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The Digital Economy, R&D Investments, and CO_2 Emissions: Unraveling Reduction Potentials in China

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Abstract: This study explores the relationships between the digital economy, R&D investment, and carbon emissions, as well as the mediating role of financial technology (fintech). Despite a growing body of research, the impact of the digital economy on carbon emissions remains contested, partly due to the limited scope and inconsistent measures in existing studies. Additionally, while R&D is a pivotal driver of modern development, its potential quadratic effects on carbon emissions in China remain unexplored. By employing a comprehensive Digital Economy Index and analyzing panel data from 2011 to 2020 across Chinese regions, this study provides new insights into how digitalization and innovation influence carbon emissions. The findings reveal a positive linear correlation between the digital economy and CO_2 emissions over the last decade. Moreover, R&D investments exhibit an inverse U-shaped relationship with emissions, acting as an effective factor in reducing CO_2 emissions. Notably, the turning point of this relationship occurs in Quadrant I, where most regions are clustered, indicating substantial efficiency gains from early-stage R&D investments and their significant potential to enhance sustainable development. Furthermore, fintech emerges as a significant mediator in the R&D–emissions dynamic, underscoring its critical role in this context.

Keywords: CO_2 emissions; digital economy; R&D investment; fintech; inverse U-shaped relationship; Environmental Kuznets Curve (EKC); China

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1. Introduction

Greenhouse gas emissions, particularly from carbon dioxide, are the primary catalyst for global warming [1]. As of 2019, China stands as the largest contributor to carbon dioxide emissions, accounting for more than 25% of the world's total CO_2 output [2]. China's CO_2 emissions surged from 3385 to 10.79 billion metric tons (Mt) between 2000 and 2020, though there was a brief decline between 2013 and 2016 [3]. Despite these fluctuations, emissions have not yet peaked [4]. Contributing factors include a heavy reliance on coal and rapid economic and industrial expansion [5–7]. To address the issue, the Chinese government has launched numerous initiatives aimed at lowering emissions [8].

The digital economy, defined as a transformative force reshaping industry value chains [9], has become integral to economic growth and energy efficiency [10]. In 2020, the digital economy in China grew to CNY 39.2 trillion, which accounted for 38.6% of the nation's Gross Domestic Product and experienced an 8.2% growth rate, placing it second worldwide [11].

The relationship between the digital economy and CO_2 emissions remains debated. Several studies argue that advancements in digital technologies contribute to emission

reductions by facilitating technological progress and enhancing industrial efficiency [12,13]. Conversely, other research indicates that as the digital economy expands, there is a corresponding rise in energy consumption and emissions [14,15]. Moreover, some studies suggest a non-linear dynamic, where the influence of the digital economy on emissions increases at first and later declines as development continues [16,17]. This intricate relationship corresponds with the Environmental Kuznets Curve (EKC) theory, which suggests that economic growth initially leads to an increase in pollution levels, but eventually results in a decrease as a nation achieves a specific level of development, leading to what is known as the 'green effect' [18]. Despite these insights, current research on the digital economy's effects is fragmented, highlighting the need for a more unified and comprehensive approach to measuring digital economy effects, beyond isolated aspects such as digital infrastructure or industrial scale. These approaches may not entirely encompass the digital economy as a system that is fundamentally fueled by digital information, knowledge, and technology [19].

Beyond the influence of the digital economy, research and development (R&D) is essential for growth driven by innovation. From 2006 to 2017, R&D spending increased across all 30 provinces in China [20]. However, the direct relationship between R&D investments and CO_2 emissions remains underexplored, with conflicting findings. While technological advancements resulting from R&D often lead to reductions in CO_2 emissions [21], the high costs of new technologies can sometimes increase emissions if their benefits are not immediately realized or broadly adopted [22]. The fluctuation in how R&D influences CO_2 emissions aligns with the Environmental Kuznets Curve (EKC) theory, which posits that environmental degradation tends to rise with initial economic growth but eventually diminishes as economies mature [18]. However, the alignment of regional R&D investments with the EKC in China remains unexplored.

Innovation demands significant and sustained capital investment, frequently exceeding internal financing capabilities [23]. Financial technology (fintech) has markedly enhanced financial support for innovation and green R&D [24,25]. In China, fintech policies have been shown to support sustainable innovation and enhance business performance without increasing risk [26]. By December 2021, China was home to 183,511 registered fintech firms, reflecting a rise of 36,082 new companies—a 28.08% increase compared to the previous year [27]. This study posits that the investment in R&D influences CO_2 emissions through the mediating effect of fintech, an area that has not been extensively investigated.

Our study makes three key contributions. Firstly, by utilizing a detailed index of the digital economy, we present a more nuanced evaluation of its impact on carbon emissions during the past ten years (2011–2020). This advancement addresses the shortcomings of prior research, which depended on less granular indices, and provides a clearer picture of the trends in digital economy development and its impact on CO_2 emissions. Secondly, our analysis of regional R&D intensity and associated carbon emissions reveals a previously underexplored U-shaped relationship between R&D investment and emissions in China, offering new insights into this complex dynamic. Finally, our study clarifies the mediating role of fintech in the R&D–emissions nexus, enhancing our understanding of how fintech influences the effectiveness of R&D investments in mitigating emissions.

2. Literature Review

2.1. Digital Economy and Carbon Emissions

The digital economy, a term coined by Tapscott in 1996 [19], refers to an economic framework that heavily relies on information and communication technologies (ICTs). In 2020, the Chinese government elaborated on this concept in its White Paper on the Development of China's Digital Economy, characterizing it as a new economic paradigm

where digital knowledge and information act as essential production elements, digital technology propels key operations, and modern information networks function as vital conduits [28]. Bukht and Heeks (2017) [29] further delineated the digital economy into three distinct layers: core, narrow, and broad. The core layer encompasses digital industrial elements such as telecommunications, IT consulting, software development, and information services [30]. Meanwhile, the narrow layer focuses on the platform economy and digital services, while the broad layer comprises the algorithmic economy, new industries, mechanized agriculture, and e-commerce [31]. This framework highlights the digital economy as a by-product of the fusion of digital technology with diverse economic, social, and lifestyle dimensions [32]. It involves economic activities centered around digital technology, where digital platforms serve as the primary conduit and the infrastructure for digital empowerment providing critical support.

From a microeconomic perspective, digital technologies facilitated by the digital economy can minimize energy use, lower input costs, enhance production and sales channels, and boost the efficiency of economic output [33]. Lyu et al. (2022) [34] suggests that digital technologies can improve industrial and supply chain efficiencies, drive greener economic activities, and foster innovation. The digital economy promotes the formation of industrial chains or clusters through Internet-based platforms, which enhances economic benefits and energy utilization efficiency through scale effects and technological externalities [35]. At the macro level, various researchers contend that the digital economy aids in cutting down greenhouse gas emissions by optimizing resource allocation, promoting industrial transformation, and fostering regional technological innovation [30]. This transition not only diminishes dependence on fossil fuels but also enhances the efficiency of energy utilization [36,37]. Li et al. (2021) [38] found that digitalization in China from 2011 to 2017 directly reduced CO_2 emissions and lowered adverse impacts from energy use, especially in regions less reliant on coal.

On the flip side, Usman et al. (2021) [39] found that in nations characterized by elevated CO_2 emissions, digitalization may not yield beneficial effects on the environment. The management, enhancement, and upkeep of digital technologies and data centers require a substantial amount of energy and resources, potentially undermining improvements in carbon emissions efficiency [40]. In 2020, data centers and 5G base stations in China utilized more than 200 billion kilowatt-hours of power, which represented almost 3% of the country's overall electricity use [16]. Wang et al. (2022) [37] argue that while industrial digitization might aid in reducing emissions, the expansion of the digital industry itself could drive up CO_2 emissions, counteracting any positive effects. Zhang et al. (2022) [41] found that the digital economy growth contributes to higher emissions in Chinese provinces.

In summary, while digitalization holds promise for reducing CO_2 emissions through enhanced environmental awareness and cleaner energy practices, it also risks increasing emissions due to higher energy demands associated with technological advancements. This overall effect reflects an Environmental Kuznets Curve (EKC), where the digital economy's influence on CO_2 emissions continues to rise until a certain level of development is reached; beyond this threshold, emissions begin to decline. Li et al. (2021) [17] found that digitalization could ultimately improve environmental quality after reaching a certain threshold, supporting the notion that further digitalization can lead to reduced CO_2 emissions.

This study aims to understand the overall influence of regional digital economy levels on carbon emissions from 2011 to 2020. If rising CO_2 emissions are associated with increasing digital economy levels, it may indicate an earlier stage of the EKC. Here, emissions rise before potential reductions occur as the digital economy matures and technological advancements are more fully realized. The current research lacks thorough assessments of the digital economy index, with many studies relying on single indicators [39]. This study

advocates for analyzing the environmental impacts of a composite digital economy index, incorporating key indicators from the three layers proposed by Bukht and Heeks (2017) [29]. Such an assessment is crucial for evaluating the effectiveness of policies and initiatives and aligning them with broader environmental goals. Given the increasing number of policy documents on the digital economy over the past decade in China, this study hypothesizes that the expansion of the digital economy has an increasing influence on carbon emissions, corresponding to the earlier stages of the Environmental Kuznets Curve (Table 1).

Table 1. Table of hypotheses.

Hypothesis Number	Hypothesis Description
H1	*The expansion of the digital economy increased CO_2 emissions in China, suggesting it is at an early stage of the Environmental Kuznets Curve.*
H2	*R&D investments have an inverse U-shaped effect on CO_2 emissions.*
H3	*Fintech mediates the relationship between the U-shaped R&D investments and CO_2 emissions.*

2.2. R&D Investment and Carbon Emissions

R&D investments have been a major focus for the Chinese government, which has sought to boost innovation across all 30 provinces between 2006 and 2017 [20]. The impact of R&D on carbon emissions is complex. On one hand, R&D is often recognized for its potential to reduce emissions by enhancing energy efficiency and facilitating the transition to renewable energy sources. For example, Paramati et al. (2021) [42] demonstrated that in 25 countries within the European Union, higher R&D investments led to increased renewable energy use, which, in turn, helped reduce CO_2 emissions. Other studies also suggest that R&D is critical in reducing emissions by fostering innovation, with corporate R&D in G6 countries improving firms' environmental performance [43] and R&D outputs in Beijing contributing to reductions in annual CO_2 emissions [6].

Conversely, some studies suggest that R&D investments do not always reduce emissions and may even lead to increases. Koçak and Ulucak (2019) [44] found no significant correlation between R&D investment and carbon emissions in OECD countries. Additionally, resource-intensive R&D activities can increase emissions, as new technologies often require high implementation costs and are not immediately effective or widely adopted [22]. Fernández et al. (2018) [45] highlighted how R&D expenditures raised energy consumption and CO_2 emissions across China, the United States, and European countries between 1990 and 2013. Yu and Xu (2019) [46] reported that R&D investments in China led to higher industrial emissions at both national and regional levels.

These findings reflect the dual nature of R&D's impact on CO_2 emissions: while it can promote Regional Science and Environmental Economics and clean energy use, its overall effect is complex and varies depending on the scope of technological innovations associated with it. This study hypothesizes that the link between R&D and carbon emissions exhibits an inverse U-shaped relationship, where initial R&D expenditures increase energy usage, but further R&D enhances efficiency to the point of reducing emissions (Table 1).

2.3. Fintech as a Mediator

Fintech broadly refers to the incorporation of internet-based technologies, including cloud computing and big data, into conventional financial services [47]. The advancement of fintech has been shown to positively influence corporate innovation by mitigating information asymmetries and enhancing financial support for R&D investments [48]. Innovation activities often require substantial financial resources beyond the capacity of internal financing alone, necessitating significant external funding [23]. Firms engaged in intensive R&D, which are typically characterized by high information asymmetry and limited tangible

collateral, frequently encounter substantial credit constraints in conventional financial markets [49]. The widespread challenge of information asymmetry between companies and stakeholders, compounded by the inability of Small and Medium-sized Enterprises (SMEs) to provide sufficient 'hard' information, exacerbates financing challenges [50,51]. Consequently, promising innovation projects may be abandoned in favor of tangible assets over intangibles [52].

Fintech addresses these issues by expanding traditional credit supply through the synthesis of diverse data sources, including unconventional ones such as social media [24]. Technologies such as cloud computing, artificial intelligence, and big data enable the development of alternative credit scoring models based on non-traditional financial data, facilitating credit access for SMEs without extensive financial records [53]. Additionally, fintech reduces transaction and regulatory costs, increases market liquidity, and enhances security price informativeness, thereby alleviating financing constraints [54]. It also improves information transmission by enabling direct trade of money through platforms like Peer-to-Peer (P2P) lending, crowdfunding, and big data credit platforms, which cater to firms struggling to secure traditional financing [55,56]. By aggregating data from financial experts, news sources, and crowdsourced financial advice, fintech reduces information asymmetry and mitigates agency problems [57–59]. Furthermore, fintech enhances corporate risk-taking by improving internal information processing and decision making [60,61].

Consequently, fintech increases funding availability from diverse stakeholders, thereby facilitating R&D investments, with a more pronounced effect in larger and less transparent firms [48]. The positive association between fintech development and innovative activities underscores its role in enhancing firm competitiveness and economic growth. This study hypothesizes that fintech, by supporting R&D investments, acts as a significant moderator in amplifying the effect of R&D investment on CO_2 emissions, a relationship not previously explored (Table 1).

3. Study Design

3.1. Model Construction

To address our hypotheses, we employed fixed effects models with standard errors clustered at the regional level. Our analysis consisted of three models:

Base Model: This model evaluates the direct effects of the digital economy and R&D on CO_2 emissions:

$$CO_{2i} = \beta_0 + \beta_1 R\_D_i + \beta_2 DIG_i + \beta_3 FDI_i + \beta_4 Population_i + v_i \quad (1)$$

Quadratic Model: To explore potential non-linear effects of R&D on CO_2 emissions, we introduced a quadratic term for R&D expenditure:

$$CO_{2i} = \beta_0 + \beta_1 R\_D_i + \beta_2 DIG_i + \beta_3 R\_D_i^2 + \beta_4 FDI_i + \beta_5 Population_i + v_i \quad (2)$$

Interaction Model: This model includes an interaction term between the squared R&D investment and fintech to evaluate the mediating effect of fintech on the inverse U-shaped relationship between R&D and CO_2 emissions:

$$CO_{2i} = \beta_0 + \beta_1 R\_D_i + \beta_2 DIG_i + \beta_3 (R\_D_i^2 \times FIN)_i + \beta_4 FDI_i + \beta_5 Population_i + v_i \quad (3)$$

In these models, CO_{2i} represents regional carbon dioxide emissions, measured in metric tons. R_D_i denotes regional expenditure on research and development for industrial enterprises, measured in CNY 10,000. DIG_i is the digital economy index, reflecting digital development level in each region. $Population_i$ accounts for regional population size, which

may influence emissions due to varying energy demands. FIN measures digital financial inclusion, which could affect R&D investment levels and thus emissions. FDI_i stands for foreign direct investment, measured in USD million, controlling for external capital flows that might impact industrial activity and emissions. The term v_i captures unobserved factors influencing CO_2 emissions.

We used a one-way fixed effects approach to control for time-invariant unobserved heterogeneity within regions, such as local economic conditions and regulatory environments. Although a two-way fixed effects model could account for both regional and temporal effects, it might introduce complexity and bias, especially if uniform time effects do not fully capture regional policy variations or economic fluctuations. The one-way fixed effects model isolates time-invariant factors unique to each region, ensuring that our results reflect the specific impact of regional characteristics on CO_2 emissions, while accounting for temporal variations. This approach aligns with our objective to understand regional disparities in emissions.

3.2. Variable Measurement and Description

(1) Assessment of Digital Economy Development Level

This study assesses the Digital Economy Index (DEI) across multiple dimensions: Digital Industrialization, Digital Infrastructure, Industry Digitalization, Digital Inclusive Finance, and Digital Innovation Capacity (Table 2). These indicators collectively capture the core components of the digital economy, ranging from foundational infrastructure to digital services. The Core Layer is represented by software and IT service revenue, as well as R&D expenditures, which illustrate the pillars of digital industrialization and innovation. The Narrow Layer includes metrics such as e-commerce volume and computers per 100 employees, indicating the integration of digital platforms in business operations. The Broad Layer encompasses digital infrastructure and inclusive finance, highlighting broader digital connectivity and the use of digital tools in financial services. This comprehensive framework aligns with the Chinese government's 2020 definition of the digital economy, addressing its key structural components.

Table 2. The digital economy development level index measurement system.

First Level Index	Secondary Indicators	Indicator Description	Weight
Digital Infrastructure Level	Broadband Ports	Number of broadband access ports	0.0608
	Broadband Users	Number of broadband access users	0.0625
	Base Station Density	Mobile phone base station density	0.0155
	Domain Names	Number of domain names	0.0264
	Mobile Penetration	Mobile phone penetration rate	0.0908
	Optical Cable Length	Length of long-distance optical cable per unit area	0.0225
Digital Industrialization Level	Software Revenue (%)	Software business revenue as a percentage of GDP	0.0207
	IT Service Revenue (%)	IT service revenue as a percentage of GDP	0.0128
	Info Service Employees	Number of employees in the information service industry	0.0332
	Telecom Revenue (%)	Total telecommunications business revenue as a percentage of GDP	0.0528

Table 2. *Cont.*

First Level Index	Secondary Indicators	Indicator Description	Weight
Industry Digitalization Level	E-commerce Volume	Enterprise e-commerce transaction volume	0.095
	E-commerce Proportion	Proportion of enterprises engaged in e-commerce activities	0.0478
	Computers per 100 Employees	Number of computers per 100 employees in enterprises	0.0728
	Websites per 100 Enterprises	Number of websites per 100 enterprises	0.1149
Digital Inclusive Finance Index	Inclusive Finance Index	Digital Inclusive Finance Index	0.1061
Digital Innovation Capacity	R&D Personnel	Full-time equivalent of R&D personnel in industrial enterprises above designated size	0.0295
	R&D Expenditure	R&D expenditure of industrial enterprises above designated size	0.0298
	R&D Projects	Number of R&D projects in industrial enterprises above designated size	0.0239
	Tech Contract Value	Total transaction value of technology contracts	0.0145
	Patent Applications	Number of authorized patent applications	0.019

To ensure consistency and accuracy, the DEI development level is assessed using the entropy value method, which objectively assigns weights to each indicator. This method avoids the subjectivity and redundancy issues that can arise from manual assignment of weights or overlapping data. All data are standardized prior to analysis, using the following normalization formula to adjust for differences in units and scales:

$$\text{Normalized Value} = \frac{x - min(x)}{max(x) - min(x)} \tag{4}$$

where x denotes the original indicator values. After normalization, we employ the entropy value approach to calculate indicator weights. The methodology consists of these sequential steps:

1. Calculation of Proportion p_{ij}: The proportion for each indicator j for each region i is calculated as:
$$p_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \tag{5}$$
2. Entropy Calculation: The entropy e_j for each indicator is computed as:
$$e_j = -k\sum_{i=1}^{n} p_{ij}\ln\left(p_{ij} + \epsilon\right) \mathrm{v_i} \tag{6}$$
where
$$k = \frac{1}{\ln(n)} \tag{7}$$
and ϵ is a small constant to prevent taking the log of zero.
3. Redundancy: The redundancy d_j is then derived from the entropy:
$$d_j = 1 - e_j \tag{8}$$
4. Weight Assignment: The weight w_j for each indicator is calculated as:
$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{9}$$

5. Comprehensive Index Calculation: The comprehensive DEI for each region is derived by summing the weighted normalized values:

$$\text{Comprehensive Index} = \sum_{j=1}^{m} w_j \times \text{Normalized Value}_{ij} \quad (10)$$

This approach ensures that the impact of each indicator on the final index corresponds to its relative informational significance. The DEI values are calculated to reflect cross-sectional differences among provinces, aligning with the model's focus on regional effects. The resulting DEI values provide a comparative assessment of digital economic development across Chinese provinces, as presented in Table 2.

(2) Sample Source and Descriptive Analysis

Carbon Emissions (CO_2): Data of carbon emissions encompass Scope 1 (direct emissions from industrial processes, transportation, waste management, agriculture, construction, and land-use changes), Scope 2 (indirect emissions from heating, cooling, and purchased electricity), and Scope 3 (indirect emissions from goods sourced from outside the province). Total emissions were calculated as the sum of these scopes and expressed in metric tons of CO_2. Data sources include the China Industrial Statistical Yearbook, China Energy Statistical Yearbook, China Agricultural Statistical Yearbook, China Urban Statistical Yearbook, and China Environmental Statistical Yearbook, supplemented by emission factors from the Intergovernmental Panel on Climate Change (IPCC).

Fintech Index: This index is based on the "Peking University Digital Financial Inclusion Index of China" [62], developed by the Ant Group Research and Institute Peking University Digital Finance Research Center. It captures digital financial inclusion across three key aspects: the range of services offered, the extent of their usage, and the degree of digitization. The index is constructed from 33 indicators, providing a comprehensive measure of digital financial services at the provincial level. These dimensions are core aspects of fintech, particularly in the delivery of financial services via digital platforms.

Digital Economy Index: This index reflects the digital economy's development across provinces, constructed using the entropy value method. Key indicators include digital industry, digital infrastructure, and digital integration applications, sourced from the China Statistical Yearbook and the National Bureau of Statistics, as well as from the "Peking University Digital Financial Inclusion Index of China".

Other Variables: Foreign direct investment (FDI), population, patents, and R&D expenditure data were sourced from the National Bureau of Statistics. These control variables account for potential economic and demographic influences on carbon emissions.

Table 3 summarizes key variables across 243 observations, revealing significant regional variation. CO_2 emissions and FDI show considerable range, reflecting diverse regional emissions profiles and investment climates. R&D and the Digital Economy Index (DIG) also vary widely, underscoring differences in innovation and digital infrastructure. Population size, fintech levels, and patent activity further highlight substantial regional disparities.

Table 3. Summary statistics.

Variable	N	Mean	SD	Min	P50	Max
CO_2	243	-1.24×10^{-15}	1	−1.84	0.306	2.17
FDI	243	3.24×10^{-17}	1	−0.581	−0.421	4.45
R&D	243	4.93×10^{-17}	1	−0.731	−0.372	4.27
Population	243	-2.25×10^{-16}	1	−1.42	−0.182	3.01
DIG	243	1.54×10^{-16}	1	−1.42	−0.286	4.68
Fintech	243	1.90×10^{-15}	1	−2.25	−0.0143	2.41
Patents	243	-5.57×10^{-17}	1	−0.599	−0.378	6.18

4. Empirical Results

Model 1 shows a significant positive relationship between the Digital Economy variable (DIG) and CO_2 emissions ($p < 0.01$), with a coefficient of 0.089 (Table 4). This supports Hypothesis 1, indicating that the expansion of the digital economy is associated with increased CO_2 emissions across Chinese regions from 2011 to 2020 (Figure 1).

Table 4. Fixed effects model results.

Variable	Model 1	Model 2	Model 3
FDI	0.143 (0.778)	0.059 (0.330)	−0.248 (−1.239)
R_D	0.278 *** (3.340)	0.632 *** (5.272)	0.756 *** (6.120)
I(R_D^2)		−0.082 *** (−3.983)	−0.227 *** (−4.583)
$R\_D^2 \times FIN$			0.060 ** (3.209)
DIG	0.089 ** (2.837)	0.078 * (2.564)	0.053. (1.709)
Population	0.012 (0.026)	0.071 (0.153)	0.106 (0.235)
Constant	-1.375×10^{-15} (0.273)	-1.377×10^{-15} (0.252)	-1.369×10^{-15} (0.241)
R^2	0.13759	0.1941	0.22811
Region FE	Yes	Yes	Yes
Year FE	No	No	No
Observations	243	243	243
Regions	27	27	27

Note: ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

The positive trend observed in the digital economy's influence on carbon emissions suggests that China is likely in the early to middle stages of the Environmental Kuznets Curve (EKC). During this phase, emissions rise as a result of higher energy consumption from digital infrastructure and industrial digitization. This points to the environmental trade-offs of digital advancement due to the current technologies not yet achieving significant improvements in energy efficiency, especially in industrial manufacturing where the potential for energy waste reduction through smart systems and automation is substantial. Alternatively, this may indicate that a shift is needed toward more efficient energy solutions to ensure that environmental sustainability keeps pace with economic growth.

Model 2 reveals a negative coefficient for R&D ($p < 0.01$), supporting Hypothesis 2 (Table 4). The coefficient of −0.082 indicates a reversed U-shaped relationship between R&D expenditures and CO_2 emissions. The model suggests that R&D initially increases emissions, but this effect diminishes once a threshold is reached (Figure 2). The vertex of the U-shaped curve, marking the point where the relationship between R&D and CO_2 emissions shifts, occurs at approximately CNY 8.27 million in R&D expenditure and 34,678.75 metric tons of CO_2 emissions. This threshold lies within Quadrant I of R&D expenditure levels, implying that regions with higher R&D investments initially experience increased emissions, but beyond this point, further R&D increases lead to emission reductions.

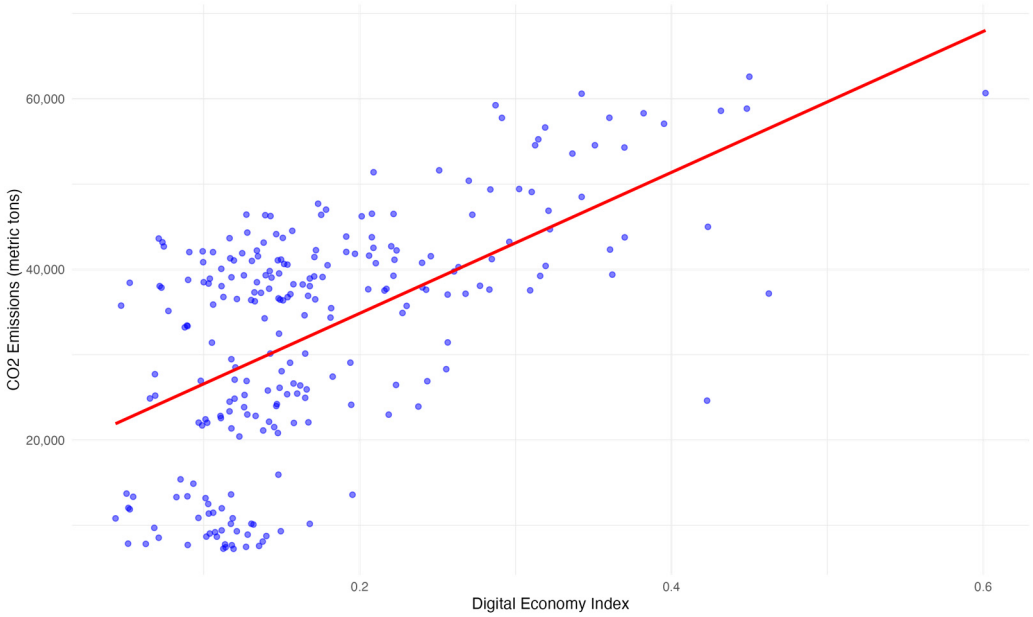

Figure 1. Correlation between Digital Economy Index and carbon emissions. The red line represents the predicted CO_2 emissions from the model, adjusted for control variables (FDI, R&D, and population). Data points are actual CO_2 emissions.

The observed inverse U-shaped relationship between R&D investment and carbon emissions aligns with the EKC theory. Early R&D investments lead to higher emissions largely due to the energy-intensive nature of developing new technologies, such as building prototypes, manufacturing devices, or scaling production. However, once the critical threshold is reached, further investment results in more efficient and green technologies that reduce emissions. This underscores the importance of sustained investment in R&D for mitigating impact on the environment over time.

Model 3 shows a positive coefficient for the interaction term between R&D and fintech (0.060, $p < 0.05$), supporting Hypothesis 3, which posits that fintech activity mediates the emissions increase associated with R&D (Table 4). When both R&D and fintech activity rise together, their combined effect on CO_2 emissions is stronger than when R&D increases alone, intensifying the emissions impact. Additionally, the diminishing returns of R&D on emissions, as indicated by the U-shaped relationship, are further exacerbated in regions with higher fintech activity. This suggests that the emissions reduction that occurs after a threshold level of R&D investment is more pronounced in areas with greater fintech involvement.

Given the significant mediating role of fintech in the relationship between R&D and carbon emissions, financial inclusion, powered by fintech advancements, is essential for accelerating and amplifying environmental benefits of R&D as investments in firms grows, particularly in regions where traditional financing may be limited.

The full effects of digital transformations often unfold over extended periods, as businesses and markets gradually adapt to emerging technologies. Likewise, R&D investments typically involve long-term projects, where the benefits—such as innovations or new technologies—take years to materialize, commercialize, and influence outcomes like CO_2 emissions. This delayed impact can result in an underestimation of the explained variance. To address this, the study incorporates a one-period lag approach, accounting for potential time dependencies and autocorrelation, as verified through robustness testing.

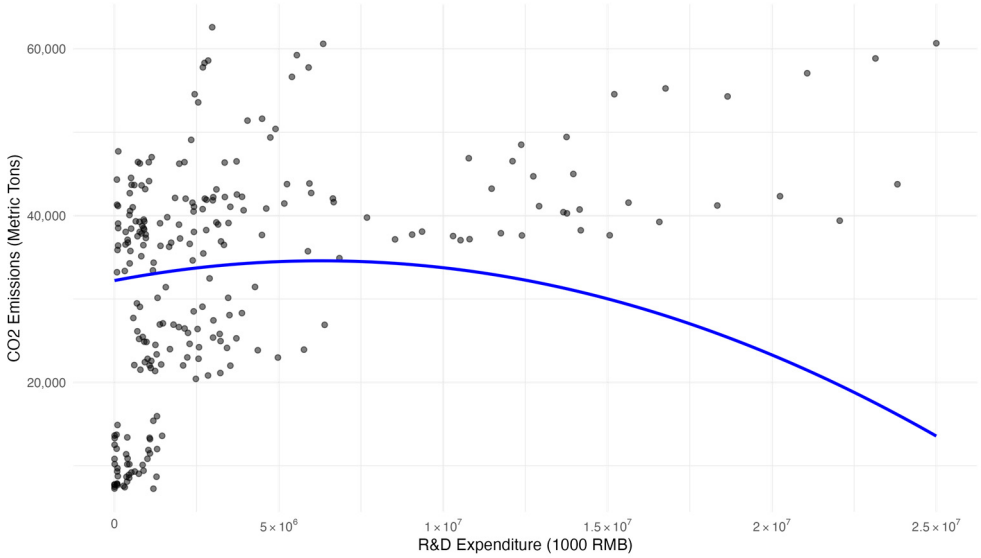

Figure 2. Correlation between R&D expenditure and carbon emissions. The blue curve represents the predicted CO_2 emissions from the model, adjusted for control variables (FDI, digital economy, and population). Data points are actual CO_2 emissions.

5. Robustness and Endogeneity Tests

5.1. One-Period Lag Approach

To address potential endogeneity due to reverse causality, we implemented a one-period lag approach by lagging the dependent variables by one period (Table 5). This method mitigates the temporal lag in the influence of economic factors on emissions, thereby reinforcing the robustness of our findings with respect to the timing of effects. The results presented in Columns 1 through 3 corroborate our hypotheses and affirm the robustness of the timing effects.

Model 3 explained 41% of the variability (R^2 = 0.6193), indicating a moderate fit. This level of explanatory power likely reflects data aggregation, which may obscure finer regional variations. Studies on the digital economy and green development frequently yield similar outcomes, as regional disparities in digital adoption complicate the measurement of its impact on CO_2 emissions [63]. Nevertheless, the models demonstrate a significant and consistent effect of the predictors on CO_2 emissions across regions.

Table 5. Robustness test using one-period lag approach.

Variable	Model 1	Model 2	Model 3
FDI	0.17117 (1.486)	0.19299 (1.679)	0.29885 (2.490) *
R_D	−0.22304 (−1.541)	0.05168 (0.259)	0.13553 (0.682)
I(R_D^2)		−0.10566 (−1.992) *	−0.32193 (−3.338) ***
$R\_D^2 \times$ FIN			0.11967 (2.669) **
DIG	0.64894 (6.819) ***	0.58617 (5.884) ***	0.51068 (4.997) ***
Population	0.10436 (1.171)	0.05516 (0.600)	0.08130 (0.892)
Constant	0.08378 (1.520)	0.18214 (2.470) *	0.29541 (3.510) ***
Observations	243	243	243
Regions	27	27	27
Region FE	No	No	No
Year FE	No	No	No
R^2	0.3831	0.3945	0.4145

Note: ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

5.2. Instrumental Variable (IV) Approach

To tackle simultaneity and reverse causality concerns, we employed the Instrumental Variable (IV) approach using Two-Stage Least Squares (2SLS), with patents serving as instruments. This method isolates exogenous variation in the endogenous variable by utilizing instruments that are uncorrelated with the error term but correlated with the endogenous regressor. Patents, measured by the number of patent applications of industrial enterprises, serve as proxies for innovative output, capturing the tangible effects of R&D expenditures. We enhanced the finding robustness by incorporating both regional fixed effects (Model 1) and regional plus time fixed effects (Model 2), as detailed in Table 6 (Columns 4–6 and Columns 7–10, respectively). This approach substantiates hypotheses 1–3, improving model accuracy and robustness.

Table 6. Robustness test using Instrumental Variable (IV) approach.

	2SLS Accounting with Regional Fixed Effects			**2SLS Accounting with Regional and Time Fixed Effects**		
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
FDI	0.219 (2.019) *	0.229 (2.129) *	0.338 (3.037) **	0.396 * (3.074)	0.179 (1.511)	0.442 ** (2.841)
R_D	−0.256 (−1.881)	0.045 (0.248)	0.188 (1.025)	−0.641 ** (−3.220)	0.683 * (2.348)	0.648 * (2.248)
I(R_D^2)		−0.101 (−2.496) *	−0.308 (−4.117) ***		−0.267 *** (−3.795)	−0.552 *** (−3.893)
$R\_D^2 \times FIN$			0.115 (3.229) **			0.158 * (2.288)
DIG	0.559 (6.896) ***	0.518 (6.328) ***	0.430 (5.047) ***	0.644 *** (7.255)	0.409 *** (4.380)	0.332 ** (3.298)
Population	0.128 (1.511)	0.064 (0.732)	0.076 (0.879)	0.267 * (2.645)	−0.092 (−0.855)	0.005 (0.041)
Constant	-1.427×10^{-15} (0.000)	0.099 (1.538)	0.236 (3.105) **	-1.454×10^{-15} (0.000)	0.262 ** (3.022)	0.457 *** (3.796)
Observations	243	243	243	243	243	243
Regions	27	27	27	27	27	27
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
R^2	0.3726	0.3878	0.4059	0.3431	0.3465	0.3563
F-value of weak instrumental variables	414.9 ***	414.9 ***	414.9 ***	370.2 ***	370.2 ***	370.2 ***
Wu–Hausman	8.9105×10^{-14}	0.561	0.172	0.00193 **	0.0181 *	0.00414 **
Wald test	35.34 ***	30.09 ***	27.53 ***	35.5 ***	29.6 ***	26.08 ***

Note: ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Higher R^2 values in these models relative to those with only regional fixed effects suggest that regional fixed effects alone capture more variation in the dependent variable, providing a superior model fit compared to the inclusion of both regional and time fixed effects. The high F-values indicate strong instruments, meaning they are well correlated with the endogenous variables and provide a robust basis for 2SLS estimation. The Wald test assesses the overall significance of the model, specifically testing the joint significance of the explanatory variables. The Wald test results, highly significant across all models ($p < 0.001$), affirm that the models are well specified and that the explanatory variables, including those instrumented, significantly explain the dependent variable.

5.3. Control Function Approach

The Control Function (CF) approach addresses endogeneity by isolating and adjusting for the endogenous components of explanatory variables, correcting for correlations between these components and the error term. This method enhances estimation accuracy, model specification, and robustness. In our study, fintech and patents are employed as control variables for R&D, with residuals from the first stage incorporated to address endogeneity.

Notably, the CF approach is adept at managing non-separable models, as demonstrated by Imbens and Newey (2009) [64], who used control variables to identify and estimate models with multidimensional disturbances under conditions of instrument independence and strict monotonicity in the reduced form. This flexibility allows it to address complex

relationships and endogeneity issues, including models with non-separable disturbances of unspecified dimension.

The significance of digital economy impacts, U-shaped relations of R&D, and the moderating role of fintech is consistent with previous results (Table 7). The Durbin–Wu–Hausman test confirms the endogeneity assumption, with a high F-statistic from the first-stage regression indicating strong and relevant instruments. High R^2 values indicate that the instruments effectively capture the variation in the endogenous variable, reinforcing their validity. Standard errors support the robustness of the estimates, regardless of the heteroskedasticity presence, further confirm the validity and robustness of the Control Function approach.

Table 7. Robustness test using Control Function approach.

Variable	Model 1	Model 2	Model 3
FDI	0.275 * (2.51)	0.370 ** (3.31)	0.505 *** (4.12)
R_D	0.8625	2.711 *** (3.34)	1.951 * (2.28)
I(R_D^2)		−1.267 *** (−3.78)	0.44082
$R\_D^2 \times$ FIN			0.099 * (2.53)
DIG	0.582 *** (7.22)	0.473 *** (5.47)	0.436 *** (5.03)
Population	0.097 (1.18)	0.144 (1.65)	0.163 (1.88)
Constant	−0.000 (0.00)	1.262 *** (3.74)	1.059 ** (3.08)
u_R_D_hat	0.124 (0.72)	0.091 (0.50)	0.276 (1.42)
u_R_D2_hat		1.236 *** (3.63)	NA
I(R_D2_hat)			−0.939 ** (−2.64)
First stage R^2 for R_D	0.8777788	0.8777788	0.8777788
First stage R^2 for R_D^2		0.8777788	0.8008123
Observations	243	243	243
Regions	27	27	27
DWH Test (*p* value)	36.482 ***	101.23 ***	98.132 ***
First Stage F-statistics	96.319 ***	164.956 ***	164.956 ***
Residual Std. Error	0.789	0.7685	0.7599

Note: ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

6. Conclusions

The findings indicate that the expansion of the digital economy is associated with increased CO_2 emissions in China, suggesting that the country remains in the early stages of the Environmental Kuznets Curve (EKC), where emissions rise before reductions are realized. R&D investments exhibit an inverse U-shaped relationship with carbon emissions: initial investments drive higher emissions, while later-stage investments foster green technologies that mitigate emissions. The vertex for R&D expenditures and CO_2 emissions is CNY 8,268,629.31, a value located in Quadrant I, where R&D expenditure is most concentrated, underscoring its potential for CO_2 reduction. Additionally, fintech amplifies the impact of R&D on emissions by improving financial access, highlighting its crucial role in sustainable development.

This study has several limitations. First, it utilizes panel data from 2011 to 2020, which may not fully capture the most recent developments in the digital economy and R&D investments. Second, while the analysis encompasses all Chinese provinces and direct-administered municipalities, focusing on specific geographical clusters could provide additional insights into regional variations.

Future studies could extend this analysis with more recent and comprehensive data to gain a deeper and more accurate understanding of the evolving dynamics. Comparative regional analyses may reveal region-specific patterns on how the diminishing effects of R&D on emissions vary across China. Additionally, future studies could focus on a meso-industrial or micro-enterprise perspective, exploring the role of specific R&D components

and industry sectors. Urban district-level panel data could also be used to increase the sample size and granularity of the analysis.

7. Policy Implications

Given the findings of this study, it is essential for policymakers to acknowledge how the digital economy influences CO_2 emissions. Although the growth of digital infrastructure and the digitization of industries have contributed to rising emissions from 2011 to 2020, targeted measures are essential to promote the adoption of energy-efficient digital technologies and reduce the carbon footprint of this expansion. This necessitates the implementation of focused strategies that encourage sustainable practices in the digital economy. This could involve offering incentives for the development and use of green technologies, enhancing energy efficiency benchmarks, and fostering digital innovations that advance environmental Regional Science and Environmental Economics.

Additionally, the inverse U-shaped correlation between investments in research and development and carbon emissions highlights the need for continued and focused investment in innovation, particularly in green technologies. Policymakers should facilitate this by establishing a long-term mechanism to promote robust support for R&D initiatives that prioritize environmental outcomes, including subsidies, tax incentives, and grants for firms engaged in developing sustainable technologies. This mechanism should be based on the non-linear and phased characteristics of R&D's impact, ensuring that early-stage investments, which may increase emissions, are balanced by long-term policies aimed at promoting green innovation. By developing a scientifically informed low-carbon policy framework that considers these stages, the government can ensure the ongoing effectiveness, consistency, and long-term viability of carbon reduction programs while fostering innovation in technology. Prioritizing R&D in these policies facilitates a more direct pathway to achieving substantial CO_2 reductions.

The dual nature of fintech, acting simultaneously as a possible driver of rising emissions and a promoter of sustainable innovation, underscores the importance of adopting a balanced strategy in policy development. To fully leverage the benefits of fintech while addressing its early drawbacks, policymakers need to concentrate on a few pivotal aspects. Primarily, committing resources to enhance digital infrastructure is essential for support of the development of advanced green finance platforms that facilitate efficient and transparent transactions. Second, fostering specialized talent is essential; targeted educational and training programs should be developed to cultivate expertise in sustainable fintech innovations, with a focus on skills related to green finance technologies and eco-friendly financial solutions. Third, supporting green projects through targeted project-based incentives is vital, ensuring that initiatives promoting green lending and sustainable financial practices have access to the necessary resources and guidance. By enhancing financial inclusion and access to green financing, particularly in underserved regions, policymakers can amplify the environmental benefits of R&D and drive sustainable economic growth in the long term.

In this pivotal moment of change, backing from both government agencies and private organizations, through measures like tax incentives, financial assistance, and investment in technological advancements, serves an essential purpose. These efforts not only accelerate the implementation and uptake of digital technologies but also encourage urban redevelopment focused on enhanced efficiency and sustainability [65]. Overall, the above strategies are essential for guiding China and other rapidly developing economies toward achieving long-term environmental sustainability amidst ongoing digital and technological advancements.

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