The dynamic dependence of natural gas and renewable energy stock markets

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Abstract. We measure the dynamics dependence structure between the European renewable energy stock (ERIX) market, natural gas, and other clean energy markets from 2008 to 2021 by adopting static and time-varying copula approaches. Empirical results show strong and positive dependence between ERIX and S&P global clean energy stock markets symmetric tail dependence, which indicates S&P clean energy assets provide limited hedging condition on the ERIX market and extreme upward and downward clean prices have a similar impact on the ERIX market. Furthermore, our evidence on the co-movement mechanisms between European renewable energy and clean energy markets is helpful for policymakers and investors. Governments need to adopt fiscal policy tools for clean energy firms when renewable energy prices rise (fall) together. Investors can assess and control potential risk contagion between European renewable energy stock markets and other clean energy markets via information about co-movement mechanisms.

1. Introduction

With the rapid development of the world economy and population, climate change has a severe impact on human health and economic activity. In recent years, the United Nations Framework Convention on Climate Change (UNFCCC) paid more attention to sustainable energy finance in world climate summits. The climate finance aims at reducing emissions and fight with negative climate change impacts. The renewable energy stock is one of the sectors for climate and sustainable energy finance. However, the renewable energy industry is still in the process of developing, which requires greater amounts of capital and technology inputs. In view of the risk, investing in renewable energy higher than traditional energy since the penetration of renewable energy industries still relatively lower than fossil energy fuels, which affects the choice of producers and ultimately increases uncertainty in renewable energy markets. Moreover, the profitability and financial risks associated with renewable energy companies are the essential factors to determine the development of the renewable energy financial market. Therefore, understanding the return and volatility characteristics of clean and renewable energy stocks and the possible linkages between renewable and clean energy stock prices is the essential issue of concern for investors and policymakers.
In this paper, the main objective is to investigate the interdependence between renewable energy markets and clean energy stock markets. The motivation of this paper includes two factors. First, renewable energy industries have been received attention from governments and private investors. Investing in global renewable energy sectors reached $279 billion in 2017, which has resulted in the addition of 157 gigawatts of renewable power generation capacity [1]. The clean energy share prices on the Wilder Hill New Energy Global Innovation Index increased by 28%, which is higher than the S&P 500 share prices [2]. In 2018, the International Energy Agency reported that the demand in the renewable energy sector will cover two-thirds of the global energy investment by 2040 [3]. Second, the performance of stock markets in renewable energy sectors has been vital in recent years. With the rising role of renewable energy in the global energy markets, the renewable energy stock markets are facing great pressure and uncertainty, which include energy price and policy uncertainty, technology innovation, and the uncertainty of capital inflows.

Many studies have examined how renewable energy prices are affected by the related assets and fossil fuel prices. The first strand of research focuses on the linkages between traditional energy resources and renewable energy markets. Sadorsky [4] found a spillover effect between oil, clean energy, and technology stock markets. Wen et al. [5] detected the volatility spillover effects between Chinese clean energy and conventional energy companies. Reboredo [6] explored dependence and measured systemic risk between oil and clean energy markets and found that the oil market plays a crucial role to form risk in renewable energy markets. Reboredo and Ugolini [7] focused on that fossil energy and electricity prices affect clean energy stock returns; the results reflect that oil and electricity prices were the primary driving force to clean energy stock returns for the USA and the EU, respectively. Song et al. [8] not only investigated the dynamic spillover effect between the coal, oil, natural gas, and the renewable energy markets, but also considered investor sentiment into studies. The second strand of research that the linkages between clean energy stocks and other assets, such as gold, exchange rate, carbon prices, and others. Dutta et al. [9] investigated the return and volatility between the carbon prices and clean energy stock prices by adopting VAR-GARCH approach. Uddin et al. [2] studied that how the renewable energy markets co-move with oil, gold prices, and exchange rates markets. Liu et al. [10] first examined that the interdependence between green bonds and clean stock markets by using the static and dynamic copula approach. However, no study to date that focuses on the dynamic dependence of European renewable stock market fluctuations on other renewable energy stocks and natural gas future market. In the past three decades, the European Union (EU) plays a “flagship” role in the renewable energy industry and has taken significant measured to boost market uptake. Despite the COVID-19 spread to Europe, the renewable sectors accounted for 41% of total energy in the first quarter of 2020 (greater than in the first three months of 2019) due to a sharp drop in demand and prices. The electricity demand of Germany, Ireland, and Denmark relied on the wind energy [11].

Therefore, we contribute to the related literature in two dimensions. First, we adopt bivariate copulas to estimate the dependence structure between renewable energy stock markets. This approach not only captures information on the constant and tail dependence between variables, but also models interdependence between clean markets by constructing multivariate distribution. These results yielded by bivariate copulas, which provide us information including three ways: (i) whether the ERIX market and other clean energy markets are somewhat dependent or independent; (ii) whether there exists tail dependence between considered markets; (iii) whether dependence structure between ERIX market and other clean energy stock markets changed over time. Second, this specific information helps institutional and private investors clarify the co-movements mechanism between renewable energy markets, and has implications for governments and financial institutions to foster a stable and healthy renewable energy market.
2. Data and methodology

2.1. Data
To examine co-movement between the ERIX market, other renewable energy stock, and natural gas markets, we used daily data from 1 January 2008 to 28 January 2021. We consider the European renewable energy stock market (ERIX) as a major benchmark since this index involves the corporate stock of the ten largest alternative European renewable energy companies such as solar, water, biomass, wind energy [9]. Other renewable energy stock markets include: (i) the Wilder Hill Clean Energy Index is denoted by ECO. This index is equal to the weighted average of the corporate stocks of 42 renewable energy and technology companies in the US; (ii) the S&P Global Clean Energy Index is denoted by S&PGCE. This index is calculated from the weighted average of the corporate stocks of global 30 renewable energy, technology, and facilities companies; (iii) natural gas future (GAS) in the Intercontinental Exchange. The reason for choosing natural gas including two ways. On the one hand, according to International Energy Agency, natural gas is an essential component of low-carbon energy. It provides the flexibility demands to support the penetration of renewables components for industries producing. On the other hand, energy prices are the crucial factor for the choices of producers. To ensure that all series settle accounts with the same currency, we convert the natural gas price by adopting the GBP/USD reference rate published by the Bank of England. We calculate the return rate as \( r_{t,t} = \left( \ln p_{i,t} - \ln p_{i,t-1} \right) \times 100 \), where \( p_{i,t} \) denotes the price at time \( t \) for variable \( i \).

Table 1 shows that the descriptive statistics for the return of renewable energy stocks. The standard deviation of GAS experienced the greatest price return volatility. The series of S&PGCE and ECO show left-skewed, and the other series show right-skewed. In terms of kurtosis, all values are higher than 3, which indicates that each variable has leptokurtosis distribution with a fat tail. The Jarque-Bera test reveals that no return series match the normal distribution. The ADF unit root test suggests that all return series are stationary. The Pearson correlation coefficients show that all series are positive to ERIX returns.

|          | ERIX   | S&PGCE | ECO   | GAS    |
|----------|--------|--------|-------|--------|
| Mean     | 0.0002 | 0.0000 | 0.0002| 0.0004 |
| Median   | 0.0002 | 0.0005 | 0.0004| -0.0003|
| Maximum  | 0.2241 | 0.1983 | 0.1563| 0.4422 |
| Minimum  | -0.1681| -0.1391| -0.1499| -0.1575|
| Std. Dev. | 0.0250 | 0.0193 | 0.0221| 0.0323 |
| Skewness | 0.0301 | -0.1473| -0.2112| 2.5557 |
| Kurtosis | 10.4158| 16.7470| 8.9547| 32.8542|
| Jarque-Bera | 7821.0500 | 26886.9500 | 5067.8260 | 130462.4000 |
| ADF      | -55.1199*** | -51.2476*** | -38.5689*** | -56.7569*** |
| Correlation | 1  | 0.510  | 0.733  | 0.111  |
| Observations | 3368 | 3368  | 3368  | 3368  |

Note: Correlation is the Pearson correlation for measuring the linear correlation between ERIX and each series, *** indicates statistical significance at the 1% level.

2.2. Methodology

2.2.1. Specifications of marginal models. The marginal model for renewable energy return and natural gas returns was specified as an ARMA model as:

\[ r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \phi_j \varepsilon_{t-j} + \varepsilon_t \]  \hspace{1cm} (1)
where $\sum_{i=1}^{p} \Phi_{ii} < 1, \varepsilon_t = \sigma_t \eta_t$ such that the residual $\eta_t$ is an i.i.d random variable with a zero mean and unit variance that follows a Student-t density distribution; and $\sigma_t^2$ is the conditional variance, with characterized by TGARCH specification:

$$
\sigma_t^2 = \omega + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 - \sum_{i=1}^{l} \lambda_i 1_{t-i} \varepsilon_{t-i}^2 + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2
$$

where $\varepsilon_{t-i}$ is the ARCH term and $\sigma_{t-j}^2$ is the GARCH term. $1_{t-i}$ is the indication function that equals to 1 when $\varepsilon_{t-i} < 0$ and zero otherwise. The asymmetric effects are captured by the parameter $\lambda$ captures in such a way that when $\lambda > 0$, the negative shock leads to a greater impact on future volatility than a positive shock of the same magnitude.

2.2.2. Copula approach. Copulas are mathematical functions that connect the marginal distribution to form joint distribution [12], which captures non-linear and asymmetric relations between clean energy return, natural gas returns. $C(.; ;)$ is related to the CDF of a random vector. For continuous $F_X$ and $F_Y$, $C$ is expressed as:

$$
C(u, v) = F_{XY} \left( F_X^{-1}(u), F_Y^{-1}(v) \right),
$$

where $u = F_X(x)$ and $v = F_Y(y)$ are calculated by the probability of integral transformation, which are uniformly distributed over $[0,1]$, and $F_X^{-1}(u)$ and $F_Y^{-1}(v)$ representing the generalized inverse distribution functions of the marginal $F_X$ and $F_Y$, respectively.

We estimate the bivariate copula model by using the inference function for the margins (IFM)[13]. First, we obtain the marginal distribution of each univariate by maximum likelihood estimation; Second, computing the standardized residuals by applying marginal cumulative distribution function:

$$
\hat{u}_{ERIX,t} = F_{ERIX}^{-1} \left( \eta_{ERIX,t}; \hat{\theta}_{ERIX} \right),
$$

$$
\hat{\vartheta}_{i,t} = F_i \left( \eta_{i,t}; \hat{\theta}_i \right),
$$

where $\hat{u}_{ERIX,t}$ is standardized residuals of the European renewable energy market (ERIX) and $\hat{\vartheta}_{i,t}$ is other clean energy markets ($i$ (S&PGCE, ECO, or GAS) for $t$ to $T$). And the parameters of the copula are obtained by the equation as:

$$
\hat{\theta}_c = \arg \max_{\theta_c} \sum_{t=1}^{T} \ln C(\hat{u}_t, \hat{\vartheta}_t; \theta),
$$

Finally, we select the optimal copula model by calculating Akaike information criteria (AIC), the formula can be written as:

$$
AIC = 2k - 2 \sum_{t=1}^{T} \ln C(\hat{u}_t, \hat{\vartheta}_t; \theta).
$$

where $k$ is the number of parameters.

Kendall's tau ($\tau$) is a rank correlation coefficient that is used to measure concordance [14]. Kendall's $\tau$ can capture non-linear dependencies that cannot be measured with linear correlation. The Kendall’s tau coefficient is defined as:

$$
\tau = 4 \int_{0}^{1} \int_{0}^{1} C(\hat{u}_t, \hat{\vartheta}_t) dC(\hat{u}_t, \hat{\vartheta}_t) - 1
$$

The time-varying correlation for copula is constructed as:

$$
\rho_t^* = \eta (\alpha_c + \beta_c \rho_{t-1}^* + \gamma_c (u_{0,t-1} - 0.5)(u_{0, t-1} - 0.5))
$$
where \( \Lambda(\cdot) \) is a logistic transformation function to restrict the coefficients \( \rho^*_c \) to be in the range \((-1,1)\); \( \alpha_c \) is the constant term. The autoregressive term \( \beta_c \) captures persistence effect \( (0 \leq \beta_c < 1) \) and \( \gamma_c \) depicts the variation effect independence.

3. Results and Discussions

3.1. Marginal distribution models

| Table 2. Parameter estimates of the marginal distribution models. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Gas | ERIX | S&PGCE | ECO |
| Mean equation | | | | |
| \( \mu \) | 0.000 | 0.001 | 0.000 | 0.000 |
| (0.000) | (0.000) | (0.000) | (0.000) |
| \( \phi_1 \) | -0.278 | 0.186 | 0.197*** | 0.362*** |
| (1.017) | (0.347) | (0.112) | (0.207) |
| \( \phi_2 \) | 0.293 | -0.158 | -0.063 | -0.323 |
| (1.011) | (0.349) | (0.114) | (0.210) |
| Variance equation | | | | |
| \( \omega \) | 0.000 | 0.000*** | 0.000 | 0.000*** |
| (0.000) | (0.000) | (0.000) | (0.000) |
| \( \alpha \) | 0.027 | 0.032*** | 0.054 | 0.040*** |
| (0.056) | (0.004) | (0.026) | (0.011) |
| \( \beta \) | 0.942*** | 0.912*** | 0.910*** | 0.915*** |
| (0.074) | (0.008) | (0.035) | (0.014) |
| \( \lambda \) | 0.058*** | 0.082*** | 0.062*** | 0.070*** |
| (0.002) | (0.016) | (0.009) | (0.016) |
| Skew | 1.080*** | 1.000*** | 0.964*** | 0.892*** |
| (0.024) | (0.023) | (0.022) | (0.022) |
| Shape | 4.541*** | 5.222*** | 7.182*** | 8.859*** |
| (0.124) | (0.411) | (0.487) | (1.311) |

Diagnostic tests

| ARCH(7) | 0.725 | 0.828 | 0.408 | 0.586 |
| K-S test | 0.376 | 0.913 | 0.701 | 0.020 |
| Likelihood | 7846.431 | 8296.453 | 9851.846 | 8964.065 |

Note: ***, indicate significance at the 1% levels; Values in parentheses indicate standard errors; KS denote the Kolmogorov–Smirnov. ARCH (7) denotes Engle’s LM test for the ARCH effect in residuals up to 7th order.

Table 2 shows the parameter estimates results for the marginal models calculated by Eq.(1)-(2). The parameters p, q are non-negative integers selected the AIC values. For mean equation, the coefficient of AR displays positive and significant for S&PGCE and ECO. The coefficients of MA are not significant for all variables. For the variance equation, the coefficients of ARCH term (measured by the \( \alpha \) coefficient) and GARCH term (measured by the \( \beta \) coefficient) has positive and statistically significant for all variables, except lagged squared residuals in variables GAS and S&PGCE. The coefficients of \( \beta \) are strongly significant for all variables, which demonstrates that the return volatility at time \( t - 1 \) positively affect the returns at time \( t \). The leverage effect exists in all variables, which indicates that negative shocks at time \( t - 1 \) have the more significant impact on time \( t \) than positive shocks. Moreover, the sum of estimated parameters \( \alpha \) and \( \beta \) close to 1 and satisfied \( \alpha + \beta < 1 \), which shows obvious volatility cluster effects for variables. For Diagnostic tests, the results in Kolmogorov–Smirnov
test reveals autocorrelation, and ARCH statistics give no evidence of ARCH effects in models. Our results support the non-linear inference of the sample data and provide the nonlinearity evidence of the conditional variance. As a result of diagnostic tests, the copula model accurately captures the dependence between natural gas and the renewable energy stock markets by constructing the marginal distribution models.

3.2. Results for dependence structure

First, we select the optimal copula model according to the minimum AIC value. Table 3 reports the value of AIC for different copula models. The best copula fit for the pair ERIX-GAS and ERIX-ECO are the Frank copula. The upper and lower tail in the Frank copula are zero, which indicates that variables are asymptotically independent under the extreme events. For the pair ERIX-S&PGCE, the optimal model is Student-t copula with symmetric upper and lower tail dependence between the ERIX and S&PGCE stock markets. This dependency model indicates that bad information from the S&PGCE stock market to the ERIX stock market has a similar effect as good information about high returns.

| Pairs                          | Copulas | \( \rho \)  | \( v \)  | Kendall’s tau | Tail  | AIC  |
|-------------------------------|---------|------------|---------|-------------|-------|------|
| GAS-ERIX                      | Gaussian | -58.55     | -1758.78 | -1752.65    |       |      |
| S&PGCE-ERIX                   | Student-T | -59.33     | -1805.18 | -1779.11    |       |      |
| Clayton                       | -44.98  | -1467.87   | -1461.73 |             |       |      |
| Gumbel                        | -40.71  | -1602.17   | -1596.04 |             |       |      |
| Frank                         | -68.91  | -1654.4    | -1792.91 |             |       |      |
| Joe copula                    | -21.55  | -1176.24   | -1170.11 |             |       |      |
| BB1                           | -52.63  | -1791.38   | -1648.26 |             |       |      |
| BB6                           | -38.5   | -1599.75   | -1587.48 |             |       |      |
| BB7                           | -49.81  | -1744.98   | -1732.71 |             |       |      |
| BB8                           | -66.03  | -1599.87   | -1587.60 |             |       |      |

Note: The best copula models were selected by minimum AIC value (in bold).

| Pairs                          | Copulas    | \( \rho \)  | \( v \)  | Kendall’s tau | Tail  | AIC  |
|-------------------------------|------------|------------|---------|-------------|-------|------|
| GAS-ERIX                      | Frank      | 0.867***   | 0.096   |             |       | -68.91 |
| S&PGCE-ERIX                   | Student-t  | 0.637***   | 8.828*** | 0.310       | 0.171 | -1805.18 |
| ECO-ERIX                      | Frank      | 0.996***   | 0.099   |             |       | -1792.91 |

Note: *** indicate significance at the 1% levels; Values in parentheses indicate standard errors. The Gaussian copulas only have one parameter while the Student-t copulas have two parameters.

The estimation results of the static bivariate copula are reported in Table 4. Different copula families have a different range of parameters, thus we calculate the values of Kendall’s tau to compare the dependence degree between considered market. All estimated copula parameters are positive and statistically significant, implying a positive interdependence between ERIX and other clean energy stock markets. Regarding as the values of Kendall’s tau, there is weak dependence between ERIX and GAS, and also between ERIX and ECO with the low values (0.096 and 0.099, respectively). In contrast, there is a relative strong dependence between ERIX and S&PGCE. (0.310). Furthermore, the static bivariate copulas are not allowed to capture the parameters change over time. To capture the dynamic characteristics of returns co-movements between clean energy markets, we apply the time-varying
bivariate copulas; this approach is capable of checking the robustness of the results from the static bivariate copulas.

Table 5 reports the coefficients for the time-varying bivariate copulas. The coefficient of $\beta_c$ shows statistically significant, which indicates the last period affect the current period in the correlations for all pairs. And the coefficient of $\gamma_c$ captures significant variation in the dependence parameter for all pairs. By comparing the AIC value of time-invariate and time-varying copula (the last column of Table 4 and Table 5), we observe that time-varying bivariate copula shows more optimal than static. Our evidence confirms the robustness of findings from static analysis.

Table 5. Parameter estimation of the time-varying bivariate copulas

| Pairs          | Time-Varying Copulas | $\alpha_c$ | $\beta_c$ | $\gamma_c$ | $\nu$ | AIC   |
|---------------|----------------------|------------|-----------|------------|-------|-------|
| GAS-ERI       | Time-Varying Frank   | 0.006      | 0.975***  | 0.137      |       | -94.694|
| X             |                      | (0.005)    | (0.015)   | (0.093)    |       |       |
| S&PGCE-ERIX   | Time-Varying Student-t | 0.026     | 0.941***  | 0.536***   | 21.360*** | -2289.239 |
| ECO-ERI       | Time-Varying Frank   | 0.001      | 0.988***  | 0.243 ***  |       | -1967.510|
| X             |                      | (0.001)    | (0.004)   | (0.070)    |       |       |

Note: *** indicates significance at the 1% levels; Values in parentheses indicate standard errors.

The results for the static and time-varying parameter copulas from 2008 to 2021 are shown in Figure 1. The sample period covers the 2008 Global Financial Crisis, European Debt Crisis and COVID-19. First, we observe that the strong volatility of dependence degree from 2008 to 2012. This a turbulent period the global economic outlook deteriorated and the large shocks to most financial assets, and thus intensify correlations. Especially, the dependence degree between ERIX and S&PGCE reached a peak in 2010 (almost 0.5), and also between ERIX and ECO in 2012. Then, it is worth noting that the correlation coefficients for the pair ERIX-GAS and ERIX-ECO significant dropped during the period of 2012 to 2014; further, the reason may be global economic conditions gradually recovered after financial shock, which led to lower aggregated demand and risk synergy between European renewable energy and natural gas markets, and US renewable energy markets (ECO). After 2016, the dependence degree between ERIX and ECO significantly lower than the previous period with the worsening global economic condition and energy commodity prices slumped continually, leading to negative correlations. Finally, we observe a dramatically upward trend between ERIX and S&PGCE, and ERIX and ECO after 2020, a period during which the COVID-19 pandemic outbreak [11], leading to manufacturing, aviation, supply chains, and companies around the world were struck. The global renewable energy industries under the great pressure and incurred further damage, again leading to intensified correlations between the European renewable energy and S&P global clean energy markets, and US renewable energy markets (ECO).

Figure 1. Static (red line) and time-varying (blue line) estimate for the optimal copula.

Overall, our empirical results expose three ways: (i) The findings of the time-varying bivariate copulas checked the robustness of the results from static analysis. (ii) ERIX and GAS stock returns, and ERIX and S&PGCE stock returns show positive time-varying dependence. In contrast, ERIX and ECO
stock returns reflect that negative after the European subprime mortgage crisis. (iii) tail dependence only exists between ERIX and S&PGE stock markets. Thus, due to the flow of market information, considered markets participated in the period of booms and busts together.

4. Conclusion and policy implications
Providing renewable energy finance supports for private investors and institutional investors are the best way to accelerate the transition from dirty energy to low-carbon energy. In this study, first, we investigate the dependence structure between the European renewable energy stock and other clean energy stock markets. Our sample period covered from 2008 to 2021, which included the global financial crisis, the Eurozone debt crisis, and the COVID-19. Our results mainly show positive dependence between ERIX market and other clean stock markets; thus, for investors, the clean energy assets offer limited hedging alternatives in the ERIX markets. Our results are consistent with Liu et. al’s [10] findings. In addition, we find the evidence of symmetric tail dependence between ERIX and S&P global clean markets. Hence, we suggest investors focus more on ERIX market price swings when investing in S&P global clean stock markets, and vice versa. Further, our evidence on the interdependence between ERIX and clean energy markets, which is useful for forming green financial policies. Specifically, when renewable energy prices rise (fall) together, the government needs to adopt fiscal policy tools for clean energy firms. Financial and policy support have a positive impact on the development of renewable technology innovation, which are crucial factors for the energy transition. In addition, investors assess and control potential risk contagion by identifying co-movements mechanisms between ERIX market and other clean energy markets.

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