THE DIVERSE IMPACT OF ECONOMIC DIGITALIZATION ON CARBON DIOXIDE EMISSIONS ACROSS COUNTRIES

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This study examines the impact of economic digitalization on CO2 emissions by using the data of 100 countries from 2008 to 2019. First, we divide our sample into different income-level groups and use the Bayesian panel regression method to examine how economic digitalization can impact CO2 emissions in each group. Second, we conduct Bayesian quantile regression on the whole sample to determine how the different digital economies affect CO2 emissions across the quantile levels. The results obtained by the two approaches are consistent. We find that ICT infrastructure can increase CO2 emissions in the less-developed countries but help reduce CO2 emissions in the developed countries. ICT-related industry activities can help reduce CO2 emissions in nearly all the countries, but the impact differs across the countries. By contrast, ICT product and service exports can lead to an increase in CO2 emissions, but the effect is relatively small and will decrease gradually as the CO2 emissions level rises. Our results can provide helpful information and implications to policymakers to fully employ the advantages of economic digitalization to reduce CO2 emissions.

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I. Introduction

The rise in carbon dioxide ($CO2$) emissions is one of the most significant causes of climate change, air pollution, biodiversity loss, and other issues that pose a threat to the sustainability of our planet. Previous studies showed that economic growth is the primary driver of $CO2$ emissions in developed and developing countries (Iwami 2004; Heidari 2015; Mardani 2019). The digital economy is booming worldwide (Pradhan *et al.* 2019), and whether it can provide opportunities for reducing regional $CO2$ emissions is worth exploring.

In recent years, economic digitalization emerged as a central pillar in the latest wave of industrial restructuring in many nations (Wu *et al.* 2022). The progressive development of digital infrastructure has paved the way for the expansion of the economy in several countries (Liu *et al.* 2021; Yang *et al.* 2014). Advances in technology have made it easy and cost effective for businesses to operate digitally (Li *et al.* 2020). For example, cloud computing and the widespread availability of high-speed internet connection have enabled companies to store and access data and applications remotely without needing to use expensive hardware and IT infrastructure. Besides, the digital economy has opened up new opportunities for innovation and entrepreneurship (Von Briel *et al.* 2018) and lowered entry barriers for many industries, thereby making it easy for startups to compete with established players (Ablyazov and Asaul 2021). In addition, digital technologies have created entirely new business models, such as the sharing economy and platform-based businesses (Ablyazov and Asaul 2021; Pouri and Hilty 2021). The rise of social media and online communities has also created new opportunities for companies to engage with customers and build brand loyalty.

The impact of economic digitalization on $CO2$ emissions remains controversial. According to the literature, the digital economy has the potential to prevent and control pollution. The use of digital technologies can reduce the gap between the upstream and downstream sectors, which can result in optimal inventory allocation, improve the effectiveness of supply chain distribution, and minimize unnecessary transportation losses (Watanabe *et al.* 2018). In addition, the digital economy can overcome time and distance barriers (Richardson 2019), simplify the information flow stages, minimize the wasteful use of resources, enhance carbon performance (Zhang *et al.* 2022), and assist economically undeveloped regions in resolving energy-related issues (Xu *et al.* 2022). The continuous advancement of digital processes in the energy industry will lead to improved carbon efficiency, which in turn will reduce the rate of increase of digital emissions (Zhou *et al.* 2022). The improvement of digital production structures may result in safe and efficient energy consumption, increase green total factor productivity (Zhang *et al.* 2021), and promote the sustainable development of natural resources and the environment (Hosan *et al.* 2022). The implementation of digital manufacturing can lead to reduced electricity generation, optimized resource utilization, and high green innovation output and facilitate the progress of sustainable and circular economies (Yue *et al.* 2021).

Another branch of the literature revealed that economic digitalization could increase CO2 emissions. According to Yu and Zhu (2022), the digital economy can reduce CO2 emissions by increasing energy intensity but increase CO2 emissions by stimulating economic growth, thereby resulting in a net contribution to CO2 emissions. Shvakov and Petrova (2020) examined the statistics of the top 10 nations in the world in 2019 and concluded that digitalization can hamper, rather than promote, the development of a green or an energy-efficient economy. In addition, the implementation of global sustainable development goals necessitates limiting the digital economy's growth pace. The expansion of the digital economy may require an increase in energy consumption, and an increase in energy consumption may cause CO2 emissions to rise (Hossain 2014; Begum *et al.* 2015).

Some studies confirmed that the effect of economic digitalization on CO2 emissions varies by geographic location (Yu and Zhu 2022) or by economic development level (Wu *et al.* 2021), because it can be influenced by a wide range of factors, including access to digital technologies, the economic development level, and the regulatory framework in place. The empirical results of Li and Wang (2022) indicated that the digital economy and CO2 emissions have an inverted U-shaped relationship. Specifically, the digital economy will first increase, then reduce CO2 emissions.

This study enriches the literature through two approaches. For the first approach, we use the data of 100 countries and examine the impact of economic digitalization on CO2 emissions for different income-level country groups. Specifically, we employ the country classification by income method of the World Bank to divide the countries into different income groups. The World Bank categorizes global economies into four income groups based on the gross national income per capita: high, upper middle, lower middle, and low. A problem with the method is that the number of observations in each group is relatively small, and the examination of small datasets may result in a biased estimation. Nevertheless, this drawback can be effectively addressed by Bayesian estimation with prior distributions (Van de Schoot *et al.* 2015). Bayesian analyses differ from maximum likelihood estimation in their independence from large sample sizes. Unlike maximum likelihood estimation, which relies on sizable datasets, Bayesian methods allow for the analysis of small datasets without sacrificing power while maintaining precision. Lee and Song (2004) illustrated this phenomenon by demonstrating that Bayesian estimation permits the use of a considerably small ratio of parameters to observations. In their study, a ratio of 1:3 sufficed, as opposed to the conventional 1:5 ratio associated with other estimation approaches. Therefore, we conduct Bayesian multilevel regression to determine how economic digitalization can influence the CO2 emissions of each group.

For the second approach, we once again leverage the advantages of the Bayesian estimation method to address the problem of a small sample size. Specifically, we use the Bayesian quantile regression (QR) model to assess the impact of economic digitalization on CO2 emissions across various quantile levels. Notably, the higher the quantile level, the higher the CO2 emissions. Current research on quantile treatment effect estimation, such as Lin and Xu (2018) and Arain *et al.* (2020), contended that the standard estimation of the average (mean) may overlook significant causal effects. Specifically, the estimation of the mean will naturally mix the magnitude of the causal effects on various portions of the conditional distribution. Thus, by using this methodology, we may determine how economic digitalization can affect CO2 emissions quantiles.

Compared with other related studies, our approach has several advantages. First, our results can describe the whole picture of the relationship between economic digitalization and CO2 emissions. By analyzing different income-level country groups, we can find evidence for differences in the relationship across the countries. In addition, conducting QR will enable us to address the conditional distribution of the dependent variable, instead of focusing on only the dependent variable's conditional expectations (average values). We could also deal with outliers that may exert a substantial impact and carry valuable information. Second, the estimated coefficients of our approaches are more robust than those of one linear regression model. Furthermore, classical econometric assumptions such as zero mean, homoscedasticity, and normal distribution need not be strictly fulfilled when conducting QR. Thus, the method is robust for variables that do not follow a normal distribution. Last, Bayesian analysis has been widely examined, and the technique can make a statistical analysis more robust than an ordinal statistical inference (Kozumi and Kobayashi 2011).

The rest of this paper is arranged as follows: Section II illustrates the Bayesian QR model and the estimation method, Section III describes the data used for the empirical study, Section IV presents the estimation results and the discussion, and Section V provides the concluding remarks.

II. Model specification

A. Panel regression estimation through Bayesian multilevel modeling

A multilevel model can be used to estimate a random panel regression, because it allows for the modeling of hierarchical or nested data structures, in which observations are grouped into higher-level units (*e.g.*, individuals, firms, and countries), and the model accounts for the within-group and between-group variations (Gelman and Hill 2006). In this study, we employ a Bayesian multilevel model that can provide analysts with the most flexibility to model complex error structures and the contextual data characteristics of the panel data (Shor *et al.* 2007; Chib 2008). We consider the following model:

$$y_{it} = x'_{it}\beta + \gamma_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is the outcome variable for unit i and time t; γ_i is the varying intercepts of the units; x_{it} is a vector of the regressors, with β as the associated coefficient vector; and ε_{it} is the error.

For the estimation process, we use uninformative normal priors for the regression coefficients and the random effects but inverse-gamma priors for the variance parameters. Specifically,

$$\beta \sim MVN(\mu, \Sigma) \tag{2}$$

$$\varepsilon_{it} \sim i.i.d.N(0, \sigma_0^2),$$

$$\gamma_i \sim i.i.d.N(0, \sigma_\gamma^2),$$

$$\sigma_0^2 \sim IG(0.001, 0.001),$$

$$\sigma_\alpha^2 \sim IG(0.001, 0.001),$$

$$\sigma_\gamma^2 \sim IG(0.001, 0.001),$$

where MVN represents multivariate normal distribution. We conduct the parameter estimation by using STATA 17.

B. Bayesian QR

For the second approach, we conduct Bayesian QR on the pooled cross-sectional data of the entire sample to investigate how the relationship between the digitalization of the economy and CO2 emissions changes across different levels of CO2 emissions. Koenker and Bassett (1978) introduced QR to model and estimate the conditional distribution of a response variable given a set of predictor variables. We consider a sample of observations $\{(x_i, y_i); i = 1, 2, n\}$, where y_i denotes the dependent variable, and x_i represents a k-dimensional vector of the regressors. For each τ th quantile level, $\tau \in (0, 1)$, and the QR model is $y_i = x_i'\beta_\tau + \varepsilon_i$, where β_τ is a vector of the parameters at quantile τ.

Although the large sample theory for QR has received considerable attention, the Bayesian approach will allow for precise and comprehensive inferences even with a limited number of observations. Koenker and Machado (1999) demonstrated that $\rho_\tau(w)$ corresponds precisely to the asymmetric Laplace distribution (ALD). The density function of the ALD is

$$f(y \mid \mu, \sigma, \tau) = \sigma^{-1}\tau(1-\tau)\exp\left\{-\frac{\rho_\tau(y-\mu)}{\sigma}\right\}, \tag{3}$$

where μ and σ are the shift parameter and dispersion parameter, respectively. Koenker and Machado (1999) noticed that the coefficients of the QR model can be estimated by maximizing the likelihood function of the independent variable y_i by assuming that $y_i \sim ALD(\mu, \sigma, \tau)$, with $\mu = x_i'\beta$. By using this idea, Yu and Moyeed (2001) proposed the Bayesian method for QR. Let $y_i = x_i'\beta + \varepsilon_i$ and $\varepsilon_i \sim ALD(\mu, \sigma, \tau)$. Then, the joint distribution of $y = (x_1,\ldots,x_n)'$, given $X = (y_1,\ldots,y_n)'$, β, and σ, is

$$f(y \mid X, \beta, \sigma, \tau) = \frac{\tau^n(1-\tau)^n}{\sigma^n}\exp\left\{-\frac{1}{\sigma}\sum_{i=1}^{n}\rho_\tau(y_i - x_i'\beta)\right\}. \tag{4}$$

The ALD can be motivated as a scale mixture of normal–exponential distributions. This motivation will offer access to the properties of the normal distribution, which we exploit in this study to derive the sample for the QR. If we assume that $\varepsilon_i \sim N(\theta v_i, 2\sigma v_i)$ and $\theta = (1-2\tau)$, then the ALD will emerge when v_i follows an exponential distribution with a rate parameter $\sigma^{-1}\tau = (1-\tau)$. In other words, let $\mathrm{v} = (v_1,\ldots,v_n)'$ and $\varepsilon = (\varepsilon_1,\ldots,\varepsilon_n)'$, where $v_i \sim Exp(\sigma^{-1}\tau(1-\tau))$, and $\varepsilon_i \sim N(0, 1)$. Then, we obtain the hierarchical model.

$$\begin{aligned} y_i &= x_i'\beta + \theta v_i + \sqrt{2\sigma v_i}\,\varepsilon_i, \\ v \mid \sigma &\sim \prod_{i=1}^{n}\frac{\tau(1-\tau)}{\sigma}\exp\left(-\frac{\tau(1-\tau)}{\sigma}v_i\right), \\ \varepsilon &\sim \prod_{i=1}^{n}\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{\varepsilon_i^2}{2}\right). \end{aligned} \tag{5}$$

By referring to Yu and Stander (2007), we assume that $\pi(\beta) \propto 1$, and $\pi(\beta) \propto 1/\sigma$. The full conditional distribution of β is multivariate normal, with a mean of $A^{-1}X'V\tilde{y}$ and a variance of σA^{-1}, where $A = X'VX$, $V = diag(1/(2v_1),\ldots,1/(2v_n))$, and $\tilde{y} = y - \theta v$. The full conditional of σ is an inverse gamma, with a shape parameter of $3n/2$ and a scale parameter of $(\tilde{y} - X\beta)'V(\tilde{y} - X\beta)/2 + \tau(1-\tau)v$. The latent variables $v_1,\ldots,v_n$ are conditionally independent, and the full conditional of v_i^{-1} is an inverse Gaussian, with parameters $\mu_i' = |y_i - x_i'\beta|^{-1}$ and $\varphi' = (2\sigma)^{-1}$.

For the two aforementioned approaches, we run 30,000 MCMC iterations, use the first 15,000 draws as a burn-in process, and report the next 15,000 draws. We examine the mean (or the median) of the after burn-in MCMC process to conclude the effects of the regressors on the outcome. The effects are considered to be “significant” when the 95% credible interval (from 2.5% to 97.5% percentiles of the MCMC process) does not contain zero. To confirm the independence and convergence of our MCMC sampling, we examine the trace plots and ACF of the after burn-in MCMC process for each parameter. The figures can be provided upon request.

III. Data description

We collect yearly data from 100 countries from 2008 to 2019. The list of the countries is presented in the Appendix. Table 1 presents the definition of each variable, along with the data source.

We collect the CO2 emissions data (log of metric tons per capita) from the World Bank and Ritchie *et al.* (2020), which is published in OurWorldInData.org. The detailed data of the CO2 variable can be found in https://ourworldindata.org/grapher/co-emissions-per-capita.

We employ three explanatory variables, namely, ICT infrastructure (ICT), industry activities related to ICT (Industry), and ICT exports (ICT export), to gauge the extent of the economic digitalization. We choose ICT infrastructure as a metric owing to its fundamental role in shaping and facilitating digital economy development. ICT infrastructure serves as the cornerstone, which can not only foster the adoption of digital technologies but also influence economic activities, innovation, and global competitiveness. Thus, the state of the ICT infrastructure is pivotal in the evaluation of the progress and potential of a country’s digital economy. Our assessment of the ICT infrastructure relies on data from the United Nations Conference on Trade and Development (UNCTAD), specifically, the frontier technology readiness index. This index considers two facets of ICT infrastructure: its prevalence, which can ensure accessibility, and its quality, which can support sophisticated and effective usage. The prevalence aspect is represented by the percentage of the people using the internet, coupled with the quality of internet connections, which is gauged by the average download speed. The detailed description and data of the ICT variable are provided by UNCTAD as “ICT deployment” in https://unctadstat.unctad.org/datacentre/dataviewer/US.FTRI.

The second explanatory variable employed is an index from the

Table 1
Variable description

Variables	Definition	Source
Dependent variable		
CO2	Log of CO2 emissions per capita (unit: log of tons per person)	OurWorldInData.org
Economic digitalization variables		
ICT	Level of ICT infrastructure; computed using two components: (i) the proportion of the population that uses the internet, which indicates the availability of internet infrastructure, and (ii) the average download speed, which indicates the quality of internet connection (unit: 0-to-1 index)	UNCTAD
Industry	Index measuring ongoing industry activities associated with the use and adoption of and adaptation to frontier technology relevant to digitalization (unit: 0-to-1 index)	UNCTAD
ICT export	Share of ICT goods in the total merchandise export (unit: percentage)	UNCTAD
Control variables		
Population	Log of total population (unit: log of millions of people)	OurWorldInData.org
GDP per capita	Log of GDP per capita (unit: log of thousands; USD)	OurWorldInData.org
Energy	Log of energy consumption (unit: log of kilowatt-hours per person)	OurWorldInData.org

UNCTAD that evaluates the relevant industrial capacity of a country to utilize, adopt, and adapt to frontier technologies. The index encompasses three key sectors: manufacturing (with a focus on high-tech manufacturing), finance, and ICT (which frequently collaborates with other technologies). The variable can provide a comprehensive perspective of a country's readiness for the digital economy; thus, it is valuable for understanding the dynamics of digital transformation. The detailed description and data of the Industry variable are provided by the UNCTAD as "Industry activities" in https://unctadstat.unctad.org/

datacentre/dataviewer/US.FTRI.

The third variable used to measure the digital economy is ICT exports, which are quantified as the proportion of ICT goods in the total merchandise exports. The detailed description and data of the variable are provided by the UNCTAD in https://unctadstat.unctad.org/datacentre/dataviewer/US.IctGoodsShare. In addition to the aforementioned variables, we incorporate three control variables, namely, population, GDP per capita, and energy consumption, into our analysis. The detailed data of the variables can be found in https://ourworldindata.org/energy.

Table 2 provides the summary statistics of each variable within each income-level group. We divide the dataset into four groups corresponding to the four income brackets, then calculate the mean, median, standard deviation, minimum, and maximum values of each variable within each group. After examining the average values, we clearly see that the CO2 emissions levels and the digital transformation variables (ICT, Industry, and ICT export) exhibit a gradual increase,

Table 2
Descriptive statistics

Variables	Mean	Median	Standard deviation	Min.	Max.
Low-income countries					
CO2	0.198	0.153	0.150	0.063	1.001
ICT	0.110	0.093	0.088	0.000	0.444
Industry	0.359	0.347	0.124	0.130	0.694
ICT export	13.369	5.984	14.959	0.112	61.451
Population	1.277	1.246	0.309	0.788	2.050
GDP per capita	0.175	0.142	0.140	-0.084	0.623
Energy	3.017	2.928	0.328	2.597	3.932
Lower-middle-income countries					
CO2	0.262	0.098	0.216	0.900	1.439
ICT	0.230	0.191	0.155	0.010	0.845
Industry	0.395	0.378	0.189	0.000	0.967
ICT export	9.901	8.775	7.501	0.071	36.148
Population	1.246	1.211	0.780	-0.767	3.136
GDP per capita	0.659	0.650	0.245	0.163	1.151
Energy	3.616	3.605	0.370	2.860	4.529

Variables	Mean	Median	Standard deviation	Min.	Max.
Higher-middle-income countries					
CO2	0.513	0.528	0.300	0.153	1.239
ICT	0.382	0.378	0.173	0.021	0.811
Industry	0.489	0.489	0.183	0.000	0.876
ICT export	5.796	4.193	4.745	0.219	24.782
Population	1.158	0.976	0.744	-0.207	3.156
GDP per capita	1.101	1.105	0.142	0.813	1.403
Energy	4.209	4.204	0.235	3.607	4.761
High-income countries					
CO2	0.867	0.898	0.259	0.254	1.491
ICT	0.637	0.664	0.189	0.084	1.000
Industry	0.666	0.683	0.149	0.279	1.000
ICT export	10.041	6.824	10.947	1.063	60.057
Population	1.008	0.969	0.630	0.034	2.517
GDP per capita	1.488	1.459	0.189	1.134	1.925
Energy	4.597	4.551	0.237	4.196	5.118

Note: The summary statistics of each variable are calculated using the pooled data.

corresponding to the income level of the countries. Likewise, energy consumption demonstrates a proportional relationship with the average income level of the countries.

Table 3 presents the correlation matrix of the variables based on the pooled data. GDP per capita and energy consumption exhibit a positive correlation with CO2 emissions. This observation is evident, because high-income and developed countries typically manifest higher levels of CO2 emissions than their less-developed counterparts. Most of the variables we employ to gauge economic digitalization display a positive correlation, with the exception of the association between ICT infrastructure and ICT exports. The anticipated positive relationship is grounded in the notion that a well-developed ICT infrastructure can generally improve a country's ability to manufacture and export ICT products. However, the mere presence of infrastructure will not ensure success in export markets, and the magnitude of the correlation is relatively small. Meanwhile, the correlations between the digital economy variables (ICT, Industry, and ICT export) and CO2 emissions exhibit inconsistencies. Thus, the relationships merit careful

Table 3
Correlation matrix

	CO2	ICT	Industry	ICT export	Population	GDP per capita	Energy
CO2	1.000						
ICT	0.583	1.000					
Industry	0.410	0.628	1.000				
ICT export	0.079	-0.036	0.172	1.000			
Population	0.024	0.033	0.195	-0.026	1.000		
GDP per capita	0.753	0.771	0.567	-0.093	-0.022	1.000	
Energy	0.773	0.740	0.529	-0.131	-0.070	0.947	1.000

examination.

IV. Results and discussion

A. Impact of economic digitalization on CO2 emissions in different income-level countries

We report the results of the Bayesian panel regression for the different income-level country groups in Table 4.

a) Effects of ICT infrastructure on CO2 emissions

In Table 4, when the data of the whole sample are used, the estimated coefficients show that ICT infrastructure can significantly reduce CO2 emissions. However, when the different income-level country groups are examined, the results show that ICT infrastructure exerts diverse impacts on CO2 emissions. Specifically, in the low-income countries, ICT infrastructure can significantly increase CO2 emissions. By contrast, ICT infrastructure can help reduce CO2 emissions in the middle-income and high-income countries. In addition, the impact increases across the high-income countries. The results are similar to the findings of Khan *et al.* (2018). In this study, we find that ICT decreases CO2 emissions in the high- and middle-income countries but increases CO2 emissions in the low-income countries. The negative impact of ICT infrastructure on CO2 emissions in the less-developed nations may result from the use of numerous inefficient ICT equipment.

The direct use of resources to create and use ICT equipment in daily life, short product life cycles, e-waste, and exploitative applications are potential issues faced by less-developed nations. By contrast, middle- and high-income countries have energy-efficient technologies that can reduce energy consumption and thus reduce CO2 emissions.

b) Effects of ICT-related industry activities on CO2 emissions

We also observe the different effects of ICT-related industry activities on CO2 emissions among the countries. ICT-related industry activities do not affect CO2 emissions in the low-income and lower-middle-income countries. At the same time, such activities can help reduce CO2 emissions in the upper-middle-income and high-income countries. According to Usman *et al.* (2021), this relationship depends on the specific ICT-related industry. Some ICT-related industries can reduce CO2 emissions by providing technology and services that can help other industries reduce their carbon footprint. For example, the cloud computing industry can offer energy-efficient computing resources and thus reduce the energy consumption of other industries. Such industries are generally popular in advanced countries. By contrast, some ICT-related industries, such as electronic device manufacturing and other ICT product manufacturing, can contribute to CO2 emissions through the extraction of raw materials, the energy-intensive manufacturing process, and supply chain emissions. Such manufacturing industries are typically developed in emerging countries.

c) Effects of ICT trade on CO2 emissions

According to Table 4, though all the estimated coefficients of ICT export are positive, they are statistically insignificant. However, though the export of ICT products and services may not directly impact CO2 emissions, it can contribute to CO2 emissions through the transportation and production processes involved in the exportation of products and services (Sinha 2018).

TABLE 4
BAYESIAN PANEL REGRESSION MODEL ESTIMATIONS

Variables	All countries		Low-income countries		Lower-middle-income countries	
	Mean	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$
Intercept	0.346	[-0.264, 0.983]	-0.352*	[-0.695, -0.103]	-1.451*	[-2.624, -0.461]
ICT	-0.723*	[-1.165, -0.281]	0.168*	[0.045, 0.292]	-1.140	[-2.505, 0.208]
Industry	-0.597	[-1.337, 0.141]	-0.048	[-0.142, 0.046]	-1.237	[-2.829, 0.330]
ICT export	0.001	[-0.009, 0.010]	0.000	[-0.001, 0.000]	0.022	[-0.014, 0.058]
Population	0.001	[-0.001, 0.003]	-0.008*	[-0.011, -0.006]	0.000	[-0.002, 0.002]
GDP per capita	0.005	[-0.025, 0.035]	0.390*	[0.340, 0.439]	0.409*	[0.244, 0.594]
Energy	0.00019*	[0.00018, 0.00021]	0.00008*	[0.00003, 0.00013]	0.00022*	[0.00014, 0.00029]

Variables	Upper-middle-income countries		High-income countries	
	Mean	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$
Intercept	0.555	[-0.384, 1.369]	0.501	[-2.013, 3.038]
ICT	-0.134	[-0.444, 0.179]	-2.475*	[-3.209, -1.739]
Industry	-0.817*	[-1.519, -0.160]	-0.615*	[-2.870, -1.522]
ICT export	0.008	[-0.008, 0.025]	0.006	[-0.030, 0.041]
Population	0.001	[-0.001, 0.003]	-0.014	[-0.037, 0.003]
GDP per capita	0.077*	[0.044, 0.109]	0.011	[-0.025, 0.046]
Energy	0.00015*	[0.00012, 0.00017]	0.00022*	[0.00019, 0.00024]

*Note: [P2.5, P97.5] is the 95% credible interval; * indicates a significant coefficient with the 95% credible interval*

B. Impact of economic digitalization on CO2 emissions at different quantile levels

In this section, we verify the different effects of economic digitalization on CO2 emissions across the countries by using the QR method. High quantile levels are associated with countries with high CO2 emissions, and vice versa. Table 5 shows the estimated results of the Bayesian QR for each parameter. In general, most of the coefficients are significant in all the quantiles, with a 95% credible interval. The signs of the estimated coefficients do not change much in most of the quantiles. We recognize the changes in the magnitude of all the coefficients across the different quantile levels. Figure 1 illustrates the estimated coefficients of each explained variable at different quantile levels to verify the changes comprehensively.

a) Effects of ICT infrastructure on CO2 emissions

ICT infrastructure exerts different impacts on low and high quantile levels of CO2 emissions. In the low-CO2-emissions countries (quantile levels of 0.1 and 0.2), ICT infrastructure increases CO2 emissions. By contrast, ICT infrastructure can help reduce CO2 emissions in the middle- and high-CO2-emissions countries. The impact increases across the high quantiles. The results are similar to the findings in Section IV. The countries with low emissions are typically the less-developed countries. As a result, the ICT equipment and systems in such countries are typically low technology and energy intensive, thereby increasing CO2 emissions. By contrast, the countries with high emissions typically have superior technology. Therefore, developing their ICT infrastructure can help such countries reduce their CO2 emissions.

b) Effects of ICT-related industry activities on CO2 emissions

ICT-related industry activities (related to the use and adoption of and adaptation to ICT in manufacturing, finance, and other sectors) can help reduce CO2 emissions at all CO2 emissions levels. The application of ICT in industries can significantly reduce pollution in countries with extremely low CO2 emissions, which is demonstrated by the relatively high coefficient of Industry in such countries. However, for countries with an average level of CO2 emissions, the effect is reduced, perhaps because such countries have been using ICT in their industries for a long time; thus, the marginal benefits of ICT application are not as high

TABLE 5
ESTIMATED RESULTS OF BAYESIAN QR

Variables	τ = 0.1		τ = 0.2		τ = 0.4	
	Mean	[$P_{2.5}$, $P_{97.5}$]	Mean	[$P_{2.5}$, $P_{97.5}$]	Mean	[$P_{2.5}$, $P_{97.5}$]
Intercept	-6.670*	[-7.027, -6.292]	-7.487*	[-7.753, -7.241]	-8.288*	[-8.555, -8.039]
ICT	0.245*	[0.091, 0.391]	0.002	[-0.116, 0.106]	-0.139*	[-0.234, -0.039]
Industry	-0.282*	[-0.414, -0.143]	-0.250*	[-0.375, -0.116]	-0.104	[-0.214, 0.000]
ICT export	0.007*	[0.005, 0.009]	0.006*	[0.005, 0.008]	0.004*	[0.002, 0.005]
Population	0.089*	[0.071, 0.106]	0.073*	[0.061, 0.086]	0.050*	[0.042, 0.059]
GDP per capita	0.539*	[0.462, 0.621]	0.372*	[0.321, 0.419]	0.164*	[0.110, 0.217]
Energy	0.594*	[0.538, 0.646]	0.756*	[0.722, 0.794]	0.922*	[0.884, 0.961]
Variables	τ = 0.6		τ = 0.8		τ = 0.9	
	Mean	[$P_{2.5}$, $P_{97.5}$]	Mean	[$P_{2.5}$, $P_{97.5}$]	Mean	[$P_{2.5}$, $P_{97.5}$]
Intercept	-8.443*	[-8.703, -8.170]	-8.533*	[-8.746, -8.313]	-8.522*	[-8.725, -8.316]
ICT	-0.173*	[-0.275, -0.075]	-0.182*	[-0.273, -0.089]	-0.205*	[-0.289, -0.119]
Industry	-0.124*	[-0.206, -0.038]	-0.150*	[-0.235, -0.063]	-0.327*	[-0.401, -0.243]
ICT export	0.002*	[0.001, 0.004]	0.001*	[0.000, 0.003]	0.000	[-0.001, 0.002]
Population	0.043*	[0.032, 0.052]	0.028*	[0.021, 0.035]	0.031*	[0.025, 0.037]
GDP per capita	0.067*	[0.013, 0.123]	0.036	[-0.007, 0.078]	0.057*	[0.013, 0.100]
Energy	0.982*	[0.941, 1.022]	1.022*	[0.988, 1.054]	1.037*	[1.005, 1.068]

*Note: [$P_{2.5}$, $P_{97.5}$] is the 95% credible interval; * indicates the significant coefficient with the 95% credible interval*

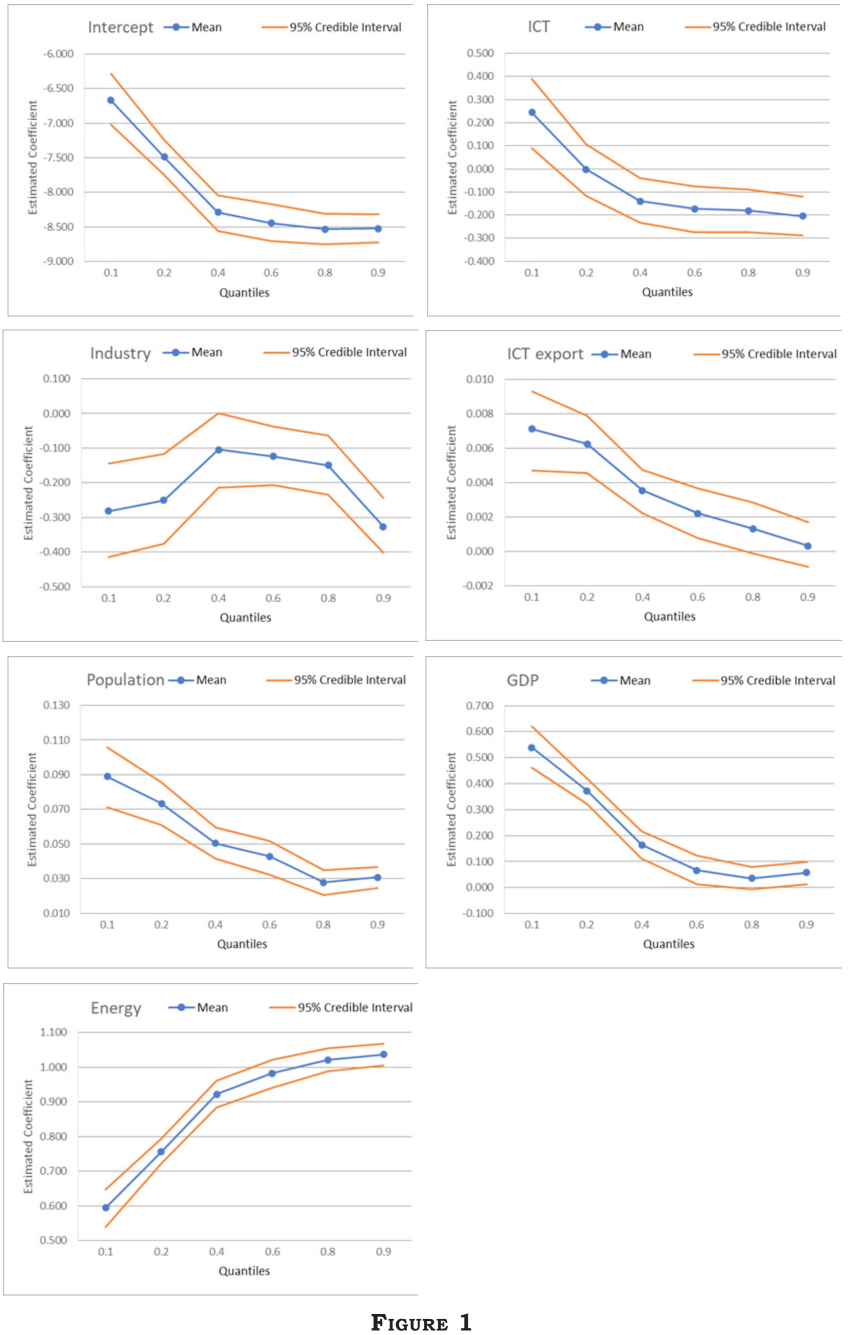

FIGURE 1

BAYESIAN ESTIMATED COEFFICIENTS FOR DIFFERENT QUANTILE LEVELS as those in less-developed countries. Specifically, the benefits of ICT-related industry activities on CO2 emissions reduction are substantial in countries with high emissions, perhaps because such countries are technology led; hence, they have new technology that can accelerate the positive impact of ICT-related industry activities on CO2 emissions reduction.

c) Effects of ICT trade on CO2 emissions

The export of ICT products and services can increase CO2 emissions, but the effect is small and will decrease gradually as the CO2 emissions level rises. According to Dong *et al.* (2021), ICT export is directly related to the manufacturing of computers and electronic and optical products, which is the main contributor to the ICT sector's embodied CO2 emissions. The production of ICT products and services can also contribute to CO2 emissions, because the production process can be energy intensive and involve using raw materials with a high carbon footprint. The carbon footprint of ICT products and services will depend on the manufacturing process and the energy sources used to power the process. Less-developed countries will suffer this effect more than developed countries owing to their technological backwardness.

C. Robustness checks

In this section, we assess the robustness of our Bayesian estimated results by comparing them with fixed-effects and random-effects estimations and by employing different sets of priors in the Bayesian estimation process.

Table 6 presents the outcomes of the fixed-effects and random-effects panel regression analyses for the entire sample and the individual income-level country groups. The findings obtained by the methodologies align closely with the Bayesian estimated coefficients and validate the positive correlation between ICT infrastructure and CO2 emissions in the low-income countries, which transitions to a negative association as income levels rise. In addition, the results indicate that ICT-related industry activities exert no discernible impact on CO2 emissions in the low-income and lower-middle-income countries but can help reduce CO2 emissions in the upper-middle-income countries. Furthermore, all the estimated coefficients pertaining to the export of ICT products and services are positive but lack statistical significance.

TABLE 6

FIXED-EFFECTS AND RANDOM-EFFECTS PANEL REGRESSION MODEL ESTIMATIONS

Variables	All countries		Low-income countries		Lower-middle-income countries	
	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects
Intercept	-0.816** (-1.551, 0.081)	0.298 (-0.299, 0.895)	-0.368*** (-0.456, -0.280)	-0.147*** (-0.236, -0.057)	-1.876*** (-3.136, -0.616)	-1.284*** (-2.186, -0.381)
ICT	-0.909*** (-1.358, -0.459)	-0.714*** (-1.151, -0.276)	0.182*** (0.063, 0.301)	0.067 (-0.084, 0.218)	-1.639** (-3.063, -0.214)	-1.069 (-2.385, 0.247)
Industry	-0.633 (-1.400, 0.134)	-0.584 (-1.317, 0.149)	-0.054 (-0.144, 0.036)	-0.079 (-0.194, 0.037)	-1.183 (-2.984, 0.618)	-1.234 (-2.750, 0.282)
ICT export	0.001 (-0.009, 0.011)	0.000 (-0.010, 0.010)	0.000 (-0.001, 0.000)	0.000 (-0.001, 0.001)	0.024 (-0.014, 0.063)	0.021 (-0.014, 0.056)
Population	-0.002 (-0.008, 0.005)	0.001 (-0.001, 0.003)	-0.010*** (-0.013, -0.007)	-0.001 (-0.002, 0.000)	-0.013** (-0.024, -0.001)	0.000 (-0.002, 0.002)
GDP per capita	0.040** (0.007, 0.073)	0.005 (-0.023, 0.033)	0.410*** (0.361, 0.458)	0.250*** (0.202, 0.298)	0.728*** (0.515, 0.942)	0.372*** (0.227, 0.517)
Energy	0.0002*** (0.0002, 0.0003)	0.0002*** (0.00019, 0.00023)	0.0001*** (0.0001, 0.0002)	0.000 (-0.0002, 0.0002)	0.0002*** (0.0001, 0.0003)	0.0002*** (0.0002, 0.0003)

Variables	Upper-middle-income countries		High-income countries	
	Fixed effects	Random effects	Fixed effects	Random effects
Intercept	0.909*** (0.280, 1.538)	0.614 (-0.151, 1.380)	2.557* (-0.225, 5.339)	1.182 (-1.007, 3.370)
ICT	-0.082 (-0.397, 0.233)	-0.142 (-0.456, 0.173)	-2.304*** (-3.036, -1.572)	-2.489*** (-3.240, -1.739)
Industry	-0.816** (-1.503, -0.129)	-0.789** (-1.467, -0.111)	-1.045 (-3.308, 1.219)	-0.650 (-2.898, 1.597)
ICT export	-0.009 (-0.026, 0.007)	-0.009 (-0.025, 0.007)	-0.012 (-0.048, 0.023)	-0.001 (-0.036, 0.034)
Population	0.002 (-0.005, 0.008)	0.002 (-0.001, 0.004)	-0.092*** (-0.140, -0.045)	-0.001 (-0.016, 0.014)
GDP per capita	0.079*** (0.045, 0.112)	0.077*** (0.044, 0.110)	0.030 (-0.006, 0.066)	0.000 (-0.035, 0.036)
Energy	0.0001*** (0.0001, 0.0002)	0.0002*** (0.0001, 0.0002)	0.0002*** (0.0002, 0.0003)	0.0002*** (0.00019, 0.00023)

*Note: Numbers in parentheses are 95% confidence interval; *, **, and *** indicate the significant coefficient at 10%, 5%, and 1% confidence interval, respectively*

To check the sensitivity of the Bayesian estimations when changing the priors, we use different sets of hyperparameters for σ_0^2, σ_α^2, and σ_γ^2. Specifically, we use several combinations of hyperparameters, as follows:

1. $\sigma_0^2 \sim IG(0.1, 0.1), \sigma_\alpha^2 \sim IG(0.1, 0.1), \textit{and } \sigma_\gamma^2 \sim IG(0.1, 0.1)$.
2. $\sigma_0^2 \sim IG(0.01, 0.01), \sigma_\alpha^2 \sim IG(0.01, 0.01), \textit{and } \sigma_\gamma^2 \sim IG(0.01, 0.01)$.
3. $\sigma_0^2 \sim IG(0.0001, 0.0001), \sigma_\alpha^2 \sim IG(0.0001, 0.0001), \textit{and } \sigma_\gamma^2 \sim IG(0.0001, 0.0001)$.

Table 7 presents the estimated coefficients of the specific set of hyperparameters, with $\sigma_0^2 \sim IG(0.01, 0.01)$, $\sigma_\alpha^2 \sim IG(0.01, 0.01)$, and $\sigma_\gamma^2 \sim IG(0.01, 0.01)$. The detailed results of the alternative set of hyperparameters can be provided upon request. The outcomes in Table 7 reinforce our previous observations that though the advanced economies experience a decrease in CO2 emissions with the aid of ICT infrastructure, the less-developed nations experience an increase. Moreover, nearly all the countries demonstrate a decline in CO2 emissions attributable to ICT-related industry activities, though the magnitude of the effect varies across the nations. In addition, the export of ICT goods and services exhibits a statistically insignificant impact on CO2 emissions across most income levels.

The aforementioned results confirm the robustness of our findings.

TABLE 7

BAYESIAN PANEL REGRESSION MODEL ESTIMATIONS WITH PRIORS , ,

Variables	All countries		Low-income countries		Lower-middle-income countries	
	Mean	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$
Intercept	0.283	[-0.135, 0.877]	-0.377*	[-0.596, -0.142]	-1.698*	[-2.183, -0.604]
ICT	-0.649*	[-1.165, -0.281]	0.175*	[0.100, 0.298]	-1.043	[-2.681, 0.350]
Industry	-0.511	[-1.337, 0.141]	-0.037	[-0.234, 0.118]	-1.194	[-2.308, 0.119]
ICT export	0.001	[-0.008, 0.014]	0.000	[-0.001, 0.000]	0.020	[-0.020, 0.045]
Population	0.001	[-0.001, 0.003]	-0.008*	[-0.020, -0.004]	0.000	[-0.002, 0.002]

Variables	All countries		Low-income countries		Lower-middle-income countries	
	Mean	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$
GDP per capita	0.005	[-0.021, 0.030]	0.382*	[0.325, 0.469]	0.391*	[0.271, 0.572]
Energy	0.00017*	[0.00017, 0.00020]	0.00008*	[0.00002, 0.00011]	0.00015*	[0.00013, 0.00020]

Variables	Upper-middle-income countries		High-income countries	
	Mean	$[P_{2.5}, P_{97.5}]$	*Mean*	$[P_{2.5}, P_{97.5}]$
Intercept	0.471	[-0.294, 1.183]	0.494	[-2.156, 1.028]
ICT	-0.156	[-0.502, 0.188]	-2.189*	[-3.119, -1.407]
Industry	-0.729*	[-1.318, -0.141]	-0.529*	[-2.445, -1.082]
ICT export	0.007	[-0.007, 0.014]	0.006	[-0.020, 0.031]
Population	0.001	[-0.001, 0.003]	-0.012	[-0.027, 0.011]
GDP per capita	0.069*	[0.030, 0.121]	0.011	[-0.020, 0.049]
Energy	0.00014*	[0.00011, 0.00017]	0.00018*	[0.00018, 0.00020]

*Note: [P2.5, P97.5] is the 95% credible interval; * indicates the significant coefficient with the 95% credible interval*

V. Conclusions

This study explores the effects of the growth of economic digitalization on CO2 emissions. We use the Bayesian panel regression and Bayesian QR methods to evaluate yearly data from 100 countries from 2008 to 2019. We measure the growth of economic digitalization by using three indicators: ICT infrastructure, ICT-related business activities, and ICT exports. The findings demonstrate that though ICT infrastructure can help developed countries reduce their CO2 emissions, it increases CO2 emissions in less-developed nations. Besides, nearly all the countries experienced a reduction in CO2 emissions from ICT-related industry operations, but the effect varied by nation. By contrast, the export of ICT goods and services can increase CO_2 emissions. However, the effect is relatively minor and will eventually disappear as the CO_2 emissions level rises.

Our findings can offer policymakers useful information and implications for making the most of the benefits of the digital economy in reducing CO_2 emissions. In the lower-income countries, the impact of economic digitalization on CO_2 emissions is limited, because such countries tend to have little access to digital technologies and infrastructure. However, as access to digital technologies increases in such countries, the rate of increase of emissions will rise, particularly if traditional energy sources, such as coal and natural gas, are used to power the digital infrastructure. In the lower-middle-income countries, the impact of economic digitalization on CO_2 emissions is growing, because such countries are beginning to have increased access to digital technologies and infrastructure. In the upper-middle-income countries, the impact of economic digitalization on CO_2 emissions is significant, because such countries have considerable access to digital technologies and infrastructure, as well as a well-developed energy sector. Such countries are also beginning to adopt sustainable practices, such as using renewable energy sources, which can help reduce emissions from the digital economy. In the high-income countries, the impact of economic digitalization on CO_2 emissions is also substantial, because such countries have considerable access to digital technologies and infrastructure, as well as the most developed energy sectors. Such countries are also the leaders in the adoption of sustainable practices, such as using renewable energy sources and taking steps to reduce emissions from the digital economy.

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APPENDIX

Table A1

Classification of countries by income for 2019 calendar year

High income	Upper-middle income	Lower-middle income	Low income
Australia	Albania	Algeria	Afghanistan
Austria	Argentina	Bangladesh	Burkina Faso
Belgium	Armenia	Benin	Ethiopia
Canada	Azerbaijan	Bolivia	Guinea
Chile	Belarus	Cambodia	Haiti
Croatia	Bosnia and Herzegovina	Comoros	Madagascar
Cyprus	Botswana	Cote d'Ivoire	Malawi
Estonia	Brazil	Djibouti	Mali
Germany	Bulgaria	El Salvador	Mozambique
Greece	China	Honduras	Sierra Leone
Hungary	Colombia	India	Tajikistan
Ireland	Costa Rica	Kenya	Uganda
Israel	Dominican Republic	Laos	
Italy	Ecuador	Moldova	
Japan	Georgia	Mongolia	
Kuwait	Guatemala	Morocco	
Latvia	Indonesia	Nepal	
Mauritius	Iraq	Nicaragua	
Norway	Jamaica	Nigeria	
Oman	Kazakhstan	Pakistan	
Panama	Lebanon	Philippines	
Poland	Malaysia	Sao Tome and Principe	
Portugal	Mexico	Senegal	
Romania	Montenegro	Sri Lanka	
Slovenia	Namibia	Tanzania	
United Kingdom	North Macedonia	Tunisia	
United States	Paraguay	Ukraine	
Uruguay	Peru	Vietnam	
	Russia	Zambia	
	Serbia		
	Thailand		

Source: World Bank (2020)

References

Ablyazov, T., and Asaul, V., "Development of the Arctic transport infrastructure in the digital economy." *Transportation Research Procedia 57*(2021): 1-8.

Arain, H., Han, L., Sharif, A., and Meo, M. S., "Investigating the effect of inbound tourism on FDI: The importance of quantile estimations." *Tourism Economics 26*(No. 4 2020): 682-703.

Autio, E., "Strategic entrepreneurial internationalization: A normative framework." *Strategic Entrepreneurship Journal 11*(No. 3 2017): 211-227.

Begum, R. A., Sohag, K., Abdullah, S. M. S., and Jaafar, M. "CO2 emissions, energy consumption, economic and population growth in Malaysia." *Renewable and Sustainable Energy Reviews 41*(2015): 594-601.

Chib, S., "Panel data modeling and inference: a Bayesian primer." *Advanced Studies In Theoretical And Applied Econometrics 46*(2008): 479-515.

Dong, X., Jiang, Q., and Wang, J., " Assessing embodied carbon emission and its intensities in the ICT industry: the global case." *Frontiers in Energy Research 9* (2021)

Gelman, A., and Hill, J., *Data analysis using regression and multilevel/hierarchical models*, Cambridge University Press, 2006.

Heidari, H., Katircioğlu, S. T., and Saeidpour, L., "Economic growth, CO2 emissions, and energy consumption in the five ASEAN countries." *International Journal of Electrical Power & Energy Systems 64*(2015): 785-791.

Hosan, S., Karmaker, S. C., Rahman, M. M., Chapman, A. J., and Saha, B. B., "Dynamic links among the demographic dividend, digitalization, energy intensity and sustainable economic growth: Empirical evidence from emerging economies." *Journal of Cleaner Production 330*(No. 129858 2022)

Hossain, M. S., "Multivariate granger causality between economic growth, electricity consumption, exports and remittance for the panel of three SAARC countries." *Global Journal of Management and Business Research 12*(No. 4 2012): 41-54.

Hsiao, C., *Analysis of panel data*, 4th Edition, Cambridge University Press, 2022.

Iwami, T., "Economic development and/or environmental quality:

emissions of CO2 and SO2 in East Asia." *Seoul Journal of Economics 17* (No. 1 2004): 55-83.

Khan, N., Baloch, M. A., Saud, S., and Fatima, T. "The effect of ICT on CO2 emissions in emerging economies: does the level of income matters?" *Environmental Science and Pollution Research*, 25(No. 23 2018): 22850-22860.

Koenker, R., and Bassett Jr, G., "Regression quantiles." *Econometrica 46*(No.1 1978): 33-50.

Koenker, R., and Machado, J. A., "Goodness of fit and related inference processes for quantile regression." *Journal of the American Statistical Association 94*(No. 448 1999): 1296-1310.

Kozumi, H., and Kobayashi, G., "Gibbs sampling methods for Bayesian quantile regression." *Journal of Statistical Computation and Simulation 81*(No. 11 2011): 1565–1578.

Lee, S. Y., and Song, X. Y., "Evaluation of the Bayesian and maximum likelihood approaches in analyzing structural equation models with small sample sizes." *Multivariate Behavioral Research 39*(No. 4 2004): 653-686.

Li, Y., Yang, X., Ran, Q., Wu, H., Irfan, M., and Ahmad, M., "Energy structure, digital economy, and carbon emissions: evidence from China." *Environmental Science and Pollution Research 28* (No. 45 2021): 64606-64629.

Li, Z., and Wang, J., "The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China." *Journal of Cleaner Production 351* (No. 131570 2022)

Lin, B., and Xu, B., "Factors affecting CO2 emissions in China's agriculture sector: A quantile regression." *Renewable and Sustainable Energy Reviews 94*(2018): 15-27.

Liu, W., Xu, Y., Fan, D., Li, Y., Shao, X. F., and Zheng, J., "Alleviating corporate environmental pollution threats toward public health and safety: The role of smart city and artificial intelligence." *Safety Science 143*(No. 105433 2021)

Mardani, A., Streimikiene, D., Cavallaro, F., Loganathan, N., and Khoshnoudi, M., "Carbon dioxide (CO2) emissions and economic growth: A systematic review of two decades of research from 1995 to 2017." *Science of the total environment 649*(2019): 31-49.

Pouri, M. J., and Hilty, L. M., "The digital sharing economy: A confluence of technical and social sharing." *Environmental Innovation and Societal Transitions 38*(2021): 127-139.

Pradhan, R. P., Arvin, M. B., Nair, M., Bennett, S. E., and Bahmani, S., "Short-term and long-term dynamics of venture capital and economic growth in a digital economy: A study of European countries." *Technology in Society 57*(2019): 125-134.

Raudenbush, S. W., and Bryk, A. S., *Hierarchical Linear Models: Applications and Data Analysis Methods*, Second Edition, Sage Publications, 2002.

Richardson, L., "*Digital and Platform Economies.*" in A. Kobayashi. (ed.): *International Encyclopedia of Human Geography.* Second Edition, Elsevier, Oxford, 2019: 317–321.

Ritchie, H., Roser, M., and Rosado, P., *CO_2 and Greenhouse Gas Emissions,* Published online at OurWorldInData.org., 2020. Retrieved from: 'https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions' in October 10th, 2022.

Sinha, A., "Impact of ICT exports and internet usage on carbon emissions: a case of OECD countries." *International Journal of Green Economics 12*(No. 3-4 2018): 228-257.

Shor, B., Bafumi, J., Keele, L., and Park, D., "A Bayesian multilevel modeling approach to time-series cross-sectional data." *Political Analysis 15*(No. 2 2007): 165-181.

Shvakov, E. E., and Petrova, E. A., *Newest trends and future scenarios for a sustainable digital economy development*, In Institute of Scientific Communications Conference, Springer, Cham, 2020: 1378-1385.

Usman, A., Ozturk, I., Ullah, S., and Hassan, A., "Does ICT have symmetric or asymmetric effects on CO2 emissions? Evidence from selected Asian economies." *Technology in Society 67*(No. 101692 2021)

Van de Schoot, R., Broere, J. J., Perryck, K. H., Zondervan-Zwijnenburg, M., and Van Loey, N. E., "Analyzing small data sets using Bayesian estimation: The case of posttraumatic stress symptoms following mechanical ventilation in burn survivors." *European Journal of Psychotraumatology 6*(No. 1 2015)

von Briel, F., Davidsson, P., and Recker, J., "Digital technologies as external enablers of new venture creation in the IT hardware sector." *Entrepreneurship Theory and Practice 42*(No. 1 2018): 47-69.

Watanabe, C., Naveed, N., and Neittaanmäki, P., "Digital solutions transform the forest-based bioeconomy into a digital platform industry-A suggestion for a disruptive business model in the digital economy." *Technology in Society 54*(2018): 168-188.

Wu, R., Hua, X., Peng, L., Liao, Y., and Yuan, Y., "Nonlinear effect of digital economy on carbon emission intensity based on dynamic panel threshold model." *Frontiers in Environmental Science 10*(2022).

Wu, Y., Luo, C., and Luo, L., "The impact of the development of the digital economy on Sulfur Dioxide emissions: Empirical evidence based on provincial panel data." *J. Wuhan Polytech 20* (2021): 82-88.

Xu, Q., Zhong, M., and Li, X., "How does digitalization affect energy? International evidence." *Energy Economics 107* (No. 105879 2022)

Yang, T. M., Pardo, T., and Wu, Y. J., "How is information shared across the boundaries of government agencies? An e-Government case study." *Government Information Quarterly 31* (No. 4 2014): 637-652.

Yu, H., and Zhu, Q., "Impact and mechanism of digital economy on China's carbon emissions: from the perspective of spatial heterogeneity." *Environmental Science and Pollution Research 30*(2022): 1-16.

Yu, K., and Moyeed, R. A., "Bayesian quantile regression." *Statistics & Probability Letters 54*(No. 4 2001): 437-447.

Yu, K., and Stander, J., "Bayesian analysis of a Tobit quantile regression model." *Journal of Econometrics 137*(No. 1 2007): 260-276.

Yue, X. G., Liao, Y., Zheng, S., Shao, X., and Gao, J., "The role of green innovation and tourism towards carbon neutrality in Thailand: Evidence from bootstrap ADRL approach." *Journal of Environmental Management 292*(No. 112778 2021)

Zhang, S., Ma, X., and Cui, Q., "Assessing the Impact of the Digital Economy on Green Total Factor Energy Efficiency in the Post-COVID-19 Era." *Frontiers in Energy Research 9*(2021).

Zhang, W., Liu, X., Wang, D., and Zhou, J., "Digital economy and carbon emission performance: Evidence at China's city level." *Energy Policy 165*(No. 112927 2022).

Zhou, X., Zhou, D., Zhao, Z., and Wang, Q., "A framework to analyze carbon impacts of digital economy: The case of China." *Sustainable Production and Consumption 31*(2022): 357-369.