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The Impact of Digital Finance on Green Total Factor Energy Efficiency: Evidence at China's City Level

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Abstract: The rapid development of digital finance has delivered significant benefits, such as sustainable development and economic growth. We explore the relationship between digital finance and green total factor energy efficiency (GTFEE) for the first time, filling a gap in the existing literature. This paper uses dynamic panel models to explore digital finance's impact on GTFEE at the Chinese city-level panel data from 2011 to 2018. The results show that digital finance can significantly improve urban GTFEE, and the findings remain robust with various tests. Second, the mechanism analysis indicates that digital finance can improve GTFEE by promoting urban green technology innovation and industrial structure upgrading. Further study shows that digital finance has a better effect on the improvement of GTFEE in central and western cities, small cities and non-resource-based cities, but has no significant or small impact on GTFEE in eastern cities, large cities and resource-based cities, reflecting the inclusiveness of digital finance.

Keywords: digital finance; green total factor energy efficiency; green technology innovation; industrial structure upgrading

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1. Introduction

Energy is an essential foundation for human survival and economic development [1,2], which is becoming increasingly important in the industrialization of countries [3]. The International Energy Agency (IEA) reports that global energy consumption is expected to increase by 54% by 2025 compared to 2020, while energy consumption in developing Asia is expected to double [4]. However, the surge in energy consumption will bring environmental problems [5]. Environmental pollution caused by energy consumption affects the sustainable development of the world economy and brings huge economic losses to China [6]. Under the dual pressure of economic growth and environmental protection, the key to economic growth and carbon emission reduction is gradually improving green total factor energy efficiency by considering environmental and resource factors [7]. Therefore, it is of great theoretical value and policy guiding significance to clarify the influencing factors of GTFEE and seek ways to improve GTFEE.

Meanwhile, financial development is vital in improving energy efficiency [8,9]. Baloch (2019) [10] shows an inverted U-shaped relationship between financial development and energy efficiency; only when financial development reaches a certain level it can significantly impact energy efficiency improvement. Qu et al. (2020) [8] found that financial development can influence energy efficiency through the scale economy effect, innovation driving effect, information spillover effect and structural adjustment effect. However, the nature of traditional finance has contributed to the obvious exclusion of financial services, with a large amount of high-quality financial resources concentrated in developed regions, large enterprises and high-income groups, to the exclusion of backward regions such as rural areas, small and medium-sized enterprises (SMEs) and low-income classes [11].

Private enterprises, mainly SMEs, occupy a crucial position in the national economies of various countries; in China, for example, SMEs contribute 80% of employment, 70% of patented inventions, more than 60% of GDP and more than 50% of tax revenue. Therefore, whether the "financing difficulties" of SMEs and the low-income class can be effectively alleviated is not only a matter of survival of SMEs and the low-income class, but also affects macroeconomic development and environmental changes.

The dilemma faced by the development of traditional finance needs to be solved by innovative financial models in the new era. In recent years, the emergence of digital technologies represented by big data, cloud computing, artificial intelligence, and blockchain has hugely impacted traditional finance, and digital finance has emerged [12,13]. Digital finance emphasizes the equality and inclusiveness of access to financial services for different subjects. It provides financial services for low-income groups and SMEs by sharing information, lowering the threshold of access to financial resources, and covering "service blind spots" that are difficult to be covered by traditional financial institutions [13]. Digital finance can reduce the travel activities of people to and from traditional financial institutions, thereby reducing energy consumption and improving GTFEE [14]. Meanwhile, digital finance can expand public participation in environmental protection, which will enhance GTFEE. Is it worth considering the impact digital finance has on GTFEE and the potential mechanisms of such impact? However, to date, less literature has focused on the impact of digital finance on GTFEE. In view of this, this paper attempts to analyze the relationship between digital finance and GTFEE and explore whether and how digital finance contributes to the enhancement of GTFEE.

To answer the above questions, this paper empirically investigated the impact of digital finance on GTFEE by taking Chinese city panel data from 2011 to 2018 as samples. At the same time, considering that there may be endogenous problems between digital finance and GTFEE, the research method of this paper is set as a dynamic panel model. Further, this paper explores the mechanism of digital finance influencing GTFEE using the mediation effect model.

There are two reasons for using Chinese city-level data to verify the topic of this paper. First, the BP World Energy Statistical Yearbook 2021 shows that China has become the world's largest energy consumer and carbon emitter [15]. In 2021, China's energy consumption accounted for 26.11% of the world's total energy consumption. As the largest developing country globally, the contradiction between economic development and the environment in China is also a common problem faced by many developing countries [16]. Second, China leads the world in digital finance scale and technology practices [17], and the data on digital finance in Chinese cities is available.

The main contributions of this paper are as follows: first, we expand the research related to the economic effects of digital finance. The existing literature has mainly explored the impact of digital finance on poverty rates [18], financing constraints of SMEs [19], efficiency of financial services [13], and environmental pollution [20]. To the best of our knowledge, this paper is the first to expand related research on the economic effects of digital finance from the perspective of GTFEE, filling the gaps in the existing literature. Second, we expand the related research on the influencing factors of energy efficiency. The existing literature has explored the impact of factors such as industrial structure [21], technological innovation [22], energy consumption structure [23], environmental regulation [24], urbanization [25], and financial development [9] on energy efficiency, but has not examined the impact of digital finance on energy efficiency. To the best of our knowledge, this paper is the first to expand the relevant research on the influencing factors of energy efficiency from the perspective of digital finance, filling the gaps in the existing literature. Third, we explore the impact mechanism of digital finance on GTFEE, which will help us to understand the relationship between digital finance and GTFEE more deeply. And we find that digital finance can improve GTFEE through the "green technology innovation effect" and the "industrial structure upgrading effect", the former effectively verifies the existence of the "Porter effect". Fourth, we focus on the inclusiveness of digital finance. Through a series of heterogeneity tests, we find that digital finance is more effective in improving energy efficiency in economically underdeveloped cities and energy-scarce cities, effectively verifying the existence of the inclusive function of digital finance.

The structure of this paper is as follows: Section 2 reviews the relevant literature. Section 3 summarizes the background of digital finance and presents the theoretical mechanism between digital finance and GTFEE. Section 4 provides an introduction to methodology and data. Section 5 presents the empirical results of the paper. Section 6 presents conclusions and implications.

2. Literature Review

Two branches of literature relevant to our research exist. The first branch related to this paper is the measurement of energy efficiency and the factors influencing energy efficiency. Regarding research methodology, energy efficiency measures can be divided into single factor energy efficiency and total factor energy efficiency. Early energy efficiency studies mainly referred to single factor energy efficiency, meaning that only energy as a single input factor was considered. Sun et al. (2019) [26] stated that the method of measuring single factor energy efficiency may be too simplistic, mainly because it relies only on a single input and ignores other inputs such as capital and labor. The so-called total factor energy efficiency means that production factors such as energy, capital, and labour are simultaneously used as input factors. Hu and Wang (2006) [27] proposed total factor energy efficiency based on the data envelopment method, which effectively overcomes the shortcomings of traditional single factor energy efficiency. However, the conventional calculation of total factor energy efficiency is also flawed, mainly because it does not include undesired output–pollutants [28]. Zhang et al. (2015) [29] incorporate energy consumption and pollutant emissions into total factor energy efficiency, defined as green total factor energy efficiency (GTFEE). Gao et al. (2022) [1] point out that compared with single factor energy efficiency and total factor energy efficiency, green total factor energy efficiency (GTFEE) is more effective and comprehensive to reflect the efficiency of the energy-economic system. Currently, there are two main measures of GTFEE. The first measure is data envelopment analysis (DEA) based on mathematical programming methods. The other measure is parametric stochastic frontier analysis (SFA), built on econometric techniques.

Numerous scholars from different perspectives have studied the factors influencing energy efficiency. It was found that factor endowment [30], industrial structure [21,23], technological innovation [22,26], energy consumption structure [23], energy price [31,32], trade openness [33,34], economic development [23], government intervention [35], industrial agglomeration [36,37], environmental regulation [24,38], urbanization [25,39] and financial development [8,9] are important factors that affect energy efficiency. For example, based on firm-level data from 2003 to 2017 in India, Haider et al. (2021) [22] find that investing in R&D expenditures and patenting activities can improve the energy efficiency of firms. Xin et al. (2020) [32] provide evidence that market-oriented electricity price has a stable positive correlation with energy efficiency in the short and long term. Wei et al. (2020) [34] find that increasing imports effectively improve total factor energy efficiency. Based on the data from the Japanese industry, Tanaka et al. (2021) [37] discovered that industrial agglomeration affects energy efficiency.

The other branch of the relevant literature is mainly concerned with evaluating the economic effects of digital finance. It has been shown that digital finance is an important tool for poverty alleviation [40], and it increases the financial availability of vulnerable groups such as farmers [41] thereby reducing poverty rates [18]. Meanwhile, inclusive digital finance can alleviate the financing constraints of small and medium-sized enterprises [19], thereby improving the green technology innovation of enterprises [42]. Other studies have found that digital finance has brought enormous competitive pressure to traditional financial institutions, thereby improving the efficiency of financial services [13]. In addition, Le et al. (2020) [20] and Wang et al. (2022) [43] show that inclusive digital finance effectively reduces environmental pollution.

By analyzing the above literature, few researchers have studied the relationship between digital finance and GTFEE. Even less literature explores the channels of the impact of digital finance on GTFEE. However, as a new financial business model, digital finance may impact GTFEE by affecting the macro-economy, micro-enterprises and individuals. Compared with the existing literature, this paper fills the research gap in the relationship between digital finance and GTFEE.

3. Background and Hypothesis

3.1. Background

Combining digital technology and financial services has become a new trend with the popularisation of internet technology. Digital finance originated at the end of the 20th century. The launch of Alipay in 2004 is considered the starting point of digital finance in China. In 2013, with the launch of Yu Ebao, digital finance entered the fast lane of accelerated development [13]. In just over ten years, China has been at the forefront of digital finance development worldwide. KPMG data show that in 2018, China's digital finance market reached 115 trillion RMB, and it is in a leading position in the world's technology practice. Take Alipay as an example, data from the "Ant Group 2021 Sustainability Report" shows that by the end of 2021, Alipay provides digital financial services to more than 1 billion users and 80 million MSMEs worldwide.

Digital finance refers broadly to a new financial business model in which traditional financial institutions and internet companies use digital technologies represented by big data, cloud computing, artificial intelligence and blockchain to innovate business processes, business models and financial products to realize financial activities such as payment, investment and financing [13]. The digital finance business includes the following categories: (1) third-party payment, specifically mobile payment and Internet payment. (2) Network investment, mainly including Internet wealth management represented by Yu Ebao and Lingqiantong, etc. (3) Network financing, mainly including enormous technology credit, network crowdfunding and P2P platform loans. (4) Digital currency and digital assets. (5) Other digital finance, including digital insurance, digital supply chain finance, and financial service outsourcing [13].

Since its introduction, digital finance has often been associated with fintech and financial inclusion. From the existing studies, the connotations of digital finance and fintech are almost identical. Digital finance is mainly based on the development of the digital economy, focusing on the digitization of financial services, and is more grounded in finance in terms of scope. Fintech is based on digital technology, and its development will promote the digitization of finance. The concepts of digital finance and fintech have a great deal of overlap and relevance, and the two are likely to gradually converge in the future [18]. Inclusive finance is a financial system that can effectively and holistically provide easier access to all segments and groups of society, especially the less developed regions and low-income people [13]. The United Nations initially used this concept to promote the "International Year of Microfinance 2005" and was later strongly promoted by the United Nations and the World Bank. Financial inclusion practice shows a strong correlation between digital finance and fintech. Digital finance and fintech reduce the cost of financial services and expand the coverage of financial services through digital technology. Both have become important financial inclusion sources and growth points [13].

3.2. Hypothesis

Digital finance can directly affect GTFFE by breaking space restrictions and expanding public participation in environmental protection. First, the high speed and convenience of digital finance break the space restrictions of traditional finance [44]. Various financial businesses complete transactions online through the Internet. This digital model can reduce the travel activities of enterprises and individuals to and from traditional financial institutions, thereby reducing energy consumption and improving GTFEE [14].

Second, digital finance can expand public participation in environmental protection. Digital finance uses digital technology to disclose information on green products and environmental protection activities, which helps consumers purchase environmentally friendly products and participate in various environmental protection activities. Take Alipay's "Ant Forest" function as an example, users can virtually plant trees in "Ant Forest", and then Alipay donates funds to public welfare organizations, which will organize specific work such as planting and maintenance in the real desert. Data from "Ant Group 2021 Sustainability Report" shows that by August 2021, "Ant Forest" has driven more than 600 million people (613 million) to live a low-carbon lifestyle and planted 326 million trees in 11 provinces across China (https://gw.alipayobjects.com/os/bmw-prod/2c4f049f-d96e-4108-918f-8e08027e0e22.pdf, accessed on 1 May 2022). These environmentally friendly products and activities can undoubtedly increase the participation of the whole society in environmental protection, reducing energy consumption and enhancing GTFEE. Based on the above analysis, we propose H1 as follows.

Hypothesis 1 (H1). *Digital finance has a positive effect on GTFEE.*

Digital finance indirectly affects GTFEE through green technology innovation and upgrading industrial structure.

Firstly, we propose the green technology innovation effect. Digital finance can improve green technology innovation in firms [42]. On the one hand, traditional financial institutions need to spend a lot of money to absorb the investment of those investors with small and scattered capital in the market. Digital finance, supported by digital technologies such as big data, artificial intelligence and blockchain, can absorb these investors' funds at a lower cost [45] and transform them into financial supply. Ultimately, more funds are available to companies for green technology innovation activities.

On the other hand, digital finance, with its efficient information screening and risk assessment capabilities, can effectively reduce the information asymmetry that may occur between SMEs and financial institutions during the lending process [46], thus alleviating the financing constraints of SMEs [19]. Solving financing constraints are conducive to these enterprises carrying out green technology innovation activities.

Meanwhile, green technology innovation is one of the important ways to improve GTFEE [26]. Green technology innovation reduces energy factors' input for a given output and replaces them with other production factors, thereby improving GTFEE [47,48]. Based on the above analysis, we propose H2 as follows.

Hypothesis 2 (H2). *Digital finance positively affects GTFEE through green technology innovation.*

Second, we propose the industrial structure upgrading effect. The impact of digital finance on the industrial structure is as follows. On the one hand, digital inclusive finance raises the income of residents and reduces the income gap [49]. Both the increase in income and the reduction in income gap are beneficial to the optimization of industrial structure [50]. On the other hand, digital finance promotes regional entrepreneurship by directing financial resources to entrepreneurial groups that have the ability and need but lack capital [51]. Entrepreneurship facilitates the transfer of labor to the modern sector, thus optimizing the industrial structure [52].

Meanwhile, Industrial structure upgrading is an important factor affecting GTFEE. There are different energy allocations in different industries, leading to significant differences in energy efficiency across industries [1]. According to the data of the International Energy Agency in 2007, the industry is the highest energy-using sector worldwide. Energy efficiency varies with the industrial structure [53]. Wang and Zhao (2017) [23] found that the increase in the ratio of secondary industry output to total output harms energy efficiency. Therefore, accelerating the elimination of backward production capacity, controlling the development of high pollution and high energy consumption industries, and optimizing the industrial structure can help improve energy efficiency [54]. Based on the above analysis, we propose H3 as follows.

Hypothesis 3 (H3). *Digital finance positively affects GTFEE through industrial structure updating.*

4. Methodology and Data

4.1. Data

We take all cities in China from 2011 to 2018 as the research object, and the data mainly include GTFEE measure-related data, digital finance-related data, and other city-level data. The data sources for this paper are as follows: (1) Data for measuring GTFEE are obtained from China City Statistical Yearbook and China Energy Statistical Yearbook. (2) The data on digital finance in each city comes from the China Digital Financial Inclusion Index released by the Digital Finance Research Center of Peking University. (3) For the green patent data, we first obtain the patent data of each city through the official website of the State Intellectual Property Office of China, and then use the green patent classification list defined by WIPO to clean, filter and count the patent data, and finally obtain the number of green patent applications in prefecture-level cities in China. (4) Other mechanism and control variables data are derived from the China City Statistical Yearbook.

4.2. Variables and Data

4.2.1. Dependent Variable

Green Total factor energy efficiency (GTFEE); referring to Wu et al. (2021) [55] and Li et al. (2022) [56], the GTFEE covers a set of production possibilities, including inputs, expected outputs and unexpected outputs. The undesirable-SBM model is used to calculate the Green Total factor energy efficiency (GTFEE) of Chinese cities. Meanwhile, we assume that each city is a decision-making unit (DMU), the number of which is N. Suppose that Each decision-making unit has M inputs, S_1 expected outputs and S_2 unexpected outputs, which can be represented in the form of matrices $X = (x_{ij}) \in R_{m\times n}$, $Y^g = \left(y_{ij}^g\right) \in R_{s1\times n}$, $Y^b = \left(y_{ij}^b\right) \in R_{s2\times n}$. Specifically, $s^- \in R_m$, $s^g \in R_{s1}$ and $s^b \in R_{s2}$ are the corresponding relaxation vectors of input, expected output, and unexpected output, respectively. In addition, λ is the weight vector. The basic calculation formula is as follows:

$$\begin{gathered} min\ p' = \frac{1-\frac{\left(\frac{1}{m}\right)\sum_{i=1}^{m} s_i^-}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\frac{\sum_{r=1}^{s_1} s_r^g}{y_{r0}^g}+\frac{\sum_{r=1}^{s_2} s_r^b}{y_{r0}^b}\right)} \\ s.t.\ x_0 = X\lambda + s^- \\ y_0^g = Y^g\lambda - s^g \\ y_0^b = Y^b\lambda - s^b \\ \lambda \geq 0, s^- \geq 0, s^g \geq 0 \\ s^b \geq 0 \end{gathered} \tag{1}$$

In Equation (1), s^-, which is the corresponding relaxation vectors of input, includes capital stock (K), labor force (L), and energy consumption (EU). s^g, which is the corresponding relaxation vectors of expected output, is gross regional product (GDP); s^b, which is the corresponding relaxation vectors of unexpected output, includes industrial sulfur dioxide (SO_2), industrial soot, and industrial wastewater [57].

4.2.2. Independent Variable

Digital finance (DFI). We use the "Peking University Digital Financial Inclusion Index" to measure the level of digital finance in each city [58]. The index constructs the digital financial system from three dimensions: the breadth of coverage, the depth of use and the degree of digitization of digital financial services. Specific index descriptions are shown in Table 1.

Table 1. Digital finance indicator system.

First Dimension	Secondary Dimension		Specific Indicators
Breadth of Coverage	Account Coverage		Number of Alipay accounts per 10,000 people
			Proportion of Alipay card-tied users
			Average number of bank cards tied to each Alipay account
Depth of Use	Payment Business		Number of payments per capita
			Payment amount per capita
			Ratio of the number of users who are active 50 times or more per year to the number of users who are active 1 time or more per year
	Money Funds		Number of Yu Ebao purchases per capita
			Amount of Yu Ebao purchased per capita
			Number of Yu Ebao purchases per 10,000 alipay users
	Credit Business	For individual users	Number of Internet consumer loan users per 10,000 adult Alipay users
			Number of loans per capita
			Loan amount per capita
		For micro and small business operators	Number of Internet micro and small business loans users per 10,000 adult Alipay users
			Average number of loans for micro and small operators
			Average loan amount for micro and small operators
	Insurance Business		Number of insured users per 10,000 Alipay users
			Number of insurance per capita
			Insurance amount per capita
	Investment Business		Number of people involved in Internet investment and wealth management per 10,000 Alipay users
			Number of investments per capita
			Investment amount per capita
	Credit Business		Number of users using credit-based lifestyle services (including finance, accommodation, travel, social networking, etc.) per 10,000 Alipay users
			Number of calls per natural person for credit collection
Degree of digitization	Convenience		Percentage of mobile payment transactions
			Percentage of the mobile payment amount
	Cost of financial services		Average loan interest rate for micro and small operators
			The average interest rate for personal loans

4.2.3. Mediation Variables

Green technology innovation (GTI); the main indicators to measure green technology innovation include the number of green patent applications (granted) [42,59] and green total factor productivity [60]. There are two advantages of measuring innovation by patents. One is that patent data can more directly and objectively reflect the innovation capacity of the innovation subject [61]. The other is that patent data subdivides the field of green technology innovation [42]. Therefore, we use data on green patent applications in cities to measure green technology innovation.

Industrial structure upgrading (ISU); industrial structure upgrading is reflected in the change in the proportion of each industry [62], especially the shift from the highly polluting secondary industry to the clean tertiary industry [54]. Therefore, we use the ratio of the tertiary industry's output value to the secondary industry's output value to measure industrial structure upgrading.

4.2.4. Control Variable

Referring to Wang et al. (2017) [23], Li et al. (2022) [56] and Gao et al. (2022) [63] introducing other control variables in the model. (1) Economic development level (PGDP) is expressed as per capita real GDP. (2) Economic development potential (GDPG) is expressed as the GDP growth rate. (3) Population density (POP) is expressed as the total population divided by the area of administrative divisions. (4) Government intervention (GOV) is expressed as the proportion of fiscal expenditure to the GDP. (5) Total trade (TRA). (6) FDI (FDI). We take the logarithm of all the above indexes to weaken multicollinearity.

The descriptive statistics of variables are shown in Table 2.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
GTFEE	1930	0.563831	0.180721	0.241103	1
LnDFI	1930	4.874333	0.506609	2.971952	5.713676
LnPGDP	1930	10.64405	0.571256	8.841593	13.05569
LnGDPG	1930	2.784496	0.788214	−3.65805	5.384516
LnFDI	1930	10.02489	1.901228	−0.14596	14.94127
LnTRA	1930	12.08984	2.092555	−1.38757	17.79981
LnGOV	1930	−1.74595	0.41209	−3.12626	−0.35045
LnPOP	1930	6.459114	0.931677	1.773419	11.8246

4.3. Model Setting

4.3.1. Baseline Model: Dynamic Panel Data Model

The panel models can be divided into static panel models and dynamic panel models according to whether the explanatory variables contain the lag term of the explained variables. Since various factors such as economic development, government intervention, and trade opening in the previous stage (or multiple stages) will affect subsequent energy utilization, GTFEE is path-dependent [1]. If the path dependence of GTFEE is not considered, the model may have systematic bias. Therefore, referring to Hao et al. (2022) [64], this paper introduces the one lag period of GTFEE (GTFEE_{it-1}) as an explanatory variable in the model and establishes the following dynamic panel model to verify the impact of digital finance on GTFEE.

$$\mathrm{GTFEE}_{it} = \beta_0 + \beta_1 \mathrm{GTFEE}_{it-1} + \beta_2 \mathrm{DFI}_{it} + \sum_{i=1}^{N} \beta_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \tag{2}$$

In Equation (2), subscript i represents city, t represents year. GTFEE_{it} is the dependent variable, representing the green total factor energy efficiency. DFI_{it} is the independent variable, representing the level of digital finance. X_{it} represents a set of other variables that affect GTFEE_{it}, including the economic development level (PGDP), the economic development potential (GDPG), population density (POP), government intervention (GOV), total trade (TRA) and FDI (FDI). δ_i represents city fixed effect, which are used to capture differences between individuals that do not vary over time. δ_t represents year fixed effect, which is used to capture variables that do not vary with individuals, but vary with time. ε_{it} represents the error term.

Specifically, we use the System Generalized Method of Moments (SYS-GMM) to estimate model (2). SYS-GMM can overcome the "weak instrumental variables" problem of Difference GMM (DIFF-GMM), reduce potential bias and correct endogeneity problems [65]. To ensure the robustness of the results, we add DIFF-GMM to empirically estimate model (2) in the benchmark regression of Section 5.

4.3.2. Mediating Effect Model

To further examine the possible theoretical mechanism through which digital finance (DFI) affects GTFEE, we adopt a three-step mediating effect model for verification [66], as shown in Equations (2)–(4). The first stage is to verify the effect of digital finance on GTFEE, as represented in Equation (2). If the coefficient β_2 is significantly positive, it means that digital finance has a significant effect on GTFEE. The second stage is to verify the effect of digital finance on the mechanism variable (ME), as represented in Equation (3). If the coefficient α_1 is significant, it means that digital finance has a significant effect on the mechanism variable. The third stage is to verify the effect of digital finance and mechanism variables (ME) on GTFEE, as represented in Equation (4). If the coefficient of γ_2 of DFI is not significant or if the coefficient of γ_2 is significant but its absolute value decreases ($\gamma_2 < \beta_2$), it proves that digital finance affects GTFEE through mechanism variables (ME).

$$ME_{it} = \alpha_0 + \alpha_1 \mathrm{DFI}_{it} + \sum_{i=1}^{N} \alpha_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \tag{3}$$

$$\mathrm{GTFEE}_{it} = \gamma_0 + \gamma_1 \mathrm{GTFEE}_{it-1} + \gamma_2 \mathrm{DFI}_{it} + \gamma_3 ME_{it} + \sum_{i=1}^{N} \gamma_i X_{it} + \delta_i + \delta_t + \varepsilon_{it} \tag{4}$$

5. Empirical Results

5.1. Baseline Model Results

We establish the dynamic panel model to verify the impact of digital finance on GTFEE. First, the results of the White test show that the p-value is equal to 0.000, and it can be inferred that the model has heteroskedasticity. Hence, the model uses robust standard errors to solve the heteroskedasticity problem.

Meanwhile, two prerequisites must be satisfied to use the dynamic panel model. First, there is no second-order and higher-order autocorrelation in the residual series of the difference equation. Second, there is no over-identification of instrumental variables. Table 3 reports the baseline regression results for model (2). The results show that the AR (2) statistic is insignificant, indicating no second-order series correlation between the residuals and the independent variable. The p-value of the Sargan test is close to 1, meaning that the instrumental variables selected by the model are reasonable and effective, and there is no over-identification. In conclusion, the estimation results of the dynamic panel are reliable and consistent.

Table 3. The results of the baseline model.

	DIFF-GMM		**SYS-GMM**	
	(1)	**(2)**	**(3)**	**(4)**
L.GTFEE	0.131 **	0.073	0.614 ***	0.592 ***
	(0.051)	(0.053)	(0.034)	(0.032)
LnDFI	0.056 ***	0.156 ***	0.058 ***	0.053 ***
	(0.013)	(0.020)	(0.018)	(0.016)
LnPGDP		0.050		0.078 ***
		(0.031)		(0.022)
LnGDPG		0.006		0.018 ***
		(0.005)		(0.005)
LnGOV		−0.404 ***		−0.173 ***
		(0.058)		(0.037)
LnPOP		−0.016		−0.089 ***
		(0.014)		(0.016)
LnTRA		0.019 **		0.008
		(0.009)		(0.006)
LnFDI		0.034 ***		0.007 **
		(0.011)		(0.003)
_cons	−0.796 ***	−2.015 ***	−0.141	0.370 **
	(0.084)	(0.390)	(0.170)	(0.156)
N	1370	1370	1651	1651
AR(1)	0.000	0.000	0.000	0.000
AR(2)	0.159	0.327	0.654	0.564
Sargan	1.000	1.000	1.000	1.000

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Columns (1) and (2) of Table 3 are the results estimated by the DIFF-GMM method, and columns (3) and (4) are the results estimated by the SYS-GMM method. The results from columns (1)–(4) show that whether using DIFF-GMM or SYS-GMM, digital finance has a significant positive effect on GTFEE in the presence or absence of control variables, at the significance level of 1%. Taking column (4) of Table 3 as the criterion, the coefficient of LnDFI is 0.053, indicating that for every 1% increase in the digital finance development level of a city, the city's GTFEE increases by about 5%. The results verify Hypothesis 1.

In addition, the results in column (4) of Table 3 show that the first-order lag term of GTFEE is also significantly positive at the level of 1%. GTFEE has certain path dependence, and the previous GTFEE will affect the current GTFEE. Regarding the control variables, the coefficients of LnPGDP, LnGDPG and LnFDI are significantly positive, indicating that economic development and FDI play an important role in promoting GTFEE. However, LnGOV and LnPOP significantly negatively affect GTFEE, and LnTRA has an insignificant effect on GTFEE.

5.2. Mediating Effect Test

The Section 3.2 of the Hypothesis theoretically analyzed how digital finance improves GTFEE through green technology innovation and industrial structure upgrading. This section examines the possible theoretical mechanism according to the intermediary effect model. The regression results are shown in Table 4. Columns (1) and (4) show that digital finance improves GTFEE.

Table 4. The results of mediating effect test.

	GTI			**ISP**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	GTFEE	**LnGTI**	**GTFEE**	**GTFEE**	**LnISU**	**GTFEE**
L.GTFEE	0.592 ***		0.624 ***	0.592 ***		0.592 ***
	(0.032)		(0.029)	(0.032)		(0.031)
LnDFI	0.053 ***	0.068 **	0.037 ***	0.053 ***	0.043 ***	0.015 *
	(0.016)	(0.034)	(0.013)	(0.016)	(0.011)	(0.008)
L.LnGTI		0.737 ***				
		(0.020)				
LnGTI			0.024 ***			
			(0.008)			
L.LnISU					0.825 ***	
					(0.017)	
LnISU						0.035 ***
						(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.370 **	−0.814 **	0.396 ***	0.370 **	−0.435 ***	0.420 ***
	(0.156)	(0.340)	(0.136)	(0.156)	(0.106)	(0.093)
N	1651	1651	1651	1651	1651	1651
AR(1)	0.000	0.003	0.000	0.000	0.002	0.000
AR(2)	0.564	0.503	0.472	0.564	0.498	0.431
Sargan	1.000	1.000	1.000	1.000	1.000	1.000

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Columns (2) of Table 4 test the effect of digital finance on green technology innovation. The coefficient of LnDFI is 0.068, which is positive at the significance level of 5%, suggesting that for every 1% increase in the level of digital financial development, the level of green technology innovation increases by 6.8%. In column (3), the coefficient of LnGTI is significantly positive, indicating that green technology innovation can significantly improve GTFEE. Meanwhile, after adding the variable LnGTI, the coefficient of LnDFI is still significantly positive, but its absolute value relatively falls compared to the benchmark regression's result in column (1). Regarding the results of columns (1)–(3), it can be concluded that digital finance promotes green technology innovation, finally enhancing the GTFEE, proving a mediation effect of green technology innovation. Hypothesis 2 is verified.

Regarding industrial structural upgrading, the coefficient of LnDFI in column (5) of Table 4 is 0.043, which is positive at the significance level of 1%, suggesting that for every 1% increase in the level of digital financial development, the level of industrial structural upgrading increases by 4.3%. In column (6), the coefficient of LnISU is significantly positive, suggesting that industrial structure upgrading can significantly improve GTFEE. Similarly, after adding the variable LnISU, the coefficient of LnDFI in column (6) is 0.015, which is less than that of column (4). Regarding the results of columns (4)–(6), it can be concluded that digital finance can improve urban GTFEE by improving industrial structure, proving a mediation effect of industrial structure upgrading. Hypothesis 3 is verified.

To summarize, the theoretical analysis in Section 3.2 is proved to be correct. On the one hand, digital finance promotes the green technology innovation of cities by absorbing small-scale investment, alleviating the financing constraints of small and medium-sized enterprises, and improving the service efficiency of traditional financial institutions to improve GTFEE. On the other hand, digital finance optimizes the industrial structure by improving residents' income, reducing income inequality and promoting entrepreneurship. The upgrading of industrial structure means reducing production departments with high energy consumption and increasing energy-saving departments, thus improving GTFEE.

5.3. Robustness Test

(1) Replacing dependent variable.

The results of GTFEE may vary significantly with different measurement methods. To avoid bias in the GTFEE measure on the estimation results, refer to Gao et al. (2022) [63], we use EBM instead of SBM to calculate GTFEE for the robustness test. Specifically, we use GTFEE measured by the EBM as the explained variable to empirically test model (2). The results in column (1) of Table 5 show that digital finance measured by the EBM still has a significant enhancing effect on GTFEE, proving the robustness of the above conclusions.

(2) Digital finance lags by one period.

Endogeneity is an important issue to be considered in empirical measurement studies. The main object of this paper is digital finance and GTFEE, and there may be a two-way causal issue between them. To overcome the endogeneity, referring to Bartik (2009) [67], we use digital finance lags by one period (L.DFI) as the independent variable for the empirical test again. The results in column (2) of Table 5 show that the impact of digital finance lags by one period on GTFEE is still significantly positive, which is consistent with the benchmark regression, indicating that the conclusions of this paper are robust.

(3) Deleting municipality.

In China, municipalities directly under the central government often get more preferential policies in the economy than in other cities. This advantage may interfere with the study results. To ensure the research conclusions' generality, we exclude the data of four municipalities in China (Beijing, Shanghai, Tianjin and Chongqing) and conduct the empirical test again. The results in column (3) of Table 5 show that digital finance can still significantly improve GTFEE, which is consistent with the results of the previous benchmark regressions, indicating that the conclusions of this paper are robust.

(4) Replacing the econometric model.

In order to check the validity of the SYS-GMM method, refer to Bond S (2002) [68], we also use pooled OLS and Fixed effect methods of the static panel model. The results in columns (4) and (5) of Table 5 show that the estimated coefficient obtained from the SYS-GMM lies between the estimated coefficient obtained from Pooled Ordinary Least Square (POLS) and Fixed Effect (FE) (FE = 0.047 < GMM = 0.053 < POLS = 0.064). Therefore, the results of using the SYS-GMM method are valid, indicating that the conclusions of this paper are robust.

Table 5. The results of the robustness test.

	GTFEE-EBM	L.LnDFI	Non-Municipality	POLS	FE
	(1)	(2)	(3)	(4)	(5)
L.GTFEE	0.342 ***	0.581 ***	0.612 ***		
	(0.023)	(0.036)	(0.032)		
LnDFI	0.068 ***		0.052 ***	0.064 ***	0.047 ***
	(0.014)		(0.016)	(0.017)	(0.011)
L.LnDFI		0.021 **			
		(0.009)			
Controls	Yes	Yes	Yes	Yes	Yes
_cons	−0.321 **	0.193	0.427 ***	−1.083 ***	−1.262 ***
	(0.143)	(0.166)	(0.152)	(0.166)	(0.179)
N	1653	1651	1632	1930	1930
AR(1)	0.000	0.000	0.004		
AR(2)	0.553	0.485	0.439		
Sargan	1.000	1.000	1.000		

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

5.4. Further Analysis

Due to the vast territory of China, there are huge differences in economic development, resource endowment, financial development, industrial structure and green technology innovation in various cities, and the impact of digital finance on GTFEE may be heterogeneous in different cities. We further explore the heterogeneous impact of digital finance on GTFEE by dividing cities into different samples based on three dimensions: geographic location, city size, and resource endowment.

5.4.1. Regional Heterogeneity

Cities in different geographical locations have different economic development and significant differences in their financial development. Therefore, according to their geographic locations, we divide the cities into central, western, and eastern. Then we conduct empirical tests on the two subsamples. For central and western cities, the coefficient of LnDFI in column (1) of Table 6 is 0.054, which is positive at the significance level of 1%, suggesting that for every 1% increase in the level of digital financial development, GTFEE increases by 5.4%. For eastern cities, the results in column (2) of Table 6 show that the effect of digital finance on GTFEE is insignificant. The possible explanation is that compared with the eastern cities, the central and western cities are more backward regarding traditional financial development, and SMEs in central and western cities are more constrained by financing [60]. Digital finance has the advantage of inclusiveness. The less developed the traditional finance is in the region, the greater the role of digital finance in this region [69] (Cao et al., 2021). As a result, digital finance can play a better role in improving GTFEE in central- and western cities.

Table 6. The results of further analysis.

	Central and Western	East	Small Cities	Large Cities	Non-Resource	Resource
	(1)	(2)	(3)	(4)	(5)	(6)
L.GTFEE	0.637 ***	0.536 ***	0.492 ***	0.727 ***	0.543 ***	0.678 ***
	(0.034)	(0.019)	(0.029)	(0.023)	(0.027)	(0.026)
LnDFI	0.054 ***	−0.016	0.089 ***	0.013	0.042 ***	0.029 **
	(0.014)	(0.013)	(0.017)	(0.014)	(0.015)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.634 ***	−0.090	0.018	0.267 **	−0.050	0.786 ***
	(0.150)	(0.173)	(0.199)	(0.128)	(0.151)	(0.149)
N	1059	592	910	741	994	657
AR(1)	0.001	0.000	0.000	0.003	0.000	0.000
AR(2)	0.612	0.637	0.482	0.469	0.589	0.603
Sargan	1.000	1.000	1.000	1.000	1.000	1.000

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

5.4.2. City Size Heterogeneity

According to the "Notice on Adjustment of City Size Classification Standard in 2014 and divides China's cities into five categories" (the detailed information is available at http://www.gov.cn/zhengce/content/2014/11/20/content_9225.htm, accessed on 16 April 2022), we divide China's cities into two categories: small cities and large cities. Specifically, cities with a resident population of less than 1 million are considered small cities, and cities with a resident population greater than or equal to 1 million are considered large cities. For small cities, the coefficient of LnDFI in column (3) of Table 6 is 0.089, which is positive at the significance level of 1%, suggesting that for every 1% increase in the level of digital financial development, GTFEE increases by 8.9%. In contrast, for large cities, the results in column (4) of Table 6 show that the effect of digital finance on GTFEE is insignificant. The possible reason is that compared with large cities, small cities have a lower level of green technology innovation and a worse industrial structure. Digital finance can play a greater marginal role in improving the level of green technology innovation and optimizing industrial structure in small cities. Therefore, digital finance has a greater impact on GTFEE in small cities.

5.4.3. City Resource Dependence Heterogeneity

Considering cities have different natural resource endowments, there may be huge differences in energy prices, industrial structures and levels of green technology innovation between cities. According to the "Notice of the State Council on Issuing the National Sustainable Development Plan for Resource-Based Cities (2013–2020)" (the detailed information is available at http://www.gov.cn/zwgk/2013-12/03/content_2540070.htm, accessed on 16 April 2022), we divided the sample cities into resource-based cities and non-resource-based cities. The results in columns (5) and (6) of Table 6 show that digital finance significantly improves GTFEE in both the non-resource-based and resource-based cities. At the same time, the coefficient of LnDFI in column (6) is 0.029, which is less than that of column (5), suggesting that digital finance has a greater effect on enhancing GTFEE in non-resource-based cities than in resource-based cities. The possible explanation is that compared with resource-based cities, non-resource-based cities have more scarce energy resources, higher energy prices, and greater demand for energy-saving biased technological innovations and low-energy consumption industrial upgrades, and thus digital finance has a greater impact on GTFEE in non-resource-based cities.

6. Discussion

This paper empirically investigated the impact of digital finance on GTFEE by taking Chinese city-level panel data from 2011 to 2018 as samples. At the same time, considering that there may be endogenous problems between digital finance and GTFEE, we use SYS-GMM to estimate the model. Further, this paper explores the mechanism of digital finance influencing GTFEE using the mediation effect model. However, there are still some limitations, which are possible directions for future research. First, the research sample in this paper covers only China, a developing country. Compared with developed countries, the development of traditional finance in China is relatively lagging, and this feature also provides some room for the development of digital finance in China. The impact of digital finance on GTFEE may be different in developed and developing countries. Future research needs to strengthen the generalizability of these findings in developed regions. Secondly, this paper uses the traditional mediation effect model to test the impact mechanism of digital finance on GTFEE without considering the endogeneity between the two mediating variables of green technology innovation and industrial structure and the explained variable GTFEE. The measurement method to test the impact mechanism needs to be further improved. Third, this paper uses city-level data for the empirical analysis, which is somewhat macro. In the future, if firm-level data are available, a more detailed analysis can be conducted using firm-level data.

7. Conclusions and Implications

7.1. Conclusions

The key to achieving economic growth and reducing carbon emissions is to increase GTFEE, and digital finance has become an important factor in enhancing GTFEE. This paper takes the panel data at the city level in China from 2011 to 2018 to comprehensively evaluate digital finance's impact on GTFEE.

First, we develop green total factor energy efficiency (GTFEE) to measure urban energy efficiency. Compared with single factor energy efficiency and total factor energy efficiency, green total factor energy efficiency (GTFEE) is more holistic to reflect the efficiency of the energy-economic system. Second, we use SYS-GMM to reveal the causal relationship between digital finance and GTFEE, which can effectively alleviate the endogeneity problem between them.

This paper explores the relationship between digital finance and GTFEE for the first time, filling a gap in the existing literature. We find that digital finance significantly improves GTFEE, and the conclusions remain the same across a series of robustness tests.

We discuss in depth the mechanism of the impact of digital finance on GTFEE. Through a mediating effect model, we find that digital finance can improve GTFEE by promoting urban green technology innovation and industrial structure upgrading, the former of which demonstrates the existence of the "Porter effect".

In addition, we demonstrate the existence of the inclusiveness of digital finance. Through a series of heterogeneity tests, we find that digital finance significantly improves GTFEE in central and western cities and small cities. At the same time, it has a less significant effect on GTFEE in eastern and large cities. Meanwhile, digital finance has a more significant effect on GTFEE in non-resource-based cities compared with resource-based cities. These results suggest that digital finance is inclusive, and it is easier to achieve energy conservation and emission reduction goals in economically underdeveloped and energy-scarce cities.

7.2. Implications

This paper puts forward the following policy recommendations based on the above conclusions.

(1) We examine the relationship between digital finance and GTFEE for the first time and find that digital finance significantly improves GTFEE. This finding is helpful to promote the Chinese government to further develop digital finance and fully utilize the positive impact of digital finance on energy and economy. First, government departments should follow the trend of financial digitization and improve the construction of digital financial infrastructure, so that more people and enterprises can enjoy digital financial services. Second, government departments guide traditional financial institutions to use digital technologies represented by big data, cloud computing, artificial intelligence and blockchain to innovate financial services through encouragement policies.

(2) We discuss in depth the mechanism of the impact of digital finance on GTFEE, which is beneficial to the government departments of Chinese cities to implement various policy measures to improve GTFEE. First, government departments should guide the inflow of funds to green technology-based enterprises, and increase financial support for these green technology-based enterprises to carry out green technology innovation activities. Secondly, government departments need to provide financial support for enterprises to transform from labor-intensive to technology-intensive, so as to promote the optimization of regional industrial structure.

(3) We demonstrate the existence of the inclusiveness of digital finance. Digital finance is more likely to achieve energy efficiency goals in economically underdeveloped and energy-scarce cities. Therefore, central and western cities and small cities should give full play to the inclusiveness of digital finance and make more efforts to improve the level of local digital finance in order to catch up with the financial development of eastern cities and big cities more quickly.

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