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The impact of digital economy on green finance in China

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Abstract

In response to China's dual carbon goals and the global imperative for sustainable development, this study investigates how the digital economy influences green finance (measured by carbon efficiency) across China's provinces. While prior research acknowledges the promise of digital technologies in promoting low-carbon growth, few studies rigorously quantify their impact on green finance. To address this gap, this study utilizes a balanced panel dataset of 31 Chinese provinces from 2000 to 2020. A composite digital economy index is constructed using the entropy-weighted method, and green finance is measured using a carbon efficiency metric based on the DEA-SBM model. The relationship is evaluated through Tobit regression models, with a focus on regional heterogeneity. The findings reveal that the digital economy has a significantly positive effect on green finance at the national level and in eastern and western China, but no statistically significant relationship is found in central China. Additionally, GDP growth negatively affects green finance in all regions, reflecting a persistent carbon-intensive growth pattern. The effects of energy use and industrial structure vary by region, indicating persistent regional structural disparities. The results suggest that while digitalization can serve as a critical enabler of green finance in China, its benefits are unevenly realized across provinces. This study provides novel empirical evidence on the interactions between digital infrastructure and environmental finance, highlighting the need for region-specific policy responses. The findings underscore the potential of digital transformation to align environmental objectives with economic development and provide actionable insights for policymakers aiming to harmonize growth with ecological sustainability.

Keywords: Carbon efficiency, China, DEA-Tobit model, Digital Economy, Green Finance.

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1. Introduction

In alignment with environmental imperatives and the objectives of the global Sustainable Development Goals (SDGs), green finance has emerged as a pivotal mechanism for directing investments toward sustainable development initiatives [1-3]. The concept of green finance has attracted considerable attention in recent decades, particularly in the wake of a global mobilization for sustainable development and efforts to mitigate climate change [4]. Within China, green finance has been methodically incorporated into the national development agenda, thereby aligning financial flows with low-carbon and climate-resilient investments [5]. The Chinese government has undertaken significant measures to integrate environmental considerations into economic policies. Initiatives such as the Belt and Road Guidelines for Green Development, Green Credit Guidelines, Green Finance Evaluation Program, and the Bank of China's Green Finance Talent Project underscore the government's strong commitment to green finance [6-8].

Carbon emissions efficiency serves as a critical quantitative indicator for evaluating green finance performance by measuring the ratio of economic output to carbon dioxide emissions associated with each unit of investment or financing activity [9, 10]. Carbon emissions efficiency captures the fundamental principle of green finance: maximizing economic value creation while minimizing environmental externalities [11, 12]. It provides institutional investors, policymakers, and financial institutions with a standardized framework to assess whether capital allocation decisions genuinely contribute to decarbonization objectives rather than superficially engaging in greenwashing practices [13]. By tracking carbon emissions efficiency across portfolios, loan books, and investment projects, financial institutions and market participants can demonstrate measurable progress toward climate goals while fulfilling fiduciary duties, thereby bridging the traditional gap between environmental sustainability and financial performance in contemporary capital markets [14-16].

The emerging digital economy, characterized by digital infrastructure and data-driven technologies, offers strong potential to drive sustainable growth, reduce emissions, strengthen green finance, and enhance resource efficiency simultaneously [17, 18]. However, the precise impact of digital economic development on green finance efficiency remains a subject of empirical inquiry, necessitating robust analysis to inform evidence-based policy decisions that support China's ambitious climate objectives without compromising economic development [19-22].

Against this backdrop, this study aims to explore the impact of China's digital economic development on green finance (measured by carbon emission efficiency). Panel data from 31 Chinese provinces, spanning the period from 2000 to 2020 and sourced from the China Statistical Yearbook, are employed. The study utilizes the entropy method to assess the level of digital economic development, DEA to calculate the green finance index, and the TOBIT model to assess its influence separately across Eastern, Central, and Western China, as well as nationally. This study aims to provide insights for policymakers on achieving dual carbon goals, strengthening green finance, promoting economic sustainability, and understanding the pivotal role of the digital economy in this process.

2. Literature Review

2.1. What is Green Finance and How to Measure It?

Green finance is defined as the financial sector's contribution to environmental protection and the sustainable development of the economy and society [21, 23]. It also encompasses the long-term sustainability of the financial sector itself [24, 25]. A central function of green finance is to channel financial resources into resource-efficient technologies and environmental protection industries, encourage enterprises to adopt environmentally friendly practices in production, and promote green consumption awareness among consumers [26, 27]. It is important to ensure that the financial sector maintains sustainable development and avoids excessive speculative behavior driven by short-term interests [28, 29].

Carbon emission efficiency is a key quantitative indicator for evaluating the effectiveness of green finance. Patterson defined carbon efficiency as the ratio of GDP to energy consumption [30]. In practice, energy consumption inevitably leads to pollutant emissions, among which carbon dioxide emissions are the most substantial and environmentally damaging [31]. Accordingly, similar to energy efficiency, carbon efficiency was initially measured as the ratio of GDP to CO_2 [31] emissions [32]. Other commonly applied performance indicators include per capita CO_2 emissions and CO_2 emissions per unit of energy consumption [33-35]. These indicators are widely adopted but represent single-factor measures, as they reflect only the relationship between one economic or social variable and carbon emissions. While easy to interpret and compute, they fail to account for critical factors such as capital, technological progress, labor, and industrial structure, thereby limiting their comprehensiveness [31].

In response, multifactor indicators are considered more robust for assessing carbon efficiency. Currently, many scholars employ the Data Envelopment Analysis (DEA) method, a non-parametric model used to evaluate efficiency based on multiple inputs and outputs [36]. The DEA framework, first proposed by Farrell and later expanded by Charnes, has undergone significant development [37, 38]. Variants such as SBM-DEA, SE-SBM, three-stage DEA, EBM-DEA, global Malmquist-Luenberger indices, intermediate DEA, and meta-frontier DEA have extended their applicability [39, 40]. DEA has been widely applied to measure energy and carbon efficiency across national and regional contexts [41]. In particular, the Slack-Based Measure (SBM) model with undesirable outputs is preferred when assessing carbon efficiency, as it accounts for CO_2 emissions as undesirable outputs [42]. In this model, capital and labor are typically treated as input factors, while GDP and CO_2 emissions are classified as desired and undesired outputs, respectively [43].

2.2. What is Digital Economy and how to Measure it?

The concept of the digital economy was first introduced by American scholar Tapscott [44]. Since then, the definition of the digital economy has evolved in response to the dominant digital technologies of each era. In its early stages, the term was primarily internet-centric, reflecting the dominance of internet technology in the 1990s [45, 46]. Over time, the concept expanded to encompass emerging technologies such as mobile networks, big data, blockchain technology, and the Internet of Things[47, 48].

However, this evolving approach, which is anchored to prevailing technologies, has led to definitional inconsistencies and a lack of standardization, often emphasizing technological aspects over the economic dimension. In response, the Kitamori et al. [49] provided a widely accepted definition, framing the digital economy as the economic system involving the trade of goods and services enabled by internet-based e-commerce [48]. Based on this definition, the European Union structured the digital economy around related industries and infrastructure, characterizing it as an emerging model driven by digital technologies [50]. Similarly, the Bureau of Economic Analysis in the United States developed a measurement framework closely aligned with the OECD's conceptual framework [51]. Therefore, the OECD's definition remains the most widely recognized and adopted among scholars and policymakers.

Due to the varied and often inconsistent definitions of the digital economy, its measurement presents significant challenges. This complexity is further exacerbated by limited data availability, particularly in developing countries. Issues such as missing data, poor data quality, and incomplete records hinder efforts to quantify digital economic activities accurately [52]. Nevertheless, the OECD's measurement framework remains a widely recognized and practical approach [25]. The Kitamori et al. [49] employ three primary indicators to assess the digital economy: digital infrastructure, digital economic output, and the degree of digitization. Countries may adapt these indicators according to available national data when estimating their digital economy levels. In the case of China, digital economy measurement often relies on the digital financial inclusion indicator system, which incorporates the OECD's three indicators with refinements tailored to China's national context and supported by reliable datasets [22].

2.3. Literature on the Digital Economy and Green Finance in China

A growing body of literature has examined the impact of China's digital economy on carbon emissions, energy efficiency, and green production efficiency [21, 53-55]. However, a limited number of studies have specifically focused on carbon efficiency [31]. Methodologically, most existing research adopts fixed-effects models or ordinary least squares (OLS) as baseline methods and applies threshold regression to investigate the nonlinear relationship between digital economy development and environmental indicators such as carbon emissions, energy efficiency, and green production efficiency [56-59]. In addition, some studies employ spatial Durbin models to analyze the spatial spillover effects of the digital economy on environmental outcomes [16, 60]. A smaller group of scholars acknowledges the potential time lag between digital economy advancement and its environmental impact arising from technological adaptation or delayed policy implementation and therefore utilizes GMM models to capture dynamic effects [56, 61].

Overall, despite differences in estimation techniques and study scopes, the majority of findings indicate that the digital economy significantly contributes to strengthening green finance while enhancing both energy efficiency and green production efficiency [55, 59, 60]. However, discrepancies persist across industries and regions, likely due to significant regional disparities in economic development, industrial structure, and energy composition [57, 58, 61, 62].

To achieve economic sustainability while reducing carbon emissions, it is important to examine the impact of the digital economy on green finance. This is especially relevant given China's dual carbon objectives, which emphasize both effective carbon dioxide reduction and the promotion of sustainable economic development [53, 57, 59]. Solely targeting emissions reduction without accounting for economic growth contradicts these dual objectives and may undermine policy feasibility [63]. Improvements in green finance reflect the simultaneous achievement of environmental and economic goals, thereby aligning with China's policy vision and practical realities [15].

Despite its importance, research specifically addressing green finance measured by carbon efficiency remains limited, and the few existing studies typically adopt methodologies such as spatial models, GMM, and fixed-effects estimation [18, 40, 64, 65]. However, both digital economy development levels and green finance are inherently unobservable and must be indirectly estimated through composite indicators, thereby classifying them as censored or latent variables. In such contexts, traditional econometric models may lead to biased estimation results. Therefore, the Tobit model provides a more suitable alternative for analyzing these relationships [66].

3. Theory

3.1. The Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) is a theoretical model that describes the relationship between environmental pollution and a nation's economic growth [67]. The central premise of the EKC is that pollution levels initially rise during the early stages of economic growth, reach a peak, and subsequently decline as economic development progresses, forming an inverted U-shaped trajectory [68]. Specifically, in the early phases of development, environmental degradation tends to increase as countries prioritize economic growth over ecological concerns. However, as economic maturity is achieved, nations begin to adopt cleaner technologies and implement regulatory measures that reduce pollution and enhance environmental quality.

This study examines the impact of digital economy development on green finance within the EKC framework by hypothesizing a similar inverted U-shaped relationship. In the initial phase, digital economic expansion may lead to increased environmental degradation and carbon-intensive financial activities due to the energy demands of infrastructure development and data center operations. As digital technologies mature, however, they can facilitate a shift toward green finance by improving resource efficiency, enabling advanced environmental monitoring, and fostering the development of innovative sustainable financial products.

An EKC-based analytical approach allows for the exploration of this dynamic, nonlinear relationship between digitalization and green financial development. The turning point on the curve marks the stage at which the benefits of digital technologies begin to outweigh their environmental costs. This framework offers empirically grounded insights into the optimal timing for integrating digital and green finance strategies. Moreover, it highlights the technological and regulatory preconditions necessary to move beyond the EKC inflection point and foster the development of sustainable financial ecosystems [67, 69].

3.2. STIRPAT Model

The STIRPAT model, Stochastic Impacts by Regression on Population, Affluence, and Technology, is a widely used framework in environmental research. It is designed to evaluate the environmental impacts of key factors, including population, economic development, and technological progress [70]. The model builds upon the IPAT identity and extends it into a stochastic form to explore the relationships among population, affluence, technology, structural transitions, and policy responses across various regions and time periods [71].

In this framework, population captures the demographic impact on the environment, typically measured by population size. Affluence refers to the level of economic development, often proxied by GDP. Technology reflects the role of technological advancements in shaping environmental outcomes. Transition accounts for the influence of industrial structure, commonly indicated by the share of the secondary (industrial) sector in GDP. Response represents the environmental effects of policy interventions and regulatory frameworks.

Unlike the Environmental Kuznets Curve, which primarily focuses on the nonlinear relationship between income and environmental degradation, the STIRPAT model offers a more holistic and empirically grounded analytical framework. It integrates economic, demographic, technological, and institutional variables, thereby providing a richer and more robust explanation for understanding environmental impacts [72].

4. Methodology

4.1. Data

This study utilizes panel data spanning from 2000 to 2020 across 31 provinces in China. All data are sourced from the *China Statistical Yearbook*. Based on the existing literature, the green finance index (GFI) is calculated using the DEA-SBM (Data Envelopment Analysis–Slacks-Based Measure) model, with labor and capital as inputs, GDP as the desirable output, and carbon emissions as the undesirable output [39, 40, 43].

The digital economy index (DEI) is constructed using the entropy-weighted method across three dimensions: (1) digital economic infrastructure, (2) level of digitization, and (3) digital economy output [73]. The infrastructure dimension includes the length of fiber optic cable, the number of 3G mobile phone subscribers, landline subscribers, and mobile phones per 100 households. The digitization level is captured through the number of web pages, broadband internet users, and mobile internet users. The output dimension comprises e-commerce sales and the number of employees in digital industries.

The Tobit regression model employs the digital economy index as the independent variable and green finance as the dependent variable. Drawing on the principles of the Environmental Kuznets Curve (EKC) theory and the STIRPAT model, population size, level of economic development, industrial structure, and environmental policy are recognized as key determinants of environmental outcomes [67, 70]. Accordingly, control variables include population size, affluence (measured as the logarithm of GDP), pollution control efforts (green coverage ratio), industrial structure (share of secondary industry), and energy structure (share of coal consumption) [59, 60, 74, 75]. Notably, a logarithmic transformation is applied to the GDP variable to address issues of scale and non-normality in the original data.

4.2. Method

The entropy-weighted method used to construct the digital economy indicator is defined by the following equations:

$$\boldsymbol{w_j = \frac{e^{-\lambda D_j}}{\sum_{j=1}^{9} e^{-\lambda D_j}}} \qquad (\mathbf{1})$$

$$\boldsymbol{DEI_{it} = \sum_{j=1}^{9} w_j * D_{ijt}} \qquad (\mathbf{2})$$

Where DEI_{it} denotes the digital economy indicator for province i in year t, D_{ijt} represents the value of the tertiary indicator corresponding to the $j-t$ variable for province i in year t, and w_j signifies the weight assigned to the $j-t$ variable. Here, $i = 1, 2, \ldots, 31$ denotes the 31 provinces in China, and $t = 2000, 2001, \ldots, 2020$ indicates the corresponding years.

The DEA-SBM model, which is employed to measure carbon efficiency, is defined by the following equations:

$$\rho_i^* = min \frac{1 - \frac{1}{2}\left(\frac{s_i^{l-}}{l_i} + \frac{s_i^{k-}}{k_i}\right)}{1 + \frac{1}{2}\left(\frac{s_i^{g+}}{g_i} + \frac{s_i^{uc-}}{uc_i}\right)} \qquad (3)$$

$$s.t.\ l_i = \sum_{j=1}^{n} \lambda_j l_j + s_i^{l-}$$

$$k_i = \sum_{j=1}^{n} \lambda_j k_j + s_i^{k-}$$

$$g_i = \sum_{j=1}^{n} \lambda_j g_j - s_i^{g+} \tag{4}$$

$$uc_i = \sum_{j=1}^{n} \lambda_j uc_j + s_i^{uc-}$$

$$s_i^{l-}, s_i^{k-}, s_i^{g+}, s_i^{uc-}, \lambda \geq 0$$

Where s_i^{l-} and s_i^{k-} represent the labor and capital input of ith province respectively, s_i^{g+} represents the shortfall of desirable outcome GDP of ith province, s_i^{uc-} represents the undesirable outcome excesses of CO2 emission in i province, ρ_i^* represents green finance index of i province. The range of ρ_i^* is from 0 to 1, the larger the ρ_i^* value is, the better green finance index the i province has.

China, characterized by its vast expanse, exhibits significant regional disparities in terms of economics, demographics, and energy structures [57, 58, 61, 62]. Therefore, this study conducts separate Tobit regressions for Eastern, Middle, and Western China, as well as the nation as a whole, to perform regional heterogeneity analysis. The division of China into Eastern, Western, and Middle regions is in accordance with the State Council's classification. The specific provinces corresponding to Eastern, Western, and Middle China are detailed in Appendix A, Figure A1, and Table A1. The Tobit regression equations are formulated as follows.

$$\mathrm{GF}_{i,t} = \beta_0 + \beta_1 \mathrm{DEI}_{i,t} + \beta_2 \mathrm{POP}_{i,t} + \beta_3 \mathrm{lnGDP}_{i,t} + \beta_4 \mathrm{GC}_{i,t} + \beta_5 \mathrm{IS}_{i,t} + \beta_5 \mathrm{ES}_{i,t} + \varepsilon_{i,t} \tag{5}$$

Where $\mathrm{GF}_{i,t}$ denotes the green finance for individuals i in year t, $\mathrm{DEI}_{i,t}$ represents the digital economy index, $\mathrm{POP}_{\mathrm{i,t}}$ is the population, and in $\mathrm{GDP}_{\mathrm{i,t}}$ denotes the natural logarithm of GDP. $\mathrm{GC}_{\mathrm{i,t}}$ indicates the green coverage rate, $\mathrm{IS}_{\mathrm{i,t}}$ captures the industrial structure, $\mathrm{ES}_{\mathrm{i,t}}$ refers to the energy structure, and $\varepsilon_{\mathrm{i,t}}$ represents the random error term.

5. Results

5.1. Results of GF and DEI

Based on the DEA-SBM approach, the green finance index was computed for 31 Chinese provinces from 2000 to 2020, and the results are presented in Appendix Table A3. Figure 1 illustrates distinct regional disparities in the average green finance index. The Eastern region exhibits the highest levels of green finance, followed by the Western region, while the Central region shows the lowest performance. Detailed data for each province and year are available in Appendix A, Table A3. Provinces with the highest average green finance include Beijing, Guangdong, Hainan, Qinghai, and Tibet, most of which are located in the eastern and western regions. In contrast, Guizhou, Jilin, Inner Mongolia, and Hebei mainly situated in the central region, record the lowest efficiency levels. Notably, green finance has improved significantly across all provinces over the 2000–2020 period, indicating a nationwide commitment to improving environmental performance.

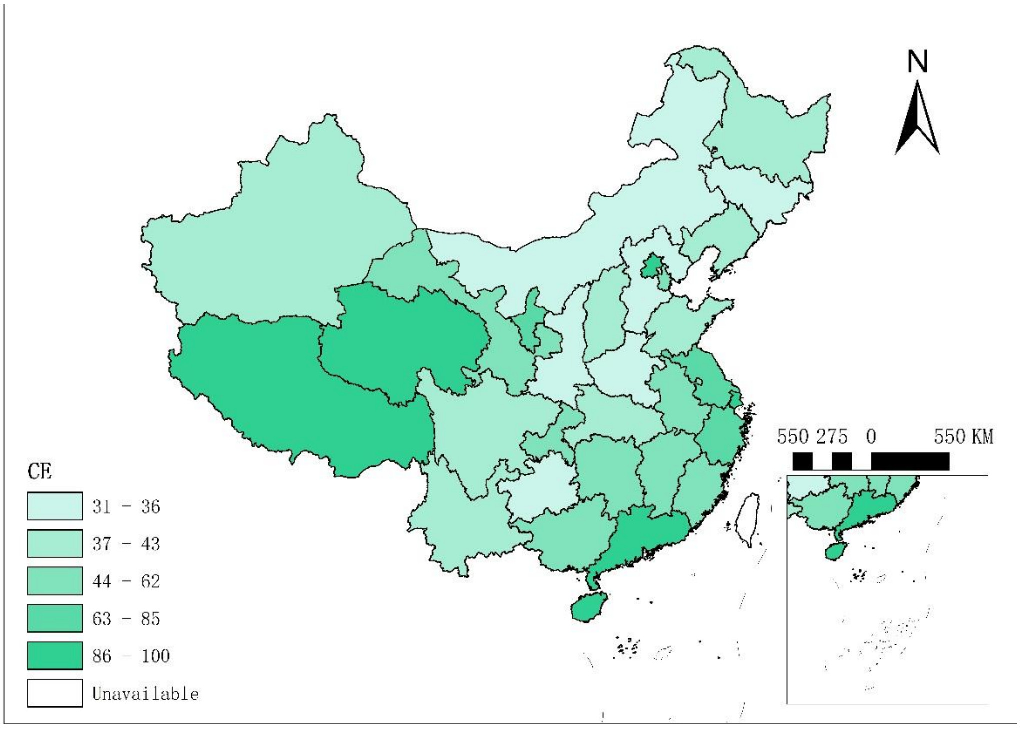

Figure 1.
Average level of green finance in 31 provinces from 2000 to 2020.

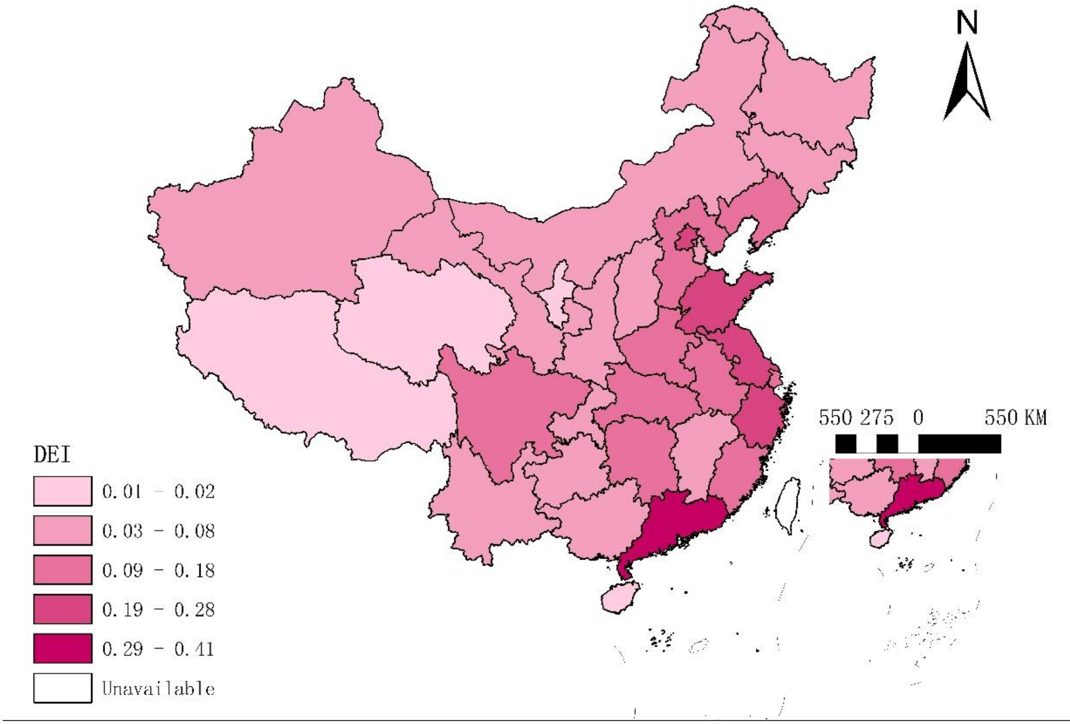

Figure 2.
Average level of digital economy in 31 provinces from 2000 to 2020.

Based on the entropy-weighted method, the digital economy index was calculated for 31 provinces from 2000 to 2020, with the results presented in the appendix Table A2. Figure 2 illustrates significant regional variation in the average digital economy levels across China. The Eastern region exhibits more advanced digital economic development, while the Central and Western regions lag behind. Detailed data for each year and province are available in Appendix A, Table A2. Provinces with the highest average digital economy levels include Guangdong, Jiangsu, Beijing, and Zhejiang, all primarily concentrated in China's Eastern region. In contrast, the lowest-ranking provinces, Tibet, Qinghai, Ningxia, and Hainan, are predominantly located in the Central and Western regions. Notably, the digital economy has grown substantially across all provinces during the 2000–2020 period, demonstrating strong national progress in digital transformation.

5.2. Empirical Results of the Tobit Regression Model

Table 1.
Descriptive statistics.

	(1)	(2)	(3)	(4)	(5)
Variables	**N**	**Min.**	**Max.**	**SD**	**Mean**
China					
GFI	651	0.243	1	0.268	0.575
DEI	651	0.000718	0.736	0.115	0.113
POP	651	258	12,624	2,775	4,311
GC	651	6.500	49.10	6.179	36.18
ES	651	0	0.945	0.137	0.740
IS	651	0.158	0.620	0.0835	0.422
lnGDP	651	4.769	11.62	1.257	8.992
Eastern China					
GFI	252	0.243	1	0.279	0.697
DEI	252	0.00910	0.736	0.144	0.177
POP	252	789	12,624	3,146	4,970
GC	252	30.30	49.10	3.619	39.45
ES	252	0	0.839	0.141	0.636
IS	252	0.158	0.565	0.104	0.419
lnGDP	252	6.267	11.62	1.102	9.525
Middle China					
GFI	189	0.260	1	0.160	0.415
DEI	189	0.0206	0.309	0.0642	0.0892
POP	189	2,372	9,941	2,172	4,953
GC	189	20.70	46.80	5.401	35.63
ES	189	0.688	0.931	0.0585	0.822
IS	189	0.254	0.620	0.0710	0.443
lnGDP	189	7.339	10.92	0.870	9.171
Western China					
GFI	210	0.281	1	0.257	0.573
DEI	210	0.000718	0.379	0.0642	0.0589
POP	210	258	8,371	2,245	2,941
GC	210	6.500	43.80	7.192	32.74
ES	210	0	0.945	0.100	0.791
IS	210	0.202	0.538	0.0594	0.406
lnGDP	210	4.769	10.79	1.324	8.190

Table 1 presents descriptive statistics for all data grouped by region. The results align with those depicted in Figure 1. The findings indicate that the average green finance in China's Central region is the lowest, accompanied by a relatively low standard deviation, suggesting limited variability among provinces. In contrast, the Western region demonstrates a higher average green finance index, accompanied by a larger standard deviation, implying considerable disparities across provinces.

Similarly, with respect to digital economy levels, the results are consistent with Figure 2. From West to East, provinces exhibit a gradual increase in digital economy development. The relatively small standard deviations across regions indicate limited regional variation in digitalization levels.

Table 2.
Regional Tobit Regression Results for China.

	(1)	(2)	(3)	(4)
	Eastern China	**Middle China**	**Western China**	**China**
DEI	1.902***	0.004	0.898***	1.627***
	(8.99)	(0.01)	(2.78)	(13.12)
lnGDP	-0.217***	-0.159***	-0.117***	-0.206***
	(-8.65)	(-4.83)	(-6.18)	(-15.68)
POP	-0.000	0.000***	-0.000***	-0.000
	(-1.60)	(6.02)	(-6.18)	(-0.80)
GC	-0.001	0.014***	0.004*	0.009***
	(-0.21)	(4.33)	(1.94)	(5.11)
ES	-0.265*	-0.228	-0.093	-0.466***
	(-1.74)	(-1.30)	(-0.83)	(-6.75)
IS	0.041	-0.487***	-0.748***	-0.038
	(0.19)	(-3.34)	(-3.46)	(-0.34)
_cons	2.685***	1.614***	1.859***	2.277***
	(9.81)	(7.10)	(14.67)	(24.07)
var(e.TE)	0.046***	0.018***	0.024***	0.038***
	(11.22)	(9.72)	(10.25)	(18.04)
N	252.000	189.000	210.000	651.000
r2				
ar2				

Note: *, **, and *** denote the 10%, 5%, and 1% levels of significance, respectively.
Standard errors in parentheses: this indicates that the values in parentheses below the estimated coefficients represent the standard errors.

Table 2 presents the regression results for China's Eastern, Central, and Western regions, as well as for the nation overall. The findings show that the development of the digital economy has a significant positive effect on green finance in the Eastern, Western, and national samples, with coefficients of 1.902, 0.898, and 1.627, respectively, all significant at the 1% level. In contrast, the effect in the Central region is not statistically significant.

Furthermore, ln GDP is significantly and negatively associated with green finance, with absolute coefficients of 0.217, 0.117, and 0.206 for the Eastern, Western, and national samples, respectively each significant at the 1% level. The energy structure exerts a significant negative effect on green finance in both the Eastern region and the national sample, with absolute coefficients of 0.265 and 0.466, respectively. Meanwhile, industrial structure shows statistical significance solely in the Western region, where it has a negative effect with a coefficient of 0.748, also significant at the 1% level.

The effects of population and green coverage on green finance are relatively weak and statistically insignificant in the Eastern region, even at the 10% significance level.

6. Discussion

It is important to note that both the digital economy index and the green finance index align closely with empirical realities in China. The eastern region, home to economically advanced cities such as Shanghai, Guangzhou, Shenzhen, and Hangzhou, is generally recognized as the most developed part of the country [40, 76]. The industrial composition in this region is dominated by secondary and tertiary industries, which lead to higher carbon efficiency and consequently promote green finance [61, 77].

By contrast, the western region of China, although rich in natural resources, exhibits lower levels of economic development [76]. This region relies heavily on traditional industries such as resource extraction and animal husbandry, which have resulted in limited digital economy development but relatively high green finance. The central region is characterized by its industrial focus, with moderate levels of digitalization and a high reliance on coal as a primary energy source [40, 78], contributing to comparatively low green finance [18].

The regression results are consistent with existing literature, indicating that the development of the digital economy exerts a significant positive influence on green finance [40], particularly in Eastern China [57]. However, the effect in Central China is statistically insignificant, likely because the region's dominant heavy industry sector is less integrated with digital technologies. Furthermore, in line with the Environmental Kuznets Curve (EKC), the results suggest that GDP growth across all regions significantly reduces green finance, implying that China's current economic expansion still incurs environmental costs in the form of increased carbon emissions [67].

Additionally, the effects of energy structure and industrial structure on green finance vary by region, reflecting substantial regional disparities across Chinese provinces [57, 58, 61]. Specifically, the energy structure exerts a negative impact on green finance in Eastern China and at the national level, while the industrial structure negatively affects green finance only in Western China.

7. Conclusion

In conclusion, this study aims to measure green finance and the level of digital economy development across 31 Chinese provinces and to examine the impact of the digital economy on green finance. In the context of the escalating global greenhouse effect, and as one of the world's largest carbon dioxide emitters, China introduced the "dual carbon" policy in 2021. Therefore, rather than focusing solely on total CO_2 emissions, it is more appropriate to examine carbon efficiency, which reflects the balance between economic growth and environmental sustainability.

This study employs the entropy-weighted method to evaluate digital economy development from 2000 to 2020, followed by the DEA-SBM approach to calculate the green finance index. Finally, a Tobit model is used to examine the impact of the digital economy on green finance in the Eastern, Central, and Western regions, as well as at the national level.

The results reveal that the digital economy is more developed in the Eastern region and less developed in the Western region. The green finance index is relatively higher in Eastern and Western China and lower in Central China. Empirical findings show that the digital economy significantly improves the green finance index in Eastern and Western China and across the country overall, but has no statistically significant effect in Central China. In contrast, GDP growth significantly reduces the green finance index in all three regions, suggesting that China's current economic trajectory remains carbon-intensive and is not yet aligned with its peak carbon goals.

Based on these findings, there are some policy implications for policymakers:

Balancing economic growth and the green finance index: Policymakers should ensure a balance between sustainable development and the green finance index.

Promote digitization in eastern and western regions: The results show that the development of the digital economy has a positive impact on green finance in eastern and western China. Policymakers should encourage and facilitate further digitization in these regions to improve environmental sustainability.

Industrial transformation in the central region: As digitalization in the central region does not have a significant impact on the green finance index, governments should focus on industrial transformation towards more sustainable models. Moving away from heavy industry to cleaner, more efficient sectors.

These recommendations are intended to help China achieve its dual carbon policy goals while maintaining sustainable economic growth and reducing its carbon emissions.

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Appendix A

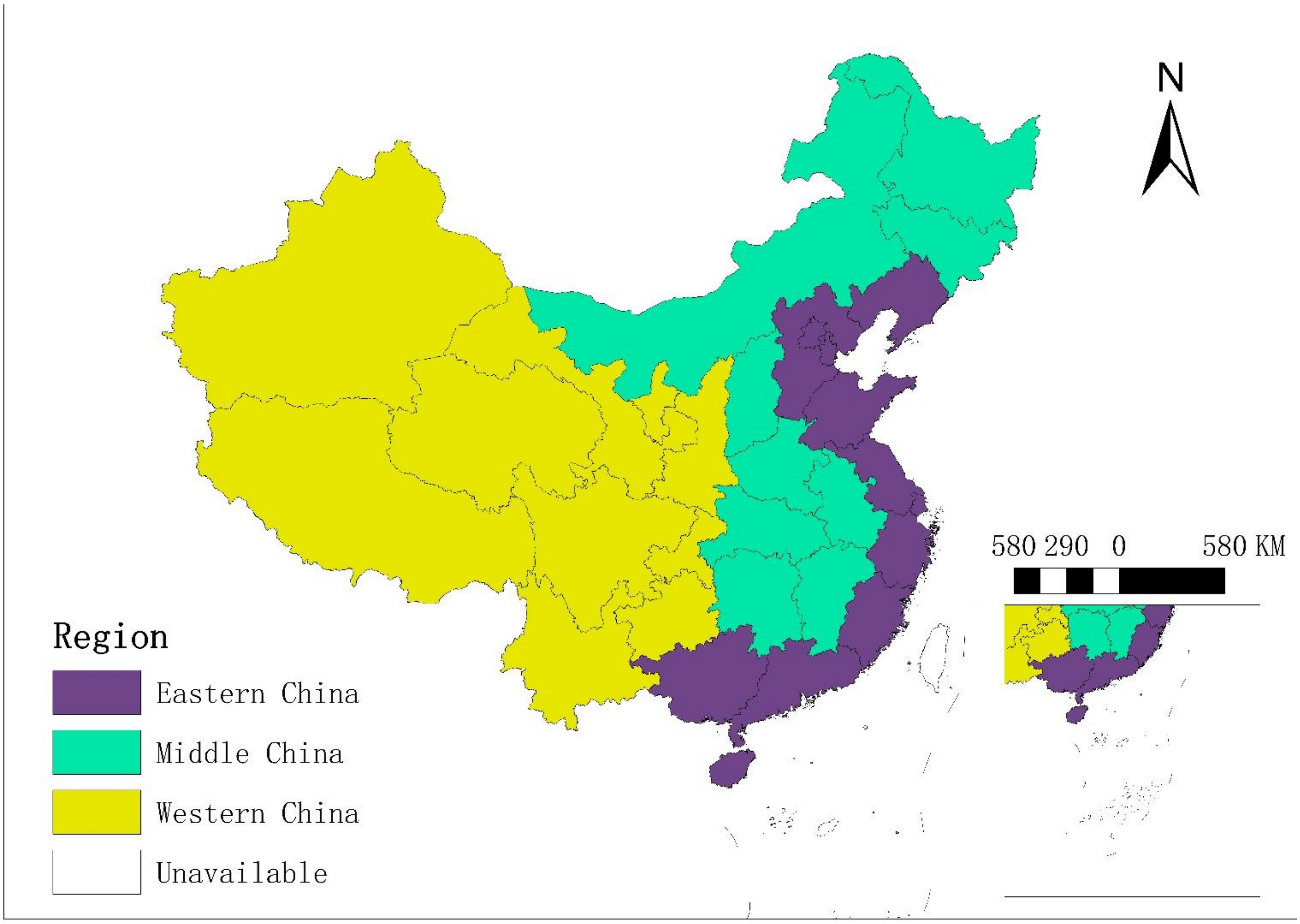

Figure A1.
The distribution of Eastern, Western, and Central regions in China.

Table A1.
The division of Central, Eastern, and Western Regions by the State Council of China.

Western China	GanSu, GuiZhou, NingXia,QingHai, ShananXi, SiChuan, Tibet, XinJiang, YunNan, ChongQing
Middle China	AnHui, HeNan, HeiLongJiang, HuBei, HuNan, JiLin, JiangXi, Inner Mongolia, ShanXi
Eastern China	BeiJing, FuJian, GuangDong, GuangXi, HaiNan, HeBei, JiangSu, LiaoNing, ShanDong, ShangHai, TianJin, ZheJiang

Table A2.
The Result of Digital Economy Index in China 31 Provinces from 2000 to 2020.

Province	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Tibet	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01
QingHai	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.02
NingXia	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.02
HaiNan	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.04	0.03	0.03	0.04	0.04	0.04	0.05	0.02
TianJin	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.05	0.06	0.08	0.07	0.07	0.07	0.08	0.08	0.09	0.05
GanSu	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.05	0.06	0.08	0.06	0.07	0.07	0.08	0.09	0.08	0.05
Inner Mongolia	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.05	0.06	0.07	0.08	0.08	0.08	0.09	0.09	0.10	0.11	0.05
GuiZhou	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.04	0.06	0.08	0.09	0.08	0.08	0.09	0.10	0.11	0.11	0.05
XinJiang	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.05	0.07	0.07	0.10	0.11	0.12	0.15	0.11	0.12	0.06
JiLin	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.06	0.06	0.07	0.09	0.08	0.07	0.08	0.09	0.08	0.08	0.06
ChongQing	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.04	0.05	0.06	0.07	0.10	0.12	0.11	0.11	0.12	0.14	0.15	0.15	0.07
HeiLongJiang	0.03	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.07	0.08	0.10	0.11	0.10	0.09	0.11	0.11	0.11	0.11	0.07
YunNan	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.06	0.08	0.11	0.12	0.11	0.10	0.11	0.13	0.14	0.15	0.07
JiangXi	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.06	0.08	0.10	0.11	0.11	0.10	0.14	0.16	0.16	0.17	0.07
ShanXi	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.06	0.07	0.08	0.10	0.13	0.11	0.10	0.11	0.13	0.12	0.13	0.08
GuangXi	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.07	0.08	0.11	0.12	0.11	0.11	0.12	0.14	0.15	0.17	0.08
ShananXi	0.03	0.03	0.03	0.04	0.04	0.04	0.05	0.05	0.05	0.06	0.07	0.08	0.10	0.13	0.13	0.12	0.13	0.13	0.15	0.15	0.16	0.08
AnHui	0.02	0.03	0.03	0.03	0.04	0.04	0.05	0.05	0.05	0.06	0.07	0.09	0.11	0.14	0.16	0.15	0.16	0.18	0.22	0.22	0.23	0.10
LiaoNing	0.05	0.05	0.05	0.06	0.06	0.07	0.07	0.07	0.07	0.08	0.09	0.11	0.13	0.16	0.18	0.17	0.16	0.17	0.18	0.17	0.18	0.11
HuBei	0.03	0.03	0.04	0.04	0.05	0.05	0.06	0.06	0.07	0.07	0.08	0.10	0.13	0.17	0.18	0.17	0.17	0.18	0.20	0.22	0.22	0.11
HuNan	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.07	0.07	0.07	0.08	0.10	0.13	0.16	0.19	0.16	0.15	0.18	0.20	0.21	0.21	0.11
FuJian	0.07	0.07	0.08	0.08	0.08	0.09	0.09	0.09	0.10	0.10	0.10	0.13	0.16	0.19	0.21	0.19	0.19	0.21	0.23	0.23	0.22	0.14
HeBei	0.06	0.06	0.07	0.07	0.08	0.08	0.08	0.08	0.09	0.09	0.10	0.12	0.16	0.20	0.21	0.20	0.20	0.22	0.24	0.24	0.24	0.14
HeNan	0.04	0.04	0.04	0.05	0.05	0.06	0.07	0.07	0.07	0.08	0.09	0.12	0.16	0.23	0.27	0.25	0.26	0.28	0.29	0.30	0.31	0.15
SiChuan	0.04	0.04	0.05	0.05	0.06	0.07	0.07	0.08	0.08	0.09	0.10	0.13	0.16	0.22	0.26	0.27	0.29	0.31	0.33	0.35	0.38	0.16
ShangHai	0.10	0.10	0.10	0.10	0.11	0.11	0.12	0.12	0.12	0.13	0.14	0.15	0.17	0.22	0.28	0.28	0.23	0.30	0.31	0.30	0.34	0.18
ShanDong	0.08	0.09	0.10	0.10	0.11	0.12	0.12	0.13	0.13	0.14	0.16	0.19	0.23	0.29	0.33	0.32	0.35	0.39	0.42	0.40	0.43	0.22
ZheJiang	0.11	0.12	0.12	0.13	0.14	0.15	0.15	0.16	0.17	0.17	0.19	0.22	0.25	0.30	0.33	0.32	0.33	0.37	0.40	0.41	0.43	0.24
BeiJing	0.14	0.15	0.15	0.16	0.16	0.17	0.18	0.18	0.19	0.20	0.22	0.24	0.27	0.32	0.35	0.34	0.36	0.43	0.44	0.47	0.48	0.27
JiangSu	0.15	0.15	0.16	0.17	0.18	0.19	0.19	0.20	0.20	0.21	0.22	0.26	0.31	0.38	0.40	0.37	0.37	0.40	0.42	0.42	0.45	0.28
GuangDong	0.17	0.18	0.19	0.20	0.22	0.23	0.24	0.26	0.27	0.28	0.32	0.38	0.45	0.58	0.62	0.60	0.60	0.66	0.71	0.72	0.74	0.41

Table A3.
The Result of Green Finance Index in China 31 Provinces from 2000 to 2020.

Province	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**Mean**
BeiJing	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
GuangDong	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
HaiNan	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
QingHai	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Tibet	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ShangHai	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.65	0.66	0.66	0.63	0.62	0.62	0.9
JiangSu	0.73	0.75	0.69	0.66	0.64	0.65	0.64	0.64	0.66	0.71	1	1	1	1	1	1	1	1	1	1	1	0.85
NingXia	0.84	0.95	1	0.76	0.77	0.73	0.74	0.74	0.74	0.71	0.74	0.75	0.76	0.82	0.75	0.71	0.71	0.71	0.71	0.71	0.71	0.76
ZheJiang	0.83	0.85	0.79	0.77	0.75	0.72	0.69	0.65	0.66	0.65	0.69	0.7	0.72	0.67	0.67	0.65	0.65	0.64	0.68	0.68	0.87	0.71
FuJian	1	1	1	1	1	0.71	0.62	0.58	0.55	0.52	0.53	0.49	0.5	0.48	0.47	0.45	0.46	0.45	0.44	0.44	0.43	0.62
GuangXi	0.87	1	1	1	0.58	0.52	0.5	0.47	0.45	0.39	0.35	0.33	0.33	0.34	0.35	0.35	0.34	0.4	0.71	1	1	0.59
TianJin	0.65	0.63	0.61	0.65	0.61	0.62	0.6	0.56	0.57	0.52	0.49	0.48	0.49	0.48	0.48	0.47	0.5	0.51	0.52	0.53	0.56	0.55
ChongQing	0.6	0.57	0.5	0.64	0.61	0.54	0.53	0.54	0.51	0.5	0.5	0.49	0.53	0.55	0.54	0.52	0.53	0.52	0.53	0.53	0.53	0.54
HuNan	1	1	1	1	0.76	0.5	0.47	0.43	0.41	0.4	0.4	0.37	0.38	0.36	0.36	0.36	0.36	0.35	0.36	0.37	0.37	0.52
GanSu	0.42	0.38	0.35	0.42	0.4	0.41	0.42	0.45	0.44	0.44	0.44	0.44	0.47	0.46	0.46	0.43	0.43	0.61	1	1	1	0.52
AnHui	0.57	0.64	0.79	1	1	0.5	0.48	0.45	0.41	0.4	0.41	0.4	0.4	0.38	0.37	0.35	0.36	0.36	0.36	0.37	0.37	0.49
JiangXi	0.65	0.63	0.51	0.54	0.51	0.5	0.48	0.48	0.48	0.48	0.48	0.47	0.49	0.46	0.48	0.43	0.43	0.42	0.42	0.42	0.42	0.48
SiChuan	0.58	0.58	0.5	0.48	0.48	0.5	0.45	0.42	0.39	0.36	0.39	0.39	0.39	0.37	0.37	0.35	0.36	0.37	0.41	0.39	0.41	0.43
ShanDong	0.63	0.58	0.52	0.47	0.45	0.42	0.41	0.39	0.39	0.4	0.4	0.41	0.41	0.4	0.39	0.38	0.38	0.37	0.36	0.36	0.35	0.42
LiaoNing	1	1	1	0.48	0.42	0.36	0.33	0.32	0.3	0.29	0.28	0.27	0.27	0.27	0.27	0.29	0.35	0.34	0.33	0.34	0.33	0.42
ShanXi	0.36	0.36	0.33	0.35	0.35	0.35	0.33	0.32	0.31	0.28	0.29	0.3	0.29	0.28	0.28	0.26	0.26	0.34	1	1	1	0.41
HuBei	0.45	0.47	0.43	0.47	0.47	0.48	0.43	0.42	0.41	0.39	0.39	0.37	0.38	0.38	0.38	0.35	0.36	0.35	0.36	0.35	0.32	0.4
XinJiang	0.48	0.44	0.4	0.47	0.44	0.43	0.44	0.44	0.44	0.41	0.41	0.41	0.38	0.36	0.36	0.33	0.33	0.31	0.31	0.29	0.28	0.39
HeiLongJiang	0.59	0.54	0.44	0.68	0.47	0.47	0.44	0.39	0.36	0.33	0.32	0.32	0.32	0.31	0.31	0.28	0.29	0.29	0.3	0.3	0.3	0.38
YunNan	0.6	0.48	0.46	0.45	0.43	0.39	0.4	0.46	0.4	0.37	0.33	0.33	0.34	0.33	0.34	0.34	0.34	0.33	0.31	0.31	0.3	0.38
ShananXi	0.46	0.43	0.39	0.44	0.43	0.42	0.39	0.37	0.35	0.34	0.34	0.34	0.34	0.33	0.33	0.32	0.32	0.31	0.31	0.31	0.29	0.36
HeNan	0.51	0.5	0.44	0.49	0.44	0.42	0.37	0.34	0.32	0.3	0.31	0.3	0.31	0.29	0.29	0.28	0.28	0.29	0.31	0.34	0.34	0.36
GuiZhou	0.35	0.31	0.28	0.32	0.32	0.33	0.34	0.37	0.39	0.37	0.38	0.39	0.39	0.37	0.38	0.35	0.35	0.35	0.35	0.34	0.33	0.35
JiLin	0.5	0.46	0.41	0.41	0.39	0.34	0.3	0.3	0.28	0.29	0.29	0.3	0.32	0.33	0.33	0.32	0.33	0.34	0.35	0.36	0.36	0.35
Inner Mongolia	0.46	0.46	0.4	0.39	0.36	0.32	0.31	0.29	0.28	0.27	0.27	0.26	0.26	0.26	0.28	0.28	0.29	0.33	0.36	0.42	0.51	0.34
HeBei	0.42	0.43	0.39	0.4	0.4	0.36	0.33	0.31	0.29	0.28	0.29	0.27	0.27	0.25	0.25	0.24	0.25	0.25	0.25	0.26	0.27	0.31