How natural disasters affect carbon emissions: the global case

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Abstract
The outbreak of the COVID-19 pandemic has once again made the impacts of natural disasters a hot topic in academia. The environmental impacts of natural disasters, however, remain unsettled in the existing literature. This study aims to investigate the impact of natural disasters on CO₂ emissions. For this purpose, we employ a panel dataset covering 138 countries over the period 1990–2018 and two dynamic panel estimation methods. Then, considering the differences in CO₂ emissions across various countries, we run a panel quantile regression to examine the asymmetry in the nexus between natural disasters and CO₂ emissions. We also discuss the mediating effects of energy consumption between natural disasters and CO₂ emissions. After conducting a series of robustness checks, we confirm that our results are stable and convincing. The empirical results indicate that natural disasters significantly reduce CO₂ emissions. Nevertheless, the impact of natural disasters on CO₂ emissions is asymmetric across different quantiles of CO₂ emissions. Furthermore, the technology level serves as an important moderating factor between natural disasters and CO₂ emissions. The mediating effect results reveal that natural disasters not only directly reduce CO₂ emissions but also indirectly promote carbon reduction by restraining energy consumption. Finally, several policy implications are provided to reduce CO₂ emissions and the damage caused by natural disasters.

Keywords Natural disasters · CO₂ emissions · Asymmetry · Mediating effect · Global analysis

Abbreviations
ADF Augmented dickey-fuller
CADF Cross-sectional augmented dickey–fuller
CD Cross-sectional dependence
CO₂ Carbon dioxide
COVID Corona virus disease
CRED Center for research on the epidemiology of disasters
D-GMM Differential GMM
EKC Environmental kuznets curve
1 Introduction

The outbreak of the coronavirus disease 2019 (COVID-19) pandemic at the end of 2019 has once again drawn scholars’ attention to the impacts of natural disasters. According to statistics from the Center for Research on the Epidemiology of Disasters (CRED 2020), the number of natural disasters has increased sharply—by 46%—in the past three decades, from 303 in 1990 to 444 in 2019. Frequent natural disasters have resulted in a diverse series of consequences. For example, it has been documented that natural disasters lead to deaths and injuries (Chen et al. 2013; Tang et al. 2017; Zhou et al. 2014), infrastructure collapse (Botzen et al. 2019; Seaberg et al. 2017), and energy market volatility (Lee et al. 2021; Schwarz and Cochran 2013). In addition, Khalid and Ali (2019) demonstrated that natural disasters can cause economic losses. This view is supported by Neumayer et al. (2014) and Salisu and Adediran (2020). According to the CRED (2020), the total economic damage caused by natural disasters has soared from USD49.78 million in 1990 to USD100.94 million in 2019—an average growth rate of 2.38% each year. Thus, the impacts of natural disasters are multifaceted (Noy 2009). At the same time, mounting carbon dioxide (CO$_2$) emissions and associated climate change issues, such as global warming, have long plagued policy-makers and scholars (Shugar et al. 2017). As reported by the International Energy Agency (IEA 2019), total global CO$_2$ emissions have experienced tremendous growth in the past three decades, from 20,516.04 million tons (Mt) in 1990 to 33,513.25 Mt in 2018. Accordingly, mitigating the impact of natural disasters and curbing global warming have become important issues to be solved, and they are at the top of the agenda of the international community. We present Fig. 1 to clearly show the spatial distribution of natural disasters and CO$_2$ emissions across the globe. Additionally, we select nine representative natural disasters, i.e., droughts, earthquakes, extreme temperatures, floods, landslides, pandemics, storms, wildfires, and volcanic activities, to calculate the proxy variable of natural disasters.

As Fig. 1 shows, great differences exist in CO$_2$ emissions across various countries, indicating that countries around the world have different economic development patterns and CO$_2$ reduction policies. This fact poses a couple of interesting questions: what is the main driving factor of global CO$_2$ emissions? Is there a “one size fits all” policy to mitigate CO$_2$ emissions in countries around the world? In recent years, a growing body of scholars has explored the driving factors of CO$_2$ emissions, which mainly include socioeconomic variables such as population (Dong et al. 2019, 2020b; Ghazali and Ali 2019), affluence (Arouri et al. 2012; Dietz and Rosa 1997; Salahuddin et al. 2018), financial development
(Shahbaz et al. 2018), and other factors related to energy consumption (Mishra et al. 2014; Paramati et al. 2017). Considering the multifaceted nature of the impacts of natural disasters, it is highly possible that they may cause changes in environmental quality. According to Markhvida et al. (2020), asset losses caused by natural disasters may affect households’ well-being, and this aspect should not be neglected in assessments of natural disaster risk. Thus, these authors propose a methodology for evaluating the impacts of natural disasters by integrating the environmental, economic, and social impacts into a unified framework. Furthermore, the literature has documented that natural disasters may cause volatility in energy prices and depress economic development (Devpura and Narayan, 2020; Felbermayr and Gröschl 2014; Liu et al. 2021), which may impede energy consumption and thereby reduce CO2 emissions. For example, the outbreak of the COVID-19 pandemic at the end of 2019 made people work at home, which greatly reduced energy consumption related to commercial enterprises and motor vehicle travel (Richardson et al. 2014). This outcome was followed by a sharp decline in gasoline demand and the oil price (Lee et al. 2021) and eventually led to a drop in CO2 emissions. In addition, the COVID-19 pandemic exerted an adverse effect on economic activities and the national income level (Kang et al. 2021), greatly restricting people’s commodity and energy consumption. All these factors indicate a negative relationship between natural disasters and CO2 emissions.

Despite the inherent policy implications of the impact of natural disasters on CO2 emissions, it is surprising that few studies explore the nexus between natural disasters and CO2 emissions. However, an explicit nexus between the two factors is important since it not only is conducive to better understanding the driving forces of CO2 emissions but also can help to assess the environmental impacts of natural disasters. Moreover, quantifying the accurate impact of natural disasters on CO2 emissions favors policy-making that pursues a synergy between reducing the impacts of disasters and mitigating CO2 emissions. In addition, considering the difference in natural disasters and CO2 emissions, heterogeneity and
asymmetry may exist in the nexus between the two factors (i.e., natural disasters and CO₂ emissions). However, to the best of our knowledge, very few studies have discussed the asymmetric environmental impacts of natural disasters. Moreover, although energy consumption is often used as an important factor when analyzing the impact of natural disasters on CO₂ emissions, few studies have empirically verified the nexus between the three variables (i.e., energy consumption, natural disasters, and CO₂ emissions). Furthermore, the mechanism through which natural disasters affect CO₂ emissions is still inconclusive in the extant literature.

To fill the known gaps in research discussed above, this study aims to investigate the impact of natural disasters on CO₂ emissions. For this purpose, we first construct a dynamic panel data model to estimate the impact of natural disasters on CO₂ emissions. We employ two estimation methods, the system generalized method of moments (SYS-GMM) and difference GMM (D-GMM) methods, and a panel dataset covering 138 countries over the period 1990–2018. To ensure the robustness of the estimation results, two proxy variables for natural disasters, Nd and Nd_a, are simultaneously used in the panel estimations. Then, given the significant differences in CO₂ emissions across various countries, we further conduct an asymmetry analysis on the nexus between natural disasters and CO₂ emissions. We also explore the potential moderating effect of the technology level on the natural disaster-CO₂ nexus. Finally, we discuss the impact mechanism between natural disasters and CO₂ emissions using energy consumption as the mediating factor. Therefore, our study contributes to the existing literature in the following way. First, this paper is one of the few studies that investigates the direct impact of natural disasters on CO₂ emissions from a global perspective. The conclusions provide new insights for formulating policies to reduce CO₂ emissions as well as the environmental and economic damage caused by natural disasters. Second, the asymmetry analysis of the nexus between natural disasters and CO₂ emissions is conducive to implementing specific policies to reduce CO₂ emissions in specific countries with different CO₂ emission levels. Third, the mediating effect analysis not only helps to verify the role of energy consumption in the nexus between natural disasters and CO₂ emissions but also promotes the development of multidimensional decision-making in terms of environmental supervision and disaster prevention.

The rest of this paper is structured as follows: Section 2 reviews the related literature. Section 3 describes the empirical model and data sources. Section 4 reports the estimation results. Section 5 further discusses the asymmetry, moderating effect, and mediating effect in the nexus between natural disasters and CO₂ emissions. Section 6 concludes and provides several policy implications.

2 Literature review

2.1 Studies on the impacts of natural disasters

The impacts of natural disasters have been investigated in extensive studies. The mainstream literature in this field aims to measure the social, psychosocial, and economic damage caused by natural disasters (Botzen et al. 2019; Coffman and Noy 2012; Gorman-Murray et al. 2014; Kalayjian et al. 2002; Lee and Fraser 2019). Among such damage, the economic impacts of natural disasters are profound and notable (Noy 2009). Thus, a growing body of scholars has shed light on the impact of natural disasters on economic development. For example, Warr and Aung (2019) examine the impact of cyclones on
poverty and inequality and propose that natural disasters can cause poverty and inequality to increase in affected areas. They add that natural disasters can affect people’s consumption by reducing their income and expenditure levels. Their findings are consistent with those of a study by Bui et al. (2014), who explore the nexus between natural disasters and income, expenditure, poverty, and inequality in Vietnam and conclude that natural disasters exacerbate expenditure, poverty, and inequality. Cassar et al. (2017), Karim and Noy (2016), and Sakai et al. (2017) confirm these findings and explain the economic losses caused by natural disasters from the perspective of micro consumer psychology and behavior. Another strand of the literature focuses on post-disaster recovery and development. For example, Heger and Neumayer (2019) investigate the impact of the 2004 Indian Ocean tsunami on Aceh’s long-term economic growth. They find that although Aceh’s economy suffered heavily because of the tsunami, aid and reconstruction efforts have led to higher economic output than that during the period before the tsunami. Forbes (2017) studies the immediate and short-term changes in consumer behavior and uncovers an obvious increase in post-disaster consumption.

2.2 Studies on the nexus between natural disasters and CO2 emissions

Based on the discussions above, previous studies focus mainly on the social and economic impacts of a natural disaster, while its environmental impacts have rarely been explored. However, due to the negative impacts of natural disasters on consumption (Bui et al. 2014; Cassar et al. 2017; Karim and Noy 2016; Sakai et al. 2017; Warr and Aung 2019), there is a strong possibility that natural disasters may reduce total energy consumption in an economy, which will eventually lead to a decline in CO2 emissions (Acheampong 2018; Begum et al. 2015). In fact, the literature has demonstrated that natural disasters have a negative impact on energy consumption. For example, using a panel dataset covering 123 countries over the period 1990–2015, Lee et al. (2021) conclude that natural disasters have a significant and negative effect on oil, renewable, and nuclear energy consumption. The authors explain that natural disasters will cause consumption poverty; the latter has an inhibiting effect on energy consumption (Azzarri and Signorelli 2020; Chakravarty and Tavoni 2013; Ogbeide-Osaretin 2021). Natural disasters may also promote energy conservation by reducing the movement of vehicles and cargo transportation. For example, the COVID-19 pandemic has led to people working at home, which has greatly restricted travel and production activities. These factors indicate a negative nexus between natural disasters and energy consumption, and therefore, they imply a mitigating effect of natural disasters on CO2 emissions. However, other scholars have obtained opposite results. Based on an unbalanced dataset covering 80 countries during the period 1961–2011, Doytch and Klein (2018) find a positive correlation between natural disasters and energy consumption, although this impact varies with different types of energy and the economic development level of a country. Specifically, for high-income countries that possess the most advanced technology, infrastructure-damaging natural disasters (e.g., meteorological and geophysical disasters) exert a positive impact on renewable energy use, while for medium- and low-income countries, natural disasters exhibit a positive effect on residential energy consumption and industrial energy consumption, respectively.

Based on the literature review above, although the nexus between natural disasters and energy consumption is still inconclusive in the existing literature, it implies an underlying relationship between natural disasters and environmental changes. However, to the best of
our knowledge, very few studies have quantified the direct impact of natural disasters on CO₂ emissions.

2.3 Literature gaps

This study’s literature review reveals that the nexus between natural disasters and CO₂ emissions is ambiguous and that several academic gaps exist in the extant literature. First, the direct impact of natural disasters on CO₂ emissions has rarely been explored in previous studies. However, investigating the nexus between natural disasters and CO₂ emissions is important since doing so helps us assess the environmental impact of natural disasters. Second, the extant literature mainly examines the impacts of one specific natural disaster at the national level. Thus, the conclusions may be specific and limited. Third, although some studies have indicated that energy consumption may serve as a mediating factor between natural disasters and CO₂ emissions, a limited body of literature has conducted in-depth studies of the impact mechanism of natural disasters and CO₂ emissions. Furthermore, due to the differences in global CO₂ emissions, heterogeneity and asymmetry may exist in the natural disaster-CO₂ nexus, which has been neglected in the previous literature. However, an explicit elaboration of the asymmetric impact of natural disasters is important since it is conducive to formulating specific policies to reduce CO₂ emissions in different countries.

3 Empirical model and data description

3.1 Model construction

This study aims to investigate the nexus between natural disasters and global CO₂ emissions. For this purpose, we construct an econometric model that regards the amount of CO₂ emissions as the explained variable and natural disasters as the core explained variable. Then, following the works of Dong et al. (2019), Kasman and Duman (2015), Kongkuah et al. (2021), Li et al. (2017), Shahbaz et al. (2013, 2017), and Wu et al. (2021), we select three factors, namely, economic development, the urbanization level, and trade openness, as the main control variables in our model. Furthermore, to examine the validity of the environmental Kuznets curve (EKC) hypothesis, we introduce the square term of economic development into the CO₂ emissions function. Thus, the multivariable framework of CO₂ emissions and their determinants is as follows:

\[
CO₂ = f(Nd, GDP, GDP^2, Urb, Tra)
\]  

where CO₂ denotes the amount of CO₂ emissions; Nd stands for natural disasters; GDP and GDP² represent economic development and its square term, respectively; Urb describes the urbanization level; Tra depicts trade openness.

Considering the possible heteroscedasticity problem in data series due to their different fluctuations, we first smooth our data by transforming CO₂ and its explained variables into logarithms. Notably, we keep Nd at its original level because the value of the proxy variable for natural disasters ranges from 0 to 1. Then, using the practices of Dong et al. (2019, 2020a, 2020b) and Shahbaz (2017, 2018) as a reference, we specify the CO₂ emissions function in log-linear form as follows:
Furthermore, considering the continuity of global CO₂ emissions and the hysteresis of environmental regulations, CO₂ emissions in the past may influence the current level of CO₂ emissions. Thus, to capture information on the dynamic behavior of global CO₂ emissions, we also introduce the lag forms of CO₂ emissions into the model as follows:

\[
\text{LnCO}_2_{it} = \beta_0 + \beta_1 Nt_{it} + \beta_2 \text{LnGDP}_{it} + \beta_3 \text{LnGDP}^2_{it} + \beta_4 \text{LnUrb}_{it} + \beta_5 \text{LnTra}_{it} + \epsilon_{it} \tag{2}
\]

where \(i\) and \(t\) indicate the country and year, respectively. \(CO_2_{i,t-k}\) stands for the \(k\)-th order of the lag term of CO₂ emissions in country \(i\), and \(k\) denotes the lag order of CO₂ emissions. \(Z\) represents a variable vector that contains a series of control variables, mainly including the logarithmic forms of economic development, the urbanization level, and trade openness. The square term of \(LnGDP\) is also included to verify the validity of the EKC hypothesis. \(\phi_k\) and \(\alpha_1-\alpha_5\) represent the coefficients to be estimated, and the EKC hypothesis holds if the coefficient of \(LnGDP^2\) (i.e., \(\alpha_3\)) is significantly negative. The variables have the same meaning as those in Eq. 1; except for \(Nd\), the other variables all take logarithmic forms. \(\alpha_0\) and \(\epsilon\) are the constant and error terms, respectively.

### 3.2 Data sources and descriptions

To estimate the model constructed above, we employ a panel dataset containing all the variables in the model. Our dataset covers 138 countries, and the time period spans from 1990 to 2018. Notably, our panel sample is unbalanced due to the contingency and suddenness characteristics of natural disasters.

The dependent variable—CO₂ emissions (denoted as \(CO_2\))—is proxied by the amount of national CO₂ emissions, and the data are collected from IEA statistics (2019). Following the work of Lee et al. (2021) and Rosselló et al. (2020), our core independent variable—natural disasters (denoted as \(Nd\))—is evaluated by the proportion of the population affected by natural disasters, and the data are extracted from the CRED (2019). Nine types of natural disasters, i.e., droughts, earthquakes, extreme temperatures, floods, landslides, pandemics, storms, wildfires, and volcanic activities, are selected as representative natural disasters (Lee et al. 2021). For the control variables, economic development (denoted as \(GDP\)) represents national gross domestic product (GDP); the urbanization level (denoted as \(Urb\)) is calculated by the proportion of the urban population in the total population; trade openness (denoted as \(Tra\)) is computed by the ratio of the international trade volume to total GDP. The data on these variables (i.e., \(GDP\), \(Urb\), and \(Tra\)) are mainly from the World Development Indicators (WDI) published by the World Bank (2019). The detailed descriptions and data sources are also listed in Table A1 in Appendix A, and Table 1 reports the descriptive statistics of the variables in the model.
4 Estimation results and analysis

4.1 Cross-sectional interdependence discussion

Since we employ a panel dataset to estimate the nexus between natural disasters and global CO₂ emissions, the cross-sectional dependence problem should receive special attention because it may lead to bias and even inconsistent estimation results if ignored (Dong et al. 2021; Grossman and Krueger 1995; Sarafidis and Wansbeek 2012). Furthermore, with the rapid development of globalization and trade liberalization, countries around the world have become increasingly connected (Dogan et al. 2017; Haseeb et al. 2018; Zhao et al. 2021b). This fact indicates the strong possibility of cross-sectional dependence in the panel sample. Therefore, before resorting to other empirical techniques, we first conduct two tests, the Breusch–Pagan Lagrange multiplier (LM) test and the Pesaran cross-sectional dependence (CD) test, to examine cross-sectional interdependence in the panel data. The test results are reported in Table 2.

From Table 2, the significant statistics of the two tests (i.e., the Breusch–Pagan LM test and the Pesaran CD test) indicate that the null hypothesis (i.e., no cross-sectional interdependence) is strongly rejected at the 1% significance level. In other words, strong cross-sectional interdependence exists in the panel sample. Thus, we should fully consider this issue in the subsequent analysis to eliminate any possible estimation bias brought by cross-sectional interdependence.

4.2 Panel stationarity analysis

After confirming the existence of cross-sectional interdependence in the panel sample, the next step is to test the panel stationarity, which is a premise for a stable long-term equilibrium relationship (Ghosh and Kanjilal 2014; Saayman 2010). Thus, in this subsection,
we use the unit root test to examine the stationarity of the data series. We first use two first-generation panel unit root tests, the Im–Pesaran–Shin (IPS) test proposed by Im et al. (2003) and the Fisher augmented Dickey–Fuller (Fisher-ADF) test developed by Maddala and Wu (1999), for a preliminary analysis of the stationarity of the panel data. The results are listed in Table 3. From the table, nearly all the variables are stable at the original level due to the significant statistics of the two tests. In other words, these data series possess a common stochastic trend, and a linear combination of these variables can eliminate this trend, thus implying an underlying long-run equilibrium between CO₂ emissions and their determinants. However, it is noteworthy that the two first-generation panel unit root tests above (i.e., the IPS and Fisher-ADF tests) do not accommodate cross-sectional dependence in the panel and may result in biased results (Dong et al. 2018; Qiao et al. 2019). Therefore, we employ a second-generation unit root test, namely, the Pesaran cross-sectional ADF (CADF) test, to further examine the stability of the data series. The Pesaran CADF test was proposed by Pesaran (2007) and is suitable for panel data with cross-sectional interdependence. The results are also reported in Table 3.

As Table 3 shows, the estimation results vary under different unit root test methods. For the original data series of the variables, the results of the three tests without a time trend are similar, while those with a time trend indicate conflicting implications. Considering that the Pesaran CADF test is more suitable due to the cross-sectional interdependence in the panel, we thus regard this approach as the benchmark method for testing panel stationarity. Based on the results of the Pesaran CADF tests, although not all data series are stable at the original level, the first-difference terms of the selected variables are stationary.

### Table 3: Results of the panel stationary tests

| Variables | Level | First difference |
|-----------|-------|------------------|
|           | Intercept | Intercept and trend | Intercept | Intercept and trend |
| **IPS test** |       |                   |       |                   |
| LnCO₂     | 1.080   | −5.844***         | −31.3613*** | −28.025***       |
| Nd        | −36.678*** | −27.218*** | −59.394*** | −44.371***       |
| LnGDP     | −2.940*** | −11.494***       | −28.084*** | −23.443***       |
| LnUrb     | −4.979*** | 3.413            | −4.156*** | −5.136***        |
| LnTra     | −8.3120*** | −6.211***       | −29.036*** | −24.343***       |
| **Fisher ADF test** |       |                   |       |                   |
| LnCO₂     | 19.458*** | 6.111***         | 50.280*** | 26.367***        |
| Nd        | 48.924*** | 16.778***        | 97.448*** | 74.166***        |
| LnGDP     | 23.367*** | 12.402***        | 48.423*** | 13.324***        |
| LnUrb     | 18.8863*** | 0.345           | 23.719*** | 3.169***         |
| LnTra     | 28.330*** | 6.381***         | 56.880*** | 24.949***        |
| **Pesaran CADF test** |       |                   |       |                   |
| LnCO₂     | −5.784*** | −0.927           | −20.445*** | −18.679***       |
| Nd        | −21.256*** | −18.200***      | −40.530*** | −35.556***       |
| LnGDP     | −8.682*** | −1.736**         | −17.613*** | −13.4888***      |
| LnUrb     | −5.082*** | 0.231            | 2.008**   | −1.654**         |
| LnTra     | −2.476*** | −1.554*          | −18.550*** | −14.395***       |

***, **, and *Indicate statistical significance at the 1, 5% and 10% levels, respectively
Thus, all the variables are integrated of order (i.e., I (1)), which can also ensure at least one long-run equilibrium relationship between CO₂ emissions and their determinants. In other words, the econometric model we construct in Eq. 3 is reasonable and economically meaningful.

### 4.3 Estimation results of the impact of natural disasters on CO₂ emissions

Following the discussions above, this subsection aims to explore the nexus between natural disasters and CO₂ emissions. Given the cross-sectional interdependence in the panel, conventional panel data estimation methods, such as pooled ordinary least squares (OLS), fixed effects (FE), and random effects (RE) estimation methods, are no longer suitable. Furthermore, the three methods rely mainly on static panel data and cannot describe the dynamic behavior of global CO₂ emissions. However, to perform a preliminary analysis of the natural disaster-CO₂ emissions nexus and to provide a reference for other advanced methods, we still estimate the model using the three conventional methods. The results are displayed in Table 4.

From Table 4, it is clear that the coefficients of \( Nd \) based on the three methods (i.e., the pooled OLS, FE, and RE methods) are consistently negative, meaning that the outbreak of natural disasters leads to decreased CO₂ emissions. This outcome is rational because natural disasters may destroy an economy’s energy consumption system and the latter is considered the main source of CO₂ emissions (Acheampong 2018; Liu et al. 2015; Porzio et al. 2013). This finding is consistent with those of the studies by Lee et al. (2021) and Doytch

| Variables | Conventional panel estimations | Dynamic Panel estimations |
|-----------|-------------------------------|----------------------------|
|           | Pooled OLS FE model RE model | SYS-GMM D-GMM |
| Ln\(CO₂\text{,t-1} \) | 0.813*** (365.86) | 0.526*** (123.27) |
| \( Nd \)  | −0.075** (−2.47) | −0.020** (−2.04) | −0.008*** (−14.39) | −0.006*** (−7.15) |
| Ln\(GDP \) | 0.323*** (2.09) | 1.826*** (11.58) | 1.844*** (62.98) | 2.473*** (23.86) |
| Ln\(GDP^2 \) | 0.011*** (3.74) | −0.025*** (−7.89) | −0.034*** (−56.51) | −0.044*** (−20.29) |
| Ln\(Urb \) | 0.074* (1.88) | 1.252*** (20.68) | 0.055*** (6.32) | 0.465*** (12.44) |
| Ln\(Tra \) | 0.170*** (6.58) | −0.055*** (−3.43) | −0.055*** (−3.45) | 0.016*** (9.31) | −0.006*** (−2.43) |
| _Cons    | −12.751*** (−6.57) | −31.109*** (−16.13) | −24.268*** (−67.48) | −34.145*** (−27.39) |
| \( R^2 \) | 0.8235 0.6748 | 0.7144 |
| AR (1)    | 0.0004 | 0.0006 |
| AR (2)    | 0.7391 | 0.5583 |
| Sargan    | 0.5316 | 0.2087 |
| Obs       | 3363 3363 | 3363 3268 | 3140 |

***, **, and *Indicate statistical significance at the 1, 5, and 10% levels, respectively; the values in parentheses represent t-statistics.
and Klein (2018), who document that natural disasters are not conducive to increasing energy consumption in a country. Natural disasters will also block the production activities in a country and thereby inhibit the consumption of national goods. Economic stagnation will lead to a reduction in energy consumption and CO₂ emissions. Nevertheless, we also observe that the absolute value of the OLS-estimated coefficient of Nd is much larger than that based on the FE or RE methods. Furthermore, the coefficients of LnGDP² are inconsistent—positive under the pooled OLS estimation method but negative under the FE and RE estimation methods. Thus, the estimation results based on the conventional methods are sensitive and unstable.

Based on the estimation results above, we confirm that the traditional estimation methods are not suitable for the panel sample and are therefore unconvincing due to some known or unknown estimation biases. Since we have constructed an econometric model based on dynamic panel data, the D-GMM method proposed by Arellano and Bond (1991) is superior to the FE estimation method. The latter is inconsistent because it will cause dynamic panel bias (Nickell 1981). Specifically, after taking the first difference of the original equation, the lag terms of the dependent and independent variables are employed as instrumental variables (IVs) in the process of D-GMM estimation. Using these variables as IVs not only provides an opportunity to estimate the dynamic impact of past economic behaviors on current CO₂ emissions but also eliminates any biases brought by potential endogeneity in the model. However, according to some studies (Che et al. 2013; Windmeijer 2005), if the time span of the sample is very long or the dependent variable is highly persistent, it is prone to lead to the weak instruments problem when using the D-GMM method, which will ultimately reduce the estimation efficiency of the D-GMM estimates. To address this problem, Blundell and Bond (1998) developed an advanced method—the system DMM (SYS-GMM) estimation method, which greatly improves estimation efficiency while avoiding any possible endogeneity problems. Therefore, we re-estimate the nexus between natural disasters and CO₂ emissions by estimating Eq. 3 using the two dynamic panel estimation methods (i.e., the D-GMM and SYS-GMM methods). Notably, the SYS-GMM method is considered the benchmark estimation method due to its higher estimation efficiency. The results are also listed in Table 4. At the same time, the optimal lag order is determined to be one based on the results of the Arellano–Bond (A-B) and Sargan tests. The latter, as shown in Table 4, meets the prerequisites for the D-GMM and SYS-GMM estimation methods.

The results of the D-GMM and SYS-GMM estimations consistently indicate that natural disasters exert a significantly negative impact on global CO₂ emissions, which coincides with the results based on the conventional estimation methods. Furthermore, it is noteworthy that the coefficients of the first-order lag term of CO₂ emissions are significantly positive. This outcome leads to two implications. On the one hand, past CO₂ emissions induced by human activities can positively affect the current level of global CO₂ emissions. In other words, due to the continuity of human economic activities, CO₂ emissions are continuous in the temporal dimension. Therefore, the dynamic panel data model we build in Eq. 3 is reasonable and reliable. On the other hand, the lag term of CO₂ emissions may influence the nexus between natural disasters and CO₂ emissions, as evidenced by the fact that the absolute values of the D-GMM and the SYS-GMM estimators are far less than those based on the conventional estimation methods. On this basis, we deduce that CO₂ emissions in the previous period can affect the frequency of natural disasters in the current period. The literature has documented that mounting global CO₂ emissions have caused an increase in extreme weather and extreme temperatures (Baker et al. 2018; Huggel et al. 2012; Shahbaz et al. 2019; Yang et al. 2021), such as global warming and glacial melting. We can
also infer that ignoring the dynamic information in the model will magnify the negative
effect of natural disasters on CO₂ emissions, which, again, emphasizes the necessity of
using a dynamic panel data model to estimate the nexus between natural disasters and CO₂
emissions.

For the control variables, the estimations based on the D-GMM and SYS-GMM meth-
ods are basically consistent, which verifies that the results are robust and convincing. Spe-
cifically, the coefficients of LnGDP and its square term are significantly positive and nega-
tive, respectively, indicating that the EKC hypothesis is valid from the global perspective.
Thus, the relationship between global CO₂ emissions and economic development shows
an inverted U-shaped curve. That is, CO₂ emissions increase in the initial stage of a coun-
try’s economic development, and as the country’s total GDP exceeds a certain level, CO₂
emissions begin to decrease. This coincides with the actual conditions because economic
development is initially anchored by energy consumption, which is accompanied by a
large amount of CO₂ emissions. However, with the rapid development of industrialization
and modernization, energy efficiency will be greatly improved, followed by a reduction in
energy consumption while maintaining the same economic growth rate, which will cer-
tainly promote carbon reduction. In addition, rapid economic development provides a hot-
bed for technological innovation, especially in the field of new energy development and
utilization, which is widely accepted as the ultimate direction of energy and the low-carbon
transition (Dong et al. 2017; Foran 2011; Wang et al. 2011; Zhang et al. 2014). Further-
more, the results indicate a positive nexus between the urbanization level and CO₂ emis-
sions. One plausible explanation is that energy-using industrial plants are usually located
in urban areas, and the improved urbanization level means the expansion of industrial
plants, which will obviously lead to more energy consumption and CO₂ emissions. Regard-
ing the impact of trade openness on CO₂ emissions, the estimation results based on the
D-GMM and SYS-GMM methods provide conflicting conclusions. The significant posi-
tive SYS-GMM estimator indicates that trade openness will induce more CO₂ emissions,
while the negative D-GMM estimator implies a negative nexus between trade openness
and CO₂ emissions. Thus, the impact of trade openness on CO₂ emissions is uncertain and
susceptible to different estimation methods. The reason may be that the economic and envi-
ronmental impacts of trade openness are complicated. For example, it is well known that
trade openness will accelerate domestic production, which requires massive energy con-
sumption. At the same time, however, trade openness can expand the technology spillovers
between countries, which is conducive to improving efficiency and conserving energy. The
combination of these factors leads to an unknown and uncertain net impact of trade open-
ness on CO₂ emissions.

4.4 Robustness check of the nexus between natural disasters and global CO₂
emissions

To ensure the reliability of the estimation results, we conduct a robustness check by using
another alternative indicator of natural disasters—Nd_a—as the core independent vari-
able. Nd_a is calculated by the ratio of the affected number to the total population of a
country, and the national population data are from the WDI published by the World Bank
(2019). Therefore, by substituting Nd_a for Nd in Eq. 3, we are able to re-estimate the
nexus between natural disasters and CO₂ emissions. Similar to the discussions above,
we still employ the SYS-GMM method as the benchmark method in this section, and for
robustness purposes, the stepwise technique and D-GMM method are used simultaneously. Table 5 shows the estimation results.

From Table 5, the coefficients of \( N_d_a \) are consistently negative, which is in-line with the estimation results in Sect. 4.3. This finding indicates that the negative nexus between natural disasters and CO\(_2\) emissions is credible and tenable. Furthermore, we observe that the EKC hypothesis still holds, as evidenced by the positive coefficient of \( \text{LnGDP} \) and the negative coefficient of its square term. Thus, we confirm that the relationship between CO\(_2\) emissions and economic development presents an inverted U-shaped curve. In addition, the opposite signs of the SYS-GMM and the D-GMM estimators again indicate the uncertainty of the environmental impact of trade openness. In sum, the estimation results are basically consistent, indicating that our results are robust and convincing.

## 5 Further discussions

### 5.1 Asymmetry analysis of the relationship between CO\(_2\) emissions and their determinants

We have discussed the impact of natural disasters on global CO\(_2\) emissions at the average level. However, considering the significant differences in economic development modes and national CO\(_2\) emissions between countries (see Fig. 1), the nexus between natural disasters and CO\(_2\) emissions may vary in different countries or regions. In other words, the impact of natural disasters on CO\(_2\) emissions may be heterogeneous and asymmetric across across

| Variables | SYS-GMM estimations | D-GMM estimation |
|-----------|---------------------|------------------|
| \( \text{LnCO}_2 \text{,t-1} \) | | |
| 0.952*** (1177.73) | 0.807*** (820.91) | 0.791*** (261.02) | 0.816*** (215.14) | 0.562*** (237.37) |
| \( N_d_a \) | | | | |
| -0.057*** (13.71) | -0.011** (-2.10) | -0.012*** (-4.46) | -0.029*** (-2.99) | -0.0153*** (-5.37) |
| \( \text{LnGDP} \) | | | | |
| 1.921*** (58.83) | 1.884*** (41.42) | 1.758*** (37.50) | 2.522*** (45.79) |
| \( \text{LnGDP}^2 \) | | | | |
| -0.035*** (-50.69) | -0.034*** (-36.65) | -0.032*** (-34.00) | -0.0456 (-41.18) |
| \( \text{LnUrb} \) | | | | |
| 0.021** (2.46) | 0.064*** (3.21) | 0.361*** (29.16) |
| \( \text{LnTra} \) | | | | |
| | | | 0.017*** (5.65) | -0.009*** (-7.88) |
| \( -\text{Cons} \) | | | | |
| 0.181*** (91.27) | -25.270*** (-65.87) | -24.886*** (-43.50) | -23.217*** (-39.44) | -34.302*** (-50.66) |
| \( AR \text{(1)} \) | 0.0000 | 0.0000 | 0.0000 | 0.0003 | 0.0006 |
| \( AR \text{(2)} \) | 0.4649 | 0.6722 | 0.6729 | 0.7510 | 0.5934 |
| \( \text{Sargan} \) | 0.3046 | 0.3444 | 0.8456 | 0.2329 | 0.4546 |

*** and ** Indicate statistical significance at the 1 and 5% levels, respectively; the values in parentheses represent t-statistics.
different quantiles of CO₂ emissions. The same conjecture also applies to other independent variables. To verify this assumption, we conduct an asymmetry analysis using the panel quantile regression method. Specifically, we select five representative quantiles (i.e., the 10, 25, 50, 75, and 90th quantiles), and the estimation results are shown in Table 6. To make the results visual, we also depict the change trend of the coefficients in Fig. 2, where the OLS estimates are highlighted as a reference for different quantile estimators. To ensure the robustness of the estimation results, we further substitute the alternative index for natural disasters \( Nd_a \) for the core independent variable \( Nd \) and run the panel quantile regression. The results are depicted in Table 6 and Fig. 3.

From Table 6 and Figs. 2–3, we find similar estimation results using \( Nd \) and \( Nd_a \) as the core independent variables, respectively, showing that our results are robust and stable. Specifically, the coefficients of \( Nd \) vary greatly with different quantiles of CO₂ emissions, indicating strong asymmetry in the nexus between natural disasters and CO₂ emissions. Specifically, the coefficients of \( Nd \) show a downward trend along the

| Table 6 | Estimation results of the panel quantile regressions of global CO₂ emissions and their determinants |
|---------|---------------------------------------------------|
| Variables | 10th | 25th | 50th | 75th | 90th |
| \( Nd \) as the core independent variable | | | | | |
| \( Nd \) | 0.028 | 0.025 | −0.031 | −0.241*** | −0.283*** |
| (0.86) | (0.90) | (−0.88) | (−5.58) | (−3.53) |
| \( LnGDP \) | 0.992*** | 1.102*** | 1.200*** | 0.898*** | −2.148*** |
| (3.94) | (7.00) | (6.30) | (3.40) | (−6.68) |
| \( LnGDP^2 \) | −0.001 | −0.004 | −0.006 | 0.001 | 0.059*** |
| (−0.09) | (−1.16) | (−1.56) | (0.09) | (5.26) |
| \( LnUrb \) | −0.016 | 0.159*** | 0.186*** | −0.175*** | −0.161 |
| (−0.46) | (5.32) | (3.69) | (3.64) | (1.12) |
| \( LnTra \) | 0.093*** | 0.105*** | 0.220*** | 0.187*** | 0.144*** |
| (2.80) | (3.84) | (5.92) | (5.29) | (3.16) |
| \( _\text{Cons} \) | −22.297*** | −23.437*** | −24.715*** | −18.825*** | 21.130*** |
| (−6.95) | (−12.10) | (−10.25) | (−5.36) | (2.75) |
| \( R^2 \) | 0.6142 | 0.6210 | 0.6119 | 0.5735 | 0.5363 |
| \( Obs \) | 3363 | 3363 | 3363 | 3363 | 3363 |

\( Nd_a \) as the core independent variable

| Variables | 10th | 25th | 50th | 75th | 90th |
|---------|-----|-----|-----|-----|-----|
| \( Nd_a \) | 0.188 | −0.022 | −0.168 | −0.473 | −1.123*** |
| (0.50) | (−0.14) | (−0.47) | (0.207) | (−3.41) |
| \( LnGDP \) | 1.053*** | 1.113*** | 1.186*** | 0.963*** | −2.601*** |
| (4.36) | (7.54) | (6.62) | (3.24) | (4.33) |
| \( LnGDP^2 \) | −0.002 | −0.004 | −0.005 | −0.001 | 0.068*** |
| (−0.34) | (−1.29) | (−1.59) | (−0.21) | (5.83) |
| \( LnUrb \) | −0.032 | 0.152*** | 0.194*** | −0.066 | −0.205 |
| (−0.90) | (4.77) | (3.87) | (−0.21) | (−1.35) |
| \( LnTra \) | 0.093*** | 0.101*** | 0.227*** | 0.151*** | 0.146*** |
| (2.90) | (3.61) | (6.61) | (3.24) | (2.56) |
| \( _\text{Cons} \) | −23.033*** | −23.556*** | −24.600*** | −19.761*** | 27.318*** |
| (−7.51) | (−12.77) | (−10.78) | (−4.97) | (3.41) |
| \( R^2 \) | 0.6142 | 0.6209 | 0.6119 | 0.5703 | 0.5334 |
| \( Obs \) | 3363 | 3363 | 3363 | 3363 | 3363 |

*** and **Indicate statistical significance at the 1 and 5% levels, respectively; the values in parentheses represent t-statistics.
distribution of CO₂ emissions, from a positive value in the 10th quantile of CO₂ emissions to negative values after the 50th quantile. The negative coefficients of natural disasters are in-line with common sense since natural disasters may affect and even destroy a country’s energy system, thereby blocking residents’ energy consumption. Furthermore, natural disasters impede human production activities. For example, the outbreak of the COVID-19 pandemic at the end of 2019 greatly influenced global productivity. According to the World Economic Outlook report published in October 2020 by the International Monetary Fund (IMF 2020), the global economy was predicted to shrink by 4.4% in 2020, equivalent to seven times the decline in 2009, which is considered the worst economic recession since the Great Depression in the 1930s. Such shrinkage would certainly lead to a reduction in energy consumption and CO₂ emissions. However, the positive signs of the coefficients imply that the outbreak of natural disasters will lead to more CO₂ emissions in countries with low-level CO₂ emissions, such as those located in the 10th and 25th quantiles of CO₂ emissions. This finding may be explained using the “technology effect.” Specifically, the “technology effect” means that countries emitting less CO₂, such as countries in Europe, tend to have more advanced technologies and stronger energy system resilience. This means that these countries have better energy infrastructures and are unlikely to collapse due to natural disasters. As a consequence, residents’ energy consumption will hardly be affected by natural disasters. In addition, with more advanced technologies, the post-disaster reconstruction work in the disaster areas of these countries will progress rapidly, which will emit a great amount of CO₂ emissions. These factors will offset or even exceed the negative

Fig. 2 Changing trend of the coefficients across various quantiles. The x-axis denotes the different quantiles of CO₂ emissions and y-axis indicates the values of various coefficients. The hatched section depicts the confidence interval of estimated coefficients at the 95% level.
impact brought by the destruction of the energy system. As another possible impact pathway, in some countries covered by many forests, a natural disaster such as a wildfire may not only cause unpredictable economic losses but also have many environmental impacts. In particular, for countries with a sparse population, the marginal effect of natural disasters on CO₂ emissions is significant. For example, in areas where natural disasters are frequent, very few CO₂ emissions come from human production activities. Additionally, the outbreak of a natural disaster, such as volcanic activity and wildfires, will have a great marginal impact on CO₂ emissions and other environmental degradation problems. After a country’s modern energy system is destroyed by natural disasters, the environmental impact of post-disaster human activities on CO₂ emissions is also notable. This situation is particularly true in some privileged countries with vulnerable energy systems. Residents in these countries may even have to return to the most primitive energy consumption patterns after a natural disaster, that is, using firewood as their main energy source. This outcome is associated with inefficient energy consumption and unreasonable CO₂ emissions. To conclude, the nexus between natural disasters and CO₂ emissions is asymmetric, conditional on different quantiles of CO₂ emissions.

For the control variables, the significant changes in the coefficients also verify the asymmetry in the nexus between CO₂ emissions and their other determinants. Specifically, the signs of the coefficients of LnGDP and its square term greatly change around the 75th quantile of CO₂ emissions. Similar results are obtained regarding the coefficients of the urbanization level and trade openness. These findings imply that the environmental system undergoes structural changes around the 75th quantile of CO₂ emissions.
emissions. Furthermore, we find that the coefficient of $\text{LnGDP}^2$ is either nonsignificant or positive, which goes against the conditions of the EKC curve. Thus, we deduce that the EKC hypothesis is no longer valid for specific countries and that the EKC hypothesis holds only at the global average level. At the same time, however, we also notice that at the 90th quantile of CO$_2$ emissions, the coefficient of $\text{LnGDP}$ is significantly negative, and its absolute value greatly exceeds the coefficient of $\text{LnGDP}^2$. On this basis, it can be inferred that CO$_2$ emissions tend to decrease when they are high, which, to some extent, conforms with the trend of the EKC curve. In addition, the positive coefficients of trade openness across the whole distribution of CO$_2$ emissions are consistent with the SYS-GMM estimation results in Sect. 4.3, again verifying the robustness of our empirical results.

Following the discussions above, asymmetry in the relationships between CO$_2$ emissions and their determinants has been verified. Furthermore, potential structural changes in the environmental system should receive special attention when policy-makers formulate specific policies for reducing the environmental impacts of natural disasters.

5.2 Moderating effect of technology on the natural disaster-CO$_2$ emissions nexus

The asymmetry analysis above indicates that the technology level may affect the nexus between natural disasters and CO$_2$ emissions. In fact, countries with higher technology levels tend to have more advanced and modernized energy infrastructures (Guelpa et al. 2019). On the one hand, a stable and integrated energy system has greater resilience to natural disasters and can therefore ensure the sustainable energy consumption of residents, even during natural disasters. Furthermore, a higher level of technology in a country is conducive to reconstructing energy infrastructures after a natural disaster, which not only favors economic recovery but also promotes national energy consumption. These factors may cause an increase in CO$_2$ emissions and offset the negative effects of natural disasters on CO$_2$ emissions. On the other hand, the rapid development of technology brings dividends to technological innovation in the development and utilization of clean energy, such as solar energy, hydrogen energy, and ocean energy. Thus, countries with advanced technologies tend to use renewable and clean energies as their main energy sources. For example, the successful development of Japan’s hydrogen energy technology has been widely applauded worldwide. This technological breakthrough relies greatly on existing technological development and will significantly promote energy conservation and carbon reduction due to the clean and low-carbon nature of hydrogen energy. From this perspective, technological innovation itself has a negative effect on CO$_2$ emissions. Based on the analysis above, we propose the following two hypotheses:

**Hypothesis I** Technology has a moderating effect on the nexus between natural disasters and CO$_2$ emissions.

**Hypothesis II** Technological progress has an inhibiting effect on CO$_2$ emissions.

To verify these two hypotheses, we further introduce the national technology level into our empirical model (i.e., Eq. 3) for a comparative analysis. The technology level (denoted as $\text{Tec}$) is proxied by the reciprocal of energy intensity, which can be calculated by the ratio of national GDP to the total primary energy consumption in a country. The data are from the WDI published by the World Bank (2019). Similarly, we
use the SYS-GMM as the benchmark estimation method and simultaneously run the D-GMM estimation to ensure the robustness of the results. Table 7 lists the estimation results. After adding the technology level, the coefficient of natural disasters increases from −0.008 to −0.005, with a reduction in the magnitude of the negative effect on CO2 emissions. These findings indicate that the technology level does indeed have a moderating effect on the nexus between natural disasters and CO2 emissions; thus, Hypothesis I is valid and tenable. In other words, technological development affects the impact of natural disasters on CO2 emissions. Moreover, we infer that the negative effect of natural disasters on CO2 emissions is magnified as the technology effect is ignored. At the same time, we find that technological progress has a significantly negative effect on CO2 emissions, and this outcome is consistent with our expectations (i.e., Hypothesis II). Furthermore, the absolute value of the coefficient of the technology level (i.e., 0.457) is much larger than that of natural disasters (i.e., 0.005), indicating that technological progress, rather than natural disasters, is the main force behind carbon reduction. Thus, although technological progress may somewhat offset the inhibiting effect of natural disasters on CO2 emissions, its negative effect can completely cover the change in the coefficient of natural disasters. Thus, from the long-run perspective, it is imperative to encourage technological innovation and introduce more advanced technologies to promote carbon reduction, especially considering that the negative effects of natural disasters come at the cost of great economic losses.

In addition, we notice that the EKC hypothesis always holds with the technology level in or out of the model, which again verifies the robustness and stability of our

| Variables | SYS-GMM estimations | D-GMM estimations |
|-----------|---------------------|------------------|
| LnCO2_{t-1} | 0.813*** (365.86) | 0.526*** (123.27) |
| | 0.532*** (43.46) | 0.150*** (17.26) |
| Nd | −0.008*** (−14.39) | −0.006*** (−7.15) |
| | −0.005*** (−4.30) | −0.002*** (−3.03) |
| LnGDP | 1.844*** (62.98) | 2.473*** (23.86) |
| | 2.205*** (19.72) | 3.163*** (22.00) |
| LnGDP^2 | −0.034*** (−56.51) | −0.044*** (−20.29) |
| | −0.036*** (−15.84) | −0.045*** (−15.03) |
| LnUrb | 0.055*** (6.32) | 0.465*** (12.44) |
| | 0.356*** (8.57) | 0.333*** (4.74) |
| LnTra | 0.016*** (9.31) | −0.006** (−2.43) |
| | 0.077*** (15.11) | −0.022*** (−9.36) |
| LnTec | −0.457*** (−30.76) | −0.936*** (−91.20) |
| _Cons | −24.268*** (−67.48) | −34.145*** (−27.39) |
| | −31.396*** (−21.60) | −47.261*** (−26.28) |
| AR (1) | 0.0004 | 0.0006 |
| | 0.0073 | 0.0518 |
| AR (2) | 0.7391 | 0.5583 |
| | 0.5224 | 0.4257 |
| Sargan | 0.5316 | 0.2087 |
| | 0.2163 | 0.1113 |

*** and **Indicate statistical significance at the 1 and 5% levels, respectively; the values in parentheses represent t-statistics.
empirical results. Furthermore, it is noteworthy that after the technology level is added to the model, the coefficients of trade openness change considerably, which indicates that technology also exerts a significant impact on the trade openness-CO₂ emissions nexus. This outcome coincides with the discussions. That is, trade openness can expand the technology spillovers between countries, and in doing so, it makes technology an important factor through which trade openness affects CO₂ emissions.

5.3 Mediating effect discussion

After basically confirming the negative effects of natural disasters on CO₂ emissions, another question arises: How do natural disasters affect CO₂ emissions? Is there a mediating effect through which natural disasters affect CO₂ emissions? As energy consumption, especially fossil energy consumption, is one of the main sources of carbon emissions, natural disasters may affect CO₂ emissions by influencing energy consumption. Additionally, considering the important role of the energy system in reducing national CO₂ emissions, it is necessary to explore the interactions between energy consumption, natural disasters, and CO₂ emissions. To verify this and identify the impact mechanism between natural disasters and CO₂ emissions, in this section, we conduct a mediating effect analysis by using energy consumption as the mediating factor. Following the work of Zhao et al. (2020; 2021a; b), we construct the mediating effect model as follows:

\[
\begin{align*}
\text{LnCO}_2_{i,t} &= \alpha_0 + \sum_{k=1}^{M} \varphi_k \text{LnCO}_2_{i,t-k} + \alpha_1 N_{d_{i,t}} + \sum_{j=2}^{5} \alpha_j Z_{i,t} + \epsilon_{i,t} \\
\text{LnEc}_{i,t} &= \theta_0 + \sum_{k=1}^{N} \gamma_k \text{LnEc}_{i,t-k} + \theta_1 N_{d_{i,t}} + \sum_{q=2}^{\infty} \theta_q Z_{i,t} + \epsilon_{i,t} \\
\text{LnCO}_2_{i,t} &= \lambda_0 + \sum_{k=1}^{M} \varphi_k \text{LnCO}_2_{i,t-k} + \lambda_1 N_{d_{i,t}} + \lambda_2 \text{LnEc}_{i,t} + \sum_{l=3}^{6} \lambda_l Z_{i,t} + \epsilon_{i,t}
\end{align*}
\]

where \( Ec_{i,t} \) depicts the energy consumption of country \( i \) in year \( t \). \( Z \) is the variable vector that contains a series of predetermined variables, mainly including the logarithmic forms of economic development, the urbanization level, and trade openness. \( \varphi_k \) and \( \gamma_k \) are the \( k \)-th order of the lag term of their corresponding dependent variables, and the specific order depends on the results of the A-B and Sargan tests. Among the three equations, Eq. 4 estimates the total effect of natural disasters on CO₂ emissions. Equations 5 and 6 jointly present the direct and indirect effects between natural disasters and CO₂ emissions, and the mediating effect of energy consumption can be ensured if \( \theta_1 \) and \( \lambda_2 \) are statistically significant. Based on the SYS-GMM method, the estimation results are reported in Table 8.

From Table 8, we observe that natural disasters significantly reduce energy consumption, while energy consumption promotes CO₂ emissions. These findings indicate that natural disasters not only have a negative direct effect on CO₂ emissions but also indirectly reduce CO₂ emissions by curbing energy consumption. This result verifies the mediating effect of energy consumption in the nexus between natural disasters and CO₂ emissions. Natural disasters may destroy the energy infrastructures in a country, especially in countries with relatively backward technology levels and weak energy resilience. In addition,
natural disasters will block the production activities of energy installations and industrial plants, thus leading to a decline in total energy consumption. Since energy consumption, especially fossil fuel consumption, is the main source of CO2 emissions (Ajmi et al. 2015; Menyah and Wolde-Rufael 2010), a reduction in energy consumption will certainly cause CO2 emissions to decrease.

Furthermore, the changes in the signs of the coefficients of the urbanization level and trade openness are notable. From the table, the signs of the two variables (i.e., LnUrb and LnTra) have reversed to negative after energy consumption has been introduced in Eq. 6. This finding implies that energy consumption also exerts an important mediating effect on the impacts of the urbanization level and trade openness on CO2 emissions. Since the total effects of the urbanization level and trade openness in Eq. 4 are both positive, we deduce that the mediating effects of energy consumption are positive. In fact, the development of urbanization and trade openness can indeed expand domestic production and energy consumption, thus inducing more CO2 emissions. In addition, the negative coefficients of LnUrb and LnTra in Eq. 6 indicate that other mediating effects may exist between the two variables and CO2 emissions. For example, the literature has documented that the urbanization level and trade openness can promote technological progress and industrial upgrading (Amin et al. 2020; Elliott et al. 2017; Sohag et al. 2015); the latter two are considered to be conducive to reducing the carbon emissions of a country. The other possible mediating factors are not discussed since we focus mainly on the impact mechanism between natural disasters and CO2 emissions.

Table 8  Estimation of the mediating effect between natural disasters and global CO2 emissions

| Variables | Total effect: Eq. (4) | Mediating effect: Eqs. (5)-(6) |
|-----------|----------------------|-----------------------------|
| LnCO2     | LnEc                 | LnCO2                       |
| LnCO2_{2,t-1} | 0.813*** (365.86) | 0.534*** (160.96)           |
| LnEc_{2,t-1} | 0.789*** (593.49) | -0.006*** (-12.30)          |
| Nd        | -0.008*** (-14.39) | -0.001*** (-2.62)           |
| LnEc      |                      | 0.341*** (103.88)           |
| LnGDP     | 1.844*** (62.98)    | 0.660*** (49.10)            |
| LnGDP^2   | -0.034*** (-56.51) | -0.010*** (-36.60)          |
| LnUrb     | 0.055*** (6.32)     | 0.048*** (9.10)             |
| LnTra     | 0.016*** (9.31)     | 0.029*** (23.22)            |
| _Cons     | -24.268*** (-67.48) | -10.859*** (-65.54)         |
| AR (1)    | 0.0004               | 0.0168                      |
| AR (2)    | 0.7391               | 0.5338                      |
| Sargan    | 0.5316               | 0.9982                      |

***Indicates statistical significance at the 1% level; the values in parentheses represent t-statistics


6 Conclusions and policy implications

To investigate the nexus between natural disasters and CO₂ emissions, we employ a panel dataset covering 138 countries for the period 1990–2018. After a series of empirical tests on the panel sample, we use two dynamic panel data estimation methods, namely, the SYS-GMM and D-GMM methods, to estimate the econometric model. Then, considering the differential spatial distribution of global CO₂ emissions, we further conduct an asymmetry analysis using the panel quantile regression method. Finally, we discuss the moderating effect of the technology level and the mediating effect of energy consumption on the relationship between natural disasters and CO₂ emissions. The main conclusions are illustrated as follows:

First, natural disasters have a significantly negative impact on CO₂ emissions. However, this environmental impact is asymmetric and depends on different quantiles of CO₂ emissions. Specifically, natural disasters promote CO₂ emissions at the lower quantiles of CO₂ emissions and reduce CO₂ emissions at the upper quantiles of CO₂ emissions, especially those quantiles far from the 50th quantile. This asymmetric impact may be attributed to the “technology effect.” Furthermore, the EKC hypothesis is valid at the global average level but invalid for specific groups of countries. In other words, only at the global average level does the relationship between economic development and CO₂ emissions show an inverted U-shaped curve.

Second, the technology level has a significant moderating effect on the nexus between natural disasters and CO₂ emissions. In other words, the introduction of technology causes a remarkable change in the coefficient of natural disasters. This finding implies that the negative effect of natural disasters on CO₂ emissions may be magnified if the technology level in a country is ignored. In addition, technological progress exerts a larger negative effect on CO₂ emissions due to the larger absolute value of the coefficient of the technology level. Thus, we infer that technology is the main force of carbon reduction.

Third, energy consumption is verified to be an important mediating factor through which natural disasters affect CO₂ emissions. That is, natural disasters can lower CO₂ emissions by reducing energy consumption in a country. We also find that energy consumption has a significant mediating effect on the impacts of the urbanization level and trade openness on CO₂ emissions, and the mediating effect is positive.

Based on the findings above, several important policy implications are highlighted as follows:

First, while the impact of natural disasters on CO₂ emissions is negative, it comes at the cost of great economic losses. Thus, governments should encourage more investment in emergency information management research to strengthen disaster prevention, mitigate damage, and attend to post-disaster reconstruction. Taking the ongoing COVID-19 pandemic as an example, governments should establish epidemic early warning mechanisms and use big data surveillance systems to track the trajectory of confirmed cases. Furthermore, policy-makers should improve the energy system’s ability to resist natural disasters. An important measure is to ensure the stability of energy prices. For example, following the practice of stock markets, governments can strengthen the supervision and management of energy markets by setting a daily limit on energy prices. Furthermore, energy delivery networks should be reinforced to ensure a sustainable energy supply during natural disasters.

Second, given the role of technological progress as the dominant factor in carbon reduction, policy-makers should encourage more investment in technological innovation,
especially in the exploration and development of renewable and other alternative energy resources. Such increased investment can also lead to two aspects of technological dividends. On the one hand, with an improved level of technology, the stability and resilience of energy infrastructures will be enhanced, thereby reducing economic damage and speeding up post-disaster reconstruction. On the other hand, it will facilitate the development of low-carbon technologies and promote the diversification of the energy system. Furthermore, countries should establish post-pandemic carbon reduction targets, thus forming an anchoring effect to facilitate the achievement of carbon peaking and carbon neutrality goals.

Third, the EKC hypothesis indicates a possible pathway that we can pursue to establish a synergy between environmental protection and economic development. However, the inverted U-shaped curve between economic development and CO2 emissions is no longer valid for specific groups of countries. This finding implies that countries should adjust their economic development patterns and shift to a green growth mode. Currently, economic development is still anchored by energy consumption, and thus, policy-makers can adjust their energy consumption structure. For instance, since energy consumption may serve as an important mediator between trade openness and CO2 emissions, one effective measure is to adjust the trade structure by imposing tariffs and other policies. Specifically, policymakers should encourage the trade in technology and low-carbon commodities to achieve a low-carbon and modern energy consumption structure.

This study analyzes the impact of natural disasters on CO2 emissions from an empirical perspective, providing fresh evidence on the environmental damage caused by natural disasters. Nevertheless, some limitations remain. The COVID-19 outbreak at the end of 2019 is a typical epidemic natural disaster. However, due to data unavailability, this study did not cover the duration of the COVID-19 pandemic. In future research, we will continue to track damage data on COVID-19 and study the dynamic impact of natural disasters on global CO2 emissions. Furthermore, we examine only the potential role of energy consumption in the nexus between natural disasters and CO2 emissions. Other factors, such as renewable energy facilities, are not considered in the mediating effect analysis. Thus, it would be interesting to discuss other impact mechanisms between natural disasters and CO2 emissions in future research.

### Appendix A

See Table A1.

| Variables | Definitions | Data sources |
|-----------|-------------|--------------|
| CO2       | Carbon dioxide (CO2) emissions | IEA (2019) |
| Nd        | Affected ratio by natural disasters | CRED (2019) |
| GDP       | Gross domestic production (GDP) | World Bank (2019) |
| Urb       | Proportion of urban population to total population | World Bank (2019) |
| Tra       | International trade volume divided by total GDP | World Bank (2019) |
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Declarations

Conflicts of interest No potential conflict of interest was reported by the authors.

References

Acheampong AO (2018) Economic growth, CO₂ emissions and energy consumption: what causes what and where? Energ Econ 74:677–692. https://doi.org/10.1016/j.eneco.2018.07.022
Ajmi AN, Hammoudel S, Nguyen DK, Sato JR (2015) On the relationships between CO₂ emissions, energy consumption and income: the importance of time variation. Energ Econ 49:629–638. https://doi.org/10.1016/j.eneco.2015.02.007
Amin A, Aziz B, Liu X (2020) The relationship between urbanization, technology innovation, trade openness, and CO₂ emissions: evidence from a panel of Asian countries. Environ Sci Pollut R 27:35349–35363. https://doi.org/10.1007/s11356-020-09777-y
Arellano M, Bond S (1991) Some tests of specification for panel data: monte carlo evidence and an application to employment equations. Rev Econ Stud 58:277–297. https://doi.org/10.2307/2297968
Arouri MEH, Youssef AB, Mhenni H, Rault C (2012) Energy consumption, economic growth and CO₂ emissions in Middle East and North African countries. Energ. Policy 45:342–349. https://doi.org/10.1016/j.enpol.2012.02.042
Azzarri C, Signorelli S (2020) Climate and poverty in Africa South of the Sahara. World Dev 125:104691. https://doi.org/10.1016/j.worlddev.2019.104691
Baker HS, Millar RJ, Karoly DJ, Allen MR (2018) Higher CO₂ concentrations increase extreme event risk in a 1.5 °C world. Nat Clim Change 8:604–608. https://doi.org/10.1038/s41558-018-0190-1
Begum RA, Sohag K, Abdullah SMS, Jaafar M (2015) CO₂ emissions, energy consumption, economic and population growth in Malaysia. Renew Sust Energ Rev 41:3594–401. https://doi.org/10.1016/j.rser.2014.07.025
Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. J Econometrics 87:115–143. https://doi.org/10.1016/S0304-4076(98)00009-8
Botzen WW, Deschenes O, Sanders M (2019) The economic impacts of natural disasters: a review of models and empirical studies. Rev Env Econ Policy 13:167–188. https://doi.org/10.1093/reep/rez004
Bui AT, Dungen M, Nguyen CV, Pham TP (2014) The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. Appl Econ 46:1751–1766. https://doi.org/10.1080/00036846.2014.884706
Cassar A, Healy A, Von Kessler C (2017) Trust, risk, and time preferences after a natural disaster: experimental evidence from Thailand. World Dev 94:90–105. https://doi.org/10.1016/j.worlddev.2016.12.042
Chakravarty S, Tavoni M (2013) Energy poverty alleviation and climate change mitigation: is there a trade off? Energ Econ 40:S67–S73. https://doi.org/10.1016/j.eneco.2013.09.022
Che Y, Lu Y, Tao Z, Wang P (2013) The impact of income on democracy revisited. J Comp Econ 41:159–169. https://doi.org/10.1016/j.jece.2012.05.006
Chen S, Luo Z, Pan X (2013) Natural disasters in China: 1900–2011. Nat Hazards 69:1597–1605. https://doi.org/10.1007/s11069-013-0765-0
Coffman M, Noy I (2012) Hurricane Iniki: measuring the long-term economic impact of a natural disaster using synthetic control. Environ Dev Econ 17:187–205. https://doi.org/10.1017/S1355777X11000350
CRED (2019) Center for Research on the Epidemiology of Disasters. https://public.emdat.be/data
CRED (2020) Center for Research on the Epidemiology of Disasters. https://public.emdat.be/data
Dietz T, Rosa EA (1997) Effects of population and affluence on CO₂ emissions. P Natl Acad Sci 94:175–179. https://doi.org/10.1073/pnas.94.1.175
| Author(s)                          | Title                                                                 | Journal/Link                                                                 |
|-----------------------------------|-----------------------------------------------------------------------|-------------------------------------------------------------------------------|
| Kang H, An J, Kim H, Ji C, Hong T, Lee S (2021) | Changes in energy consumption according to building use type under COVID-19 pandemic in South Korea. | Renew Sust Energ Rev. https://doi.org/10.1016/j.rser.2021.111294 |
| Karim A, Noy I (2016)              | Poverty and natural disasters—a qualitative survey of the empirical literature. | Singap Econ Rev 61:1640001. https://doi.org/10.1142/S0217590816400014          |
| Kasman A, Duman YS (2015)          | CO₂ emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. | Econ Model 44:97–103. https://doi.org/10.1016/j.econmodel.2014.10.022       |
| Khalid MA, Ali Y (2019)            | Economic impact assessment of natural disaster with multi-criteria decision making for interdependent infrastructures. | Environ Dev Sustain. https://doi.org/10.1007/s10668-019-00499-x               |
| Kongkuah M, Yao H, Yilanci V (2022) | The relationship between energy consumption, economic growth, and CO₂ emissions in China: the role of urbanisation and international trade. | Environ Develop Sustain 24(4):4684–4708                                      |
| Lee J, Fraser T (2019)             | How do natural hazards affect participation in voluntary association? the social impacts of disasters in Japanese society. | Int J Disast Risk Re 34:108–115. https://doi.org/10.1016/j.ijdrr.2018.11.009  |
| Lee CC, Wang CW, Ho SJ, Wu TP (2021)| The impact of natural disaster on energy consumption: international evidence. | Energ Econ 97:105021. https://doi.org/10.1016/j.jeneeco.2020.105021           |
| Li W, Wang W, Wang Y, Qin Y (2017) | Industrial structure, technological progress and CO₂ emissions in China: Analysis based on the STIRPAT framework. | Nat Hazards 88:1545–1564. https://doi.org/10.1007/s11069-017-2932-1           |
| Liu X, Ma S, Tian J, Nia Li G (2015) | A system dynamics approach to scenario analysis for urban passenger transport energy consumption and CO₂ emissions: a case study of Beijing. | Energy Policy 85:253–270. https://doi.org/10.1016/j.enpol.2015.06.007        |
| Liu L, Wang EZ, Lee CC (2021)      | Impact of the COVID-19 pandemic on the crude oil and stock markets in the USA time varying analysis. | Energy Res Lett. https://doi.org/10.46557/001c.13154                         |
| Maddala GS, Wu S (1999)            | A comparative study of unit root tests with panel data and a new simple test. | Oxford b Econ Stat 61:631–652. https://doi.org/10.1111/1468-0084.61.s1.13     |
| Markhvida M, Walsh B, Hallegatte S, Baker J (2020) | Quantification of disaster impacts through household well-being losses. | Nat Sustain 3:538–547. https://doi.org/10.1038/s41893-020-0508-7             |
| Menyah K, Wolde-Rufael Y (2010)    | Energy consumption, pollutant emissions and economic growth in South Africa. | Energ Econ 32:13. https://doi.org/10.1016/j.jeneeco.2010.08.002               |
| Mishra GS, Zakerinia S, Yeh S, Teter J, Morrison G (2014) | Mitigating climate change: decomposing the relative roles of energy conservation, technological change, and structural shift. | Energ Econ 44:448–455. https://doi.org/10.1016/j.jeneeco.2014.04.024     |
| Neumayer E, Plümper T, Barthel F (2014) | The political economy of natural disaster damage. | Global Environ Chang 24:8–19. https://doi.org/10.1016/j.gloenvcha.2013.03.011 |
| Nickell S (1981)                   | Biases in dynamic models with fixed effects Econometrica. | J Econometric Soc. https://doi.org/10.2307/1911408                               |
| Noy I (2009)                      | The macroeconomic consequences of disasters. | J Dev Econ 88:221–231. https://doi.org/10.1016/j.jdeveco.2008.02.005          |
| Ogbeide-Osaretin EN (2021)         | Analysing energy consumption and poverty reduction nexus in Nigeria. | Int J Sustain Energy 40:477–493. https://doi.org/10.1080/14786451.2020.1815744 |
| Paramatti SR, Mo D, Gupta R (2017) | The effects of stock market growth and renewable energy use on CO₂ emissions: evidence from G20 countries. | Energ Econ 66:360–371. https://doi.org/10.1016/j.jeneeco.2017.06.025          |
| Pesaran MH (2007)                  | A simple panel unit root test in the presence of cross-section dependence. | J Appl Econ 22:265–232. https://doi.org/10.1002/jae.951                           |
| Porzio GF, Fornai B, Amato A, Colla V (2013) | Reducing the energy consumption and CO₂ emissions of energy intensive industries through decision support systems—An example of application to the steel industry. | Appl Energ 112:818–833. https://doi.org/10.1016/j.apenerg.2013.05.005        |
| Qiao H, Chen S, Dong X, Dong K (2019) | Has China’s coal consumption actually reached its peak? national and regional analysis considering cross-sectional dependence and heterogeneity. | Energ Econ 84:104509. https://doi.org/10.1016/j.jeneeco.2019.104509         |
| Richardson HW, Park J, Moore II JE, Pan Q (2014) | National economic impact analysis of terrorist attacks and natural disasters. | Edward Elgar Publishing                                                        |
| Rosselló J, Becken S, Santana-Gallego M (2020) | The effects of natural disasters on international tourism: a global analysis. | Tourism Manage 79:104080. https://doi.org/10.1016/j.tourman.2020.104080       |
Saayman A (2010) A panel data approach to the behavioral equilibrium exchange rate of the ZAR. S Afr J Econ 78:57–75. https://doi.org/10.1111/j.1813-6982.2010.01232.x

Sakai Y, Estudillo JP, Fuwa N, Higuchi Y, Sawada Y (2017) Do natural disasters affect the poor disproportionately? price change and welfare impact in the aftermath of Typhoon Milenyo in the rural Philippines. World Dev 94:16–26. https://doi.org/10.1016/j.worlddev.2016.12.036

Salahuddin M, Alam K, Ozturk I, Sohag K (2018) The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO2 emissions in Kuwait. Renew Sust Energ Rev 81:2002–2010. https://doi.org/10.1016/j.rser.2017.06.009

Salisu A, Adediran I (2020) Uncertainty due to infectious diseases and energy market volatility. Energy Res Lett 1:14185. https://doi.org/10.46557/001c.14185

Sarafidis V, Wansbeek T (2012) Cross-sectional dependence in panel data analysis. Economet Rev 31:483–531. https://doi.org/10.1080/07474938.2011.611458

Schwarz PM, Cochran JA (2013) Renaissance or requiem: is nuclear energy cost effective in a post-fukushima world? Contemp Econ Policy 31:691–707. https://doi.org/10.1111/j.1465-7287.2012.00341.x

Seaberg D, Devine L, Zhuang J (2017) A review of game theory applications in natural disaster management research. Nat Hazards 89:1461–1483. https://doi.org/10.1007/s11069-017-3033-x

Shahbaz M, Tiwari AK, Nasir M (2013) The effects of financial development, economic growth, coal consumption and trade openness on CO2 emissions in South Africa. Ener Policy 61:1452–1459. https://doi.org/10.1016/j.enpol.2013.07.006

Shahbaz M, Nasreen S, Ahmed K, Hammoudeh S (2017) Trade openness–carbon emissions nexus: the importance of turning points of trade openness for country panels. Ener Econ 61:221–232. https://doi.org/10.1016/j.eneco.2016.11.008

Shahbaz M, Nasir MA, Roubaud D (2018) Environmental degradation in France: the effects of FDI, financial development, and energy innovations. Ener Econ 74:843–857. https://doi.org/10.1016/j.eneco.2018.07.020

Shahbaz M, Gozgor G, Adom PK, Hammoudeh S (2019) The technical decomposition of carbon emissions and the concerns about FDI and trade openness effects in the United States. Int Econ 159:56–73. https://doi.org/10.1016/j.inteco.2019.05.001

Shugar DH, Clague JJ, Best JL, Schoof C, Willis MJ, Copland L, Roe GH (2017) River piracy and drainage basin reorganization led by climate-driven glacier retreat. Nat Geosci 10:370–375. https://doi.org/10.1038/ngeo2932

Sohag K, Begum RA, Abdullah SMS, Jaafar M (2015) Dynamics of energy use, technological innovation, economic growth and trade openness in Malaysia. Energy 90:1497–1507. https://doi.org/10.1016/j.energy.2015.06.101

Tang B, Chen Q, Chen X, Glik D, Liu X, Liu Y, Zhang L (2017) Earthquake-related injuries among survivors: A systematic review and quantitative synthesis of the literature. Int J Disast Risk Re 21:159–167. https://doi.org/10.1016/j.ijdrr.2016.12.003

Wang R, Liu W, Xiao L, Liu J, Kao W (2011) Path towards achieving of China’s 2020 carbon emission reduction target—a discussion of low-carbon energy policies at province level. Ener Policy 39:2740–2747. https://doi.org/10.1016/j.enpol.2011.02.043

Warr P, Aung LL (2019) Poverty and inequality impact of a natural disaster: Myanmar’s 2008 cyclone Nargis. World Dev 122:446–461. https://doi.org/10.1016/j.worlddev.2019.05.016

Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. J Econometrics 126:25–51. https://doi.org/10.1016/j.jeconom.2004.02.005

World Bank (2019) World Development Indicators. https://databank.worldbank.org/source/world-development-indicators/preface/on.

Wu R, Wang J, Wang S, Feng K (2021) The drivers of declining CO2 emissions trends in developed nations using an extended STIRPAT model: a historical and prospective analysis. Renew Sust Energ Rev 149:111328. https://doi.org/10.1016/j.rser.2021.111328

Yang Z, Kagawa S, Li J (2021) Do greenhouse gas emissions drive extreme weather conditions at the city level in China? evidence from spatial effects analysis. Urban Clim 37:100812. https://doi.org/10.1016/j.uclim.2021.100812

Zhang S, Andrews-Speed P, Ji M (2014) The erratic path of the low-carbon transition in China: evolution of solar PV policy. Ener Policy 67:903–912. https://doi.org/10.1016/j.enpol.2013.12.063

Zhao J, Jiang Q, Dong X, Dong K (2020) Would environmental regulation improve the greenhouse gas benefits of natural gas use? A Chinese Case Study Ener Econ 87:104712. https://doi.org/10.1016/j.eneco.2020.104712

Zhao J, Dong X, Dong K (2021) Can agglomeration of producer services reduce urban–rural income inequality? the case of China. Aust. Economic Papers 60(4):736–762
Zhao J, Shahbaz M, Dong X, Dong K (2021b) How does financial risk affect global CO₂ emissions? the role of technological innovation. Technol Forecast Soc 168:120751. https://doi.org/10.1016/j.techfore.2021.120751
Zhou Y, Li N, Wu W, Liu H, Wang L, Liu G, Wu J (2014) Socioeconomic development and the impact of natural disasters: some empirical evidences from China. Nat Hazards 74:541–554. https://doi.org/10.1007/s11069-014-1198-0

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