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Digital Trade and Global Environmental Quality: The Moderating Role of Energy Justice

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Abstract

The potential of digital trade (DTE) and energy justice (EJ) to support environmental quality requires in-depth exploration because the environmental gains of DTE can be compromised in economies where EJ is not ensured. This study explores the environmental effects of DTE and EJ on ecological footprint (EF) utilizing panel data from 147 economies from 2005 to 2023. The empirical results are estimated using panel data estimators namely fixed effects, random effects, the system generalized method of moments (GMM) and the method of moments quantile regression (MMQR). The GMM estimates suggest that DTE exerts a positive and significant influence on the environment. However, the MMQR results demonstrate that the effect of DTE on EF varies in sign and magnitude across quantiles. The positive effect is observed in median and higher quantiles while the negative effect is noted in lower quantiles. Finally, the results suggest a moderating role of EJ in the environmental effect of DTE. That is, the interactive effect of DT with EJ exerts a significantly positive effect on environmental quality. This finding suggests that ensuring EJ in home economies strengthens the environmental benefits of digital trade integration. These findings offer important policy implications for advancing digitalization strategies along with ensuring EJ to promote global environmental sustainability.

Keywords: Digital trade, energy justice, environmental quality, resource endowment, ecological footprint.

1. Introduction

Global trade is a topic of great interest for economists and policymakers these days because the world economy has witnessed its significant growth over the last decade. The UN Trade and Development (UNCTAD) projected that, in 2025, total global trade of goods and services would surpass $35 trillion for the first time (UNCTAD, 2025). The literature suggests that trade openness has led to an increase in carbon emissions through increased production activities (scale effect), transportation and natural resource degradation (Ghazouani & Maktouf, 2024; Balogh & Mizik, 2021). Conversely, the literature also highlights that trade promotes green innovations and the use of clean and green technologies, which help in mitigating environmental degradation practices (Brenton & Chemutai, 2021). Trade proponents also suggest that increased income that comes with trade openness increases the demand for cleaner production (Shafik and Bandyopadhyay, 1992). Studies such as Inglesi-Lotz (2018) and Mapapu & Phiri (2018) also assert that trade poses dual consequences, that is, it offers risk of increasing carbon emissions as well as opportunities to reduce pollution.

While these debates on the environmental repercussions of trade remain ongoing, the rapid expansion of digitalization in global trade has fundamentally introduced a new chapter in the history of trade, representing diverse environmental implications. Digitalization changes the way goods and services are traded. At different stages of the supply chain, digitalization can reduce the trade cost. Moreover, due to technological developments services are rising in trade as they are providing necessary infrastructure and helping the digitalization of other types of services (Benz, Jaax, & Yotov, 2022). At the same time, new services such as e-payments and cloud computing are arising in the global market (Aoki et al., 2023). When it comes to the environmental impacts, digitalization has significant and diverse implications (Mazhar et al. 2025; Majeed, 2018; Hu et al., 2023). According to Hu et al. (2023), through industrial productivity, digital infrastructures promote low-carbon development. However, researchers have also raised questions about its unintended negative consequences. Hilty & Huber (2018) reported environmental deterioration due to electronic waste and energy consumption that come with digitalization.

Digital trade (DTE), which is considered a subset of overall trade and an engine of rapid economic growth, has seen a tremendous increase in recent years. According to UNCTAD, global digital trade exports increased from \$1.2 trillion to \$4.46 trillion and digital trade imports increased from \$0.84 trillion to \$3.7 trillion from 2005 to 2023 (UNCTAD, 2024). Such increasing trends of DTE indicate its potential in world trade and its importance for sustainable development. In policy discussions, DTE is broadly referred to as trade in the digital era. More precisely, it is defined as the cross-border exchange of goods and services through electronic platforms, and it includes any good that is digitally ordered or digitally facilitated but physically delivered (OECD, 2025). It is a distinct concept from digitalization as it refers to the actual transactional flow of goods and services through electronic platforms, rather than a process of adopting digital technologies. Chiappini and Gaglio (2024) highlight its importance by arguing that DTE serves as a major pathway for knowledge distribution, transmission of sustainable technologies and offers unique opportunities for economies worldwide as it facilitates data exchange. However, the role of DTE in influencing environmental sustainability is not certain.

On one hand, digital exports are known to stimulate green development by reducing carbon emissions (OECD, 2023). Through virtual and online transaction services, DTE contributes to economic structural optimization and reduces the consumption of fossil fuels (Wang et al., 2024). DTE also facilitates knowledge dissemination, technological transfer and information and communication technology (ICT) for transmission of environmental sustainability, potentially reducing carbon emissions (Sun et al, 2024). Apart from direct effects, DTE contributes to environmental quality through indirect effects such as structural changes (growth of high-tech industries), technological upgrading (adoption of energy-efficient tech) and improving human capital through skills enhancement (Cai, 2025). On the other hand, in the early stages of development, DTE can have disorderly expansion, leading to energy-intensive activities. Yang and Ai (2025) demonstrated that in regions with weaker digital infrastructure, DTE expansion intensifies environmental degradation. This is because at lower levels of financial digital trade service, capital flows require enormous energy through cloud systems and data centers. It is therefore crucial to capture the dual impacts of DTE on the environment.

To understand the full environmental implications of DTE, it is important that we move beyond its direct impacts and focus on factors that can moderate its impact, too. Among many factors, energy justice (EJ) is the most important. The concept of EJ is a much broader concept, focusing on energy accessibility and fairness in regard to its allocation (McCauley et al., 2019). It entails that everyone in the community, regardless of their socioeconomic status or geography, has access to clean energy that is also reasonably priced (Sovacool and Drupady, 2016). Because energy-related operations have a significant impact on current and future generations, while energy-related policies are formulated, it is essential that indigenous populations and the local cultures are respected (Ciplet, 2021). EJ may moderate the impact of DTE on without fair and equitable access to energy, DTE alone may not guarantee environmental benefits. Digital infrastructures and energy systems are interdependent and while digitalization is essential for efficient and effective use of energy infrastructure, EJ ensures that the transition to the digital economy is equitable and sustainable. Wu et al. (2026) demonstrate how the digital economy can reduce carbon emissions but the benefits depend on energy structure and resource conditions. According to Wu et al. (2026), the benefits of the digital economy are stronger where energy systems are equitable. Similarly, digital technology innovation can promote EJ (Yang et al., 2023) and the development of the digital economy and DTE, which promotes EJ through technological processes (Li et al., 2025). Despite these few available studies on digitalization and its impact on EJ, there is no study that focuses on the other way around.

Despite growing research on DTE and its effects on the environment, there are significant research gaps that need to be addressed. First, existing studies have established that DTE has a positive impact on the environment but have used narrow indicators for environmental quality. For example, Wang et al. (2024) explored how DTE reduces fossil fuel consumption E7 countries, while Li et al. (2024) confirmed that DTE has low-carbon effects across 46 countries and Dai et al. (2025) demonstrated that DTE improves green total factor productivity in different Chinese provinces. However, these studies focus on single environmental indicators such as carbon emissions or green total factor productivity and limit the broader environmental contexts. In contrast, this study utilizes ecological footprint (EF), which is a comprehensive and multidimensional indicator that accounts for diverse bio-capacity indicators (Galli et al., 2020). Second, the EJ dimension as a moderator is unexplored. Even there are very few studies that have modeled EJ as the core independent variable. Recently, Sohail et al. (2025) showed that EJ exerts a positive influence on environmental sustainability in a global panel of 95 countries. However, they did not consider the role of DT and the moderating role of EJ in their model. The moderating role of EJ is vital because the benefits from DTE may be weak in carbon-dependent economies unless EJ strengthens the environmental effects of DTE. Third, the existing studies provide limited geographical coverage. For instance, Li et al. (2024) cover only 46 countries, finding heterogeneity across development levels, Dai et al. (2025) are limited to a single country (China) where results are more pronounced in developed regions, and Cai (2025) finds that DTE reduces carbon emissions but restricts analysis to 27 European Union countries. This way, the generalizability to various development contexts is restricted. The narrow geographical focus is limited because the relationship between DTE and EF might differ across regions and development contexts, ignoring the heterogeneity.

Our study distinguishes itself and attempts to address these gaps by answering the following questions: First, what are the effects of DTE and EJ on global environmental quality across 147 economies from 2005 to 2023? Second, do the effects of DTE and EJ on global environmental quality vary across different levels of EF? Finally, how does EJ moderate the effect of DTE on global environmental quality?

Unlike the past studies, such as Cai et al. (2025), our study introduces a broader temporal and geographical scope. It covers a panel of 147 countries, allowing for the capture of heterogeneity across different economic contexts and extends analysis to 2025, whereas many existing studies end in 2021 (Li et al., 2024; Yang et al., 2024). Secondly, it employs panel quantile regression to check how the results vary for different levels of ecological footprints to reveal systematic heterogeneity. Finally, it introduces the moderating role of EJ in the DTE-environment context to check if it strengthens or weakens the impact of DTE. These findings are useful for policymakers and international development organizations seeking environmental sustainability in a global economy. The findings highlight the importance of EJ in harnessing the environmental benefits of DT.

2. Literature Review

To situate this study in the existing knowledge on trade, environment and digital trade, the literature review is systematically organized. We begin by providing a broader context of trade-environmental relationships and establishing their theoretical foundation. Then the literature narrows to examine studies on digitalization and DTE as forces that impact the environment. Finally, we review the role of EJ in determining environmental quality and then we conclude by identifying gaps in the existing literature and present the contribution of our study.

2.1 Trade-Environment Theories

The relationship between trade and environment has been a key area of interest for scholars since 1990, particularly when globalization intensified (Forslid et al., 2018). On one hand, trade has brought opportunities for economic prosperity; on the other hand, it has brought challenges worldwide. One of the major issues is the environmental challenge, particularly climate change, due to the production of greenhouse gases (GHG) (Lenzen et al., 2012). CO2 emissions, which constitute GHG, mostly come from manufacturing, usage and transportation of items that are produced for trade purposes (Zhang and Liu, 2025).

Trade-environmental relationships have been studied from various theoretical perspectives. A foundational theoretical framework decomposes the impact of trade on the environment into three effects (Antweiler et al., 2001). First is the scale effect, which suggests that higher production that is driven by the trade opening, increases resource consumption and carbon emissions (Antweiler et al., 2001; Ling et al., 2015; Majeed & Mazhar, 2020; Farooq et al., 2022). Next is the technique effect, which captures how an increase in income comes with trade expansion, increases the demand for environmental quality and leads industries to adopt cleaner technologies (Grossman and Krueger, 1991). Finally, the composition effect shows how trade can shape the structure of economic output of a country depending on its factor endowment (Antweiler et al., 2001).

Building on these decompositions, the environmental Kuznets curve (EKC) suggests that during early stages of economic growth and development, pollution increases because the scale effect dominates as trade expands, but after a certain threshold, it starts decreasing as the technique effect overtakes and strict regulations are enforced. Similarly, due to the composition effect, industrial structure shifts towards cleaner sectors (Grossman and Krueger, 1991). Some advanced economies show that, as trade increases, at higher levels of development and growth, large-scale renewable energy adoption and carbon-reducing technologies are enabled. Organization for Economic Co-operation and Development (OECD) data show that despite increasing trade volumes, carbon intensity has decreased, supporting the pathway suggested by EKC (Bekun et al., 2021).

Pollution haven hypothesis (PHH) implies that with trade liberalization, pollution-intensive industries shift to the countries with weak regulations (Copeland and Taylor, 1994; Sabir et al., 2020). This phenomenon is demonstrated in textile and steel production, which shifted from Europe and the US to South Asia and Southeast Asia. In countries like Bangladesh, India and Vietnam, carbon footprints have increased due to these global value-chain movements (World Bank, 2021). Similarly, in line with trade liberalization, foreign direct investment in extractive industries in Sub-Saharan Africa has grown, contributing to local environmental degradation (UNCTAD, 2022).

In addition to the EKC and PHH, Porter's hypothesis is also an important theory. It contends that strict environmental regulations can induce innovation, boost competition and increase efficiency, leading firms to produce clean products for trade (Porter and Linde, 1995). Recent research shows that economies are more likely to adopt green technologies in production when trade openness combines with strict regulatory frameworks (Zhou et al., 2024).

2.2 Digital Trade Impacts

The existing literature, however, focuses on traditional trade opening without focusing on digital trade. Few studies have focused on the environmental impacts of DTE. Wang et al. (2022) link digitizable product trade and carbon emissions across 94 countries from 2001 to 2019. The study employs the stochastic impacts by regression on population, affluence, and technology (STIRPAT) framework to find how digitizable products trade impacts CO2 emissions and the findings suggest reductions in the CO2 emissions as digitizable product trade expands. The main mechanism identified is technology effect, according to which digitizable products bring efficiencies as cleaner technologies are promoted. However, the study only focuses on digitizable product trade, whereas DTE itself is a broader concept that involves structural upgrading as well as human capital. Secondly, this study employs CO2 emissions as the measure of environmental quality which is a more limited measure than ecological footprints. Moreover, STIRPAT framework does not account for heterogeneity and therefore MMQR approach adopted in our study addresses this limitation.

Li et al. (2024), in their study, construct a multidimensional DTE development index for 46 countries (2007-2021) from six main aspects: scale of digital trade, trade potential, digital innovation, digital infrastructure, digital skills and security, and digital trade environment. The findings show that digital trade has a low carbon effect, but the results vary according to the development level and changes in the level of DTE. The emphasized mechanism includes innovation, skills and digital infrastructure. The study is useful in understanding how bigger economies with larger trade scales have higher DTE development, but it does not decompose heterogeneous effects across different levels of environmental quality. Whereas our study employs quantile regression to bridge this gap. Moreover, it focuses on 46 countries which may be insufficient to make a conclusion for global economies.

Yang et al. (2024) investigate how digital exports, together with financial stability and energy security, determine green growth for 33 leading energy-consuming economies. The study employs a cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model and panel quantile regression and the core findings suggest that digital exports and financial stability promote green growth. Whereas, energy security hinders long-run green growth. The study claims to be the first to link digital exports and overall offers valuable evidence that digital exports can lead to green productivity. However, digital exports can be a narrow indicator, because they primarily capture trade in ICT goods and services and represent only one dimension of DTE. Secondly, it focuses on 33 top energy-consuming countries only, limiting inference for smaller economies. Furthermore, the model captures long-run dynamics but ignores the moderating role that digital exports might have.

Dai et al. (2025) address a critical gap in the literature and explore the impact of DTE on green total factor productivity in China from 2005 to 2021, constructing panel data across 30 provinces. The study employs industry structure, innovation capability, energy, human capital, regulation, technology and R&D as control variables and utilizes fixed effect models for causal identification. For their empirical framework, the authors link to endogenous growth theory. It is found that DTE increases green total factor productivity and FDI and trade openness moderate this impact positively. The study also does heterogeneity analysis across different Chinese regions to get more nuanced insights and suggests that results are more pronounced in developed Chinese regions. However, fixed effects may not capture non-linear heterogeneity and this is where our study fills the gap by employing MMQR. Moreover, the study is useful in understanding the link between DTE and green total factor productivity; however, as the study period ends in 2021, it may not capture the impact of COVID-19 on DTE. Secondly, the outcome variable is green total factor productivity, which combines economic output with environmental constraints but a different ecological footprint. Moreover, the study cannot be used to generalize as the findings are China-specific.

An important study by Li et al. (2025) investigates the potential role of DTE in the synergetic control of pollution and carbon emissions (SCPCE). By using panel data of 93 countries (2009-2021), it analyzes the impact of DTE on the synergetic control of pollution and carbon emissions empirically. The findings suggest a U-shaped relationship in high-income countries and countries with robust digital infrastructure. Whereas for low-income countries, no significant impact is found. This suggests that DTE affects SCPCE through industrial upgrade, technological innovation and energy-efficient practices. The study suggests that government interventions in environmental issues could be one of the major mediating factors. This study offers novelty for its use of robust empirical strategies such as heterogeneity analysis and instrumental variables. However, the paper itself acknowledges the limitation of the lack of comprehensive data on DTE. Moreover, there may be the problem of endogeneity, as better environmental outcomes could also mean stronger regulations.

A latest study by Cai (2025) empirically explores the impact of DTE on CO2 emissions for 27 European Union countries and provides policy-relevant insights for European Union climate targets. The findings of this reveal that DTE significantly reduces carbon emissions. The mechanisms include structural, innovation and human capital which are enhanced due to the digitalization. The author also performed heterogeneity analysis to show that the impact is more pronounced where digital infrastructure is already robust. The impact is also stronger for the highly innovative countries. While EU regional focus provides valuable policy insights, the results cannot be generalized for low-income countries. Moreover, it does not account for EJ as a moderating factor which our study introduces as a novel contribution.

Furthermore, a study by Yang et el. (2026) uses a spatial Durbin model to examine the relationship between DTE and environmental quality and if DTE has spillover effects in the neighboring regions in China. The results suggest that DTE has significant positive impacts on environmental quality and therefore generates a “green effect”. Secondly, the study finds a significant positive spillover effect of DTE in the neighboring areas. Finally, it suggests important transmission mechanisms, such as industrial and consumption structure upgrading. The study offers a good methodological contribution and detects whether the environmental benefits of DTE are genuine through a spatial econometric framework. However, as it is restricted to China, generalizability is limited. The authors also offer great insights and contextual support to quantile regression in our study. Their study identifies differences in the Chinese regions, whereas our quantile framework identifies distribution globally.

Beyond regional-level studies, Wu et al. (2026) examine the impact of the digital economy on carbon emissions in 286 prefecture-level cities in China. The findings show that the digital economy index reduces carbon emissions mainly due to energy structure optimization, scale of energy consumption and renewable energy facilitation. The study is important because it suggests that the impacts are more pronounced in resource-based and small cities, suggesting potential heterogeneity. It is also methodologically strong as it uses an instrumental variable approach. It is useful in understanding how digitalization and digital economy benefits are linked to EJ, providing evidence for our study. However, the digital economy is broad and the study does not focus specifically on DTE. The digital economy may encompass other aspects along with trade and therefore is a broader construct.

2.3 Energy Justice and Environmental Quality

While the exciting literature on trade and environment is broad, it has been developed separately from EJ, an equally important variable. Acheampong and Opoku (2023), using data on 47 sub-Saharan African countries, confirm that improvements in energy access are associated with tangible environmental gains. The study indicates that improving access to electricity translates into a reduction in deforestation. A very important study by Etensa et al. (2026), explores the relationship between EJ and environmental degradation. It also investigates the moderating role of EJ by employing the STIRPAT model. Their findings reveal that EJ mitigates environmental degradation while energy poverty significantly increases it. Moreover, it was found that EJ moderates green energy poverty and hence improves the environment. Sohail et al. (2025) apply advanced econometric methods to analyze the impact of digital infrastructure and EJ on sustainable development for a global sample. The findings confirm that both digital infrastructure and EJ enhance sustainable development. In the context of DTE, the integration of EJ is critical. The environmental benefits of DTE come from green innovation and structural transformation and these benefits may only be realized when energy activities are equitable. Wu et al. (2026) empirically investigated that the environmental benefits of the digital economy index are mainly through renewable energy facilitation and optimization of energy structures. While these studies are important to understand the role of EJ in elevating the environmental quality, none of them covered the moderating impact it can have on DTE.

2.4 Conclusion, Research Gaps and Contribution

The existing studies reviewed in this section reveal that the field of trade, particularly DTE, is rapidly evolving but the gaps remain. The exciting literature suggests that trade brings both risks and opportunities for the environment (Ghazouani & Maktouf, 2024; Brenton & Chemutai, 2021). Furthermore, digitalization and DTE overall bring positive impacts, but heterogeneity exists. Studies such as Wang et al. (2022) and Li et al. (2024) state that the level of positive and negative impacts of DTE may change through structural and technological levels. Moreover, human capital in economies also determines this level (Wang et al., 2022). Finally, energy justice contributes to environmental quality (Sovacool and Drupady, 2016). However, certain gaps persist. First, the environmental indicators, such as CO2 emissions and green total factor productivity, taken in these studies are narrow. EF, which is a broader environmental measure, is absent from literature. EF covers cropland, forest land, built-up lands, fishing grounds, and carbon absorption (Global Footprint Network, 2026). Second, no existing study has focused on EJ as a moderating factor in the DTE-environment relationship. Third, the geographic scope of the existing literature is limited. Most countries are confined to a single country or regional group. The present study addresses all three gaps. First, it introduces EF as a more comprehensive measure of environmental quality across a global panel of 147 economies. Moreover, it is the first study that explicitly introduces EJ as a moderating variable and applies MMQR for the heterogeneity across different levels of EF.

3. Model, Data, and Empirical Methodology

3. Model and Data

This section aims to build an econometric model to assess how DTE and EJ impact on environmental quality. This study develops a multivariate estimation model incorporating the EF as an indicator of environmental quality, where reducing EF improves environmental quality. The impact of DTE and EJ is analyzed on the environment, controlling the effect of economic growth (EG), population density (PD) and resource endowment (REN) following (Li et al., 2025). While Li et al. (2025) only analyzed the impact of DTE on emissions, this study adds EJ as an additional focus variable to check the environmental impacts of both DT and EJ globally, utilizing EF as an environmental quality indicator. The specific model set up is as follows:

$$lnEF_{i,t} = f(lnDT_{it}, EJ_{it}, lnEG_{it}, lnPD_{it}, REN_{it}) \quad (A)$$

The logarithmic form of Eq. (A) generates the following equation.

$$lnEF_{it} = \alpha_0 + \alpha_1 lnDT_{it} + \alpha_2 EJ_{it} + \sum_{i=3}^{5} \alpha_i X_{it} + \varepsilon_{it} \quad (B)$$

Where, EF_{it} represents environmental quality measured through ecological footprints per capita, X represents controlled variables set and ε_{it} is error term. Regarding control variables, EG representing development level of economy, PD capturing demographic trend; and REN indicating resource endowment as resource abundance directly influences environmental pressure, energy structure, and economic behavior. The analysis covers 147 global economies for period 2005-2023. Table 1 explains the definition of variables used in empirical analysis.

Table 1: Variable Description

Variables	Description	Source
EF	Ecological footprint global hectare per person	Global Footprint Network (2026)
EG	The gross domestic product (GDP) per capita (constant 2015 US$) is a financial measure of the market value of all final services and products made over a specific time period and measured as constant US$ 2015.	World Bank (2026)
PD	Population density (people per sq. km of land area)	World Bank (2026)
REN	Resource endowment captured through renewable energy consumption % of final energy consumption	World Bank (2026)
DTE	Total digitally delivered export services in US$ in millions	World Trade Organization (2025)
EJ	Energy justice is measured as the ratio of access to electricity, rural (% of rural population) and access to electricity, urban (% of rural population)	Author's own calculations

3.2 Baseline Regression (Direct and Moderating Effect)

The dynamic form of Eq. (A) generates the following equations.

$$lnEF_{i,t} = \beta_0 + \rho lnEF_{i,t-1} + \beta_1 lnDTE_{i,t} + \beta_2 lnEG_{i,t} + \beta_3 lnPD_{i,t} + \beta_4 REN_{i,t} + \mu_i + \varepsilon_{i,t} \quad (1)$$

$$lnEF_{i,t} = \gamma_0 + \delta lnEF_{i,t-1} + \gamma_1 EJ_{i,t} + \gamma_2 lnEG_{i,t} + \gamma_3 lnPD_{i,t} + \gamma_4 REN_{i,t} + \mu_i + \varepsilon_{i,t} \quad (2)$$

$$lnEF_{i,t} = \phi_0 + \vartheta lnEF_{i,t-1} + \phi_1 lnDTE_{i,t} + \phi_2 EJ_{i,t} + \phi_3 lnEG_{i,t} + \phi_4 lnPD_{i,t} + \phi_5 REN_{i,t} + \mu_i + \varepsilon_{i,t} \quad (3)$$

$$lnEF_{i,t} = \varphi_0 + \omega lnEF_{i,t-1} + \varphi_1 lnDTE_{i,t} + \varphi_2 EJ_{i,t} + \varphi_3 lnDTE_{i,t} * EJ_{i,t} + \varphi_4 lnEG_{i,t} + \varphi_5 lnPD_{i,t} + \varphi_6 REN_{i,t} + \mu_i + \varepsilon_{i,t} \ (4)$$

In equation 1, the lagged dependent variable shows a dynamic effect and the four coefficients present the influence of the independent variables on the dependent variable. The primary objective of this research is to assess the causal relationships between DTE, EJ and EF. The focus of research is on the coefficient associated with elasticity between DTE, EJ and EF. Equation 1 captures the direct role of DTE on EF and equation 2 captures the direct role of EJ on EF. After detecting the direct impact of DTE and EJ, the study then explores how EJ acts as a moderator in the DTE and environmental nexus. Firstly, it added both DTE and EJ into the estimation model (Eq. 3) to see their average effect on environmental quality and the interaction term in EQ. 4 is added to assess the moderating role of EJ in the relationship between DTE and EF.

The baseline model incorporates pooled ordinary least squares (POLS), fixed effects (FE), random effects (RE) and one-step system generalized method of moments (GMM) method. The system GMM is the main focused estimation strategy as it utilizes orthogonality conditions, delivering consistent and efficient parameter estimates along with tackling endogeneity issues. Minimizing a quadratic form of the sample moment condition generates GMM estimator as:

$$\hat{\theta}_{gmm} = \arg min\, h(\theta)' \hat{\Omega}^{-1} h(\theta)$$

The orthogonality conditions between the instruments and the errors derive the following conditions:

$$E[Z'\epsilon] = 0$$

Where Z is the matrix of instruments and ϵ is a vector of errors.

In a system GMM framework, the estimator is built by jointly using moment conditions that are derived from both the first differences and the level equations. Combining these moment conditions into a single system, the GMM estimator achieves greater efficiency and reduces biased estimates relative to the difference GMM that only relies on differenced equations. The system GMM method estimates two equations simultaneously. The first is the regression in first differences, where lagged values in levels are used as instruments for the difference endogenous variables. The second is the regression in levels, where lagged differences are used as instruments to control potential endogeneity following the approach of Blundell & Bond (1998). This expanded set of internal instruments improves efficiency (Greene, 2002, p.308).

While EJ influences environmental outcomes through cleaner energy access and policy frameworks, environmental degradation may also induce policy responses that improve EJ.

Similarly, DTE estimates may suffer from endogeneity. To address simultaneity bias, lagged values of EJ and DTE are used as instruments within a system GMM framework, along with the lagged dependent variable. To address the instrument proliferation problem, the instrument matrix was collapsed to reduce the number of instruments without sacrificing their explanatory power. Furthermore, the lag depth of the GMM-style instruments was restricted to 2-3 lags instead of using all available lags. System GMM can handle problems like heteroscedasticity and correlation in error terms. To check for serial correlation, the AR (2) test is commonly used. The method relies on internal instruments, specifically lagged levels and lagged differences, which are considered appropriate and effective, as explained by Roodman (2009).

In alignment with Shayanmehr et al. (2023), MMQR regression is also employed to know the coefficient values within quantiles. The MMQR approach combines quantile regression with moment-based estimation and provides a flexible and reliable way to estimate the conditional quantiles of a response variable. The Jarque-Bera test was applied to assess the distributional profile of the outcome variable (EF). The test outcome suggests that the Jarque-Bera statistic (2444.0) is statistically significant ($p < 0.05$), rejecting the null hypothesis of normality. Hence, the use of MMQR is justified, as it does not rely on the normality assumption and is robust to outliers and distributional asymmetries. Moreover, MMQR enables the heterogeneous effects of DTE and EJ across different quantiles of EF, which is particularly relevant given the non-normal nature of the data. MMQR examines the correlation among variables at various quantiles of the dependent variable (EF). This method has a variety of applications as it may detect both linear and non-linear impacts (Baba Ali et al., 2023). Unlike mean-based estimators, MMQR allows the effect of DT and EJ justice to vary across different quantiles-low, medium and upper environmental performance levels, which reflects structural differences among economies. The conditionally quantile of QY(τ/X) for random variables can be expressed as follows:

$$Y_{it} = \alpha_i + X'_{it}\beta + \sigma(\delta_i + Z'_{it}\gamma)U_{it}$$

Where Z functions as a vector of recognized transformations of notable elements. The definition of σ(.) is: $P\{\sigma(\delta_i + Z'_{it}\gamma) > 0\} = 1$. U is an unknown random component.

$$Q_y(\tau \mid Xit) = (\alpha_i + \delta_i q(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau)$$

In the above equation, the main variable quantile regression is shown by $Q_y(\tau \mid Xit)$ and explanatory variables are shown by X'_{it}. Within the context of equations 1,2, 3 and 4, the empirical framework of the study can be extended as:

$$QlnEF_{i,t}(\tau_k \mid Xi) = \delta_i + \varphi_{1\tau} lnDTE_{i,t} + \varphi_{2\tau} lnEG_{i,t} + \varphi_{3\tau} lnPD_{i,t} + \varphi_{4\tau} REN_{i,t} + \varepsilon_{i,t} \quad (5)$$

$$QlnEF_{i,t}(\tau_k \mid Xi) = \delta_i + \varphi_{1\tau} EJ_{i,t} + \varphi_{2\tau} lnEG_{i,t} + \varphi_{3\tau} lnPD_{i,t} + \varphi_{4\tau} REN_{i,t_i} + \varepsilon_{i,t} \quad (6)$$

$$QlnEF_{i,t}(\tau_k \mid Xi) = \delta_i + \varphi_{1\tau} lnDTE_{i,t} + \varphi_{2\tau} EJ_{i,t} + \varphi_{3\tau} lnEG_{i,t} + \varphi_{4\tau} lnPD_{i,t} + \varphi_{5\tau} REN_{i,t} + \varepsilon_{i,t} \quad (7)$$

$$QlnEF_{it}(\tau_k \mid Xi) = \delta_i + \varphi_{1\tau} lnDTE_{it} + \varphi_{2\tau} EJ_{it} + \varphi_{3\tau} lnDTE_{it} * EJ_{it} + \varphi_{4\tau} lnEG_{it} + \varphi_{5\tau} lnPD_{it} + \varphi_{6\tau} REN_{it} + \varepsilon_{i,t} \quad (8)$$

4. Results and Discussion

The descriptive statistics in Table 2 show that EF shows moderate average values but substantial variation across countries. DTE and GDP show particularly large dispersion, reflecting differences in technological development and economic capacity. In contrast, EJ values are relatively moderate with limited dispersion, suggesting that most countries fall within a comparable range in terms of fair energy access and distribution. PD varies widely and such variation may influence environmental pressure and resource consumption. REN shows moderate variability across countries.

Table 2: Descriptive Statistics

Variables	Mean	S.D.	Minimum	Maximum
Ecological footprint per capita	3.3673	2.5282	0.4856	16.4278
Digital trade	15295.3	49217.3	0.39	649255.6
Energy justice	0.76	0.35	0.008	1.09
Gross domestic product	14176.1	19274.7	253.4	112417.9
Population density	195.85	645.55	1.632	8241.9
Resource endowment	32.45	28.81	0.12	97.4

4.2 Baseline Regression Estimates

Table 3 reports the empirical results of Model 1. The effect of DTE on EF is negatively significant across all estimation methods. The system GMM estimates in column (5) show that DTE has a significant and negative effect on EF. The coefficient on DTE indicates that a 1% increase in DTE significantly reduces EF by 0.0184%. This result aligns with Wang et al. (2024), who argue that digital trade promotes economic structural optimization through virtual and online transactions, thereby reducing reliance on fossil fuels. In addition, DTE facilitates knowledge dissemination, technology transfer, and the diffusion of ICT-based environmental practices, which can enhance environmental quality (Sun et al., 2024). Several mechanisms may explain this relationship. DTE enables paperless processes, including e-invoicing, single-window online systems, and online product promotion, all of which reduce resource use. It also supports more efficient and environmentally friendly logistics through e-procurement, optimized transport systems, and smart warehousing. More broadly, these effects operate through structural transformation, innovation, and human capital development associated with digitalization, as highlighted by Cai (2025) in the case of 27 European Union countries.

Table 3: Baseline Regression Estimates Model 1

Variables	POLS	FE	RE	SGMM
Lag (EF)				0.60239*** (0.0325)
DTE	-0.01399*** (0.00439)	-0.00641*** (0.0044)	-0.0085*** (0.00435)	-0.01838*** (0.00168)
GDP	0.00003*** (0.0005)	0.00019*** (0.0044)	0.00981* (0.00113)	0.18245** (0.0153)
PD	0.000049*** (0.00003)	0.00019** (0.00047)	0.00093** (0.00036)	0.00032 (0.00025)
REN	-0.01221*** (0.00033)	-0.00763*** (0.0063)	-0.00966*** (0.0056)	-0.00147*** (0.00018)
Constant	1.14716*** (0.03307)	1.23754*** (0.03655)	1.2079*** (0.04867)	1.0264*** (0.0879)
Breusch Pagan Test	16566.58***			
Hausman Test		126.27***		
Sargan (prob.)				0.098
AR (1) prob.				0.000
AR (2) prob.				0.092
Observations	2488	2469	2469	2326

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 4: Baseline Regression Model 2

Variables	POLS	FE	RE	SGMM
Lag (EF)				0.6442*** (0.0305)
EJ	-0.21703*** (0.03156)	-0.2895*** (0.0308)	-0.3199*** (0.0302)	-0.0710*** (0.0103)
GDP	0.4319*** (0.0069)	0.1998*** (0.0197)	0.3054*** (0.0152)	0.1506*** (0.0133)
PD	0.00003*** (0.00001)	0.00058** (0.00004)	0.00008** (0.00003)	0.00067** (0.0068)
REN	-0.00458*** (0.00037)	-0.00731*** (0.00065)	-0.0074*** (0.0006)	-0.00166*** (0.0002)
Constant	2.4499*** (0.0613)	0.28175 (0.1688)	1.1775*** (0.1361)	0.8534*** (0.0773)
Breusch Pagan Test	15376.6***			
Hausman Test		90.38***		
Sargan(prob.)				0.069
AR(1) prob.				0.000
AR(2) prob.				0.086
Observations	2488	2488	2488	2344

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 4 shows that the coefficient of the lagged EF (0.6442) is positive and statistically significant, indicating a high degree of persistence in EF over time. This suggests that past levels of environmental degradation strongly influence current levels. However, since the coefficient is less than one, the adjustment toward equilibrium is gradual, with approximately 35.6% of the deviation corrected in each period. The parameter estimate on EJ (0.071) is positive and significant, suggesting that an incline in EJ reduces EF. EJ helps tackle ecological implications through the policy formulation process that requires involvement of the community in the energy decision-making process (Sovacool & Dworkin, 2015). Fair and equitable distribution of energy resources for society is important for sustainable development (Sohail et al., 2025). Ciplet (2021) also supports these findings.

The role of GDP is positive and significant, which is consistent with Majeed & Tauqir (2020). The Sargan test statistics verify the validity of the instruments used. The results suggest that the instruments are appropriately specified and are neither weak nor under-identified. AR (1) probability reports the correlation of the lagged dependent variable and AR (2) probability value reports that the null hypothesis of no second-order serial correlation is not rejected in the global panel, indicating that moment conditions are correctly specified.

4.3 Moderating Role of Energy Justice

The estimates in Table 5 explore how EJ acts as a moderator in the DTE and environmental nexus. Table 5 adds both DTE and EJ into the estimation model (Eq. 3) to see the individual effect on environmental quality and adds an interaction term (Eq. 4) to assess the moderating role of EJ in the relationship between DTE and EF.

Table 5: Baseline Regression Results of Models 3 and 4

Variables	POLS	FE	RE	SGMM	SGMM
Lag (LEF)				0.6144*** (0.0315)	0.5953*** (0.0318)
DTE	-0.00967*** (0.00164)	-0.0014*** (0.00171)	-0.00148*** (0.0015))	-0.0038*** (0.0864)	-0.0056*** (0.0239)
EJ	-0.2304*** (0.0314)	-0.2932*** (0.03036)	-0.32167*** (0.0297)	-0.0818*** (0.0105)	-0.0298*** (0.0107)
GDP	0.4464*** (0.0072)	0.2405*** (0.0200)	0.3408*** (0.0156)	0.1693*** (0.0142)	0.1937*** (0.0156)
PD	0.00002* (0.0001)	0.0009** (0.0005)	0.00058 (0.0039)	0.00064 (0.0084)	0.0001 (0.0007)
REN	-0.0045*** (0.0003)	-0.0061*** (0.0065)	-0.0063*** (0.0059)	-0.0017*** (0.0016)	-0.0019*** (0.0017)
DTE*EJ					-0.0187*** (0.0017)
Constant	2.554*** (0.0634)	1.6606*** (0.1728)	1.5031*** (0.1398)	1.9698*** (0.0828)	1.0877*** (0.0894)
Breusch Pagan Test		15482.8***			
Hausman Test			72.70***		
Sargan P value				0.243	0.093
AR(1) P value				0.000	0.000
AR(2) P value				0.805	0.086
Observations	2488	2488	2488	2344	2238

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 5 shows the environmental effects of DTE and EJ in column (4) and the moderating role of EJ in column (5). A 1% increase in DTE decreases EF by 0.0038% and 0.0056%, respectively. The interactive term of DTE and EJ in the fifth column shows a significant and positive effect on environmental quality by reducing EF (0.0187%), indicating that while DTE reduces barriers to renewable technologies adoption, promotes green innovation and technology transfer, EJ promotes equitable access to affordable, reliable, and clean energy and equitable renewable adoption. Their interaction effect can promote higher energy efficiency and lower fossil dependence, improving environmental quality. Li et al. (2025) also indicated that the development of the digital economy and DTE promotes EJ through the technological process.

4.4 Quantile Regression Analysis

The analysis is also extended to explore whether the level of environmental performance of DTE and EJ differs from quantile to quantile (10th, 25th, 50th, 75th, and 95th). The effect of DTE and EJ may differ between countries with low EF and those with high EF. Quantile regression captures this heterogeneity across the entire distribution of EF rather than assessing only the average effect. The MMQR model is particularly effective in assessing how the marginal effects of DTE and EJ vary across the distribution of EF and shows considerable heterogeneity in estimated regression coefficients. The estimates of direct effects of DTE and EJ on the environment for models 5 and 6 are reported in Tables 6 and 7.

Table 6: Quantile Regression Estimates Model 5

Dependent variable: Ecological Footprint					
	10th	**25th**	**50th**	**75th**	**95th**
DTE	0.01145*** (0.0050)	0.0287*** (0.00392)	-0.0438*** (0.0037)	-0.0639*** (0.0046)	-0.0968*** (0.0074)
GDP	0.45617*** (0.0095)	0.4607*** (0.0077)	-0.0437*** (0.00372)	0.46997*** (0.0090)	0.47861*** (0.0145)
PD	-0.00064 (0.00018)	0.00024 (0.00015)	0.00086 (0.00004)	0.00014*** (0.00071)	0.00047*** (0.0027)
REN	-0.0024*** (0.0004)	-0.0029*** (0.00329)	-0.0037*** (0.00316)	-0.0039*** (0.00381)	-0.0049*** (0.00061)
Constant	3.2012*** (0.0791)	2.9177*** (0.0620)	2.6688*** (0.0593)	2.3379*** (0.07347)	1.7972*** (0.1174)
Observations	2469	2469	2469	2469	2469

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 7: Quantile Regression Estimates Model 6

Dependent variable: Ecological Footprint					
	10th	**25th**	**50th**	**75th**	**95th**
EJ	-0.1696*** (0.0392)	-0.1932*** (0.0316)	-0.2143*** (0.0318)	-0.2389*** (0.0402)	-0.2844*** (0.0665)
GDP	0.44481*** (0.0082)	0.4384*** (0.0066)	0.4327*** (0.0066)	0.42608*** (0.0084)	0.4138*** (0.0138)
PD	0.0005*** (0.0018)	0.0004*** (0.0015)	0.00027 (0.0015)	0.00019 (0.0018)	0.00017 (0.0031)
REN	-0.0041*** (0.0004)	-0.0043*** (0.00036)	-0.0045*** (0.00036)	-0.0047*** (0.0005	-0.0053*** (0.0007)
Constant	2.9915*** (0.0742)	2.722*** (0.0591)	2.481*** (0.0592)	2.2003*** (0.075)	1.6803*** (0.1251)
Observations	2488	2488	2488	2488	2488

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

The results in Table 6 show that DTE has a dual effect on environmental quality, as the sign of influence differs across different quantiles. The positive contribution of DTE on the environment is noted in 50th, 75th and 95th quantiles, and its magnitude increases from lower to higher quantiles, indicating that the use of digital services for trade improves environmental conditions in regions having higher environmental degradation, particularly those with larger EF. DTE improves environmental quality and therefore generates “green effect” through industrial and consumption structure upgrading, as indicated by Yang et el. (2026). Wu et al. (2026) show that the digital economy index reduces carbon emissions mainly due to energy structure optimization, scale of energy consumption and renewable energy facilitation. However, the digital economy is a broader concept and may encompass other aspects along with trade.

Table 6 also reports that the magnitude of the negative influence of DTE on the environment increases as we move from 10th to 25th quantile. This shows that the adverse impact is more prominent in regions with smaller EF. In regions with lower EF, the expansion of DTE often requires new infrastructure such as data centers, telecommunications networks, and logistics facilities. The construction and energy demand of this infrastructure can temporarily increase energy consumption and emissions, leading to a negative environmental effect. In the early stages of DTE development, the disorderly expansion of digital infrastructure and insufficient technology penetration depth can lead to energy-intensive activities and can intensify environmental pollution (Che et al., 2024). The coefficient of EJ is negative and significant across all quantiles indicating that promoting EJ improves environmental quality across all quantiles and the marginal impact tends to increase as the quantile level increases. The results aligned with (Sovacool & Dworkin, 2015; Ciplet, 2021). The moderating effects of EJ on DTE and the environment of models 7 and 8 are reported in Tables 8 and 9.

Table 8: Quantile Regression Estimates Model 7

Dependent variable: Ecological Footprint					
	10th	**25th**	**50th**	**75th**	**95th**
DTE	0.00064*** (0.0023)	0.00058*** (0.0025)	-0.00056*** (0.0029)	-0.00046*** (0.0023)	-0.0090*** (0.00046)
EJ	-0.10039*** (0.0532)	-0.16921*** (0.0414)	-0.2528*** (0.03425)	-0.31235*** (0.0367)	-0.4139*** (0.0528)
GDP	0.00021*** (0.0789)	0.00023*** (0.0613)	0.00025*** (0.0587)	0.00022*** (0.0544)	0.00021*** (0.0775)
PD	0.00077* (0.0026)	0.00062** (0.0020)	(0.0004 (0.0017)	0.0003 (0.0018)	0.0072 (0.0026)
REN	-0.0186*** (0.0066)	-0.01025*** (0.0051)	-0.0095*** (0.0042)	-0.0089*** (0.0046)	-0.0081*** (0.0065)
Constant	1.4420*** (0.0568)	1.6133*** (0.0443)	1.8213*** (0.0365)	-1.0089*** (0.00045)	1.2220*** (0.0583)
Observations	2488	2488	2488	2488	2488

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 9: Quantile Regression Estimates Model 8

Dependent variable: Ecological Footprint					
	10th	**25th**	**50th**	**75th**	**95th**
DTE	0.00209*** (0.0436)	0.00167*** (0.0345)	-0.0109*** (0.0274)	-0.0678*** (0.0284)	-0.0700*** (0.0416)
EJ	-0.0682 (0.088)	-0.1239 (0.0708)	-0.385*** (0.0557)	-0.5712*** (0.057)	-0.909*** (0.086)
DTE*EJ	-0.0321*** (0.008)	-0.0103*** (0.0071)	-0.0198*** (0.0056)	-0.0408*** (0.0058)	-0.079*** (0.0088)
GDP	0.00083*** (0.089)	0.00022** (0.0703)	0.00028** (0.0558)	0.00023** (0.0580)	0.00024*** (0.0844)
PD	0.00078*** (0.0072)	0.0006 *** (0.0015)	0.00036 (0.0017)	0.00018 (0.0287)	0.00039 (0.0259)
REN	-0.0115*** (0.0806)	-0.0104*** (0.00636)	-0.0099*** (0.00542)	-0.0086*** (0.0525)	-0.0073*** (0.0767)
Constant	1.4281*** (0.079)	1.5982*** (0.059)	1.8293*** (0.048)	1.9945*** (0.045)	1.294*** (0.071)
Observations	2376	2376	2376	2376	2376

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 8 shows that the effect of DTE on environmental quality is negative (increases EF) in the 10th and 25th quantiles and positive (decreases EF) in the 50^{th}, 75^{th} and 95^{th} quantiles. For example, in Table 9, the results for the 10^{th} quantile reveal that a 1% rise in DTE is associated with a 0.00209%, and 0.001675% increase in EF, respectively, whereas at the 50th,75th and 95th quantiles, the same increase in DTE results in 0.0109% 0.0678 and 0.07% decrease in EF. This result indicates that DTE has a negative effect on the environment in regions or contexts where EF is relatively low, while DTE improves the environment in regions with higher EF. Therefore, in areas with high EF, advancing digitalization of trade could serve as a more effective catalyst for improving environmental quality. DTE can negatively influence the environment, as in its early stages of development, the disorderly expansion of digital infrastructure and insufficient technology penetration depth can lead to energy-intensive activities, which can intensify environmental pollution (Che et al., 2024; Li et al., 2025). The coefficient of EJ is negative and significant across all quantiles, indicating that promoting EJ improves environmental quality across all quantiles and the marginal impact tends to increase as the quantile level increases. The results aligned with (Sovacool & Dworkin, 2015; Ciplet, 2021).

The interaction term in Table 9 is significant and negative across all quantiles indicating that both DTE and EJ are essential for improving environmental quality across all quantiles. The positive and significant interaction term between DTE and EJ suggests that EJ acts as a catalyst, enhancing the effectiveness of DTE in reducing EF. This finding implies that in countries with stronger EJ frameworks, DTE contributes more significantly to environmental sustainability. Furthermore, DTE may not be clean if EJ is carbon-intensive and efficiency of digital technology innovation can promote energy justice (Yang et al., 2023). Besides, the development of the digital economy and digital trade promotes energy justice through technological processes (Li et al., 2025).

The quantile regression plot in Figure 1 indicates that the magnitude of EJ substantially increases from lower to upper quantiles, highlighting that EJ improves environmental quality and in countries having higher environmental degradation, improvement in EJ has a larger beneficial impact. The fair distribution of energy is crucial, especially when environmental problems are severe. Figure 2 indicates that the coefficient of DTE is positive at the lower quantile but declines at the higher quantile, thus having a heterogeneous impact on the environment. The magnitude level of the impact of DTE is slightly increasing from the lower and upper quantiles, indicating that DTE may initially harm the environment but support the environment in more polluted economies through technological adoption and efficiency gains. The moderating plot in Figure 3 shows that EJ strengthens the impact of DTE on EF. The slope increases as we move from lower to upper quantile, indicating that the moderating role of EJ is stronger in countries with higher EF, highlighting that without equitable and sustainable energy systems, the expansion of DTE may have greater environmental pressure.

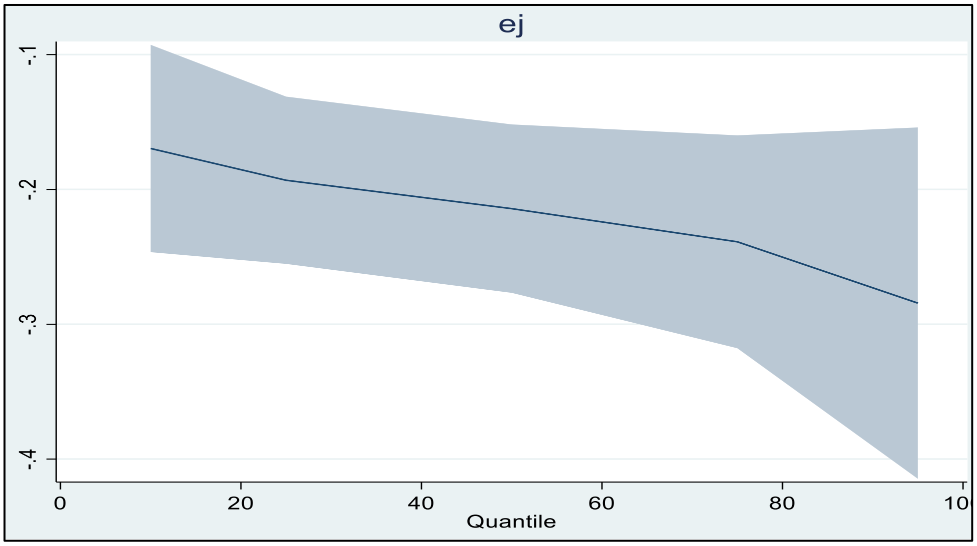

Figure 1: Quantile Plot of Energy Justice

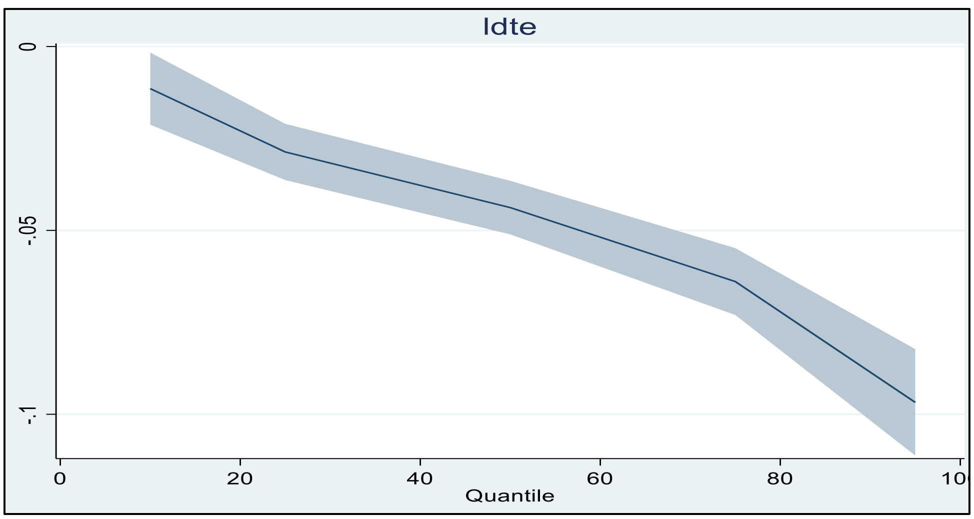

Figure 2: Quantile Plot of Digital Trade

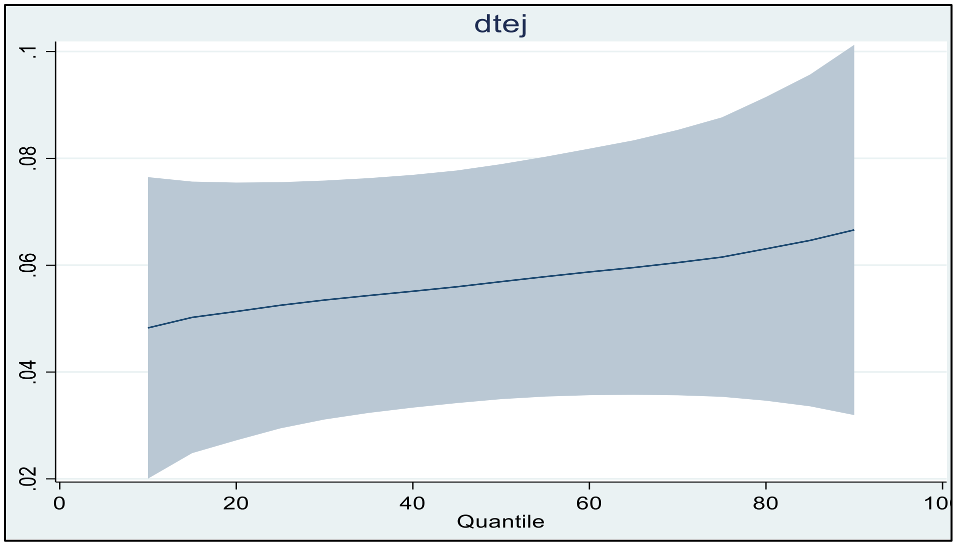

Figure 3: Quantile Plot of Digital Trade*Energy Justice

5. Conclusion

This study examines the effects of DTE and EJ on environmental quality across 147 countries from 2005 to 2023. Using comprehensive panel data and multiple empirical techniques, we analyze both the direct effects of DTE and EJ on EF, as well as the moderating role of EJ in the DTE–EF relationship. The results indicate that both DTE and EJ significantly reduce EF, thereby improving environmental quality.

These findings can be interpreted through established theoretical frameworks. The negative effect of DTE on EF at median and higher quantiles supports the EKC, suggesting that beyond a critical threshold of development, digitalization facilitates structural transformation and the adoption of cleaner technologies, as highlighted by Grossman & Krueger (1991). In contrast, the positive impact of DTE on EF at lower quantiles is consistent with the PHH, indicating that in the early stages of digital adoption, carbon-intensive activities may intensify, as suggested by Copeland & Taylor (1994).

However, the PHH alone does not fully explain these dynamics. The results suggest that the environmental benefits of digital trade are contingent upon equitable energy access, highlighting the critical moderating role of energy justice in translating digitalization into environmental gains.

Quantile regression analysis reveals that in lower quantile countries having lower EF (10^{th}-25^{th}), DTE increases ecological pressure rather than reducing it. This is likely because these countries are in an early stage where scale effects dominate. In contrast, countries with median and high EF (50^{th}-95^{th} quantiles), DTE reduces EF, which can be attributed to more advanced industrial structures and greater adoption of green innovation, as suggested by Zhou & Guo (2025). These results suggest that the environmental benefits of DTE are conditional on existing infrastructure and levels of economic development. EJ, however, reduces EF in all quantiles, but the effect is stronger in high-emission countries.

Most importantly, this study performs interactive analysis to check the moderating role of EJ in the impact of DTE on EF. The interaction between DTE and EJ suggests that EF decreases and environmental quality improves across all the quantiles, including the lower quantiles where DTE alone had negative impacts on the environment. When energy access is equitable, DTE is channeled through cleaner energy systems and EJ prevents energy-intensive activities that come with the early stage of DTE development (Che et al., 2024). Furthermore, due to equitable energy access, the pool of firms that adopt green technologies increases, and therefore DTE comes with enhanced environmental benefits (Wu et al., 2026). This analysis suggests that EJ significantly amplifies the environmental benefits of DTE.

The research findings in this study put forward the following policy implications. For high-emission countries, investments in DTE should be made to reduce EF, together with EJ initiatives. These countries can get maximum environmental benefits, as they usually have higher levels of green innovation and a higher level of industrial structure. However, for low-emission countries, promoting just DTE may not translate into reduced EF. Policy makers need to consider ensuring EJ policies to harness the environmental benefits of DTE.

This study has some limitations despite conducting a comprehensive analysis of DTE and its role in EF. First, the study focuses on EJ as a moderator of the DTE and EF relationship. However, other channels and factors, such as human capital and technological innovation, may mediate or moderate the effect of DTE on environmental quality. Second, in the global panel, countries combine at different stages of development and digitalization. Although quantile regression addresses heterogeneity at varying levels of emissions, the understanding would further deepen if the analysis were done by income group or region. Third, the EJ variable measures the rural-urban electricity access ratio, which is only the distributive dimension of EJ (Sovacol & Dworkin, 2015).

Future studies could construct and use composite indices for EJ and incorporate other dimensions. Future research can consider instrumental variables quantile regression analysis to address heterogeneity as well as endogeneity problems. Moreover, future research could consider a dynamic panel threshold model to capture the evolving relationship between DTE, EJ and EF.

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Availability of Data

The dataset is available from the corresponding author upon reasonable request.

Declaration of AI Use

In this research paper no AI tool is used in either generating or rephrasing the text. No AI tool is used for generating data, analysis, or the core intellectual content of the study. The methodology, results, and interpretations were entirely developed by the authors.

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