for this observation. First, consumers' economic situation was harmed by the pandemic, hence their demand for green energy, which is more expensive than traditional fossil fuel energy, decreased over time. With lower demand, the price of green energy drops. Second, the negative correlation between three variables is caused by omitted reasons, for example, improvement of PV solar panel technologies. Significant technology breakthroughs may happen during the given years, which lowers the cost of green energy generation.

For further study, the negative coefficient of green energy price could be analyzed to ensure whether the increasing number of infected patients is the only causation. For investors, the study suggests that the price of green energy will further decrease, so investors might choose to exercise caution when investing in the industry in the near future.

Under the pandemic economic circumferences, the rate of return of green energy is not affected when most of the traditional and emerging industries, such as real estate and traditional manufacturing industries, are struggling to survive. To a large extent, it implies the importance of environmental issues and global society's overall dependence on green energy. The reason behind the strong vitality of green energy prices might be the worldwide energy revolution. With urgency to solve environmental problems by decreasing carbon emissions, the demand for green energy in the countries that require it remains stable. To policymakers trying to accelerate the energy revolution, formulating policies advocating green energy and green energy-related industries, such as solar penal producers, could be considered effective. Based on the lower price of green energy, a decrease in price of devices for green energy makes turning green more affordable to customers. Hence, more consumers may switch to renewable energy from traditional fossil fuels.

5. Conclusion

The existing studies related to green energy and the pandemic are mostly about changes in green investment after the pandemic and effects of the pandemic on the regional economy. This paper focuses on the correlation between green energy rate of return and number of confirmed cases in China and the rest of the world. To a large extent, the study results indicate the response of green energy prices to the state of the pandemic. The tested VAR (12) model provides a prediction of impact on the green energy price by the pandemic that stationary will occur after the tenth period.

The ARMA-GARCH model results show that green energy price from January 20th of 2020 to July 29th of 2022 is statistically significant and negatively correlated with the number of confirmed cases. In other words, the price of green energy is lower over the pandemic. However, the rate of return of green energy during the given period is not affected by the pandemic.

The study result also shows a high risk in investing in green energy in recent times, so it is not suggested to invest in such assets with high portfolio weight. On the other hand, because of the low price of green energy, it could be a chance for policymakers to support green energy-associated industries to accelerate the energy revolution.

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