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The role of green finance in reducing CO_2 emissions: An empirical analysis

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Abstract

This study examines the relationship between green finance and carbon dioxide (CO_2) emissions in the top ten economies that support green finance (Canada, Denmark, Hong Kong, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, and the United States). This study uses quantile on quantile regression (QQR), introduced by Sim and Zhou (2015), to examine the dependence structure between different quantiles of green finance and CO_2 emissions. Our overall findings confirm the negative impact of green finance on CO_2 emissions; however, this relationship varies across the different quantiles of the two variables. This variation might be due to green finance market conditions (e.g., bearish or bullish) and country-specific market conditions. The findings in the study confirm that green finance is the best financial strategy for reducing CO_2 emissions.

Keywords: CO_2 emissions; Green bonds; Green finance; Quantile on quantile regression

1. Introduction

Since the beginning of the industrial revolution, the financial sector has been a powerful pillar of human growth. The primary role of the global financial sector is to make efficient use of the global savings. Proper use of investment enables improvement in people's quality of life. However, because of the collapse of the financial system, people have invested their savings in real-estate bubbles and environmentally damaging projects, including those that exacerbate human-induced climate change (Sachs, 2014). Previously, the financial sector ignored the ecosystem, which enabled the emergence or worsening of environmental issues, such as habitat and natural resource depletion, climate change, and pollution.

Finance plays a crucial role in the anthropogenics (i.e., human impact on the environment), yet very little has been done to incorporate environmental issues into finance (Scholtens, 2017). Over the past few years, the financial sector has paid attention to green investments, thereby advancing sustainable growth (Falcone et al., 2018). According to Sachs (2015), green financial instruments can help achieve a green environment. In the process, financial intermediaries and markets have designed financial instruments, such as green bonds, green home mortgages, green loans for commercial buildings, environmental home equity programs, "go green" auto loans, small business administration express loans, and climate credit cards. In addition, Australia launched its first environmental deposit initiative, which consists of medium-to long-term finance tools, which not only finance environmentally friendly projects and business activities but also support sustainable development and climate-related projects directly (NATF, 2007).

Green finance is an intersection between environmentally friendly behavior and the financial and business world (Scholtens, 2017), however, few studies have link finance with

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ecology. Scholtens (2009) studied the link between the performance and social responsibility of financial institutions. Li and Jia (2017) concluded that environmental finance/sustainable finance is the most effective way to reduce environmental degradation. Green finance encourages investment in new technologies and innovations, including renewable energy (Böhringer et al., 2015). Thus, we are motivated to examine the dynamic impact of green finance on the carbon dioxide (CO_2) emissions of the top ten countries that support green finance (Canada, Denmark, Hong Kong, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, and the United States).

This study makes three contributions to the existing literature. First, compared to prior studies, which mostly stress the role of financial development, instead of only the effect of green finance on environmental variables, this study presents a pioneering examination of green finance and CO_2 emissions. Secondly, this study uses the QQR approach that captures the heterogeneous and asymmetric relationship between green finance and CO_2 emissions. Unlike quantile regression, the QQR approach can regress the independent variable's quantiles on the dependent variable's quantiles and thus provide more information (Lin and Su, 2020). Thirdly, this is one of the first studies to consider the ten most advanced economies in which green finance has been used significantly. The empirical findings on the impact of green finance on their corresponding CO_2 emissions act as benchmarks for other countries. Finally, our empirical analysis provides new insights into the asymmetric response of CO_2 emissions to green finance use at different quantiles.

After this introduction, the paper consists of following sections. Section 2 is the literature review, Section 3 describes our data and methodology, Section 4 presents our results, and our conclusion and recommendations are in Section 5.

2. Literature review

Global warming is one of the biggest threats facing the world. The United Nations sustainable development goals (SDGs) focused attention on the growing concern over environmental pollution and degradation of natural resources and hence paved the way for introducing modern concepts such as sustainable growth. Previously, the financial sector ignored the ecosystem, but the financial sector has increasingly begun to consider environmental issues and introduced various financial products that specifically target environmental protection, such as green bonds.

To date, few studies have linked finance to ecology. Wang and Zhi (2016) suggest that environmental sustainability can be achieved through developing financing for solar energy. A similar study by Li and Jia (2017) also concludes that environmental finance/sustainable finance is the most effective way to reduce environmental degradation. Sustainable finance/green finance encourages investment in new technologies and innovations, including renewable energy (Jones, 2015). However, previous studies ignored the relationship between green bonds (a proxy for green finance) and CO_2 emissions. Green bonds are long-term financial instruments in which the proceeds from green bonds are used solely to finance projects that are environmentally friendly or reduce pollution in the environment. For example, green bond revenues are used to support solar energy, clean water, and clean transport projects.

Moreover, to check the relationship between CO_2 emissions and their determinants, previous studies have used econometrics tests including Granger causality, error correction models (ECM), FMOLS, DOLS models, vector error correction models (VECM), bootstrap causality tests, and autoregressive distributed lag models (ARDL). The main flaw in these methods is that they examine only the linear relationship between the variables. Po and Huang (2008) argue that linear methods do not consider short-term volatility and sudden data-series changes. Anoruo (2011) finds that linear models assume linearity between series, but the macro series might not support this assumption in reality. Because of financial crises, sudden policy changes, domestic tensions, and financial market complexity create regime-switching behavior, which introduces nonlinearity to the relationship between green finance and CO_2 emissions.

A critical review of the literature on CO_2 emissions shows that previous studies have examined the relationship between CO_2 emissions and other macroeconomic variables, but to the best of our knowledge, no studies have been carried out that empirically examine the relationship between green finance and CO_2 emissions using quantile on quantile (QQR) approaches. This approach is particularly intriguing in this context because the link between green finance and CO_2 emissions can be contingent on the economic cycle and the size and sign of green finance (green bonds). Therefore, CO_2 emissions are expected to respond differently due to positive and negative changes in green finance. In periods of high economic expansion, CO_2 emissions usually remain high, whereas during economic slumps they are low. In this regard, although recognizing that CO_2 is a complex and multifaceted phenomenon and its relation to green finance depends on many of factors, the nature of the link between CO_2 emissions and green finance can vary, depending on the state of the economy (expansion or recession). Hence, a positive change in green finance might have a larger effect on CO_2 emissions than a negative change.

3. Data and methodology

This study uses bivariate QQR to examine the nexus between green finance and CO_2 emissions. Green bonds are used as a proxy for green finance, and we use per capita green bonds market capitalization to measure green bonds and per capita CO_2 emissions to measure CO_2 emissions. We collect monthly data from November 2008 to June 2019 from Datastream. We consider the top ten economies with top green finance capitalization (green bonds): Canada, Denmark, Hong Kong, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, and the United States. These advanced economies were selected for two key reasons. First, according to the World Air Quality Project (AQI), these economies have serious pollution problems; for example, the United States, Japan, Hong Kong, United Kingdom, and Canada have very low air quality; Norway, Denmark, and Switzerland have moderate air quality; and Sweden and New Zealand are the only two countries with reasonable air quality.[1] Second, these economies with high green bond capitalization.

3.1. Quantile unit-root test

Given the nature of the data used in the analysis, which is asymmetrically distributed, the standard augmented Dickey-Fuller (ADF) test might not be sufficient. Therefore, we use a quantile autoregressive unit-root test (QAR), as propounded by Koenker and Xiao (2004) and extended by Galvao (2009). Koenker and Xiao (2004) conduct a Monte Carlo test on interest rate dynamics, with several comparative analyses. We find that, in general, under an asymmetric distribution of disturbance, the QAR procedure produces a better result than traditional ADF. Further, Galvao (2009) extends the method to accommodate covariate stationarity and a linear time trend. The QAR test is carried out on individual quantiles of the distribution of the variable for time, as the conventional ADF test ignores this asymmetry, so a significant distinction is seen between traditional ADF and QAR. Following Galvao (2009), we estimated the τth conditional quantile function of *y* as follows:

$$Q_\tau^y\left(y_t \middle| I_t^y\right) = \mu_1(\tau) + \mu_2(\tau)t + \alpha(\tau)y_{t-1} + \sum_{i=1}^{p} \alpha_i(\tau)\Delta y_{t-i} + f_\mu^{-1(\tau)} \tag{1}$$

Assuming that $f_y(.|I_t^y)$ is the conditional distribution of y_t, given I_t^y, y_t is the strict stationarity of a given set of past information $I_t^y = (y_{t-1}, y_{t-2} \ldots, y_{t-s})' \varepsilon\ R^s$. Q_τ^y is the τth quartile of y conditional on I_t^y, and f_μ^{-1} represents the inverse of the common distribution function of error. Finally, we test quartile stationarity using *t*-statistics for a given null hypothesis $H_0\ \alpha(\tau) = 1$.

3.2. Quantile cointegration

We use a stochastic quantile cointegration model introduced by Xiao (2009) to examine the long-run comovement of the variables used in the study (green finance and the environment, proxied by CO_2 emissions). The Xiao (2009) model is a noteworthy advance over the Engle and Granger (1987) model in that it introduces coefficients that vary with quantiles. While the Engle and Granger (1987) model assumes that the cointegrating vectors β are constant, the cointegrating coefficients in the model proposed by Xiao (2009) are $\beta = (\beta 1, \ldots, \beta i)$ are assumed to vary because of shock effects. Also, the Xiao (2009) model decomposes the error term into a pure innovation portion and a portion correlated with the leads and the lags in Δx_t. This addresses the difficulty in identifying β_t from $\beta_t{}' x_t$, considering $\beta = \beta_t$ a function of μ_t.

If $v_t = \Delta x_t$ is a zero-mean stationary order of $(n+1)$ that is represented in v_t and μ_t, then, the traditional cointegration equation can be expressed as follows:

$$y_t = \alpha + \beta_t' x_t + \sum_{i=-n}^{n} \Delta x_{t-i}' \Pi_j + \varepsilon_t \tag{2}$$

To represent the quantile of y_t conditional on f_t, the τth quantile of ε_t should be denoted as $Q_\varepsilon(\tau)$, given $f_t = (x_t, \Delta_{t-i}, \forall i)$. Hence:

$$Q_\tau^y\left(y_t \middle| I_t^x\right) = \alpha(\tau) + \beta(\tau)' x_t + \sum_{i=-n}^{n} \Delta x_{t-i}' \Pi_j + f_\varepsilon^{-1(\tau)} \tag{3}$$

Xiao (2009) derives a stability test for the cointegrating coefficient from the following equation:

$$Q_\tau^y\left(y_t \middle| I_t^x\right) = \alpha(\tau) + \beta(\tau)' x_t + \gamma(\tau)' x_t^2 \sum_{i=-n}^{n} \Delta x'_{t-i} \Pi_j + \sum_{i=-n}^{n} \Delta x^{2'}{}_{t-i}\, r_j f_\varepsilon^{-1(\tau)} \tag{4}$$

Following Xiao (2009), we estimated the critical values of $\mathrm{Sup}\left|\widehat{V_n}(\tau)\right|$ using 1000 Monte Carlo simulations. The null hypothesis (H_0) for all quantiles is $\beta(\tau) = \beta$, in which we use the test statistics under the supermum rule of absolute value differences in $\widehat{V_n}(\tau) = (\widehat{\beta}_n(\tau) - \widehat{\beta})$

3.3. QQR regression

This study applies the QQR approach, which enables us to investigate the impact of quantiles of green finance on the quantiles of CO_2 emissions. The asymmetric distribution of the two variables in a preliminary test indicates that the QQR regression choice is the appropriate tool for modeling the relationship. Ordinary least squares (OLS) regression relies on assumptions that are often not met by data. OLS can also be misleading in its single conditional mean-coefficient generalization when data with multimodal distribution are used; quantile regression is more suitable and enables us to explore the different dimensions of the relationship between the dependent variable and the independent variable.

Moreover, standard quantiles regression estimates only the conditional mean effects of independent variable (IV) *x* on various quantiles of dependent variable (DV) *y*. The QQR approach is an extension of quantiles regression introduced by Sim and Zhou (2015) to address the numerous shortcomings inherent in traditional quantile regression. Thus, we deal with the issue of interdependence using the QQR method. Furthermore, the QQR method has become well known across disciplines—for example, Sharif et al. (2020) use QQR for modeling ecological footprint, Farooq et al. (2020) for financial markets, Arain et al. (2020) for tourism, and Benigno (2016) for stock returns. This approach is becoming more popular because it provides a complete dependence structure between the proposed variables that help policy makers to

[1] https://aqicn.org/rankings/.

design policies. However, this approach has one limitation: it accommodates only two variables because it is a bivariate nonparametric estimation.

We use the single-equation model introduced by Sim and Zhou (2015) in this study based on the system of equations by Ma and Koenker (2006). Having previously modeled the τ-quantile of CO_2 emissions as a function of its lagged values, we now present the τ-quantile of $CO2_t$ as a function of green finance, represented by GF_t, in the following equation:

$$CO2_t = \beta^\theta(GF_t) + \mu_t^\theta \tag{5}$$

Because we have no prior knowledge of the relationship between GF and CO_2, the factor loading $\beta^\theta(.)$ is unknown. μ_t^θ is the error term with zero θ quantiles. Taking the first-order Taylor expansion of $\beta^\theta(.)$, around GF^τ, we transform Eq. (5) into a linear equation as follows:

$$\beta^\theta(GF_t) \approx \beta^\theta(GF^\tau) + \beta^{\theta'}(GF^\tau)(GF_t - GF^\tau) \tag{6}$$

The double indexing of $\beta^\theta(GF^\tau)$ and $\beta^{\theta'}(GF^\tau)$ in θ and τ indicates that both $\beta^\theta(GF^\tau)$ and $\beta^{\theta'}(GF^\tau)$ are functions of θ and τ. Eq. (6) can be revised as:

$$\beta^\theta(GF_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(GF_t - GF^\tau) \tag{7}$$

Then, Eq. (7) is substituted into the initial QQR Eq. (5) to obtain

$$CO2_t = \underbrace{\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(GF_t - GF^\tau)} + \mu_t^\theta \tag{8}$$

The $\underbrace{\quad}$ portion of Eq. (8) is the θ^{th} conditional quantile of CO_2 emissions. This expression captures the association between the θ^{th} quantiles of green finance and the τ^{th} quantiles of CO_2 emissions, given that β_0 and β_1 are both indexed in θ and τ, unlike in the standard conditional quantile function. The $\underbrace{\quad}$ portion of Eq. (8) captures dependence between green finance and CO_2 emissions over the entire distribution of GF and CO_2 emissions.

3.4. Testing the validity of the QQR approach

To verify the QQR approach's validity, we compare the QQR results to the traditional quantile regression results. In estimating the traditional quantile regressions for comparison, we average the indexed τ parameters that are missing in the conventional quantile, as in the following equation:

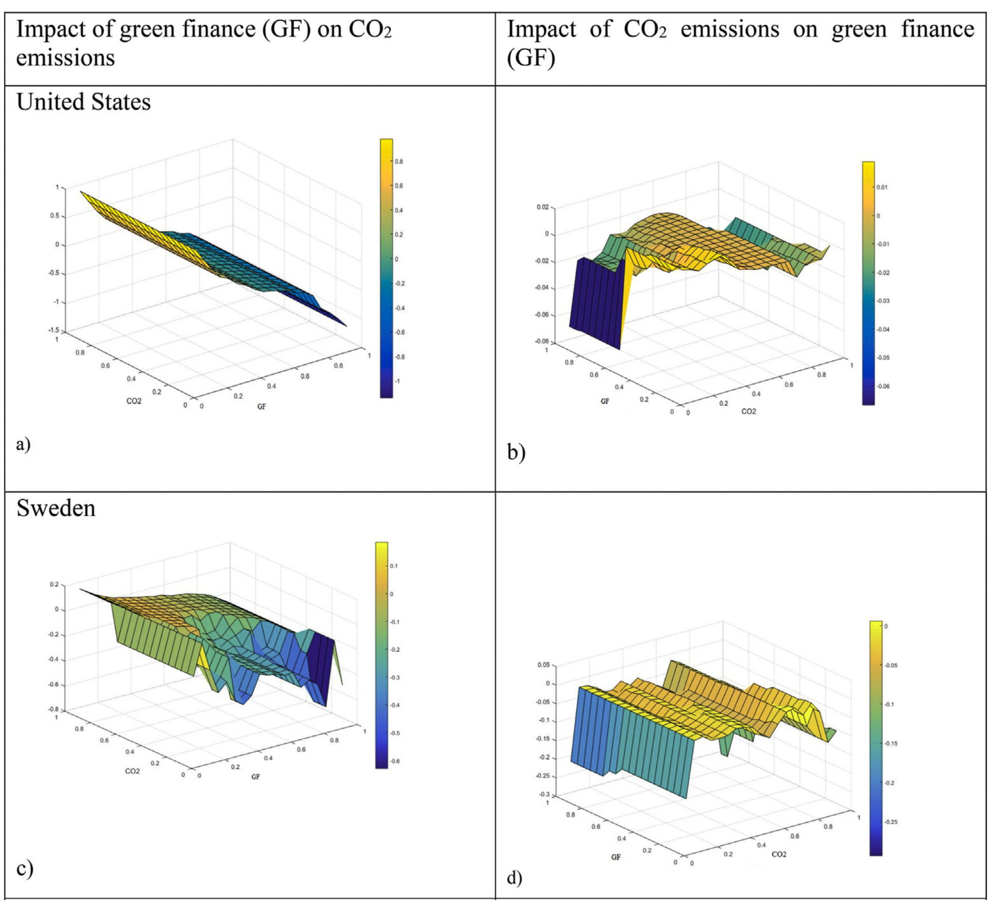

Fig. 1. a–t; note, this graph depicts the estimates of the slope coefficient, β (τ, θ), which is placed on the z-axis against the quantiles of the GF (τ) x-axis and quantiles of the CO2 (θ) on the y-axis. The color bar colors measure the degree of the co-movement or correlation between variables under investigation (GF and CO_2). The red color corresponds to the slope coefficient's positive and growing values, while the dark blue color corresponds to negative and strong values of the slope coefficient. The light blue and the light green colors correspond to weak or insignificant values of the slope.

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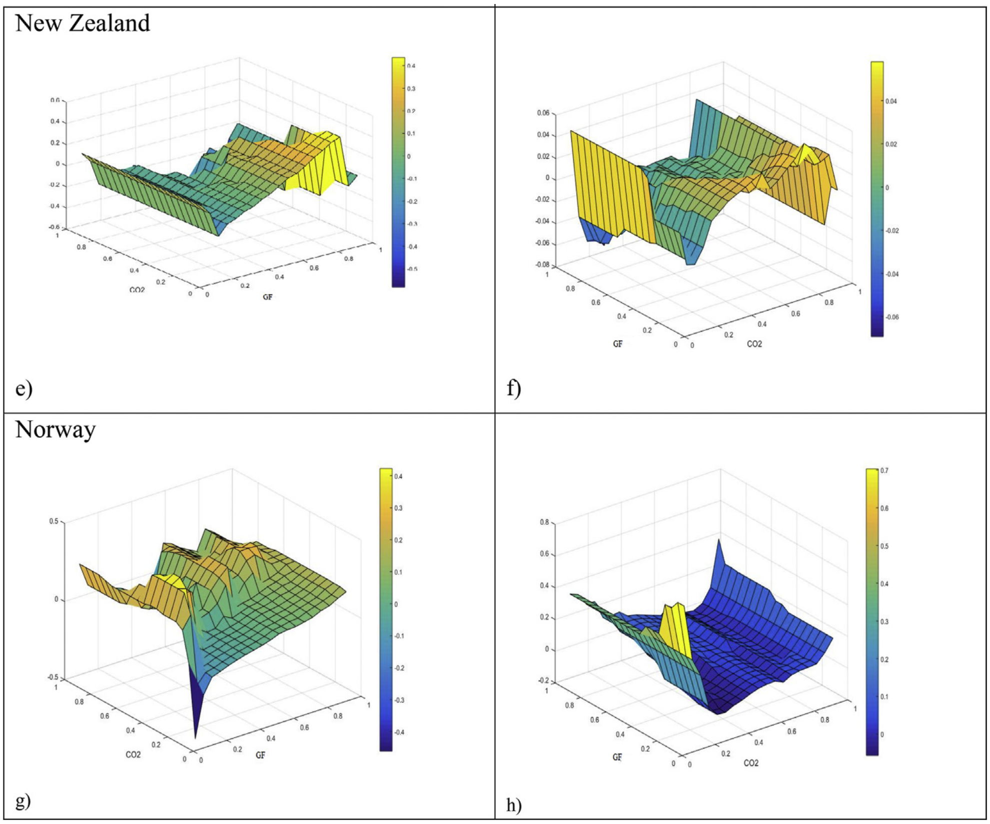

Fig. 1. (continued)

$$y_1(0) \equiv \overline{\overline{\widehat{\beta}}}(\theta) = \frac{1}{s}\sum_{\tau}\widehat{\beta}_1(\theta,\ \tau) \tag{9}$$

where $\overline{\overline{\widehat{\beta}}}$=averaged parameters from the QQR regression.

3.5. Mean and quantile granger causality

Granger (1969) found that a variable Z_t does not Granger cause another variable Y_t if a lagged Z_t does not predict Y_t, given the lagged Y_t. Assume that we have an explanatory vector $X_t = (X_t^Y, X_t^z)' \varepsilon \mathbb{R}^d$, $d = s + q$, where X_t^z is the previous information set of $Z_t, X_t^z = (z_{t-1}, \ldots\ldots z_{t-q})' \varepsilon \mathbb{R}^q$.Based on Z_t and Y_t, we have the following null hypothesis of Granger non-causality.

$$H_0^{Z \nrightarrow Y} : F_Y\left(\left(y|_t^Y, X_t^z\right) = F_Y\left(y \middle| X_t^z\right), \text{for all } y\varepsilon\mathbb{R} \tag{10}$$

where $F_Y((.|_t^Y, X_t^z) =$ refers to the conditional distribution function of Y_t, given$(X|_t^Y, X_t^z) =$. However, in this study, we follow Troster (2018) and use an S_t test based on the QAR function for the entire$\pi \in \Gamma \subset [0, 1]$. We form the following null hypothesis of non-Granger causality:

$$\text{QAR}(1) : Q^{\frac{y}{\tau}}\left(Y \middle| X\frac{y}{t}, X\frac{z}{t}\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \beta(\tau)Z_{t-1} + \sigma_t\Phi_{u^{-1}}(\tau). \tag{11}$$

Eq. (11) $\theta(\tau) = \mu_1(\tau)$, $\mu_2(\tau)$is calculated in equally spaced quantiles based on the maximum likelihood method, whereas the standard normal distribution function is expressed by $\Phi_{u^{-1}}$. We estimated Eq. (11) with lagged variables of another variable in the QAR framework to correct the causality sign among purposed variables. Finally, we constructed the QAR (1) model based on Eq. (11) as follows:

$$Q^{\frac{y}{\tau}}\left(Y \middle| X\frac{y}{t}, X\frac{z}{t}\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \beta(\tau)Z_{t-1} + \sigma_t\Phi_{u^{-1}}(\tau). \tag{12}$$

4. Results and analysis

4.1. Descriptive statistics, unit root tests, and quantile cointegration

Table 1 lists the descriptive statistics (see the supplementary material available online Table S1) for green finance and CO_2 emissions in all the sample countries over the sample

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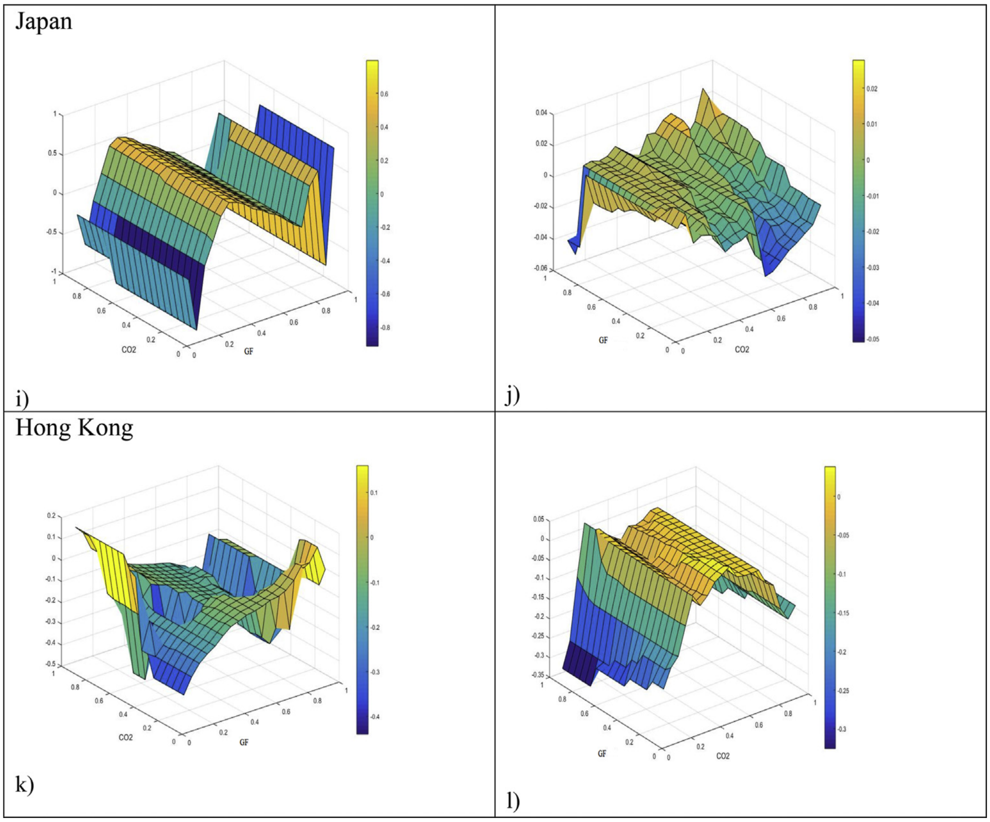

Fig. 1. (continued)

period. The United States has the highest mean of per capita CO_2 emissions, followed by Canada, Norway, Japan, and New Zealand; the lowest of per capita CO_2 emissions is found in Switzerland, followed by Sweden, Denmark, Hong Kong, and the United Kingdom. For green finance, the highest per capita green bonds market capitalization is in Japan, followed by the United Kingdom, Denmark, Hong Kong, and the United States; Switzerland and New Zealand have the lowest mean per capita green bonds market capitalization. Thus, the United States has the highest pollution during the sample period, and based on the sample population, the IEP (2015) shows it is one of the top CO_2 emitters. Japan has the highest mean per capita green bonds market capitalization among the sample countries, which shows it highly encourages green finance for green projects. To check the normality of the residuals, we use the well-known Jarque−Bera test (JB). The JB test outcomes confirm the nonnormality of the variables, which encourages the use of nonparametric estimation for examining dependence among the variables. Table 1 also shows the results of ADF, Phillips-Perron (PP), and ZA unit-root tests. The unit-test results confirm that both variables are stationary at I (1). Table 2 lists the quantile unit-root test results (see the supplementary material available online Table S2). The QAR results are consistent with the findings of the ADF, PP, and ZA unit-root tests. Both variables are stationary at I (0) at lower quantiles of both variables; however, they become stationary at 1 (1) on all their quantiles.

After conducting the unit-root tests, we conducted quantile cointegration as proposed by Xiao (2009). Table 3 presents the coefficients of the cointegration model $\beta(\tau)$ and $\widehat{\gamma}\,(\tau)$ over the different quantiles of both variables (see the supplementary material available online Table S3). Overall, we confirm that the long-run relationship does not remain the same in the lower to upper quantiles of green finance and CO_2 emissions. Furthermore, we find heterogeneous/varying links between green finance and CO_2 emissions among the sample countries. The quantile cointegration findings in Table 3 also confirm the nonlinear relationship between green finance and CO_2 emissions.

4.2. QQR regression

Fig. 1a-t show the results of QQR, with overall a negative relationship between green finance and CO_2 emissions in the United States. We find a positive effect of green finance on CO_2 emissions on the lower quantile of green finance (0−0.2) and lower to upper quantiles of CO_2 emissions (0−0.95). At the same time, we find a strongly negative relationship between green finance and CO_2 emissions on the lower to higher quantiles of green finance (0−0.96) and the lower to higher quantiles of CO_2 emissions (0−0.8). Overall, we find a positive effect of CO_2 emissions on green finance and a strongly positive relationship in the area that combines the two variables (lower to high quantiles (0−0.8). In the United States,

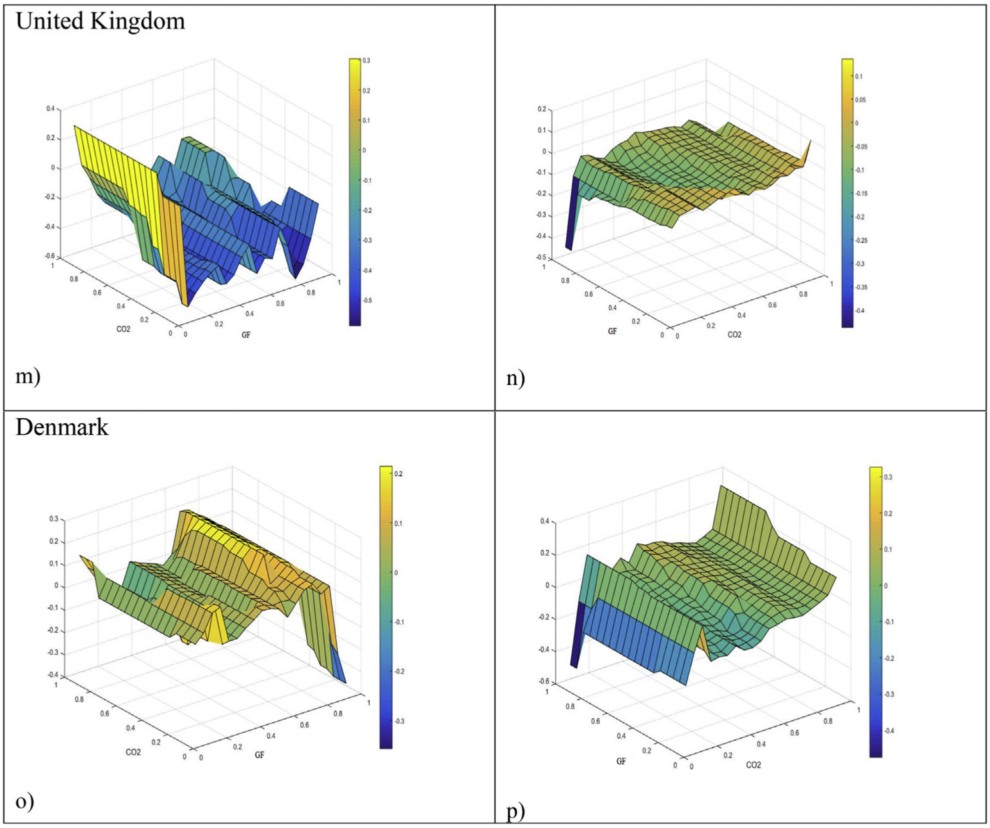

Fig. 1. (continued)

any increase in green finance leads to a decrease in environmental degradation (CO_2 emissions). However, the relationship between the two variables does not remain same over their quantiles.

The study shows that green finance and CO_2 emissions are negatively linked on all quantiles in Sweden. This negative effect is very strong in the middle to higher quantiles of green finance and middle to higher quantiles of CO_2 emissions. The impact of CO_2 emissions overall is also positive. However, on the lower quantiles of CO_2 emissions (0.4−0.5) and lower to higher quantiles of green finance (0.2−0.8) we find a negative relationship. These results suggest that, in Sweden, green finance reduces CO_2 emissions. Furthermore, the relationship between the two variables is not homogeneous over the quantiles; however, when CO_2 emissions increase, demand for green investment also increases.

In New Zealand, overall, we find a weak relationship between green finance and CO_2 emissions. However, on high quantiles of CO_2 emissions (0.7−0.8) and low to high quantiles of green finance (0.4−0.8), we find a highly positive correlation, whereas in the area that combines low to middle quantiles of the two variables (0.2−0.5), we find a very weak correlation. The findings suggest that when CO_2 emissions increase (peak), demand for green investment also increases. The findings also show an asymmetric association between green finance and CO_2 emissions.

In Norway, we find an overall weak correlation between green finance and CO_2 emissions. However, on the lower to middle quantiles of green finance (0.2−0.5) and lower to middle quantiles of CO_2 emissions (0.2−0.6), we find a strong negative association between the two variables. The effect of CO_2 emissions on green finance is positive overall. However, we find a negative relationship at the low quantiles of CO_2 emissions and low quantiles of green finance (0.2−0.4), whereas on the high quantiles of the two variables, the relationship becomes very strong. The findings for Norway suggest that because of higher CO_2 emissions, the demand for green finance also increases, but CO_2 emissions do not attract green investment at the initial stage.

We find a mixed effect of green finance on CO_2 emissions in Japan. The area that combines high quantiles of green finance and low to middle quantiles of CO_2 emissions indicates a positive relationship, however, on the upper quantiles of green finance and CO_2 emissions, we find a negative relationship. The main reason for this relationship between green finance and CO_2 emissions is that when pollution increases, demand for green finance investment also increases.

We find an overall negative relationship between green finance and CO_2 emissions in Hong Kong. This negative relationship becomes very strong in the area that combines upper quantiles of green finance (0.8−0.95) and middle to high quantiles of CO_2

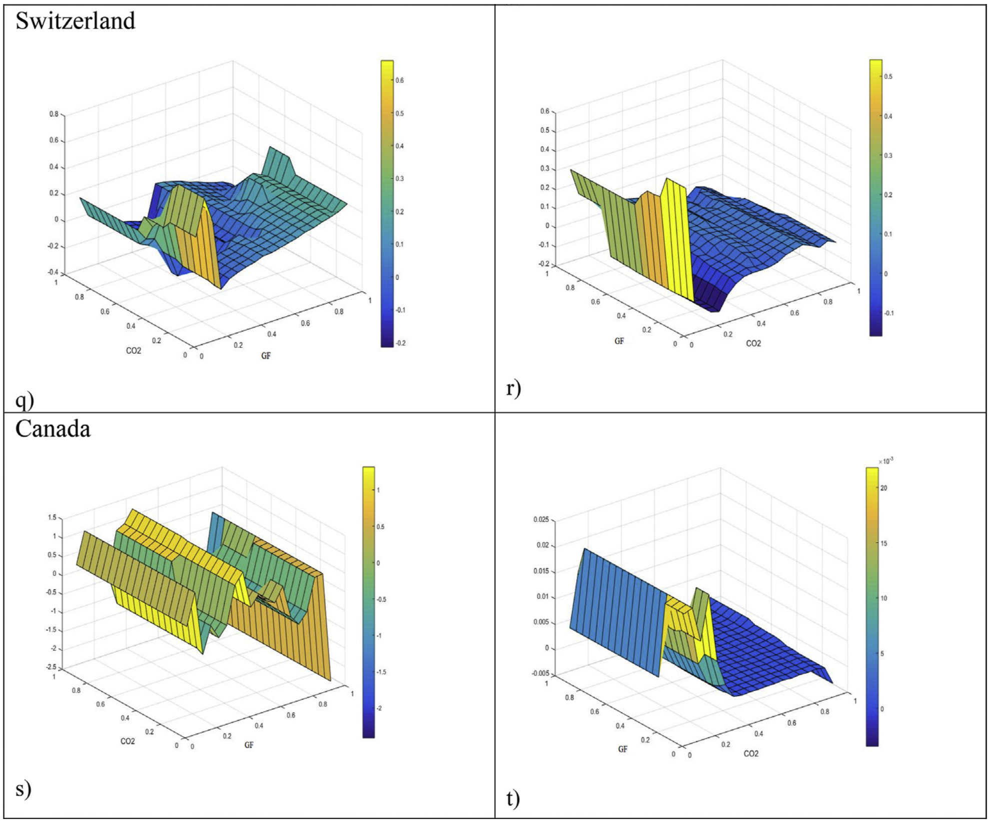

Fig. 1. (continued)

emissions (0.5−0.7). However, we also find a positive correlation at the low to middle quantiles of green finance (0.4−0.6) and high quantiles of CO_2 emissions. The effect of CO_2 emissions on green finance is positive at high quantiles of both variables, but we find a negative relationship between the low quantiles of CO_2 emissions and the middle to upper quantiles of green finance.

We find an overall negative relationship between green finance and CO_2 emissions in the United Kingdom, as in other advanced countries. We observe a strong negative link at the low to high quantiles of green finance (0.2−0.95) and middle to upper quantile (0.5−0.8) of CO_2 emissions.

In Denmark, we find an overall weak negative relationship between green finance and CO_2 emissions; on lower quantiles of green finance (0.2−0.4) and middle to high quantiles of CO_2 emissions (0.6−0.8) the two variables have a positive correlation. However, at high quantiles of green finance (0.8−0.9) and low quantiles of CO_2 emissions, the two variables are strongly negatively linked, and on low quantiles of CO_2 emissions (0.2−0.4) and low to the high quantiles of green finance (0.2−0.95), we find a negative relationship.

In Switzerland, as in other countries, we find an overall negative effect of green finance on CO_2 emissions, with a strongly negative relationship between the two variables on the lower quantiles of CO_2 emissions and lower quantiles of green finance.

We find mixed results about the relationship between green finance and CO_2 emissions in Canada, showing that a negative relationship exists at high quantiles of green finance (0.8−0.95) and low to middle quantiles of CO_2 emissions (0. -0.7). However, a negative relationship is found at the high quantiles of the two variables and a positive relationship on the low quantiles of green finance and low to high quantiles of CO_2 emissions. The findings confirm the asymmetric effect of green finance on CO_2 emissions.

A few studies confirm that green initiatives improve environmental quality. For example, Mathews et al. (2010) show that sustainable initiatives play a significant role in reducing environmental degradation. Similarly, Tolliver et al. (2019) also find that green finance reduced CO_2 emissions by 108 million tons. Flammer (2018, pp. 1−22) and Wang et al. (2018) also conclude that green finance improves environmental performance and encourages green innovation. Similarly, in line with World Bank projections, Wang et al. (2018) reports that two energy projects in China, financed by green finance (green bonds), are expected to reduce CO_2 by 12.6 million tons annually. Green finance funds investment in soil, green transport, clean energy, energy conservation, low-carbon utilities, and water and waste, which gradually reduces environmental burdens.

4.3. Comparison of quantile regression and QQR estimates

QQR can be conducted using the framework of standard quantile regression. The QQR method decomposes the standard quantile regression estimates to obtain coefficients for various quantiles of exogenous variables. We regress the θth coefficient of CO_2 emissions on the τth coefficient of green finance. The difference between standard quantile regression and QQR is that standard quantile regression is measured by θ whereas QQR parameters are measured by both θ and τ. Therefore, QQR comprises more information regarding green finance and CO_2 emissions than standard quantile regression. The quantile regression features can be revealed using the QQR approach due to its ability to perform "decomposition." Technically, quantile regression parameters indexed by θ can be generated using an average of QQR parameters along τ. To conduct quantile regression estimations, we summarize the estimated QQR parameters (in Eq. 13) with an average along τ.

$$\gamma_1(\theta) \equiv \overline{\widehat{\beta_1}} = \frac{1}{s}\sum_{\tau}\widehat{\beta_1}(\theta,\tau) \tag{13}$$

The validity of QQR parameters is can be checked by comparing the QR approach estimates with those from averaging τ parameters with the QQR approach. Figures S1 a-j illustrate the estimates of standard quantile regression and QQR for green finance and CO_2 emissions for the top ten economies that support green finance (see the supplementary material available online Figures S1). The figure confirms that standard quantile regression and QQR estimates show the same pattern, regardless of the quantile, in all countries. Hence Figure S1 confirms the validity of quantile on quantile estimates.

4.4. Granger causality in quantiles

After conducting quantile on quantile estimation, we enrich our analysis using a Granger-causality test in quantiles, with the results presented in Table 4 (see the supplementary material available online Table S4). We employed an S_t test for the logarithm series of green finance and CO_2 emissions based on 19 grid equally spaced (0.5−0.95). The findings confirm that in Hong Kong and the United Kingdoms, at low quantiles green finance does not Granger cause CO_2 emissions, and in the United States, Norway, and Sweden, at middle quantiles green finance does not Granger cause CO_2 emissions. However, in the rest of the countries studied, green finance does Granger cause CO_2 emissions. Overall, our results confirm bidirectional causality between green financing and CO_2 emissions in the sample countries.

5. Conclusion and recommendation

This study examines the relationship between green finance and CO_2 emissions in the top ten economies that support green finance. We employ QQR regression to examine the asymmetric impact of green finance on CO_2 emissions. The overall findings show the negative impact of green finance on CO_2 emissions in selected economies. However, the relationship between green finance and CO_2 emissions varies on different quantiles of the two variables in these top ten economies.

5.1. Practical implications

Reducing the negative externality of human economic activities is a global task. Proponents strongly reinforce the importance of green finance as a mitigation measure to minimize economic externalities without compromising significant economic growth. Based on the negative relationship between green finance and CO_2 emissions, we recommend the following policies to promote green finance development.

1. The government should use fiscal policies to promote green finance development and use fiscal funding to guide credit funding and social capital into green investment, green credit, and green securities.
2. The government should improve the green financial system, prioritize green activities in the approvals processes, and simplify the green, ecological, and low-carbon industries application process.
3. The government should provide a green financial development policy in underdeveloped regions and lower the issuance and trading thresholds for green bonds and green securities.
4. Developing countries should employ green financing to help benefit the environment.

5.2. Directions for future research

Our study can be extended by exploring comovement between green finance and other financial markets from a portfolio perspective to attract more investment.

Declaration of competing interest

Authors has no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2021.03.002.

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