ISSN: 2029-4913 / eISSN: 2029-4921

Article in press

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

https://doi.org/10.3846/tede.2026.25408

INCLUSIVE FINANCE AND CARBON PRODUCTIVITY: A NEW PERSPECTIVE FROM OECD COUNTRIES

Xiaoli HAO[1,2], Hongze LIANG[1,3], Qingyu SUN[1], Ke LI[1], Haitao WU[4,5,6]✉

[1]*School of Economics and Management, Xinjiang University, Urumqi, China*
[2]*Engineering Research Center of Northwest Energy Carbon Neutrality, Ministry of Education, China*
[3]*School of Economics and Finance, Xi'an Jiaotong University, Xi'an, China*
[4]*School of Economics, Beijing Institute of Technology, Beijing, China*
[5]*Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing, China*
[6]*International Business School, Hainan University, 570228 Haikou, China*

Article History:
- received 10 May 2024
- accepted 9 October 2025
- first published online 31 July 2026

Abstract. Within the severe context of climate change, enhancing Carbon Productivity (*CP*) to mitigate the rise in carbon emissions during economic development is pivotal for fostering a low-carbon economic transition. Financial Inclusion (*FI*), by expanding financial services, has enabled the allocation of capital to various sectors, including those focused on environmental sustainability. Nonetheless, the precise effect of *FI* on *CP* remains ambiguous at the international level. This study, based on the data from 33 OECD member countries from 2010 to 2019, empirically examines the impact of *FI* on *CP*. Our findings indicate: (1) *FI* directly enhances *CP*, with a marginal effect of 0.014%. This direct impact remains robust after undergoing various robustness checks and addressing endogeneity concerns. (2) Panel quantile regression further confirms this causal relationship, showing that the impact of *FI* on *CP* is consistently positive. However, the positive impact exhibits an "increase-decrease" inverted "V" pattern as *CP* improves. (3) Mechanism analysis of indirect impact reveals that the low-carbon consumption, energy structure, and technology upgrades exert significant partial mediating effects. (4) The positive impact of *FI* on *CP* varies across different contexts, showing a range of heterogeneities. The impact is particularly stronger in non-Eurozone countries, in settings with higher levels of income inequality, and during the period of stricter environmental regulation.

Keywords: financial inclusion, carbon productivity, OECD countries, PCA, DDF-GML.

JEL Classification: Q56, G20, Q43.

✉Corresponding author. E-mail: ***haitao.kungfuer@gmail.com***

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) underscores that greenhouse gas emissions are the primary driver of global warming, meanwhile projecting that global temperatures will exceed 1.5 degrees Celsius by 2030 (Intergovernmental Panel on Climate Change [IPCC], 2023). The continuous increase in global carbon emissions necessitates curbing emission growth during economic development. Carbon Productivity (*CP*), widely accepted as an effective measure of how economic activities can grow while reducing carbon emissions, reflects the efficiency of managing an economy's carbon footprint alongside economic growth. Enhancing *CP* is central to achieving the dual goals of economic and environmental sustainability in global climate change mitigation efforts. The Paris Agreement and the determination and implementation of Nationally Determined Contributions (NDCs) by countries underscore the urgency of enhancing *CP*. Meanwhile, advancements and cost reductions in renewable energy technologies (Luderer et al., 2022), make improving *CP* and promoting economic transition to low-carbon feasible (Peng et al., 2023).

However, achieving this transition will require not only technological innovation and policy support, but also significant financial investment to foster the adoption of low-carbon solutions. Consequently, financial inclusion emerges as an essential factor. Financial Inclusion (FI) is defined as the availability of financial products and services – such as transactions, payments, savings, credit, and insurance – that are both useful and affordable for individuals and businesses, ensuring these services are delivered responsibly and sustainably. This concept was initially brought to attention by Chibba (2009). By ensuring wider access to essential financial resources for broader social groups and economic sectors, *FI* helps expand financing support for low-carbon domains. Recent technological advancements have accelerated the rise of digital finance, further emphasizing the capacity of *FI* to improve energy efficiency, encourage green investments, and advance sustainable development goals (Anu et al., 2023). Thus, *FI* is one of the potential tools for enhancing *CP*.

Organization for Economic Co-operation and Development (OECD) member states constitute pivotal actors in shaping the global economic landscape and advancing climate change mitigation efforts. According to the World Bank, the combined GDP of the 38 OECD member countries in 2022 reached 59.79 trillion USD, accounting for nearly 59% of the global GDP, highlighting the OECD's significance in the global economy. Meanwhile, according to IEA calculations, in 2018, 80% of the OECD's energy was derived from fossil fuels, and the OECD's CO_2 emissions exceeded 10.7 billion tons in 2022, constituting over 30% of total global emissions. This high carbon energy consumption poses significant challenges to climate change mitigation, with many OECD countries striving to reduce carbon emissions from their economic activities, decrease carbon intensity, and improve *CP* (Sæther, 2021). Therefore, we aim to explore key inquiries concerning OECD countries: How does *FI* affect *CP*? Does a nonlinear relationship exist between the two? Is it possible for *FI* to directly and significantly boost *CP*? What are the underlying mechanisms of its impact? Does heterogeneity exist in this effect? Addressing these questions offers critical guidance for OECD countries in leveraging financial inclusion to facilitate low-carbon transitions and inform global sustainable development.

This study offers distinctive academic value. First, although prior research has extensively examined the *FI*–carbon emissions nexus, empirical investigations into the linkage between *FI* and *CP* remain scarce. *CP* not only involves controlling carbon emissions but also reflects how efficiently carbon emissions can be reduced while pursuing economic growth, which is a more profound concept compared to merely focusing on carbon emissions. Therefore, this study explores a relatively underexamined issue, aiming to enrich the existing literature in this area. Second, this study constructs a novel set of *FI* indicators specifically for OECD countries, covering both "traditional financial inclusion" and "digital financial inclusion" dimensions, as well as the two major facets of "access" and "usage" within each. This comprehensive and in-depth depiction enables a more systematic assessment of the development level of *FI* in OECD countries. In contrast, existing studies tend to focus on either traditional or digital financial inclusion, thus failing to capture the synergistic effects between the two.

Finally, drawing on cross-country data from OECD member states, the key marginal contribution of this study lies in demonstrating that *FI* significantly enhances *CP*, with particular emphasis on both the underlying mechanisms and the heterogeneity of this effect. In terms of mechanisms, we find that *FI* can boost *CP* through three major pathways: promoting low-carbon consumption, driving low-carbon energy structure transitions, and enhancing low-carbon technology upgrades. Regarding heterogeneity, this paper provides new insights from both macro and micro perspectives. Specifically, the positive impact of *FI* on *CP* is more pronounced in non-Eurozone countries, in contexts marked by higher income inequality, and when environmental regulation is stronger. Moreover, as we reinforce the causality tests, we observe that the positive effect of *FI* on *CP* follows an "increase-then-decrease" inverted "V" pattern as *CP* improves. Collectively, our findings not only enrich the theoretical framework linking financial inclusion and low-carbon development but also offer additional valuable marginal contributions by filling gaps in the existing literature. These insights provide practical guidance for advancing the transition to a low-carbon economy through the promotion of financial inclusion.

This paper continues with the following organization: Literature review is in Section 2. Section 3 outlines the theoretical framework and research hypotheses. Research design is detailed in Section 4. Empirical findings are in Section 5. Additional analysis is presented in Section 6. We summarize in Section 7, summarizing major findings and suggesting recommendations.

2. Literature review

2.1. Financial inclusion

Since the beginning of the 21st century, *FI* has garnered widespread attention from the academic community. The essence of *FI* emphasizes access and efficacy in financial services (Beck et al., 2009), convenience and low cost, and inclusiveness (Park & Mercado, 2018), based on which scholars have developed multidimensional measurement systems. As digital technologies continue to evolve and integrate into financial services, the connotation of *FI* has been further extended (Aziz & Naima, 2021). Khera et al. (2021) incorporated digital *FI* into the comprehensive assessment of *FI* from the perspective of access and usage, constructing a comprehensive evaluation system widely applied in cross-national studies (Oanh, 2024; Wu, 2023). Studies on China's digital *FI* are numerous, with many adopting the Digital *FI* Index developed by Peking University, which provides a comprehensive quantitative depiction of China's digital *FI* (Guo et al., 2020). Besides the application of digital technology (Shaikh et al., 2023), factors such as banking efficiency (Karpowicz, 2014), income and education (Fungáčová & Weill, 2015; Wang & Guan, 2017), political and demographic development (Kabakova & Plaksenkov, 2018) also impact financial inclusion.

2.2. Carbon productivity

Carbon Productivity (*CP*) measures the capability to achieve higher economic growth while controlling or even reducing carbon emissions. Regarding measurement techniques, various studies have evaluated *CP* through specific metrics, including carbon emissions relative to

GDP output (Zhang et al., 2018) and energy use (Ferreira et al., 2018). Carbon emission is closely related to energy structure and green productivity (Bai et al., 2024; Yasmeen et al., 2024). However, these single indicators lack comprehensiveness due to the involvement of multiple input factors and the output of economic benefits and carbon emissions in production. Consequently, numerous researchers have adopted the TFP (Total Factor Productivity) index as a method for assessing *CP* (Zhou et al., 2010), focusing on how production activities deviate from the production frontier, aiming to maximize economic benefits while minimizing carbon emissions. SFA (Stochastic Frontier Analysis) and DEA (Data Envelopment Analysis) are increasingly recognized as prevalent approaches for evaluating *CP*. DEA, which does not assume a predefined production frontier function and is capable of processing several inputs and outputs at once , has led to the widespread use of many improved DEA models to measure *CP* under the premise of treating carbon dioxide as an undesired output (Li & Lin, 2015). Regarding factors influencing *CP*, scholars have explored the impacts of trade openness (Marques & Caetano, 2020), urban growth (Wang et al., 2022), and energy transition (Dong et al., 2022) on CP.

2.3. The nexus of FI and CP

Research spanning multiple countries examining the nexus of *FI* and *CP* has primarily concentrated on two dimensions. Initially, it explores the impact of *FI* on carbon emissions. Current studies have identified varying effects: in E7 countries, *FI* exhibits a negative correlation with carbon emissions at the 25th and 50th quantiles (Qin et al., 2021). Conversely, in the "Next Eleven" countries, an increase in carbon emissions was observed as a result of *FI* (Khan et al., 2022). Additionally, research indicates that in 31 Asian countries, there was a noted rise in carbon emissions attributed to greater *FI* (Le et al., 2020). However, in OECD economies, it facilitated a decrease in carbon emissions (Hussain et al., 2023). Moreover, evidence from 103 countries indicates a non-linear relationship between *FI* and CO_2 emissions, characterized by an inverted U-pattern, lending support to the Environmental Kuznets Curve (EKC) hypothesis (Renzhi & Baek, 2020). Secondly, additional research has delved into how digital finance and digital *FI* impact carbon emissions. For instance, prior research finds that e-finance initiatives contributed to lowering carbon emissions in OECD countries (Elheddad et al., 2021), whereas digital *FI* was found to be positively associated with carbon outcomes across 76 economies (Khan et al., 2023).

2.4. Research gaps, theoretical foundations, and marginal contributions

Although a large body of work has examined the nexus between *FI* and carbon emissions or carbon intensity, with studies concentrating on regions such as Asia, the E7 and OECD countries and on how financial development, inclusion or digital finance influence aggregate emissions, research on *FI*'s role in raising Carbon Productivity (*CP*) and advancing a low-carbon economic transition remains scarce. While total emissions capture only pollution volume, *CP* measures the economic output generated per unit of CO_2 emitted, thus providing a more complete indicator of how economic growth and emissions reduction can proceed in tandem (Yang et al., 2021). Improvements in *CP* reflect not only lower emissions or carbon intensity but also greater emissions-reduction potential during growth (Sun et al., 2021), a perspective that goes beyond conventional emission-control studies. Existing studies typically assess traditional *FI* and digital *FI* separately, often using traditional metrics as proxies for overall inclusion and overlooking the combined effects when both dimensions develop together. Systematic cross-country research on how a composite *FI* drives *CP* enhancement and underpins a shift to low-carbon growth is virtually nonexistent.

From a theoretical standpoint, Schumpeter's theory of finance and innovation holds that a mature financial system stimulates continuous technological change and industrial upgrading by supplying firms with capital. Goldsmith's financial-structure theory further argues that the depth and diversity of financial institutions determine the efficiency of resource allocation, guiding savings toward the most productive investments. Financial Inclusion (*FI*), by expanding the reach of credit, payment and savings services across the economy, improves intermediary functions, reduces factor misallocation and raises total factor productivity (Uras, 2014). The rise of digital *FI* enhances these effects by lowering information asymmetries and transaction costs (Jin et al., 2023), directing more funds to high-efficiency sectors and firms and improving the combination of labor, capital and energy inputs. These mechanisms both reduce wasteful energy use and sustain output growth with lower emissions (Shahbaz et al., 2022), thereby raising *CP*. In addition, the robust financial intermediation enabled by *FI* development supports green innovation, fosters the development and deployment of low-carbon technologies, and further enhances *CP* through improved energy efficiency.

The nexus between composite *FI* and *CP* has not yet been systematically examined. This study fills that gap by providing a comprehensive analysis of how *FI* influences *CP*, representing significant marginal contributions to the literature. First, from a cross-country perspective, we develop an OECD-level *FI* index that integrates traditional and digital dimensions while capturing both accessibility and usage. This is the first systematic investigation of the *FI*–*CP* relationship and shifts the research focus from carbon emissions to carbon productivity across nations. Second, we establish a theoretical framework for how *FI* affects *CP* and empirically test both direct and indirect channels. Upon confirming *FI*'s positive impact on *CP*, we identify the underlying mechanisms and key mediating paths. Third, panel quantile regressions reinforce the causal link between *FI* and *CP* and reveal that *FI*'s positive effect follows an inverted-V pattern as *CP* increases. Finally, we document multiple dimensions of heterogeneity and nonlinearity. In particular, *FI*'s impact on *CP* varies by monetary region, level of income inequality and stage of environmental regulation. These findings offer concrete guidance for OECD countries seeking to design targeted strategies, enhance *CP*, and address climate change challenges.

3. Theoretical framework and research hypotheses

3.1. Direct impact of FI on CP

First, *FI* enhances the efficiency of resource allocation. By extending access to credit and other financial services to underserved regions and small-scale economic agents, *FI* optimizes the combination of labor, capital, and energy inputs. The broader dispersal of financial resources prevents idle capital and misallocation, directing inputs toward sectors with superior output-to-emission ratios. When previously excluded workers and firms secure financing, they can invest in more efficient production processes and energy-saving equipment, refining the mix of labor, capital, and energy and thus raising overall production efficiency while holding GDP constant and reducing carbon emission outputs. Second, *FI* bolsters capital formation and investment capacity. Its expansion through wider market reach and diversified funding channels improves the transformation of savings into productive capital. As more households and enterprises engage with the formal financial system, the aggregate investment pool grows, accelerating capital accumulation. On one hand, lowered financing thresholds and costs empower Small and Medium-Sized Enterprises (SMEs) and emerging sectors to obtain necessary funds, driving total factor productivity higher. On the other hand, ample financial resources enable firms to upgrade existing machinery and gradually adopt low-carbon technologies, such as energy-efficient production lines or clean energy installations, thereby reducing carbon intensity without sacrificing output. Third, *FI* raises information efficiency and mitigates risks. An inclusive financial system leverages digital platforms and internet connectivity to gather and process diverse credit and transactional data, significantly reducing information asymmetries. With richer data, financial institutions can more precisely evaluate potential investments and channel funds toward those with superior *CP*. Concurrently, *FI* offers inclusive lending and insurance instruments that spread financial risk for firms and households undertaking green investments or low-carbon transitions. When the financial sector underwrites green technologies, for example through loans under Germany's KfW Energy Efficiency Programme or guarantees issued by the United Kingdom's Green Investment Bank (2012–2017), producers face lower uncertainty in adopting emission-reducing processes, which in turn strengthens incentives for innovation.

Finally, *FI* strengthens financial intermediation, enhancing the efficiency of fund mobilization and risk distribution. The expansion of *FI* enables intermediaries to reach a broader base of savers and investors and fully perform their roles in channeling funds, settling payments, and sharing risks. As more individuals from remote areas and low-income groups join the formal financial sector, institutions accumulate greater pools of idle capital, which they can deploy to productive industries at reduced costs. This not only raises the utilization efficiency of financial resources but also disperses financial risk across a wider spectrum. Increased efficiency in fund allocation directs capital swiftly toward sectors exhibiting higher *CP*, preventing prolonged capital lock-in within carbon-intensive, low-efficiency industries. Moreover, alongside the enhanced risk distribution function that accompanies comprehensive *FI* development, the adoption of advanced digital technologies, such as blockchain, big data analytics, and artificial intelligence, enables real-time identification and early warning of credit, environmental, and other risks based on vast data sets. This contributes to the overall resilience of the financial system and better supports the advancement of low-carbon technologies and industries. In summary, *FI* delivers a direct uplift to *CP*. *FI* refines the allocation efficiency of labor, capital, and energy, fosters more robust capital formation and technological upgrading, enhances information flows, strengthens financial intermediation, and disperses risk effectively. Together, they systematically raise the marginal returns on input factors while restraining carbon emissions, thereby expanding GDP growth relative to carbon growth and achieving an overall enhancement in *CP*. Following the discussed analysis, we put forward Hypothesis 1:

H1: *FI can effectively enhance CP.*

3.2. Indirect impact of FI on CP

3.2.1. Mediating effect of low-carbon consumption

FI can effectively promote low-carbon consumption, thereby enhancing CP. The expansion of *FI* increases the availability and coverage of financial products and services, making it easier for consumers to obtain funding through small-amount credit. Behavioral economics suggests that consumers apply high discount rates to future benefits. *FI*, by providing credit support, eases consumers' budget constraints, lowers the threshold for purchasing low-carbon products, reduces time discounting, and raises willingness to buy such products, ultimately stimulating low-carbon consumption. Moreover, advances in digital *FI* facilitate the direct delivery of government subsidies and tax incentives for low-carbon products and consumers, further lowering purchase costs or increasing disposable income to enhance consumers' purchasing power, thereby encouraging low-carbon consumption. For example, green finance subsidies directly reduce the retail prices of electric vehicles and energy-efficient appliances. Finally, as *FI* coverage expands, producers can more efficiently access government subsidies and tax incentives, helping to lower production costs. This further decreases market prices, improves competitiveness and market penetration, and reinforces consumer demand for these products. In this way, *FI* helps establish a positive supply-demand feedback loop in the green goods market, enabling economic growth to be increasingly driven by low-carbon consumption and aligning growth with emissions reduction, thus ultimately raising *CP*. Accordingly, we formulate the following hypothesis:

H2: *FI can effectively enhance CP by promoting low-carbon consumption.*

3.2.2. Mediating effect of low-carbon energy structure

FI can substantially drive the adoption of low-carbon energy, facilitating a shift toward a low-carbon energy structure and thereby raising *CP*. First, the development of digital *FI* has markedly lowered the barriers for small and medium investors to back low-carbon firms (Gomber et al., 2018). Under traditional finance, clean energy companies rely predominantly on large institutional or government funding, leaving smaller investors with limited access. Digital platforms, however, enable these investors to participate via online equity trading services, green investment funds and similar channels. Second, from the production side, SMEs often struggle to secure financing due to low credit ratings. The expansion of *FI* helps these small low-carbon and renewable energy enterprises obtain additional capital support (Innovations for Poverty Action [IPA], 2017; Le et al., 2020), which can accelerate production of low-carbon and renewable energy and, through technology-driven cost reductions, further lower their production expenses. As these energy sources become more cost-competitive, they increasingly displace high-carbon alternatives, driving up the large-scale supply of low-carbon energy. Moreover, *FI*'s growth also empowers governments to incentivize households and firms to adopt low-carbon energy products. As the user base expands, low-carbon energy becomes more prevalent adopted in everyday life and business activities, gradually reducing dependence on traditional high-carbon fuels. This evolution of the energy structure cuts economy-wide emissions output, ultimately enhancing *CP*. Following the discussed analysis, we propose Hypothesis 3:

H3: *FI can effectively improve CP by enhancing the low-carbon energy structure.*

3.2.3. Mediating effect of low-carbon technology upgrading

FI can significantly advance the adoption and enhancement of low-carbon technologies, thereby raising *CP*. First, the expansion of digital *FI* reduces financing constraints for firms engaged in green R&D. Tools such as blockchain and big data analytics enable financial institutions to better identify high-quality firms with genuine demand for green capital, improving the precision of green credit allocation. These capabilities broaden financing channels and lower borrowing costs, directly fostering increased green investment in low-carbon innovation (Zhou et al., 2022). Second, the ongoing development of both traditional and digital *FI*, by integrating offline and online services, breaks down regional barriers and extends financial outreach. This expansion of the financial market raises the overall volume of social financing, providing an incremental source of funds for low-carbon technology projects beyond existing green loans and investments (Feng et al., 2022). Third, credit-rationing theory shows that under conventional banking, SMEs are often excluded because their financial information is opaque, leading to high loan origination costs and expensive post-loan supervision. Digital *FI* remedies this by enabling financial institutions to construct databases on SMEs or to access firms' financial data via online channels, thereby reducing information asymmetry (Tang et al., 2020). This improved transparency allows lenders to more accurately assess the credit risk of SMEs engaged in low-carbon innovation, thereby promoting technology upgrades. Finally, the adoption of artificial intelligence and other digital technologies in financial services helps financial institutions align their risk preferences with the specific profiles of various low-carbon technology innovators, improves capital allocation efficiency (Gomber et al., 2018), and further strengthens support for upgrading low-carbon technologies. Following the discussed analysis, we propose Hypothesis 4:

H4: *FI can effectively enhance CP by promoting the upgrading of low-carbon technologies.*

Figure 1 below presents the structure of the theoretical analysis.

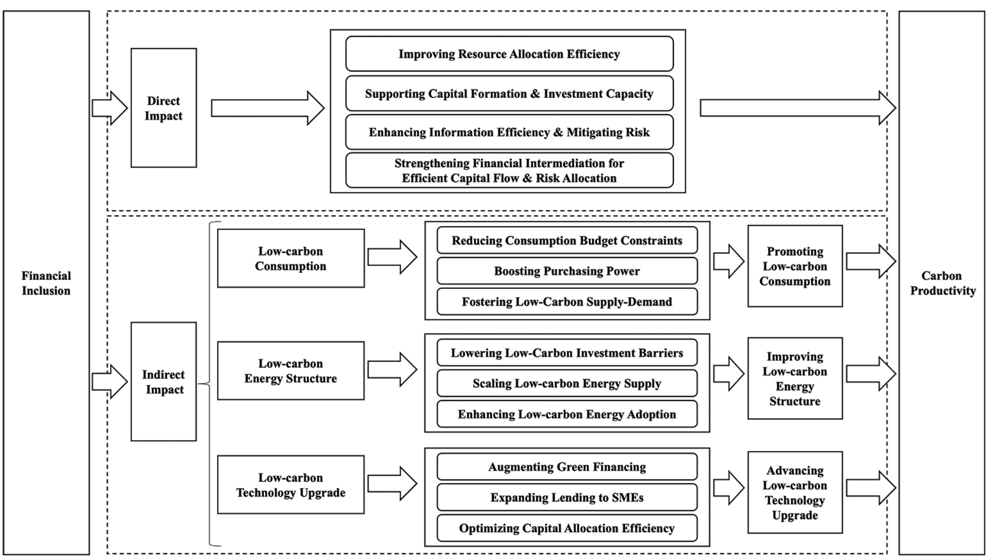

Figure 1. Theoretical analysis framework diagram

4. Research design

4.1. Model design

To verify the impact of *FI* on *CP*, this study constructs a series of regression models following this logic: First, Section 4.1.1 introduces the baseline model to directly test the effect of *FI* on *CP* (Hypothesis 1). Second, the panel quantile regression in Section 4.1.2 further assesses the causal link identified in the baseline analysis. Third, mechanism analysis models in section 4.1.3 are used to further verify the indirect effects, including the promotion of low-carbon consumption (Hypothesis 2), improvement of low-carbon energy structure (Hypothesis 3), and enhancement of low-carbon technology upgrading (Hypothesis 4). In this section, we focus on the design of the models mentioned above, which serve as the foundation for verifying the causal relationships. Finally, to ensure the clarity and credibility of causal inference, this study adopts multiple econometric methods and models, including panel Tobit regressions, Two-Stage Least Squares (2SLS), and difference GMM, to perform robustness checks and address endogeneity, as elaborated in Section 5.4 and 5.5.

4.1.1. Benchmark regression model

This research empirically investigates the effect of *FI* on *CP* by establishing a benchmark model for analysis as follows:

$$\ln CP_{it} = \alpha_0 + \alpha_1 \ln FI_{it} + \gamma Controls_{it} + \mu_i + \omega_t + \varepsilon_{it}, \quad (1)$$

where CP_{it} represents carbon productivity for country *i* in year *t*, *FIit* captures the degree of financial inclusion for the same, and $Controls_{it}$ includes various control variables. μ_i reflects country-level fixed effect, ω_t indicates time-specific fixed effect, and ε_{it} corresponds to the disturbance term.

4.1.2. Further confirmation of causality: panel quantile regression model

To strengthen the identification of causality between *FI* and *CP*, we apply the panel quantile regression approach proposed by (Koenker, 2004) to assess whether *FI*'s impact on *CP* persists across varying *CP* levels. The model is constructed as follows:

$$\ln CP_{it}(\tau) = \partial_0(\tau) + \partial_1(\tau) \ln FI_{it} + \gamma(\tau) Controls_{it} + \mu_i(\tau) + \omega_i(\tau) + \varepsilon_{it}. \quad (2)$$

In Eq. (2), τ represents different quantile levels, with a value range of $\tau \in (0,1)$.

4.1.3. Mechanism analysis model

We utilize the mediation effect analysis method, as suggested by (Baron & Kenny, 1986), to explore the potential impact mechanisms stemming from low-carbon consumption, low-carbon energy structure, and upgrading of low-carbon technology, by constructing a mediation model as follows:

$$\ln CP_{it} = \alpha_0 + \alpha_1 \ln FI_{it} + \gamma Controls_{it} + \mu_i + \omega_t + \varepsilon_{it}; \quad (3)$$

$$\ln M_{it} = \delta_0 + \delta_1 \ln FI_{it} + \gamma Controls_{it} + \mu_i + \omega_t + \varepsilon_{it}; \quad (4)$$

$$\ln CP_{it} = \delta_2 + \delta_3 \ln FI_{it} + \delta_4 \ln M_{it} + \gamma Controls_{it} + \mu_i + \omega_t + \varepsilon_{it}, \quad (5)$$

where, *M* represents the mediating variables, including low-carbon consumption (*lncons*), low-carbon energy structure (*lnstruc*), and low-carbon technology upgrading (*lnlowtec*). Eq. (3) is the benchmark regression model, assessing the immediate influence of *FI* on *CP*. Eq. (4) examines how *FI* impacts the intermediary variables. Finally, Eq. (5) evaluates the effects of intermediary variables in conveying the influence from *FI* to *CP*, focusing on the indirect impact.

4.2. Variable design and data sources

4.2.1. Core explanatory variable

Referring to existing studies (Khera et al., 2021, 2022), we apply a three-stage Principal Component Analysis (PCA) method to construct a comprehensive *FI* index that integrates both conventional and digital components. This index captures *FI*'s two core dimensions: access and usage. In the initial phase, 13 indicators are chosen to capture the "supply" and "demand" aspects of *FI*, from which four tertiary indicators for "access" and "usage" are derived via PCA. During the intermediary phase, PCA is applied separately to 'access' and 'usage' dimensions within banking and financial institutions, as well as through digital platforms, to distinguish between "traditional" and "digital" financial inclusion aspects, thereby creating two secondary indicators. The final phase involves applying PCA once more to amalgamate "traditional" and "digital" *FI* into a singular "comprehensive" *FI* indicator. The structure of the indicator system is depicted in the Table 1 below:

Table 1. System of financial inclusion indicators and data sources

Primary indicator	Secondary indicator	Tertiary indicator	Specific indicator	Data source
Comprehensive financial inclusion	Traditional financial inclusion	Access	Access to bank infrastructure	
			ATM coverage (Per 100,000 adults)	IMF
			Bank branch coverage (Per 100,000 Adults)	FAS
		Use	Financial institution account ownership (% of population 15+)	World Bank Findex
			Deposits at financial institutions (% of population 15+)	
			Debit card ownership (% of population 15+)	
			Wage receipt via bank accounts (% of population 15+)	
			Utility bill payment via bank accounts (% of population 15+)	
	Digital financial inclusion	Access	Access to digital infrastructure	
			Cellular network subscriptions (Per 100 people)	ITU
			Online banking (% of population in last three months)	OECD
		Use	Balance checks via mobile phone or internet (% population 15+)	World Bank Findex
			Making digital payments (% of population 15+)	
			Receiving wages via mobile phone (% of population 15+)	
			Paying utility bills via mobile phone (% of population 15+)	

4.2.2. Dependent variable

In this study, Carbon Productivity (*CP*) for 33 OECD member countries is evaluated using the Directional Distance Function (DDF) in conjunction with the Global Malmquist-Luenberger (GML) index. When constructing the productivity variable related to environment or green development by the GML index method, designating pollutants or carbon emissions as undesired outputs is necessary (Song et al., 2020). In this paper, carbon dioxide emissions are considered as an undesired output. Three input factors are labor, capital, and energy. We build *CP* based on the DDF, utilizing the GML index (the detailed calculation process is provided in Appendix). In constructing carbon productivity (*CP*), the input variables include labor input (measured by the employed labor population, in millions), capital input (measured by gross fixed capital formation, in current million USD), and energy input (measured as total oil equivalent, in tons). The Gross Domestic Product (GDP, in current million USD) serves as the desirable output, while the undesirable output is CO_2 emissions (in million tons). All data are sourced from *OECD.Stat*.

4.2.3. Other variables and data sources

To mitigate model specification bias, this study includes additional variables likely to influence *CP*. Details regarding the control and other variables, along with their data origins, are presented in Table 2.

The theoretical analysis previously discussed involves three major mechanisms through which *FI* impacts *CP*. To validate these mechanisms, this study designates three mediating variables: low-carbon consumption (*lncons*), low-carbon energy structure (*lnestruc*), and low-carbon technology upgrading (*lnlowtec*). Additionally, we incorporate income inequality (*incineq*) and environmental regulation (*regu*) as key variables in the heterogeneity analysis, serving respectively as the grouping variable and the threshold variable (see Sections 6.2 and 6.3 for details). The settings of *lncons*, *lnestruc*, *lnlowtec*, *incineq*, *regu*, and the variables for robustness testing, along with their data sources, are all presented in Table 2.

4.2.4. Scope of research and data sources

The time frame of this study spans from 2010 to 2019. As of 2023, there are 38 countries in the OECD organization. This paper excludes five member countries – Lithuania, Latvia, Colombia, Costa Rica, and Iceland – selecting the remaining 33 member countries as the subjects of the study. This is because Lithuania, Latvia, Colombia, and Costa Rica did not join the OECD during 2010, and Iceland was excluded due to significant gaps in its *FI* measurement data. Data related to labor, capital, and GDP mentioned in the dependent variable *CP* come from the World Bank Open Data. Data on energy consumption and CO_2 emissions is sourced from the International Energy Agency (IEA) database. Other variable sources are outlined in Table 2 above. Missing values were estimated through linear interpolation. Table 3 reports the summary statistics of key variables.

Table 2. Detailed variable information

Variable category	Variable name	Variable symbol	Meaning & unit	Data source
Control variables	Urbanization level	*urban*	Urban population proportion (%)	World Bank Open Data
	Financial market depth	*fmd*	IMF's composite index measuring financial market size and liquidity	IMF Financial Development Index Database
	International investment level	*FDI*	Ratio of FDI inflows to GDP (%)	World Bank Open Data
	Internet development level	*internet*	Internet penetration rate (%)	World Bank Open Data
	International Trade Level	*trade*	Ratio of total trade to GDP (%)	UNCTAD STAT
Mediating variables	Low-carbon consumption	*lnconsu*	Log of per capita low-carbon energy consumption (kWh equivalent)	World Energy Statistics Review
	Low-carbon energy structure	*lnestruc*	Log of low-carbon energy's share in primary energy consumption (%)	World Energy Statistics Review
	Low-carbon technology upgrading	*lnlowtec*	Log of inverse carbon emissions per energy consumption unit (TJ/ton)	IEA Database
Robust test variables	Alternative carbon productivity	*lnsbm*	Log of carbon productivity index by the SBM-GML method	–
	Demand-based carbon productivity	*lndcp*	Log of demand-based carbon productivity, disposable income per unit of energy-related carbon emissions (2015 USD/kg)	OECD.Stat
	Government R&D expenditure on environment	*rd*	Proportion of government R&D budget dedicated to environmental research (%)	OECD.Stat
	Economic freedom	*free*	Economic Freedom Index by The Heritage Foundation	The Heritage Foundation
Hetero-geneity analysis variables	Income inequality	*incineq*	Inequality in income distribution based on data from household surveys estimated using the Atkinson inequality index (%)	UNDP Human Development Data
	Environmental regulation	*regu*	Environment-related tax revenue to GDP (%)	OECD.Stat

Table 3. Statistical overview of variables

	(1)	(2)	(3)	(4)	(5)
	N	mean	Sd	min	Max
lncp	330	0.184	0.298	–0.577	0.744
lnfi	330	2.788	1.047	–1.965	4.266
urban	330	77.59	11.29	52.66	98.04
fmd	330	0.588	0.294	0.0509	0.998

End of Table 3

	(1)	(2)	(3)	(4)	(5)
	N	mean	Sd	min	Max
fdi	330	4.373	11.43	–40.33	81.29
internet	330	79.90	12.97	31.05	98.14
trade	330	1.009	0.618	0.263	3.784
lnconsu	330	8.933	1.085	4.422	11.27
lnestruc	330	2.844	0.920	–1.471	4.256
lnlowtec	330	1.719	0.302	1.248	2.763
lnsbm	330	0.450	0.243	–0.564	0.996
lncb	330	1.242	0.251	0.588	1.813
rd	330	2.646	1.946	0.0500	11.52
free	330	71.45	6.414	53.20	84.40
regu	330	2.301	0.892	–1.120	4.640
incineq	330	16.81	5.386	8.591	33.95

5. Results of empirical analysis

5.1. Benchmark regression results analysis

Table 4 displays regression analyses from columns (1) through (6), where control variables are progressively included. Both without control variables and with their gradual inclusion, the estimated coefficient of *FI* on *CP* remains significantly positive. After all control variables are added, it is significant at the 5% level, supporting that *FI* can effectively improve *CP* in the OECD member countries, thus validating Hypothesis 1. From Column (6), we observe that the coefficient for *FI* is a significantly positive 0.014, indicating that a 1% rise in *FI* corresponds to a 0.014% improvement in *CP*.

Column (6) presents the outcomes following the complete inclusion of control variables. Within these controls, neither financial market depth (*fmd*) nor international trade level (*trade*) demonstrates significance. This may be because the financial markets in most OECD countries are already highly developed, with high liquidity, a wide range of market participants, and complex financial instruments; the financial market depth may have reached a certain saturation point, making its marginal impact on *CP* insignificant. International trade often brings implicit carbon emissions that are difficult to directly reflect , and the foreign trade of OECD countries already has a distinct low-carbon characteristic (Can et al., 2021), thus it does not contribute to improving *CP*. In Column (6), the influences of control variables, specifically international investment level (*fdi*) and internet development level (*internet*), on *CP* are notably divergent – *fdi* detracts from, while *internet* enhances, this measure. International investment, although often accompanied by technology transfer, may be ineffective in enhancing *CP* across many OECD economies that already possess advanced technological capabilities and high income levels (Ma et al., 2023), and may even serve as an impediment. The increase in internet penetration not only optimizes production, logistics, and energy management, enhancing energy efficiency , but also promotes information sharing, green technology innovation, and green consumption patterns (Lin & Zhou, 2021), thereby effectively enhancing *CP*.

Table 4. Benchmark regression results

	(1)	(2)	(3)	(4)	(5)	(6)
lnfi	0.013*	0.013*	0.013**	0.013**	0.013**	0.014**
	(1.99)	(1.93)	(2.15)	(2.09)	(2.25)	(2.39)
urban		−0.017	−0.018	−0.018	−0.020*	−0.018
		(−1.44)	(−1.51)	(−1.54)	(−1.83)	(−1.59)
fmd			−0.116	−0.121	−0.075	−0.083
			(−0.84)	(−0.89)	(−0.49)	(−0.54)
fdi				−0.000	−0.001**	−0.001**
				(−1.39)	(−2.20)	(−2.15)
internet					0.003***	0.003***
					(3.45)	(3.25)
trade						−0.052
						(−0.88)
Constant	0.140***	1.482	1.576*	1.625*	1.625*	1.424
	(7.18)	(1.59)	(1.73)	(1.76)	(1.76)	(1.64)
Observations	330	330	330	330	330	330
R-squared	0.170	0.192	0.197	0.201	0.201	0.253
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Robust t-statistics in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Unless otherwise noted, The following tables are the same.

5.2. Strengthening causality: analysis of panel quantile regression results

We employ panel quantile regression to further validate the causal relationship between *FI* and *CP*. Specifically, regression analyses are performed at the 20%, 40%, 60%, and 80% quantiles of *CP* to assess how *FI*'s impact varies across the distribution, allowing us to capture potential heterogeneity in its positive influence. Table 5 displays the results.

Table 5 shows that at the 20%, 40%, 60%, and 80% quantiles (corresponding to Columns (1) through (4)), the estimated coefficients of *lnfi* are 0.047, 0.097, 0.031, and 0.014, respectively, all statistically significant at the 5% level. These findings confirm that the positive effect of *FI* on *CP* holds across different *CP* levels, providing further support for the causal relationship. Specifically, a 1% rise in *FI* is associated with increases in *CP* of 0.047%, 0.097%, 0.031%, and 0.014%, respectively. We further discovered an interesting conclusion: As *CP* increases, the positive impact of *FI* follows an "increase-decrease" inverted "V" pattern, i.e., the positive effect increases when *CP* is lower and shows a declining trend when *CP* is higher.

At lower phases of *CP*, numerous economical carbon reduction opportunities within economic activities remain underexploited. Advancing *FI* enables a wider range of consumers and firms to obtain critical financial support for improving energy use efficiency and embracing clean energy alternatives. At this stage, even modest progress in *FI* can yield a notable rise in *CP*.

Table 5. Results of panel quantile regression

	(1)	(2)	(3)	(4)
	0.2	0.4	0.6	0.8
lnfi	0.047***	0.097**	0.031***	0.014***
	(0.011)	(0.049)	(0.010)	(0.003)
urban	–0.007***	0.043***	0.016**	0.002***
	(0.000)	(0.015)	(0.008)	(0.000)
fmd	0.515***	–1.128*	–0.019	0.410***
	(0.019)	(0.599)	(0.184)	(0.024)
fdi	–0.002***	0.005***	0.002*	–0.001**
	(0.000)	(0.002)	(0.001)	(0.000)
internet	0.008***	0.001	0.009***	0.001**
	(0.000)	(0.002)	(0.002)	(0.000)
trade	–0.215***	0.067	–0.075***	–0.148***
	(0.018)	(0.052)	(0.011)	(0.011)
Observations	330	330	330	330
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Standard errors in parentheses.

However, once *CP* enters a higher stage, further improvements become increasingly complex and costly to achieve. A higher *CP* level typically indicates that OECD countries have already reached a relatively advanced threshold in terms of green and low-carbon innovation. At this point, a "rebound effect" (Yıldırım et al., 2022) may emerge, triggered by further advancements in green innovation. That is, while the widespread adoption of green technologies and energy-saving measures improves efficiency per unit of product or service, it simultaneously reduces the cost of energy use per unit, which may unintentionally lead to a rise in total energy consumption. For instance, improved energy efficiency can reduce production costs and prompt enterprises to expand output, or encourage consumers to increase consumption due to lower costs, thereby potentially increasing overall carbon emissions. This rebound effect limits the marginal role of FI in further enhancing *CP* at higher stages, as its ability to support and incentivize green and low-carbon innovation as well as energy-saving behavior becomes less effective in generating additional improvements in *CP*.

5.3. Mediation mechanism analysis

Table 6 displays the findings from the mediation mechanism study.

Table 6, Column (1), indicates that *FI* exerts a significantly positive direct effect on *CP*. Column (2) reports a coefficient of 0.096 for *lnfi* on *lnconsu*, demonstrating a substantial effect confirmed at the 1% level, highlighting *FI*'s contribution to promoting low-carbon consumption. Integrating the mediator variable *lnconsu* in Column (3) adjusts *lnfi*'s coefficient to 0.010 from Column (1)'s 0.014 direct impact, yet this effect remains statistically important, retaining its significance at the 5% confidence level. From this, we can calculate the mediating effect size of *lnconsu* to be 0.004 (0.014 – 0.010 = 0.004), accounting for approximately 27.3% of the total effect. This indicates that *FI* effectively enhances *CP* by promoting low-carbon consumption, thus validating Hypothesis 2.

Column (4) of Table 6 reports a 0.010 coefficient for *lnfi* affecting *lnestruc*, which is highly significant at the 1% level, reflecting *FI*'s capacity to improve the composition of the energy system. Column (5) incorporates the mediator *lnestruc* alongside Column (1), leading to a reduction in *lnfi*'s coefficient to 0.009 from the initial 0.014 seen in Column (1), yet it retains statistical relevance at the 10% level. The contribution of *lnestruc*'s mediating role is quantified at 0.005 (0.014 – 0.009 = 0.005), representing about 34.5% of the overall effect, confirming that optimizing the energy structure through *FI* significantly boosts *CP*, thereby supporting Hypothesis 3.

Table 6's Column (6) presents a 0.017 coefficient for *lnfi*'s effect on *lnlowtec*, achieving significance at the 1% level, illustrating how *FI* aids in advancing low-carbon technology. Following this, Column (7) integrates the mediator *lnlowtec* with Column (1), where *lnfi*'s coefficient shifts to 0.010 from Column (1)'s direct impact of 0.014, maintaining its significance at the 5% level. The mediating role of *lnlowtec* contributes 0.004 (0.014 – 0.010 = 0.004) to the overall effect, making up about 26.8%. This confirms that *FI* significantly contributes to boosting *CP* via advancements in low-carbon technology, thereby supporting Hypothesis 4.

Table 6. Mediation mechanism analysis results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lncp	*lnconsu*	*lncp*	*lnestruc*	*lncp*	*lnlowtec*	*Lncp*
lnfi	0.014***	0.096***	0.010**	0.101***	0.009*	0.017***	0.010**
	(3.02)	(3.25)	(2.03)	(3.36)	(1.85)	(4.95)	(2.19)
lnconsu			0.039**				
			(2.04)				
lnestruc					0.046**		
					(2.52)		
lnlowtec							0.212**
							(2.50)
CVs	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
R-squared	0.9730	0.9775	0.9734	0.9676	0.9737	0.9881	0.9736
Obs.	330	330	330	330	330	330	330
Sobel test	Z = 1.730, P = 0.084			Z = 2.016, P = 0.044		Z = 2.234, P = 0.025	
Proportion of total effect that is mediated		0.273		0.345		0.268	
Bootstrap	Z = 1.70, P = 0.089			Z = 2.02, P = 0.043		Z = 2.07, P = 0.039	

5.4. Robustness tests

To improve the rigor and credibility of causal inference, this study carried out multiple robustness checks grounded in the benchmark regression. These checks assess the consistency of model outputs from various perspectives, aiming to rule out possible disturbances arising from data irregularities, model specification bias, and variable selection concerns. By employing alternative estimation methods and regression models, adjusting sample ranges to address outliers, substituting dependent variables, and introducing bootstrap resampling techniques, this study systematically and comprehensively strengthens the support for benchmark regression results, providing a more solid empirical foundation for causal inference. For the benchmark regression, Table 7 outlines the findings from the robustness examinations.

Table 7. Results of benchmark regression robustness test

	(1)	(2)	(3)	(4)	(5)
	tobit	*Winsor*	*lnsbm*	*lndcp*	*Bootstrap*
lnfi	0.014**	0.016**	0.016**	0.011**	0.014***
	(2.44)	(2.39)	(2.23)	(2.23)	(2.75)
urban	–0.018	–0.018	–0.025	–0.011	–0.018*
	(–1.63)	(–1.57)	(–1.57)	(–1.60)	(–1.86)
fmd	–0.083	–0.087	–0.216	–0.008	–0.083
	(–0.55)	(–0.57)	(–1.23)	(–0.11)	(–0.71)
fdi	–0.001**	–0.001**	–0.000	0.000	–0.001
	(–2.20)	(–2.17)	(–1.38)	(1.60)	(–1.33)
internet	0.003***	0.003***	0.003*	–0.001	0.003***
	(3.32)	(3.27)	(1.81)	(–0.57)	(3.08)
trade	–0.052	–0.054	–0.139	0.083**	–0.052
	(–0.90)	(–0.92)	(–1.52)	(2.07)	(–1.19)
Constant	1.827*	1.418	2.360*	1.857***	1.424*
	(1.92)	(1.61)	(1.98)	(3.66)	(1.86)
Observations	330	330	330	330	330
R-squared	–	0.255	0.370	0.878	0.253
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: Robust t-value in parentheses; Robust z-value is in parentheses of column (5).

First, an alternative estimation method is used. Considering that the *CP* calculated through the DDF-GML method has clear upper or lower bounds (production possibility frontier), this study switches the estimation method, adopting the Tobit model as suggested by existing research for re-estimation, with results shown in column (1). Second, the sample is trimmed. To reduce the impact of outliers in the benchmark regression, we remove extreme *lnfi* values at the 2.5% and 97.5% quantiles prior to performing the regression analysis. The outcomes are presented in column (2). Third, the dependent variable is replaced. The Carbon Productivity (*CP*) calculated by the DDF-GML is replaced with the *CP* calculated by the SBM-GML method

(*SBM*), and the demand-based carbon productivity (*dcp*). Regression outcomes after the replacement are shown in columns (3) and (4). Fourth, the Bootstrap resampling method is used for parameter estimation. To reduce sample selection bias and achieve unbiased convergence to the overall distribution, thereby increasing estimation accuracy, Bootstrap resampling is used for parameter estimation, with results shown in column (5). After conducting robustness tests using the methods above, the core explanatory variable *lnfi*'s coefficient consistently exhibits positivity and significance, maintaining at a minimum the 5% significance threshold. This demonstrates the reliability of the benchmark regression outcomes.

5.5. Endogeneity treatment

To further ensure the robustness of causal inference, this study addresses potential endogeneity issues, such as bidirectional causality and omitted variable bias, by designing and implementing a series of endogeneity treatment methods. These methods include instrumental variable regression, lagged variable regression, and dynamic panel regression models (specifically, the Difference GMM approach), aimed at mitigating the impact of endogeneity on regression results.

Table 8 displays the results of endogeneity treatment. To mitigate endogeneity caused by bidirectional causality, following the method by Arellano and Bond (1991), this research utilizes the core explanatory variable's one-period lag (*L.lnfi*) as an IV variable and the 2SLS technique is applied for the regression, with findings documented in Table 8, column (1). Moreover, when suitable or reliable external instruments are unavailable, Lewbel's method of constructing instruments from data heteroscedasticity to address endogeneity (Lewbel, 2012), has been broadly adopted (Acheampong & Said, 2024). We apply the Lewbel two-stage least square (Lewbel IV-2SLS) to manage the potential endogeneity, with results shown in column (2). It is crucial to note that the 2SLS and Lewbel IV-2SLS models, in columns (1) and (2) respectively, did not encounter under identification or insufficient instrumental strength. The Lewbel IV-2SLS method did not present overidentification issues. The 2SLS model is just-identified, with one instrument perfectly aligned with one endogenous variable, avoiding any overidentification issues. These observations confirm the validity of the instruments selected.

Additionally, incorporating the one-period lag (*L.lnfi*) or two-period lag (*L2.lnfi*) of the core explanatory variable into the benchmark regression helps mitigate endogeneity arising from reverse causality, with the corresponding results reported in columns (3)–(4), respectively. To counter endogeneity bias from omitted variables, we incorporate the explained variable's one-period lag (*L.lncp*) as a surrogate for missing variables into the benchmark regression and employ the robust difference GMM approach for the dynamic panel regression, with the outcomes displayed in column (5). The Sargan test result is 0.142, supporting the validity of instrument selection. The Arellano-Bond test reveals significant first-order autocorrelation (AR (1) = 0.004), aligning with the anticipated features of a dynamic panel model. Meanwhile, the assessment for second-order autocorrelation shows no statistical significance (AR (2) = 0.107), indicating no evidence of second-order autocorrelation issues and thus supporting the accuracy of the difference GMM model's estimation results.

Table 8. Results of endogeneity treatment

	(1)	(2)	(3)	(4)	(5)
	2SLS	Lewbel IV-2SLS	lag one	lag two	DIF-GMM
L.lnce					0.258***
					(3.77)
L.lnfi			0.016***		
			(3.10)		
L2.lnfi				0.022***	
				(3.16)	
lnfi	0.022***	0.018**			0.013*
	(3.49)	(2.28)			(1.90)
urban	–0.029***	–0.018*	–0.029***	–0.038***	–0.032***
	(–3.23)	(–1.89)	(–3.10)	(–4.88)	(–4.29)
fmd	–0.069	–0.090	–0.043	0.039	0.160
	(–0.57)	(–0.77)	(–0.26)	(0.26)	(1.55)
fdi	–0.001*	–0.001*	–0.001***	–0.001***	–0.001*
	(–1.83)	(–1.81)	(–3.04)	(–3.54)	(–1.88)
internet	0.004***	0.003***	0.004***	0.004***	0.006***
	(4.43)	(3.67)	(4.22)	(4.40)	(4.57)
trade	–0.047	–0.056	–0.052	–0.072	–0.037
	(–1.15)	(–1.32)	(–0.81)	(–1.10)	(–0.61)
Constant	2.667***	1.821**	2.132***	2.804***	
	(3.36)	(2.20)	(3.28)	(5.01)	
Observations	297	330	297	264	231
R–squared	0.978	0.973	0.341	0.411	–
Country FE	YES	YES	YES	YES	–
Year FE	YES	YES	YES	YES	–
Under-identification test	0.000***	0.020**	–	–	–
Weak-identification test	315.615	39.833	–	–	–
Over-identification test	–	0.085	–	–	–
AR (1)	–	–	–	–	0.004
AR (2)	–	–	–	–	0.107
Sargan test	–	–	–	–	0.142

Note: Columns (1), (2), and (5) report robust z-statistics in parentheses; columns (3) and (4) report robust t-statistics.

The Kleibergen-Paap rk LM statistic is used to test for under-identification, the Cragg-Donald Wald F statistic for weak identification, and the Hansen J statistic for over-identification; the under-identification test is significant at the 5% level, indicating no under-identification problem; the weak identification test exceeds the 15% critical value, suggesting the absence of weak instrument bias; the over-identification statistic in column (2) is not significant at the strict 5% level, confirming that there is no over-identification problem.

Given the potential endogeneity stemming from reciprocal causality or omitted variables, observations from columns (1) to (4) display that the coefficient of *lnfi* and its lagged terms consistently remains significantly positive. This underscores the robustness of the important role played by *FI* in enhancing *CP*.

6. Further analysis of heterogeneity

6.1. Heterogeneity of monetary regions

In the OECD countries, more than 40% use the euro, and among the 33 countries studied in this paper, 15 are Eurozone countries. Given the variation in whether the subjects of the study are part of the Eurozone, along with diverse socio-economic factors, the influence of *FI* on *CP* could exhibit heterogeneity. Thus, the study categorizes the sample into two groups for analysis: Eurozone countries (Eurozone) and countries outside the Eurozone (Non-Eurozone). Table 9 displays the outcomes respectively.

Table 9. Results of monetary regional heterogeneity analysis

	(1)	(2)
	Eurozone	Non-Eurozone
lnfi	0.014***	0.021*
	(3.82)	(2.03)
urban	0.005	–0.048***
	(0.46)	(–3.64)
fmd	–0.187	–0.014
	(–1.19)	(–0.06)
fdi	–0.000	–0.000
	(–0.80)	(–1.38)
internet	0.003	0.004***
	(1.62)	(3.26)
trade	–0.137**	–0.076
	(–2.60)	(–0.53)
Constant	–0,0985	3.755***
	(–0.14)	(3.62)
Observations	150	180
R-squared	0.336	0.391
The coefficient difference of lnfi	0.007**	
FP Test	0.03	
Country FE	YES	YES
Year FE	YES	YES

Notes: (1) Robust t-value in parentheses; (2) Given the unequal distribution and variance between the two groups, the inter-group coefficient difference test was conducted using a Bootstrap-based Fisher's Permutation test with 300 resamples to obtain empirical p-values.

The subgroup regression results in Table 9 were subjected to Fisher's permutation test, which revealed a statistically significant divergence in coefficients across the two groups. Specifically, among the 33 OECD member countries, *FI* positively and significantly impacts *CP* in both Eurozone and non-Eurozone countries, with significance verified at least at the 10% level. The coefficient of *lnfi* reaches 0.021 in non-Eurozone countries, exceeding the 0.014 observed in Eurozone countries, suggesting that *FI* exerts a stronger influence on *CP* in the non-Eurozone group.

Variations in how *FI* affects *CP* across Eurozone and non-Eurozone countries can be interpreted from three perspectives: institutional norms, marginal effects, and market penetration. First, due to economic and financial integration, Eurozone countries operate under a unified policy framework and financial market mechanism. While market integration helps reduce carbon intensity (He et al., 2024) and promotes green and low-carbon transitions , the resulting stability also limits the flexibility of *FI* in supporting localized low-carbon projects. In contrast, non-Eurozone countries enjoy greater policy autonomy, allowing *FI* to be tailored to channel financial resources into low-carbon industries more effectively, unlocking its potential to improve *CP*. Second, the high level of financial service coverage in the Eurozone means that the marginal effect of *FI* expansion has diminished, offering limited additional incentives for low-carbon consumption and investment. Conversely, non-Eurozone countries, with relatively lower levels of *FI*, can attract previously underserved consumers and businesses, significantly boosting demand for low-carbon technologies, energy, and consumption, thereby enhancing *CP*. Finally, the less mature financial markets in non-Eurozone countries enable *FI* to play a broader role beyond providing funding. *FI* fosters market efficiency by leveraging innovative payment tools and financing channels, promoting firms' use of energy-efficient technologies, and boosting consumer acceptance of green products. In comparison, the mature financial systems of Eurozone countries rely more on established mechanisms for low-carbon consumption and investment, reducing the incremental contribution of *FI* innovations.

6.2. Heterogeneity under income inequality

Existing cross-country studies have found that income inequality hampers improvements in carbon productivity (Q. Wang et al., 2023). Furthermore, the expansion of income inequality has been shown to exacerbate carbon emissions, a finding that has been confirmed in high-income countries (Baležentis et al., 2020; Knight et al., 2017). Advancing *FI* directly narrows income gaps and helps alleviate inequality, thereby contributing to the reduction of carbon emissions induced by income disparities (Rasheed et al., 2024). Therefore, under relatively higher levels of income inequality, the positive effect of *FI* on *CP* is expected to be stronger and more significant.

Drawing on the preceding analysis, this paper examines the micro-level heterogeneity in *FI*'s effect on *CP* under conditions of high- and low-income inequality. Specifically, we construct an income inequality variable (*incineq*) using data from the United Nations Development Programme (UNDP). Drawing on the existing approach to grouping income inequality (Bai et al., 2020), the sample is split into two groups, labeled "high-income inequality" and "low-income inequality", according to whether a country's annual *incineq* value is above or below the sample mean, and separate regressions are conducted for each group. Regression outcomes are presented in Table 10.

Table 10. Results of heterogeneity under the context of income inequality

	(1)	(2)
	High-income inequality	Low-income inequality
lnfi	0.017**	0.013
	(2.50)	(1.33)
urban	–0.028*	–0.011
	(–2.07)	(–0.55)
fmd	–0.200	0.186
	(–1.19)	(0.64)
fdi	–0.001	–0.001
	(–1.18)	(–1.53)
internet	0.004***	0.004***
	(3.06)	(3.16)
trade	–0.080	0.029
	(–1.57)	(0.13)
Constant	2.243**	0.586
	(2.17)	(0.40)
Observations	160	170
R-squared	0.397	0.271
Country FE	YES	YES
Year FE	YES	YES

Columns (1)–(2) in Table 10 show that under conditions of low-income inequality, the *lnfi* coefficient is positive but lacks statistical significance. In contrast, under relative high-income inequality, the coefficient not only becomes significant at the 5% level but is also larger. This implies that *FI* exerts a stronger effect on enhancing *CP* when income inequality is more pronounced.

Under conditions of high-income inequality, financial and material resources tend to be more concentrated among high-income groups, while low-income groups face more severe credit constraints and financing barriers. In such contexts, *FI* can significantly ease the financial bottlenecks faced by low-income groups in adopting energy-saving technologies and engaging in green consumption practices by improving access to credit and broadening financing opportunities across income segments. For OECD countries, *FI* can facilitate greater participation of small and medium-sized enterprises and individuals in the development or adoption of green technologies and energy-efficient equipment, thereby enhancing *CP* across both production and consumption sectors. Consequently, under high-income inequality, the improvement in resource allocation efficiency brought about by *FI* is amplified, more effectively incentivizing enterprises and individuals to pursue green and low-carbon transitions, which leads to a stronger and more significant positive effect on *CP*.

In contrast, under conditions of low-income inequality, income distribution is relatively balanced, and disadvantaged groups enjoy improved availability of financial support, meaning that disparities in resource allocation across income brackets are less pronounced compared to periods of high inequality. Given the more even income structure, the marginal contribution of *FI* to "bridging" the financing gap and promoting green investments diminishes, resulting in a positive but statistically insignificant effect on *CP*. Moreover, lower levels of income inequality suggest that financial markets, labor markets, and government subsidy mechanisms have already played a partial cushioning role, reducing the incremental impact of *FI* on *CP*. In this scenario, although *FI* may still contribute to *CP* by expanding credit supply and supporting the adoption and innovation of low-carbon technologies, its marginal contribution is limited, resulting in a positive but insignificant effect on *CP*.

6.3. Heterogeneity at different stages of environmental regulation

Environmental regulation may have a phased nature. Initially, the marginal cost of environmental regulation, such as the investment cost for pollution control, is often seen as exceeding its marginal benefits, i.e., the environmental improvements and long-term economic benefits brought about by regulation. Therefore, policymakers might adopt more lenient environmental regulatory strategies to promote short-term economic growth. However, rising environmental harm elevates societal expenses, necessitating the internalization of environmental externalities and escalating the stringency of environmental regulation. Therefore, the impact of *FI* on *CP* may exhibit heterogeneity across different phases of environmental regulation intensity. To explore the heterogeneity in the impact of *FI* on *CP* under phased environmental regulation, We construct the following Hansen panel threshold model (Hansen, 1999) for empirical analysis:

$$\begin{aligned} \ln CP_{it} &= \beta_1 + \beta_2 \ln FI_{it} I\left(\mathrm{Re}\,gu \le \lambda_1\right) + \beta_3 \ln FI_{it} I\left(\lambda_1 < \mathrm{Re}\,gu \le \lambda_2\right) + \cdots + \beta_n \ln FI_{it} I, \\ &\left(\lambda_{n-1} < \mathrm{Re}\,gu \le \lambda_n\right) + \beta_{n+1} \ln FI_{it} I\left(\mathrm{Re}\,gu > \lambda_n\right) + \gamma Controls_{it} + \mu_i + \varepsilon_{it}. \end{aligned} \tag{6}$$

In this EQUATION, *Regu* represents environmental regulation intensity, which serves as the threshold variable, while λ is identified as the threshold value under examination. The indicator function I (·) is defined such that it equals 1 if the specified condition is met, and 0 in all other cases. Possible threshold values are represented by λ_1 through λ_n.

6.3.1. Threshold test

To confirm whether distinct phases of environmental regulation exist during the study period, we first conducted a threshold effect test. Table 11 presents the findings from the environmental regulation threshold test.

Table 11. Environmental regulation threshold test results

	Number of thresholds	F-statistic value	P-value	Threshold value			Number of Sampling
				10%	5%	1%	
Environmental regulation (*regu*)	Single Threshold	16.82**	0.044	14.229	15.921	23.559	500
	Double threshold	6.84	0.434	13.042	15.867	22.177	500
	Triple threshold	5.58	0.790	19.941	22.702	27.924	500

Analysis in Table 11, specifically within columns (2) and (3), reveals that double and triple threshold tests lack statistical significance, yet the single threshold demonstrates significance at the 5% level, affirming a singular threshold effect in environmental regulation. The calculated threshold value for *Regu* is 2.740.

6.3.2. Analysis of panel threshold regression results

Upon verifying the presence of two environmental regulation phases during the study period, we conducted a single-threshold panel regression, with the results reported in Table 12.

Table 12. Panel threshold regression results

	Infi						
	Regu < 2.740	*regu* > 2.740	*urban*	*fmd*	*fdi*	*internet*	*trade*
Coefficient	0.011**	0.030***	–0.027***	–0.245*	–0.001**	0.002**	–0.010
Robust T-value	2.49	4.75	–3.08	–1.93	–2.22	2.25	–0.21

Table 12 shows that *FI* significantly enhances *CP* at or beyond a 5% significance throughout two phases. For *Regu* below 2.740, the impact of *FI* is measured at 0.011; when exceeding 2.740, this impact strengthens to 0.030. This confirms a distinct threshold effect on the nexus between *FI* and *CP*. Specifically, with *Regu* below 2.740, a 1% rise in *FI* contributes to a 0.011% increase in *CP*; above this threshold, the same 1% increase enhances *CP* by 0.03%.

The influence of *FI* on *CP* exhibits a "positive acceleration effect" with the emergence of the *Regu* threshold effect. In phases with less stringent environmental regulation, financial inclusivity contributes to broader economic engagement and diversification, thereby enhancing efficiency. This includes the adoption of technologies aimed at conserving energy and cutting emissions, which leads to an initial enhancement in *CP*. Nonetheless, once environmental regulations intensify beyond a certain threshold, these policies not only elevate pollution and emission-related expenses but also diminish investment costs in low-carbon innovations through a variety of incentivizing measures, thereby directly increasing the market demand for low-carbon technologies and solutions. For example, in 2016, Canada implemented the Pan-Canadian Framework on Clean Growth and Climate Change (PCF), marking a key step in strengthening environmental regulations. Under this framework, the Greenhouse Gas Pollution Pricing Act established a minimum national standard for greenhouse gas emissions pricing, beginning at CAD 20 per ton, which significantly increased the cost of carbon pollution and emissions. In addition, the PCF introduced multiple initiatives to spur technological innovation, including tax credits, innovation incentives, and research funding. One such example is the CAD 155 million Clean Growth Program launched by the Canadian federal government in 2018. These measures substantially reduce the investment costs of low-carbon innovation for businesses and research institutions. At this point, the role of *FI* shifts toward more directly and broadly supporting the flow of funds into low-carbon technology development and commercialization. Hence, the beneficial combined influence of financial inclusivity alongside environmental regulation significantly enhances the incremental positive effect on *CP* attributed to *FI*.

7. Research conclusions and policy recommendations

The nexus between Financial Inclusion (*FI*) or digital finance and carbon emissions or Carbon Productivity (*CP*) has been the subject of prior research. However, these studies exhibit certain limitations and gaps, such as the inability of existing *FI* indicators to comprehensively capture both traditional and digital dimensions across multiple facets, a scarcity of cross-country analyses with specifically tailored metrics, and a predominant focus on the relationship between FI, digital finance, and carbon emissions while overlooking *CP*. Utilizing data from 33 OECD member countries spanning 2010 to 2019, this study constructs comprehensive measures for *FI* and *CP*, and offers novel cross-national evidence on the nuanced effect of *FI* on *CP*, an issue that remains underexplored in the existing literature.

Our main conclusions are as follows: (1) The development of *FI* significantly enhances *CP* through its direct impact, with a marginal effect of 0.014%. This finding remains robust after various robustness checks and addressing endogeneity concerns. (2) Panel quantile regression further confirms the consistent causal relationship between *FI* and *CP*. Additionally, an intriguing pattern is observed: As *CP* increases, the positive impact of *FI* follows an "increase-decrease" inverted "V" pattern, where the positive impact is stronger at lower *CP* levels and gradually diminishes as *CP* improves. (3) The analysis of indirect impact reveals that *FI* contributes to *CP* improvement through three major intermediary mechanisms: promoting low-carbon consumption, optimizing the low-carbon energy structure, and advancing low-carbon technological innovation. (4) Further analysis uncovers significant heterogeneities across monetary regions, income inequality levels, and environmental regulation stages. Specifically, *FI* demonstrates a stronger effect on *CP* in non-Eurozone economies, under higher levels of income inequality, and during the phase with stricter environmental regulation. Based on this, the following policy recommendations are proposed:

(1) Focus *FI* on key low-carbon areas

This study identifies three major mechanisms through which *FI* enhances *CP* indirectly. Therefore, the development of *FI* should concentrate more on critical areas of the low-carbon transition, such as supporting low-carbon consumption, promoting low-carbon technology innovation and diffusion, and optimizing the low-carbon energy structure. Specifically, governments and financial institutions should prioritize channeling financial resources toward low-carbon transition projects in high-carbon-emission industries, green technology innovation enterprises, and clean energy promotion initiatives. By offering targeted financial services such as green loans, green bonds, and low-interest financing policies, the financial barriers for related projects can be lowered, accelerating *CP* improvement.

(2) Formulate context-specific *FI* strategies

Countries should develop tailored policies based on their economic conditions, *CP* levels, and financial development status. In countries with lower *CP* levels, policy efforts should prioritize the uptake of foundational low-carbon technologies and clean energy by broadening *FI* coverage to extend financial support to more enterprises and households. In countries with higher *CP* levels, emphasis should shift toward fostering innovation in advanced low-carbon technologies and promoting the circular economy, thereby accelerating the move toward a zero-carbon economy through the use of sophisticated financial instruments.

(3) Strengthen *FI* and regulation integration

Environmental regulation serves as a crucial pathway to amplify the positive impact of *FI* on *CP*. Governments should strengthen environmental regulation and refine financial incentive policies, including carbon taxes, emissions trading schemes, and fiscal subsidies, to provide more robust policy support for green, low-carbon investment and consumption. Furthermore, financial institutions should be encouraged to develop more green financial products, such as energy-saving loans and carbon emission credit schemes, offering low-cost financing to enterprises and individuals to further strengthen the synergistic effect of *FI* and environmental regulation in boosting *CP*.

(4) Maximize *FI*'s Impact Under High Income Inequality

The study reveals that *FI* has a more pronounced positive influence on *CP* in the context of relatively high-income inequality. Policymakers should pay special attention to low-income groups during times of widening income disparity by leveraging inclusive financial tools, such as microloans, installment payment schemes, and green subsidies, to lower the economic barriers for low-income households in adopting green consumer goods (e.g., electric vehicles and energy-efficient appliances). Meanwhile, financial institutions should be incentivized to facilitate the green transformation of Small and Medium-Sized Enterprises (SMEs) by easing their financing pressures during the low-carbon transition and enhancing energy efficiency.

(5) Promote the coordinated advancement of *FI* in OECD countries

OECD countries should reinforce international collaboration in developing inclusive finance to foster its broader and more balanced progress across the region. By establishing a governance framework for *FI* among member states and accelerating the development of digital financial infrastructure, entry barriers to cross-border financial services can be lowered, thereby expanding access to financial resources for a wider range of enterprises, individuals, and households in support of carbon productivity enhancement and low-carbon transformation. Furthermore, OECD members are encouraged to formulate unified standards for digital *FI* to facilitate technological exchange and cooperative development in the digital finance domain. Advancing both traditional and digital *FI* will help improve overall financial inclusiveness and enable more countries to benefit from low-carbon development supported by inclusive finance.

A core contribution of this study is its empirical validation of the positive relationship between Financial Inclusion (*FI*) and Carbon Productivity (*CP*) across countries, along with an exploration of the underlying mechanisms and heterogeneity, thus addressing a gap in the current literature. Considering the significant influence of *FI* on *CP* within OECD nations, the findings provide fresh perspectives for promoting low-carbon development through the comprehensive development of financial inclusion. Nevertheless, our study also has certain limitations. In the mediation mechanism analysis, the mediating effect of the variable *lnconsu*, as tested through both the Sobel test and the bootstrap method, is only significant at the 10% level, which is relatively lenient in statistical inference. Furthermore, we acknowledge that the positive impact of *FI* on *CP* may operate through other potential channels. Finally, future research could further explore and validate the impact of *FI* on *CP* using alternative cross-national samples, such as emerging economies, to more comprehensively reveal its regional differences and characteristics on a global scale, providing new directions for continued research in this field.

Acknowledgements

This study was funded by the National Natural Science Foundation of China (Grant number: 72463030, 72504076); National Social Science Fund of China (Grant number: 22BJY125); Humanities and Social Sciences Research Project of the Ministry of Education (Grant number: 24XJJAZH002); Hainan Province Nanhai New Star Project Philosophy and Social Science Talent Project: Research on the Impact of Mobile Payment on Inclusive Green Growth.

References

Acheampong, A. O., & Said, R. (2024). Financial inclusion and the global net-zero emissions agenda: Does governance quality matter? *Energy Economics*, *137*, Article 107785. https://doi.org/10.1016/j.eneco.2024.107785

Anu, Singh, A. K., Raza, S. A., Nakonieczny, J., & Shahzad, U. (2023). Role of financial inclusion, green innovation, and energy efficiency for environmental performance? Evidence from developed and emerging economies in the lens of sustainable development. *Structural Change and Economic Dynamics*, *64*, 213–224. https://doi.org/10.1016/j.strueco.2022.12.008

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: monte carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Aziz, A., & Naima, U. (2021). Rethinking digital financial inclusion: Evidence from Bangladesh. *Technology in Society*, *64*, Article 101509. https://doi.org/10.1016/j.techsoc.2020.101509

Bai, C., Feng, C., Yan, H., Yi, X., Chen, Z., & Wei, W. (2020). Will income inequality influence the abatement effect of renewable energy technological innovation on carbon dioxide emissions? *Journal of Environmental Management*, *264*, Article 110482. https://doi.org/10.1016/j.jenvman.2020.110482

Bai, G., Shen, Z., Šermukšnytė-Alešiūnienė, K., Štreimikienė, D., & Li, T. (2024). Energy structure and green productivity dynamics: Investigation from OECD Countries. *Resources Policy*, *98*, Article 105309. https://doi.org/10.1016/j.resourpol.2024.105309

Baležentis, T., Liobikienė, G., Štreimikienė, D., & Sun, K. (2020). The impact of income inequality on consumption-based greenhouse gas emissions at the global level: A partially linear approach. *Journal of Environmental Management*, *267*, Article 110635. https://doi.org/10.1016/j.jenvman.2020.110635

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. https://doi.org/10.1037//0022-3514.51.6.1173

Beck, T., Demirgüç-Kunt, A., & Honohan, P. (2009). Access to financial services: Measurement, impact, and policies. *World Bank Research Observer*, *24*(1), 119–145. https://doi.org/10.1093/wbro/lkn008

Can, M., Ahmed, Z., Mercan, M., & Kalugina, O. A. (2021). The role of trading environment-friendly goods in environmental sustainability: Does green openness matter for OECD countries? *Journal of Environmental Management*, *295*, Article 113038. https://doi.org/10.1016/j.jenvman.2021.113038

Chibba, M. (2009). Financial inclusion, poverty reduction and the millennium development goals. *The European Journal of Development Research*, *21*, 213–230. https://doi.org/10.1057/ejdr.2008.17

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, *51*(3), 229–240. https://doi.org/10.1006/jema.1997.0146

Dong, F., Li, Y., Gao, Y., Zhu, J., Qin, C., & Zhang, X. (2022). Energy transition and carbon neutrality: Exploring the non-linear impact of renewable energy development on carbon emission efficiency in developed countries. *Resources, Conservation and Recycling*, *177*, Article 106002. https://doi.org/10.1016/j.resconrec.2021.106002

Elheddad, M., Benjasak, C., Deljavan, R., Alharthi, M., & Almabrok, J. M. (2021). The effect of the Fourth Industrial Revolution on the environment: The relationship between electronic finance and pollution in OECD countries. *Technological Forecasting and Social Change*, *163*, Article 120485. https://doi.org/10.1016/j.techfore.2020.120485

Färe, R., Grosskopf, S., & Pasurka, Jr, C. A. (2007). Environmental production functions and environmental directional distance functions. *Energy*, *32*(7), 1055–1066. https://doi.org/10.1016/j.energy.2006.09.005

Feng, S., Zhang, R., & Li, G. (2022). Environmental decentralization, digital finance and green technology innovation. *Structural Change and Economic Dynamics*, *61*, 70–83. https://doi.org/10.1016/j.strueco.2022.02.008

Ferreira, A., Pinheiro, M. D., de Brito, J., & Mateus, R. (2018). Combined carbon and energy intensity benchmarks for sustainable retail stores. *Energy*, *165*, 877–889. https://doi.org/10.1016/j.energy.2018.10.020

Fungáčová, Z., & Weill, L. (2015). Understanding financial inclusion in China. *China Economic Review*, *34*, 196–206. https://doi.org/10.1016/j.chieco.2014.12.004

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, *35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., & Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Quarterly*, *19*(4), 1401–1418.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, *93*(2), 345–368. https://doi.org/10.1016/S0304-4076(99)00025-1

He, M., Xiao, W., Fan, M., & Xu, Y. (2024). Heterogeneity analysis of carbon intensity influence factor and low carbon economy path in east of China. *Resources*, *Conservation* & *Recycling Advances*, *21*, Article 200208. https://doi.org/10.1016/j.rcradv.2024.200208

Hussain, M., Lin, Y., & Wang, Y. (2023). Measures to achieve carbon neutrality: What is the role of energy structure, infrastructure, and financial inclusion. *Journal of Environmental Management*, *325*, Article 116457. https://doi.org/10.1016/j.jenvman.2022.116457

Innovations for Poverty Action. (n.d.). *Climate change and financial inclusion*. https://www.poverty-action.org/sites/default/files/publications/Climate-Change-Financial-Inclusion_Final.pdf

Intergovernmental Panel on Climate Change. (2023). Summary for policymakers. In Core Writing Team, H. Lee, & J. Romero (Eds.), *Climate change 2023*: *Synthesis report*. *Contribution of working groups I*, *II and III to the sixth assessment report of the Intergovernmental Panel on Climate Change* (pp. 1–34). IPCC https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_FullVolume.pdf

Jin, L., Dai, J., Jiang, W., & Cao, K. (2023). Digital finance and misallocation of resources among firms: Evidence from China. *The North American Journal of Economics and Finance*, *66*, Article 101911. https://doi.org/10.1016/j.najef.2023.101911

Kabakova, O., & Plaksenkov, E. (2018). Analysis of factors affecting financial inclusion: Ecosystem view. *Journal of Business Research*, *89*, 198–205. https://doi.org/10.1016/j.jbusres.2018.01.066

Karpowicz, I. (2014). *Financial inclusion, growth and inequality: A model application to Colombia* (IMF Working Paper 14/166). International Monetary Fund. https://doi.org/10.5089/9781498344838.001

Khan, K., Luo, T., Ullah, S., Rasheed, H. M. W., & Li, P.-H. (2023). Does digital financial inclusion affect CO_2 emissions? Evidence from 76 emerging markets and developing economies (EMDE's). *Journal of Cleaner Production*, *420*, Article 138313. https://doi.org/10.1016/j.jclepro.2023.138313

Khan, S., Murshed, M., Ozturk, I., & Khudoykulov, K. (2022). The roles of energy efficiency improvement, renewable electricity production, and financial inclusion in stimulating environmental sustainability in the Next Eleven countries. *Renewable Energy*, *193*, 1164–1176. https://doi.org/10.1016/j.renene.2022.05.065

Khera, P., Ng, S., Ogawa, S., & Sahay, R. (2021). *Measuring digital financial inclusion in emerging market and developing economies: A new index* (IMF Working Paper 21/90). International Monetary Fund. https://doi.org/10.5089/9781513574196.001

Khera, P., Ng, S., Ogawa, S., & Sahay, R. (2022). Measuring digital financial inclusion in emerging market and developing economies: A new index. *Asian Economic Policy Review*, *17*(2), 213–230. https://doi.org/10.1111/aepr.12377

Knight, K. W., Schor, J. B., & Jorgenson, A. K. (2017). Wealth inequality and carbon emissions in high-income countries. *Social Currents*, *4*(5), 403–412. https://doi.org/10.1177/2329496517704872

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, *91*(1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006

Le, T.-H., Le, H.-C., & Taghizadeh-Hesary, F. (2020). Does financial inclusion impact CO_2 emissions? Evidence from Asia. *Finance Research Letters*, *34*, Article 101451. https://doi.org/10.1016/j.frl.2020.101451

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, *30*(1), 67–80. https://doi.org/10.1080/07350015.2012.643126

Li, K., & Lin, B. (2015). Metafroniter energy efficiency with CO_2 emissions and its convergence analysis for China. *Energy Economics*, *48*, 230–241. https://doi.org/10.1016/j.eneco.2015.01.006

Lin, B., & Zhou, Y. (2021). Does the Internet development affect energy and carbon emission performance? *Sustainable Production and Consumption*, *28*, 1–10. https://doi.org/10.1016/j.spc.2021.03.016

Luderer, G., Madeddu, S., Merfort, L., Ueckerdt, F., Pehl, M., Pietzcker, R., Rottoli, M., Schreyer, F., Bauer, N., Baumstark, L., Bertram, C., Dirnaichner, A., Humpenöder, F., Levesque, A., Popp, A., Rodrigues, R., Strefler, J., & Kriegler, E. (2022). Impact of declining renewable energy costs on electrification in low-emission scenarios. *Nature Energy*, *7*, 32–42. https://doi.org/10.1038/s41560-021-00937-z

Ma, N., Sun, W., Wang, Z., Li, H., Ma, X., & Sun, H. (2023). The effects of different forms of FDI on the carbon emissions of multinational enterprises: A complex network approach. *Energy Policy*, *181*, Article 113731. https://doi.org/10.1016/j.enpol.2023.113731

Marques, A. C., & Caetano, R. (2020). The impact of foreign direct investment on emission reduction targets: Evidence from high-and middle-income countries. *Structural Change and Economic Dynamics*, *55*, 107–118. https://doi.org/10.1016/j.strueco.2020.08.005

Oanh, T. T. K. (2024). Digital financial inclusion in the context of financial development: Environmental destruction or the driving force for technological advancement. *Borsa Istanbul Review*, *24*(2), 292–303. https://doi.org/10.1016/j.bir.2024.01.003

Oh, D.-h. (2010). A global Malmquist-Luenberger productivity index. *Journal of Productivity Analysis*, *34*, 183–197. https://doi.org/10.1007/s11123-010-0178-y

Park, C.-Y., & Mercado, R. V. (2018). *Financial inclusion*: *New measurement and cross-country impact assessment* (ADB Working Paper No. 539). Asian Development Bank.

Peng, K., Feng, K., Chen, B., Shan, Y., Zhang, N., Wang, P., Fang, K., Bai, Y., Zou, X., Wei, W., Geng, X., Zhang, Y., & Li, J. (2023). The global power sector's low-carbon transition may enhance sustainable development goal achievement. *Nature Communications*, *14*, Article 3144. https://doi.org/10.1038/s41467-023-38987-4

Qin, L., Raheem, S., Murshed, M., Miao, X., Khan, Z., & Kirikkaleli, D. (2021). Does financial inclusion limit carbon dioxide emissions? Analyzing the role of globalization and renewable electricity output. *Sustainable Development*, *29*(6), 1138–1154. https://doi.org/10.1002/sd.2208

Rasheed, S., Adeneye, Y., & Farooq, R. (2024). Income inequality and carbon emissions in Asia: Does financial inclusion matter? *Sustainable Development*, *32*(5), 5274–5293. https://doi.org/10.1002/sd.2974

Renzhi, N., & Baek, Y. J. (2020). Can financial inclusion be an effective mitigation measure? Evidence from panel data analysis of the environmental Kuznets curve. *Finance Research Letters*, *37*, Article 101725. https://doi.org/10.1016/j.frl.2020.101725

Sæther, S. R. (2021). Climate policy choices: An empirical study of the effects on the OECD and BRICS power sector emission intensity. *Economic Analysis and Policy*, *71*, 499–515. https://doi.org/10.1016/j.eap.2021.06.011

Shahbaz, M., Li, J., Dong, X., & Dong, K. (2022). How financial inclusion affects the collaborative reduction of pollutant and carbon emissions: The case of China. *Energy Economics*, *107*, Article 105847. https://doi.org/10.1016/j.eneco.2022.105847

Shaikh, A. A., Glavee-Geo, R., Karjaluoto, H., & Hinson, R. E. (2023). Mobile money as a driver of digital financial inclusion. *Technological Forecasting and Social Change*, *186*, Article 122158. https://doi.org/10.1016/j.techfore.2022.122158

Song, M., Zhu, S., Wang, J., & Zhao, J. (2020). Share green growth: Regional evaluation of green output performance in China. *International Journal of Production Economics*, *219*, 152–163. https://doi.org/10.1016/j.ijpe.2019.05.012

Sun, L.-X., Xia, Y.-S., & Feng, C. (2021). Income gap and global carbon productivity inequality: A meta-frontier data envelopment analysis. *Sustainable Production and Consumption*, *26*, 548–557. https://doi.org/10.1016/j.spc.2020.12.026

Tang, S., Wu, X., & Zhu, J. (2020). Digital finance and enterprise technology innovation: Structural feature, mechanism identification and effect difference under financial supervision. *Management World*, *36*(5), 52–66.

Uras, B. R. (2014). Corporate financial structure, misallocation and total factor productivity. *Journal of Banking & Finance*, *39*, 177–191. https://doi.org/10.1016/j.jbankfin.2013.11.011

Wang, X., & Guan, J. (2017). Financial inclusion: Measurement, spatial effects and influencing factors. *Applied Economics*, *49*(18), 1751–1762. https://doi.org/10.1080/00036846.2016.1226488

Wang, S., Xie, Z., Wu, R., & Feng, K. (2022). How does urbanization affect the carbon intensity of human well-being? A global assessment. *Applied Energy*, *312*, Article 118798. https://doi.org/10.1016/j.apenergy.2022.118798

Wang, Q., Li, L., & Li, R. (2023). Uncovering the impact of income inequality and population aging on carbon emission efficiency: An empirical analysis of 139 countries. *Science of The Total Environment*, *857*, Article 159508. https://doi.org/10.1016/j.scitotenv.2022.159508

Wu, F., Zhou, P., & Zhou, D. (2020). Modeling carbon emission performance under a new joint production technology with energy input. *Energy Economics*, *92*, Article 104963. https://doi.org/10.1016/j.eneco.2020.104963

Wu, J. (2023). Nexus analysis of financial management, digital finance and new technologies. *Global Finance Journal*, *57*, Article 100869. https://doi.org/10.1016/j.gfj.2023.100869

Yang, H., Shahzadi, I., & Hussain, M. (2021). USA carbon neutrality target: Evaluating the role of environmentally adjusted multifactor productivity growth in limiting carbon emissions. *Journal of Environmental Management*, *298*, Article 113385. https://doi.org/10.1016/j.jenvman.2021.113385

Yasmeen, R., Tao, R., Shah, W. U. H., & Shair, W. (2024). Repercussions of environmental policy stringency on carbon, energy and non-energy productivity in highly emerging economies: Perspective of green growth. *Environmental Science and Pollution Research*, *31*, 4500–4517. https://doi.org/10.1007/s11356-023-31424-5

Yıldırım, D. Ç., Esen, Ö., & Yıldırım, S. (2022). The nonlinear effects of environmental innovation on energy sector-based carbon dioxide emissions in OECD countries. *Technological Forecasting and Social Change*, *182*, Article 121800. https://doi.org/10.1016/j.techfore.2022.121800

Zhang, L., Xiong, L., Cheng, B., & Yu, C. (2018). How does foreign trade influence China's carbon productivity? Based on panel spatial lag model analysis. *Structural Change and Economic Dynamics*, *47*, 171–179. https://doi.org/10.1016/j.strueco.2018.08.008

Zhou, P., Ang, B. W., & Han, J. Y. (2010). Total factor carbon emission performance: A Malmquist index analysis. *Energy Economics*, *32*(1), 194–201. https://doi.org/10.1016/j.eneco.2009.10.003

Zhou, G., Zhu, J., & Luo, S. (2022). The impact of fintech innovation on green growth in China: Mediating effect of green finance. *Ecological Economics*, *193*, Article 107308. https://doi.org/10.1016/j.ecolecon.2021.107308

APPENDIX

Construction process for the dependent variable carbon productivity

(1) Basic assumptions

Building on the work of (Färe et al., 2007), we view each member nation as a distinct decision-making unit (DMU). It is presumed that every entity utilizes N categories of production inputs $x = (x_1, x_2, x_3 ..., x_N) \in R_+^N$, yields K categories of intended outputs $y = (y_1, y_2, y_3, ..., y_K) \in R_+^K$, and produces L categories of unintended outputs. $b = (b_1, b_2, b_3, ..., b_L) \in R_+^L$. The set of production possibilities formed by these inputs and outputs is shown below:

$$P(x) = \{(x, y, b) : x \text{ can produce } (y, b)\}. \quad (7)$$

In Eq. (7), $P(x)$ also represents joint production technology but needs to satisfy some properties, as specified below:

(1) $P(x') \supseteq P(x)$ if $x' \geq x$; (8)

(2) $(y', b) \in P(x)$ if $(y, b) \in P(x)$ and $y' \leq y$; (9)

(3) $(\lambda y, \lambda b) \in P(x)$ if $(y, b) \in P(x)$ and $0 \leq \lambda \leq 1$; (10)

(4) $y = 0$ if $(y, b) \in P(x)$ and $b = 0$. (11)

Property 1 states the strong disposability of inputs, meaning increasing or maintaining inputs does not reduce the production possibility set (Färe et al., 2007). Property 2 describes the strong disposability of intended outputs, allowing for their free reduction at a given input level. Property 3 highlights the weak disposability of undesired outputs, indicating that reducing them requires a simultaneous reduction in desired outputs, reflecting associated costs. Property 4, the axiom of null-jointness, asserts that desired outputs cannot exist without undesired outputs, underscoring their inseparability in the production process.

With Variable Returns to Scale (VRS), the Production Possibility Set (PPS) is specified through this model:

$$P(x) = \left\{(x, y, b) : \sum_{v=1}^{n} z_v x_{iv} \leq x_v, \sum_{v=1}^{n} z_v y_{mv} \geq y_v, \sum_{v=1}^{n} z_v \theta_v b_{tv} = b_v, \sum_{v=1}^{n} z_v = 1, z_v \geq 0\right\}. \quad (12)$$

The non-negative intensity variable $z_v (v = 1, ..., n)$ is used to construct the boundary of PPS. θ_v is the suppression factor. $\sum_{v=1}^{n} z_v = 1$ ensures that it meets the conditions of VRS, setting constraint $\sum_{v=1}^{n} z_v \theta_v b_{tv} = b_v$ to ensure the weak disposability of undesired outputs (Wu et al., 2020). Notably, the model must also comply with the four previously discussed property assumptions.

(2) Directional Distance Function (DDF)

The DDF calculates the proximity of DMUs to the production boundary, accounting for both desirable and undesirable outputs. It seeks to maximize the generation of desirable outputs while reducing input consumption and the production of undesirable outputs to the greatest extent possible (Oh, 2010). Notably, the production boundary corresponds to the boundary of the PPS constructed in the previous assumptions. Therefore, the DDF is defined under the constraints of the PPS.

Following the approach of Chung et al. (1997), the DDF that assesses each DMU's carbon productivity (*CP*) is specified as follows:

$$\vec{D}(x,y,b,\vec{g}) = \sup\left\{\beta \middle| (x-\beta\vec{g}_x, y+\beta\vec{g}_y, b-\beta\vec{g}_b) \in P(x)\right\}. \tag{13}$$

Eq. (13) utilizes $\vec{g} = (-\vec{g}_x, \vec{g}_y, -\vec{g}_b)$ as the direction vector to reduce inputs (labor, capital, energy), increase desired outputs (GDP), and decrease undesired outputs (CO2) simultaneously. The vector β measures the degree of DMU inefficiency, that is, the gap between DMUs and the production frontier (best production possibility). At β = 1 implies that the DMU operates at the production boundary, signifying optimal efficiency. Conversely, if β = 0, it reveals inefficiencies within the DMU, highlighting opportunities for enhancing efficiency.

(3) Global Malmquist-Luenberger Index

Adopting the methodology by Chung et al. (1997), *CP* assessment integrates the DDF and the Malmquist-Luenberger (ML) index. Nevertheless, the ML index, using a geometric mean representation, has drawbacks such as not having circularity, lacking transitivity, and not being additive, thus it cannot effectively reflect the dynamic trend of *CP* changes. Moreover, the ML index faces challenges in linear programming solvability when assessing the directional distance function over time. Consequently, this research adopts an enhanced approach, utilizing the DDF alongside the Global Malmquist-Luenberger (GML) index, an advancement on the ML index by Oh (2010), to evaluate the *CP* of each DMU.

The global production possibility set is outlined as follows:

$$P^G(x) = P^1(x^1) \cup P^2(x^2) \cup P^3(x^3) \cup \ldots \cup P^h(x^h). \tag{14}$$

Eq. (14) defines the global production possibility set $P^G(x)$ as encompassing the cumulative production capabilities of every DMU over all periods, from the first to period h. Consequently, the global DDF for each DMU in period *t* can be represented as:

$$\vec{D}^G(x^t, y^t, b^t, \vec{g}) = \sup\left\{\beta \middle| (x-\beta\vec{g}_x, y+\beta\vec{g}_y, b-\beta\vec{g}_b) \in P^G(x^G)\right\}, \tag{15}$$

$t = 1,\ldots,h$ in Equation (15). Utilizing the global DDF, the GML index along with its breakdown for any DMU between period *t* and *t* + 1 is presented as follows:

$$\begin{aligned}
&GML_t^{t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \\
&\frac{1+D^G(x^t, y^t, b^t)}{1+D^G(x^{t+1}, y^{t+1}, b^{t+1})} = \\
&\frac{1+D^t(x^t, y^t, b^t)}{1+D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \left[\frac{1+D^G(x^t, y^t, b^t)}{1+D^t(x^t, y^t, b^t)} \times \frac{1+D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{1+D^G(x^{t+1}, y^{t+1}, b^{t+1})}\right] = \\
&\frac{TE^{t+1}}{TE^t} \times \frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}} = \\
&EC_t^{t+1} \times TC_t^{t+1}.
\end{aligned} \tag{16}$$

In Eq. (16), GML_{t+1}^{t} captures the production's relative change rate for each DMU between period t and t + 1, essentially assessing *CP* as the study's focus. TE^{t} assesses each DMU's technical efficiency at time t, while EC_{t+1}^{t} denotes the shift in technical efficiency for each DMU across periods t to t + 1. TC_{t+1}^{t} quantifies the best practice gap (BPC) from each DMU's technological edge at time t to the global benchmark, and from the technological edge at t + 1 to the global standard. If the value of GML_{t+1}^{t}, EC_{t+1}^{t}, TC_{t+1}^{t}, are all greater than 1, they respectively indicate an improvement in carbon efficiency, an improvement in technical efficiency, and technological progress, while values less than 1 reflect a decline or regression in these areas. The GML index along with its detailed components help uncover the underlying trends and factors influencing carbon productivity enhancement.