



Digital financial inclusion, environment volatility and investment efficiency: demand and supply side experiences of Chinese listed renewable energy firms

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Abstract

Enhancing the investment efficiency of renewable energy firms is vital for the low-carbon energy transition and addressing climate change. However, the impact of digital financial inclusion on this process remains uncertain. This study employs panel data from 113 listed Chinese renewable energy firms from 2011 to 2020, with a two-stage Systematic GMM dynamic panel model to investigate the impact and underlying mechanisms of digital financial inclusion on the investment efficiency of renewable energy firms. In addition, the moderating role of environmental volatility is also examined. It is found that digital financial inclusion significantly improves the investment efficiency of renewable energy firms, with a more pronounced effect observed among non-state-owned firms and those located in the Southern region. The mechanism analysis shows that it improves renewable energy firms' investment efficiency by reducing financing costs and increasing R&D expenditures, but it fails to incentivize these firms by promote consumption upgrading. Moreover, different external environmental volatility has different moderating effects. Notably, the continual rise in extreme temperatures reduces the operational efficiency of equipment and weakens the incentives for digital financial inclusion. Therefore, decision makers should promote demand-driven growth and seize market investment opportunities in occasions of environment volatility.

Keywords Renewable energy firms · Digital financial inclusion · Firm's investment efficiency · Environmental factors

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1 Introduction

As the global traditional energy supply and demand pattern enters the “post-OPEC era,” uncertainty in the international energy market is gradually increasing. Especially in recent years, owing to the shortage of energy resources, system transitions, geopolitical games by large countries, and other factors at home and abroad, many contradictions and risks have accumulated in energy operations, triggering deep-seated concerns about energy security around the world (Chen & Fu, 2021). The early realization of renewable energy (RE) substitution and transition not only poses a challenge to national energy security and stable supply but also represents an important opportunity to cultivate new driving forces for economic growth (Lei et al., 2024). The International Renewable Energy Agency (IRENA) released “*Statistics on Installed Renewable Energy Capacity 2024*,” which indicates that by 2023, Renewable energy deployment in the power sector reaching a total global installed capacity of 3870 gigawatts (GW). Of these, China’s installed RE capacity accounts for more than half of the world’s new capacity. A frequent area of interest for Chinese academics and politicians is how to successfully promote RE to replace traditional energy sources. Figure 1 shows the installed renewable power capacity and growth rate in China.

Despite an optimistic outlook on Chinese RE, its share on the overall energy consumption remains constrained. Merely 29% in 2023. Explanations from previous investigations have centered on the high cost associated with investment and financing in RE. In comparison to conventional energy sources, RE firms exhibit suboptimal technological advancement, and substantial initial capital requirements. Consequently, banking intermediaries often impose elevated loan interest rates as a form of risk compensation (Aloulou et al., 2024), placing RE firms at a long-term disadvantage within the credit market. This reduced investment efficiency further hampers the sustainable growth of RE firms. A shift in consumer behavior on the demand side is essential, yet this aspect has been largely overlooked. In contrast to conventional energy products, Chinese RE products are primarily exported (Chen & Lin, 2020), with market demand confined to small “Niche Markets” (Fan & Yi, 2021). This situation results in decision-makers lacking a precise understanding of the RE market information, thereby diminishing the investment decision-making efficiency of RE firms. Therefore, whether from the supply side or from the demand side, the current RE firms lacks the competitive advantage.

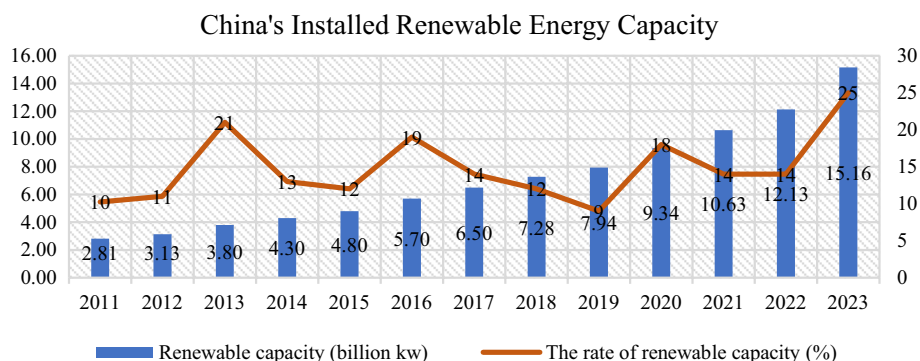


Fig. 1 China’s installed renewable energy capacity (2011–2023)

RE firms face significant uncertainty regarding their future growth and require a stable financial environment for finance service support, leading to the emergence of the concept of “green finance”. After several years of practice and accumulation, China’s green finance services has grown significantly (Fig. 2), bringing with it credit funds for RE (Wang & Fan, 2023) and prompting the RE industry to usher in a period of explosions in scale. However, in the long run, this will also lead to difficulties in RE supply at the low end of the value chain. The reason for this phenomenon is that, on the one hand, a single source of funding, mainly bank credit, has led to a mismatch of funds (Tang and Zhu, 2020). On the other hand, the high cost of information collection and processing makes traditional financial institutions more willing to invest a large amount of financial capital in low-risk processing and manufacturing segments based on profitability norms and risk control requirements (Demertzis et al., 2018). The additional cost of cumbersome approval and disbursement procedures further exacerbates this low-end phenomenon.

The dilemmas faced by the traditional financial system need to be addressed using innovative financial models in the new era (Tang & Zhu, 2020). Digital financial inclusion (DFI) aims to empower or upgrade traditional financial products with the help of modern technological achievements, can effectively expand financial channels and handle massive standardized and non-standardized information on a low-cost and low-risk basis (Suhra et al., 2024). It can improve the transparency of market information on investment and demand while providing diversified financial services for RE (Serrano-Cinca & Gutiérrez-Nieto, 2014), and it can help to promote the transformation from scale expansion to an energy-saving and efficiency orientation. Some interesting questions are: although it can be generalized that DFI has an incremental financial complementary effect, can it effectively circumvent the low-end lock-in disadvantages of the traditional financial system? In particular, in recent years, Chinese RE firms have continued to follow the traditional development mindset of directly purchasing foreign technology for low-end investment, and even undertaking large-scale processing and manufacturing based on the comparative advantage of low-cost labour. Can DFI help managers identify optimal growth paths while reducing adverse selection and moral hazard, i.e. can it improve the efficiency of RE firms investment? Answers to these questions can help clarify the transmission mechanism on the investment strategies of RE firms and facilitate the precise application of policies.

Empirical evidence suggests that behavioral drivers play an essential role in the process of RE substitution (Komendantova, 2021). Behavioral finance has shown that

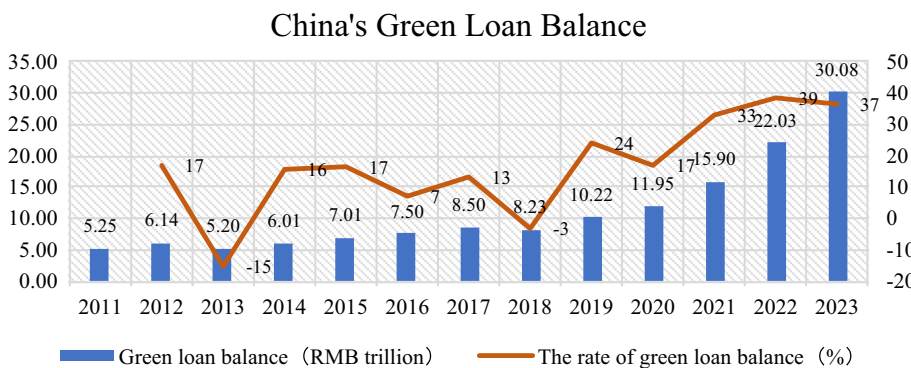


Fig. 2 Calendar year green loan balances (2011–2023)

once unanticipated changes occur in the external environment, economic agents may be affected by transmitted emotions and beliefs that influence their own investment behaviors because of their inability to accurately predict the development and future state of objective events in the environment (Griffin and Dabid, 2019; Aftab et al., 2024). That is, the effect of DFI on the investment efficiency of RE firms is strongly correlated with the external environment in which they operate. Events such as the large-scale power disruption caused by persistent heavy rainfall in Zhengzhou City in 2021 caused alarm regarding climate change. Such events will help to raise the awareness of energy conservation and environmental protection among economic agents. In the current digital environment, big data technology can effectively bring RE firms closer to consumers, making it easier for them to meet their individual needs and become more willing to buy RE products. This helps form an effective demand market that can support firms' independent innovation, which in turn generates a new investment space. Figure 3 illustrates this process. Therefore, this study sought to elucidate the role of external environmental changes in this process by exploring the impact of DFI on the investment efficiency of RE firms. The goal was to assist in the current low-carbon energy transition process.

The contributions of this study are reflected in the following aspects: First, most studies have been conducted on the macro level (Shahbaz & Jiaman, 2022; Lin & Zhang, 2024), and a few micro studies have placed more emphasis on the financial constraints of RE firms (Wu & Huang, 2022). Whereas the operating conditions and management modes of microenterprises are mostly reflected in the changes in their investment and financing behaviors (Zeng et al., 2018). In this regard, this paper adopts the investment efficiency perspective to study the impact effect and heterogeneity effect of DFI on the investment efficiency of RE firms in order to enrich the related research. Second, previous studies have focused on the supply side of RE. For this reason, this paper considers both the supply-side and the demand-side to explore the mediating mechanism of DFI on the investment efficiency of RE firms. It finds that DFI can exert an incentive effect by reducing financing costs and increasing R&D expenditures but fails to achieve it by promoting consumption upgrading. Finally, the moderating effect of external environmental volatility is also considered, and it is found that increases in Sulphur dioxide emissions, extreme weather events, RE policies, and the level of financial regulation strengthen the positive effects of DFI. In contrast, an increase in extreme temperatures reduces the operational efficiency, weakening the positive effect.

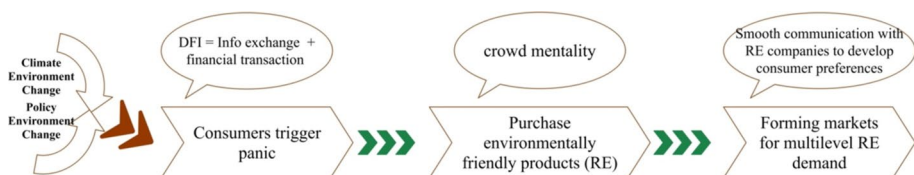


Fig. 3 Consumer behavior induced by climate change in a digital context

2 Theoretical analysis and previous research

2.1 Digital financial inclusion

As a novel financial model, the impact and path of DFI may be mainly reflected in the “incremental” and “stock” aspects. From the “incremental” perspective, DFI effectively absorbs financial resources characterized as “many, small and scattered” (Aftab et al., 2024). This intensifies the degree of competition among financial institutions, especially banking intermediaries (Aloulou et al., 2024), and provides a reservoir of financial resources for RE firms through the reservoir effect (Gomber et al., 2018). When enterprise managers have good expectations for future investment behavior, the biggest challenge they face when considering whether they can improve investment efficiency is based on their willingness to invest. From the “stock” perspective, DFI can effectively connect multi-institutional data (Yao et al., 2018), which can not only assess and screen high-quality investment projects but also tap into the potential and personalized demand of consumers for RE products and provide RE firms with customized production and the optimal path of innovation in a demand-oriented manner. This helps to improve the investment efficiency of RE firms.

2.2 Mechanisms between DFI and investment efficiency in RE firms

This research attempts to examine the four mechanisms of DFI’s impact on the investment efficacy of RE firms from both the supply and demand sides. On the supply side, the first point is the external financing cost mechanism. DFI can directly reduce financial transaction costs between banks and enterprises by broadening financing channels (Jin et al., 2024) and weakening the monopoly power of financial institutions, especially bank intermediaries (Rajan & Luigi, 1998). The resulting scale effect can also reduce subsequent financing costs such as customer acquisition and operations, all of which indirectly increase RE firms’ credit capital. In addition, DFI can also alleviate information asymmetry in the RE market by pooling idle information (Demertzis et al., 2018), simplifying the credit approval process (Wu & Huang, 2022), and establishing upstream and downstream enterprise information networks (Aftab et al., 2024) on the premise of ensuring accurate and secure data. This helps to directly reduce the cost of investor information collection and processing, and it can also improve the trust of bank intermediaries and external investors (Shahbaz & Jiaman, 2022) through the accumulation of positive reputation premiums and constraints on defaults, thus helping to promote the sustainable reduction of the cost of credit financing and improve the effectiveness of capital investment.

The second point are internal R&D expenditure mechanisms. DFI can match risky R&D projects with risk-averse external investors (Laeven & Levine, 2015), broaden funding sources for RE firms’ R&D projects, and provide a sustainable supply of funds for R&D investment projects. In addition, DFI can, to a certain extent, quickly identify real information on the market (Tang & Zhu, 2020), help enterprises better identify the optimal path of technological succession, and help RE enterprise managers make reasonable investment decisions. Enterprise managers can also observe market price fluctuations to obtain confidence and value evaluations of the outside world for innovative projects, which improves the accuracy of enterprise managers’ predictions of future R&D investment projects and ultimately helps to improve RE firms’ investment efficiency.

On the demand side, the first point is the mechanism of residents' income distribution. DFI relies on information technology to bring about changes in payment methods, enabling residents to obtain financial services at a lower cost and thereby increasing the availability of financial assets and the disposable income of residents (Lu et al., 2024). Not only can it help increase the potential purchase willingness toward RE products, but it can also make families more capable of paying the "environmental premium," which helps expand the effective demand of the RE market at scale and increase the pulling effect of market demand on the efficiency of enterprise investment.

The second point is the resident consumption upgrade mechanism. DFI can provide personalized consumer credit services (Cheng et al., 2024) in advance to meet consumer demand for different types of product and, to a certain extent, enhance the immediate consumption capacity, greatly increasing the potential consumption of RE products by residents. Further, encouraged by consumption hotspots, it guides the socialized behavior of the whole society toward the consumption of RE products. DFI has also promoted the concept of low-carbon environmental protection. Projects such as the "Ant Forest" launched by Ant Financial Services and the second-hand trading of idle fish can effectively expand residents' consumption patterns, promote the transformation of the consumption structure from homogenized consumption to low-carbon consumption, and make residents more willing to pay the "environmental premium" for RE products. This forms a low-, medium-, and high-demand market that can support the independent innovation of RE firms, giving rise to more investment space.

2.3 The moderating effect of external environmental

It is reasonable to believe that RE firms' investment decisions are influenced not only by a variety of climatic factors such as extreme weather and greenhouse gases, but also by the strategic behavior of local governments. Specifically, in terms of the climate, first, the depreciation of energy-intensive assets due to the deterioration of the climate will reduce financial institutions' willingness to invest in such assets, leading them to reduce their holdings of "climate-sensitive" assets (Aftab et al., 2024) and invest more financial capital in RE firms based on the principle of climate risk aversion (Perera et al., 2020), thereby expanding investments. Simultaneously, to create the image of environmentally friendly and high-quality enterprises, managers may be more willing to provide more accurate financial reports, prompting them to make optimal investment decisions while reducing inefficient investment behavior. Second, the deterioration of the climate may also lead to changes in adaptive behavior and awareness of environmental responsibility, prompting more residents to seek financial products and services that help to combat climate change, thus increasing consumer demand for RE products.

Regarding the policy environment, some scholars believe that policies will help guide economic agents to invest in and consume RE. On the one hand, local governments can introduce RE industry incentives, release favorable policy signals, increase the trust of economic subjects in the investment environment (Sarwar et al., 2023), guide economic subjects to increase their investment in and consumption of RE products, and affect enterprises' investment choices. However, some scholars hold the opposite opinion that government policy support, as a long-term driver, is prone to the risk of capital chain breakage (Sun et al., 2020), resulting in irrational investment and resource waste (Deng et al., 2019). On the other hand, local governments can also avoid financial risks, such as financial fraud and data loss, by introducing policies related to financial regulation, which helps guard the

bottom line of regional financial risks, thus enhancing the operational effectiveness of DFI. However, some scholars believe that enterprises' difficulty in choosing investment opportunities and investment scales increases along with more uncertainty in the regional financial regulatory environment (Treleaven, 2015). The logic behind this lies in the fact that changes in the policy environment bring about changes in the proportion of firms' liquid assets, making enterprise managers more conservative when faced with high-quality investment opportunities and ultimately reducing the efficiency of RE firms' capital allocation.

3 Study design

3.1 Sample selection

Since the data on China's DFI is relatively complete from 2011 on, referring to Yu (2022), this study took the data of RE-listed firms in Shanghai and Shenzhen during 2011–2020 as the research sample and carried out the following processing steps: first, firms listed on the ST list and delisted during the sample period were excluded; second, firms with serious missing data during the sample period are excluded; and finally, variables in the data were winsorised at 1% and 99% levels to obtain an "firm-year" observation sample. The related data of the firm-level came from the Wind Database and the China Stock Market and Accounting Research Database (CSMAR), whereas the DFI index came from the DFI Index of Peking University. The macro-level data are from the CEIC Database, and Statistical Yearbooks of the provinces.

3.2 Modeling

This study investigated the impact of DFI on the investment efficiency of RE firms. Considering that firms' investment behavior is a dynamic and continuous process, RE firms' investment efficiency in the current period is ultimately influenced by the investment decision behavior in the previous period, which ultimately affects RE firms' investment efficiency in the current period. Therefore, when the lagged terms of explanatory variables are included in the explanatory variables, this type of data is called a dynamic panel. However, endogeneity can arise simultaneously. The generalized method of moments (GMM) estimation proposed by Arellano and Bond (1991) can effectively eliminate the endogeneity problem of omitted variable bias by applying the difference-in-differences method; however, it cannot estimate variables that do not change over time. To overcome this problem, Blundell and Bond (1998) introduced level equations and proposed system generalized moments (SYS-GMM) estimation, which is widely favored by many scholars. In this regard, this study used the `xtabond2` program provided by Roodman (2006) for estimation. To further ensure the rationality of the instrumental variables, SYS-GMM estimation requires two additional tests. The first is an autoregressive (AR) test. It is primarily used to test for the serial correlation of residual terms, with the original assumption that there is no serial correlation in the residual series. The second overidentification test is the Hansen test. This is mainly used for the overall validity of the sample moment-conditional instrumental variables, and its original hypothesis is that the instrumental variables are valid. If each SYS-GMM model accepts the original hypotheses of the autoregressive and Hansen tests, the estimation results of each SYS-GMM model are valid. Based on this, the following model was constructed:

$$Inveffi_{it} = \beta_0 + \beta_1 Inveffi_{it-1} + \beta_2 DFI_{it} + Z_{it}'\sigma + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where the explanatory variable $Inveffi_{it}$ represents the i RE firm in the t year's inefficient investment, and $Inveffi_{it-1}$ is the one-period lagged term of the explanatory variable. DFI_{it} is the core explanatory variable, Z represents the set of control variables; μ_i is the individual fixed effect; λ_t is the time fixed effect; and ε_{it} represents the random error term.

The above model only portrays the overall impact of “DFI—investment efficiency of RE firms,” but the black box of the inner mechanism has not yet been opened. This requires an in-depth exploration of its intrinsic mechanism—that is, the specific channel mechanism by which DFI affects RE firms' investment efficiency. Drawing on Jiang (2022), a two-step approach is adopted to analyze the mechanism, first analyzing the impact of DFI on the mediating variables, and then discussing the impact of the mediating variables on the investment efficiency of RE firms. The following regression model is constructed:

$$Med_{it} = \alpha_0 + \alpha_1 Inveffi_{it-1} + \alpha_2 DFI_{it} + Z_{it}'\sigma + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where Med is used as a mediating variable. The supply side includes two mechanisms of action: external financing cost ($Cost$) and internal R&D expenditure ($R\&D$). The demand measurement includes two mechanisms of residents' income distribution (Upg) and residents' consumption upgrading (Req). The definitions of the other variables are consistent with those in Ep (1).

Furthermore, to test the moderating effect of changes in the external environment on the relationship between DFI and RE investment efficiency, Eq. (3) was constructed by adding external environmental proxies to Eq. (1) and referring to Yu (2022):

$$Inveffi_{it} = \beta_0 + \beta_1 Inveffi_{it-1} + \beta_2 DFI_{it} + \beta_3 DFI_{it} \times Mod_{it} + Z_{it}'\sigma + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where Mod is a proxy variable for the external environment, which mainly includes the climate and the policy environment. Here, the climate covers sulfur dioxide emissions, the number of extreme weather days, and the number of extreme temperature days. The policy environment covers the number of RE policies and financial regulation. In this section, the paper focuses on whether the cross terms $DFI \times Mod$ of the estimated coefficients are significant, and the definitions of the other variables are consistent with Eq. (1). Figure 4 shows the logic flowchart.

3.3 Indicator construction

Explained variable: Investment efficiency. The operating conditions and management modes of microenterprises are mostly reflected in changes in their investment and financing behaviors. Therefore, the perspective of investment efficiency is chosen. It is mainly portrayed by examining the deviation of the actual investment expenditure of RE firms from the ideal investment expenditure in a given year. In fact, there are several existing methods for measuring investment efficiency: the Wurgler model, the marginal Tobin's Q model, and the Richardson model. Since the Wurgler model and marginal Tobin's Q model are prone to survivor bias in the estimation process, with reference to Yu's (2022) study, this paper adopted the capital investment expenditure estimation model proposed by Richardson (2006) to construct a model to measure the investment efficiency of RE firms. This effectively combined the actual application of China's securities environment to overcome, to a certain extent, the problems of Wurgler's model and the marginal Tobin's Q model, in which the capital output term must be greater than zero. It has the advantage of directly

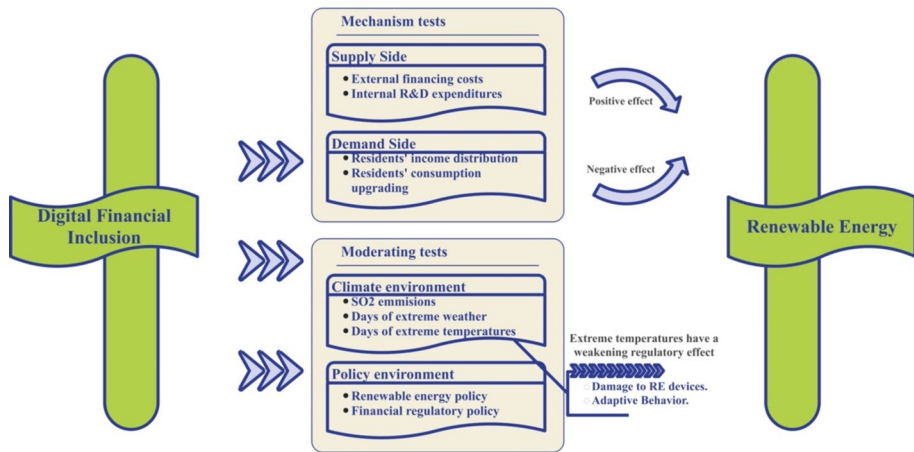


Fig. 4 Logic flow diagram

measuring the investment efficiency of a specific enterprise in a specific year, so it is a more appropriate indicator and has been widely adopted by academics. The model for estimating the expected capital investment level of a specific RE listed firms is shown below:

$$INV_{i,t} = \beta_0 + \beta_1 Growth_{i,t-1} + \beta_2 Lev_{i,t-1} + \beta_3 Cash_{i,t-1} + \beta_4 Age_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Returns_{i,t-1} + \beta_7 INV_{i,t-1} + \epsilon \quad (4)$$

This study took the model's ordinary least squares estimation residual as the investment efficiency of RE listed enterprises and selected the absolute value of the residual as a measure of inefficient investment. It should be noted that the larger the absolute value of the residual, the higher the degree of inefficient investment in RE firms and the lower the investment efficiency. Conversely, the lower the degree of inefficient investment faced by RE firms, the more efficient the investment. The variables in Richardson's investment expenditure estimation model for RE firms are listed in Table 7.

Core explanatory variable: DFI. Drawing on Wu's (2022) study, this study adopted the Digital Inclusive Finance Index compiled by the Internet Finance Research Center of Peking University, which measures the degree of DFI development at the provincial, prefectural, and municipal levels in China (excluding Hong Kong, Macao, and Taiwan) based on data provided by Ant Gold. In this study, the Digital Inclusive Finance Development Index at the prefecture and municipal levels was used as a proxy variable for the core empirical test, and the Digital Inclusive Finance Development Index at the provincial level was used as a proxy variable for the robustness test.

Mediator variables: External financing costs from the supply side. The development of DFI can provide diversified external financial support for RE firms, which helps reduce their financing costs and provide sustainable financial support for RE investment projects. The ratio of finance costs to total liabilities was selected as a measure of debt financing costs. Internal R&D expenditure: By incentivizing enterprises to increase their internal R&D investment, DFI enables RE firms to obtain greater output from limited R&D investment, thus affecting their investment efficiency. The natural logarithm of firms' R&D investments was selected as a proxy for R&D expenditure.

From the demand side, the population's income distribution and firm's growth must be realized through the final purchasing behavior of market consumers. DFI can directly increase the availability of household financial assets (Li, 2020). Therefore, per capita urban disposable income was selected as a proxy variable for demand size. Upgrades in residents' consumption: Based on the construction method of the "China Residents' Consumption Upgrade Index Report" jointly published by Suning Financial Research Institute and the National Laboratory for Finance and Development and PP Finance, the calculation formula is as follows: Survival Consumption Expenditure $\times 1$ + Development Consumption Expenditure $\times 2$ + Enjoyment Consumption Expenditure $\times 3$ = Consumption Upgrade (Upg).

Moderating variables: As mentioned above, the measures of external environmental conditions were selected mainly from two aspects: the climate and the policy environment. Climate refers to long-term changes in temperature and weather patterns, including greenhouse gas emissions and extreme weather. In terms of greenhouse gas emissions, the natural logarithm of sulfur dioxide emissions at the provincial level was selected as a proxy variable, considering data availability. In terms of extreme weather, drawing on the criteria of the China Meteorological Administration and referring to the study by Han (2018), weather with a minimum temperature lower than -10°C , a maximum temperature higher than 38°C , and local rainfall of more than 50 mm on the same day at the location of a listed firm was considered extreme weather. The number of extreme weather days at the municipal level was selected as a measure of the climate. In terms of temperature extremes, referring to Du (2022), weather where the minimum temperature of the location of listed firms was lower than 0°C and the maximum temperature was higher than 35°C was referred to as extreme temperatures. Therefore, the number of days of extreme temperatures at the municipal level was selected as a measure of the climate. The raw data were obtained from the China Integrated Meteorological Information Service System (CIMISS).

The number of RE policies at the provincial level was selected as a measure of the policy environment. The policy samples were mainly sourced from the Peking University Law Database (PKULAW), and the search scope was expanded by means of a correlation search and other means to cover the official websites of relevant departments, such as the websites of the Chinese government, the Energy Security Bureau, and regional governments. In order to ensure the comprehensiveness of the policy samples, this paper used highly relevant keywords such as "renewable energy," "clean energy," "solar energy," and "wind energy" as the search basis. In terms of financial regulatory policies, the share of regional financial regulation in the value added of the financial industry at the provincial level was selected as an indicator of the financial regulatory environment (Tang and Zhu, 2020).

Control variables: To overcome the influence of omitted variables as much as possible, this study include control variables from firm-level and province-level. The former mainly includes firm characteristics and corporate governance structure indicators, specifically firm size (Size), number of years of listing (Age), equity concentration (Top, the concentration of the first largest shareholder), growth capacity (Gro, growth rate of operating income), capital intensity (Cap, ratio of total assets to main business) and financial leverage (Lev, the ratio of total liabilities to total assets). External influences were selected from the traditional financial development level indicators and measured by the natural logarithm of the value added of the financial industry in each province.

4 Empirical results and analysis

4.1 Benchmark regression

Table 1 presents the correlation coefficients and descriptive statistics of the variables. All continuous variables were winsorized at the 1% and 99% quantiles. The mean value of *ineffi* was 0.041, which indicates that the average size of non-efficient investments in the sample was 4.1% of the total assets of RE-listed firms. The minimum value of *ineffi* was 0.001, the maximum was 0.276, and the standard deviation was 0.048, which reflects that there were large differences in investment efficiency among the different RE listed firms. In addition, the absolute value of the correlation coefficient of each variable was less than 0.55, indicating that there was no serious correlation problem among the explanatory variables.

Table 2 reports the results of the Benchmark regression results. As can be seen from the results of the various test values, the p-statistic values of the AR (2) test and the Hansen test are greater than 0.05, which indicates that all the estimates are highly acceptable. The validity of the choice of instrumental variables for the model and the absence of second-order serial correlation in the residuals also justify the estimation of the empirical regression results.

M(1) is the regression estimate using the DFI aggregate indicator as the core explanatory variable. The estimated coefficient of *DFI* was negative and significant at the 1% level, verifying that DFI has an incentive effect on RE firms' investment efficiency. To portray baseline regression result more precisely, this study further decomposed the total DFI index to three sub-indicators: the breadth of digital financial coverage (*DFI_1*), the depth of digital financial use (*DFI_2*), and the degree of digitization (*DFI_3*). These results indicated that the facilitating effect of DFI remained significant. Wu (2022), using panel data from 157 Chinese new energy listed firms, finds that digital finance can contribute to the financial performance of new energy firms, which is consistent with the findings of this paper. DFI mitigates internal financial volatility through an incremental complementary effect, reduces adjustment investment costs while ensuring the continuity of investment,

Table 1 The correlation coefficients and descriptive statistics of the variables

Variables	<i>ineffi</i>	<i>DFI</i>	<i>Size</i>	<i>Age</i>	<i>Top</i>	<i>Gro</i>	<i>Cap</i>	<i>Lev</i>	<i>FD</i>
<i>ineffi</i>	1.000								
<i>DFI</i>	-0.062*	1.000							
<i>Size</i>	0.001	0.220***	1.000						
<i>Age</i>	-0.111***	0.203***	0.505***	1.000					
<i>Top</i>	0.051	-0.110***	0.208***	-0.065*	1.000				
<i>Gro</i>	-0.062*	0.203***	0.911***	0.438***	0.195***	1.000			
<i>Cap</i>	0.141***	0.016	0.200***	0.104***	0.037	-0.186***	1.000		
<i>Lev</i>	0.013	0.150***	0.552***	0.386***	0.002***	0.506***	0.082***	1.000	
<i>FD</i>	0.052	0.541***	-0.052	-0.040	-0.073**	-0.020	-0.072**	-0.080***	1.000
Mean	0.041	228.184	22.584	9.713	33.615	21.711	2.786	0.481	8.136
SD	0.048	63.317	1.266	6.478	15.421	1.263	1.829	0.175	0.786
Min	0.001	73.480	20.300	2.000	2.197	18.500	0.260	0.060	4.977
Medium	0.026	238.050	22.400	8.000	32.410	21.700	2.210	0.500	8.261
Max	0.276	336.650	26.500	29.000	85.230	25.700	16.30	0.970	9.201

Table 2 Benchmark regression results

Variables	M(1)	M(2)	M(3)	M(4)
<i>L</i>	0.1557*** (20.99)	0.1690*** (14.60)	0.1528*** (19.20)	0.1403*** (12.25)
<i>DFI</i>	−0.0002*** (−4.65)			
<i>DFI_1</i>		−0.0001*** (−6.80)		
<i>DFI_2</i>			−0.0002*** (−4.16)	
<i>DFI_3</i>				−0.0004*** (−7.92)
<i>Size</i>	0.0915*** (17.71)	0.0866*** (11.79)	0.0985*** (13.37)	0.0942*** (8.37)
<i>Age</i>	−0.0021*** (−12.46)	−0.0020*** (−10.47)	−0.0024*** (−15.61)	−0.0023*** (−14.41)
<i>Top</i>	−0.0001 (−0.67)	−0.0001 (−1.04)	−0.0004 (−1.44)	−0.0004 (−0.64)
<i>Gro</i>	−0.0843*** (−16.74)	−0.0803*** (−11.95)	−0.0906*** (−12.75)	−0.0861*** (−8.07)
<i>Cap</i>	−0.0184*** (−12.92)	−0.0171*** (−8.77)	−0.0201*** (−11.01)	−0.0190*** (−6.84)
<i>Lev</i>	0.0269*** (5.23)	0.0273*** (4.41)	0.0244*** (3.64)	0.0307*** (4.87)
<i>FD</i>	0.0186*** (7.22)	0.0155*** (6.55)	0.0189*** (7.68)	0.0148*** (8.17)
<i>Constant</i>	−0.1396*** (−10.43)	−0.2270*** (−6.79)	−0.2675*** (−9.23)	−0.1769*** (−7.13)
Firms fixed effect	YES	YES	YES	YES
Province fixed effect	YES	YES	YES	YES
<i>AR (1)</i>	−4.05	−4.09	−3.95	−4.02
<i>AR (2)</i>	−0.27	−0.23	−0.25	−0.40
<i>Hansen test</i>	79.87	79.53	80.01	83.27

All z-statistics are shown under the estimated coefficient

*** 1% of significance level. ** 5% of significance level. * 10% of significance level

and enables enterprise managers to have good expectations of future investment behavior. In addition, through the stock optimization effect, it captures and efficiently analyzes market demand information, helps enterprise managers judge the market potential and other aspects of the situation, prevent the RE industry from becoming a low-end “processing manufacturing industry” and effectively improve RE firms’ investment efficiency.

4.2 Robustness tests

This study used several methods to test the robustness of the benchmark regression model. The first considered the robustness of replacing the caliber of calculation of the core explanatory variables, and the provincial-level DFI index was selected as the core explanatory variable; M(1) in Table 3 is the regression estimation of the total DFI indicator, and

Table 3 Robustness tests

Variables	Replacement of explanatory variables				Endogeneity test
	M(1)	M(2)	M(3)	M(4)	M(5)
<i>L</i>	0.1415*** (24.43)	0.1422*** (15.30)	0.1302*** (24.38)	0.1491*** (26.50)	0.1548*** (4.07)
<i>DFI</i>	−0.0004*** (−4.68)				−0.0001*** (−2.90)
<i>DFI_1</i>		−0.0002*** (−4.69)			
<i>DFI_2</i>			−0.0008*** (−5.79)		
<i>DFI_3</i>				−0.0002*** (−4.38)	
<i>Size</i>	0.1104*** (17.62)	0.0961*** (14.13)	0.1221*** (18.26)	0.1013*** (14.30)	0.0158 (1.60)
<i>Age</i>	−0.0027*** (−21.33)	−0.0022*** (−15.17)	−0.0031*** (−12.73)	−0.0026*** (−16.06)	
<i>Top</i>	−0.0001 (−1.13)	−0.0015** (−2.59)	−0.0001 (−1.00)	−0.0001 (−1.07)	0.0001 (0.06)
<i>Gro</i>	−0.1024*** (−16.39)	−0.0892*** (−13.23)	−0.1112*** (−17.57)	−0.0945*** (−13.32)	−0.0134 (−1.40)
<i>Cap</i>	−0.0231*** (−13.87)	−0.0194*** (−10.93)	−0.0256*** (−15.38)	−0.0209*** (−11.08)	0.0008 (0.30)
<i>Lev</i>	0.0231*** (3.16)	0.0269*** (5.03)	0.0172*** (2.64)	0.0295*** (4.93)	0.2169 (1.61)
<i>FD</i>	0.0174*** (6.36)	0.0075*** (5.08)	0.0298*** (7.31)	0.0134*** (6.05)	0.0094*** (2.80)
<i>Constant</i>	−0.1972*** (−8.77)	−0.1139*** (−4.25)	−0.1800*** (−6.75)	−0.1927*** (−8.90)	−0.0672 (−1.40)
Firms fixed effect	YES	YES	YES	YES	
Province fixed effect	YES	YES	YES	YES	
<i>AR (1)</i>	−3.96	−3.95	−3.88	−4.00	
<i>AR (2)</i>	−0.32	−0.31	−0.31	−0.30	
<i>Hansen test</i>	74.11	80.14	75.85	75.49	
<i>R-squared</i>					0.4809
<i>weak identification tests</i>					359.627

All z-statistics are shown under the estimated coefficient

*** 1% of significance level. ** 5% of significance level. * 10% of significance level

M(2)–M(4) are the regression estimations of the sub-indicators of DFI, respectively. The regression coefficients of *DFI* are significantly negative at the 1% level for both total DFI indicators and sub-indicators, confirming the robustness of the benchmark regression results.

Second, there may be endogeneity bias due to causal inversion, which affects the accuracy of the baseline regression. RE firms require substantial cash flow to invest in their projects, and DFI can provide long-term financial support. Simultaneously, investment profits in turn provide returns to external investors in the form of dividends, bonuses and interest

on debt. To eliminate this endogeneity bias, this study re-estimated the benchmark model using the two-stage least squares. Referring to Wang (2021), the historical (1984) number of landline telephones per 100 people and per capita postal and telecommunication services were selected as instrumental variables for the development of DFI.

On the one hand, the volume of postal and telecommunication transactions is an excellent measure of how developed communication systems are, and the DFI benefits from the rapid diffusion and application of Internet technology, which satisfies the relevance requirement. On the other hand, the effect of postal and telecommunication services in 1984 on the efficiency of current RE firm's investment is negligible, thus satisfying the exogeneity requirement. $M(5)$ is the regression estimation of the instrumental variables test. The results showed that there were no weak instrumental variables or over-identification problems, and the instrumental variable selection was valid. After using the instrumental variable selection method to mitigate the endogeneity problem, the promotional effect of *DFI* on the investment efficiency of RE firms remained significant. Both the robustness tests and the endogeneity treatment indicated that the core findings of this study were robust.

4.3 Heterogeneity analysis

For the purpose of further exploring the effect of DFI on subjects with different characteristics, this paper includes an in-depth discussion from two perspectives: enterprise ownership heterogeneity and geographic location heterogeneity. $M(1)$ and $M(2)$ in Table 4 present the estimation results for firm ownership heterogeneity. The empirical results showed that digital inclusion can effectively improve the investment efficiency of private RE firms; however, its effect on state-owned enterprises (SOEs) was not significant. The reason may be that, compared with private enterprises that are highly dependent on their own accumulation and financing, RE SOEs have been strongly supported by local governments and financial institutions for quite a long time and have always been in the main position in the field of investment and financing. The state-owned background of large banks also tends to tilt credit resources to RE SOEs. At the same time, RE SOEs have more seriously inefficient investments owing to soft budget constraints and centralized corporate governance structures. The non-significant regression coefficient of *L* further confirmed this hypothesis. Wu (2022) also found that DFI would play a greater role in non-state-owned RE firms. Private RE firms have a relatively low tolerance for potential risks and a greater need for financial capital protection in project investment activities. Therefore, the promotional effect of DFI on private enterprises' investment efficiency is more obvious.

$M(3)$ and $M(4)$ in Table 4 show the estimation results on the heterogeneity between the northern and southern regions. The regression coefficient of *DFI* on the investment efficiency of RE firms in the southern region is significantly negative at the 1% level, while the effect is not significant in the northern region. The empirical results showed that digital inclusion does not have a significant impact on RE firms' investment efficiency in the northern region but can effectively improve it in the southern region. A possible reason for this is that the northern region has been relying mainly on high-carbon energy to develop heavy industrial industries for a long time and is facing a more severe double dilemma of weak economic growth and a shortage of energy resources. Shahbaz & Jiaman (2022), using Chinese provincial data from 2011 to 2017, finds that against this backdrop, local governments have focused more on scaling up RE, further locking it into a "low-end lock-in" situation. This situation makes the enterprises, after obtaining external financing funds, seize the low-end market share and use the funds in the development of a number of short

Table 4 Heterogeneity analysis

Variables	Nature of shareholding		Geographical position	
	Non-state-owned	State-owned	Northern regions	Southern regions
	M(1)	M(2)	M(3)	M(4)
<i>L</i>	0.1684*** (5.21)	−0.0520 (−0.42)	0.1528** (19.20)	0.1494*** (9.55)
<i>DFI</i>	−0.0003*** (−3.42)	−0.0004 (−1.09)	0.0001 (0.29)	−0.0002*** (−3.17)
<i>Size</i>	0.0952*** (7.13)	0.0134 (0.24)	−0.1203*** (−2.81)	0.0562*** (4.86)
<i>Age</i>	−0.0022*** (−7.86)	−0.0023** (−2.26)	−0.0010** (−2.16)	−0.0018*** (−10.30)
<i>Top</i>	0.0002*** (4.36)	−0.0015*** (−2.87)	−0.0001 (−0.48)	−0.0563 (−0.47)
<i>Gro</i>	−0.0912*** (−7.28)	0.0211 (0.39)	0.1319*** (3.25)	−0.0563*** (−5.06)
<i>Cap</i>	−0.0222*** (−6.59)	0.0073 (0.53)	0.0336*** (3.59)	−0.0136*** (−3.88)
<i>Lev</i>	0.0436*** (4.73)	−0.0128 (−0.17)	−0.0008 (−0.12)	0.0328*** (4.58)
<i>FD</i>	0.0061 (1.22)	0.0266* (1.83)	−0.0102 (−0.81)	0.0148* (1.94)
<i>Constant</i>	−0.0449 (−0.81)	−0.2270*** (−6.79)	−0.1668** (−2.28)	−0.0224*** (−0.31)
Firms fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
<i>AR (1)</i>	−3.33	−1.82	−2.88	−3.43
<i>AR (2)</i>	−0.26	0.33	−0.42	0.09
<i>Hansen test</i>	60.63	10.02	13.41	52.50

All z-statistics are shown under the estimated coefficient

*** 1% of significance level. **5% of significance level. *10% of significance level

and quick projects, ignoring the core technology R&D and innovation activities, which ultimately causes the distortion of enterprise investment and the disorderly expansion of the industry. This is contrary to the goals of energy conservation and environmental protection in the RE industry.

4.4 Intermediation test

In the previous section, this paper empirically tested if DFI has a significant positive impact on RE firms' investment efficiency using a benchmark regression. Then, does it affect investment efficiency by influencing other variables? This influential role is reflected not only in supply-side investment funds but also in demand-side energy use behavior. To this end, this study introduced intermediary variables from the supply and demand sides on the basis of data availability. On the supply side, two intermediary variables were introduced: external financing costs and internal R&D expenditures. On the demand side,

two intermediary variables were introduced: the distribution of residents' income and the upgrading of residents' consumption.

The results of the supply-side intermediation mechanism regressions for M(1)–M(2) are presented in Table 5. Here, M(1) tested the mediating role of external financing costs. The results showed that the regression coefficient of *DFI* on the intermediary variable (*Cost*) was significantly negative. This indicates that *DFI* greatly reduces the unnecessary transaction adjustment cost of RE firms, and the marginal investment costs of enterprises can decrease with an increase in investment opportunities, which helps alleviate the phenomenon of resource mismatch to a certain extent and makes the enterprise managers adjust the investment structure to the consensual level (Jin et al., 2024). Meanwhile, M(2) tested the mediating role of internal R&D expenditure. The results showed that the regression coefficient of *DFI* on *R&D* was significantly positive. This shows that, on the one hand, *DFI* alleviates the financial shock of enterprises by increasing their financial products and ensuring the financial continuity of their R&D investment projects. However, evaluating an R&D investment program allows it to maintain the optimal amount of R&D investment.

Table 5 Mediated mechanism test results

Variables	supply-side		Demand-side	
	<i>Cost</i>	<i>R&D</i>	<i>Inc</i>	<i>Upg</i>
	M(1)	M(2)	M(3)	M(4)
<i>L</i>	−0.0309*** (−16.85)	2.2730*** (11.53)	25.0110*** (16.84)	−0.0284*** (−14.73)
<i>DFI</i>	−0.0001*** (−2.59)	0.0168*** (6.67)	0.3742*** (13.03)	−0.0008*** (−30.78)
<i>Size</i>	−0.0142*** (−7.90)	1.6050*** (19.79)	−27.721*** (−18.02)	0.0053*** (3.42)
<i>Age</i>	0.0001 (1.64)	−0.0354*** (−6.79)	−0.6213*** (−4.70)	−0.0001 (−0.79)
<i>Top</i>	−0.0001 (−1.01)	−0.0010 (−0.72)	−0.2193*** (−8.73)	0.0002 (4.60)
<i>Gro</i>	0.0158*** (8.04)	−0.9469*** (−14.23)	32.3533*** (19.45)	−0.0050*** (−3.09)
<i>Cap</i>	0.0052*** (9.75)	−0.5862*** (−30.02)	7.6883*** (16.29)	−0.0016*** (−3.35)
<i>Lev</i>	0.0608*** (23.81)	0.0833 (0.73)	−4.5380*** (−3.70)	0.0090** (2.25)
<i>FD</i>	0.0057*** (4.39)	−0.1780*** (−3.19)	−2.3563*** (−2.90)	0.0066*** (−5.34)
<i>Constant</i>	−0.0670*** (−3.12)	1.3811* (1.76)	−134.2864*** (−11.68)	1.8743*** (128.64)
Firms fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
<i>AR (1)</i>	−2.64	−2.83	−2.31	−2.53
<i>AR (2)</i>	−1.10	−1.36	0.17	1.59
<i>Hansen test</i>	74.66	81.08	86.25	86.13

All z-statistics are shown under the estimated coefficient

*** 1% of significance level. ** 5% of significance level. * 10% of significance level

This suggests a significant partial mediating effect of both external financing costs and internal R&D expenditure.

M(3)–M(4) report the regression results for the demand-side mediation mechanisms. Specifically, M(3) tested the mediating role of the distribution of residents' income. The results showed that the regression coefficients of *DFI* on *Inc* were significantly negative. M(4) tested the mediating role of residents' consumption upgrading. The results showed that the regression coefficients of *DFI* on *Upg* were significantly negative. This finding indicates that DFI significantly inhibits the upgrading of residents' consumption structures. This result was inconsistent with the expectations of the present study. In other words, DFI increases basic survival consumption. Using China's 283 prefecture-level cities, Cheng et al. (2024) also finds that digital financial inclusion leads to increased residential consumption, mainly for high-carbon products. A possible reason for this is that the existence of consumption habits makes residents more rational about emerging products such as RE. The sticky information theory proposed by Mankiw and Reis (2002) argues that both lower trust and higher consumption adjustment costs constrain residents' willingness to purchase new products. Thus, under the effect of sticky consumption, they will continue to buy inexpensive high-energy products, and enterprises will further expand the production scale of high-energy products to meet growing consumer demand, which will seriously compress the market space of RE firms and reduce the investment efficiency of RE firms.

4.5 Moderating effects of the external environment

The discussion in the previous section suggested that DFI influences investment behavior by reducing external financing costs and increasing internal R&D expenditures, an abundance of financial capital will help improve the investment efficiency of RE firms. In contrast, whether it is income incentives or conceptual guidance, residents make their original consumption decisions under the effect of consumption habits, then creating a crowding-out effect on RE firm's investment, which also provides useful insights for governmental policymaking. Global storm activity and intensity fluctuations (Webster & Holland, 2005), the climate, and policy environments have been in a state of adjustment and change, and frequent changes will undoubtedly constitute a huge exogenous impact on the process of DFI and investment efficiency of RE firms. Therefore, the next section focuses on the direction and strength of these unintended forces.

M(1)–M(3) in Table 6 show the estimated results for the climate. With respect to the cross-term regression results, both sulfur dioxide (*SO2*) and extreme weather (*Ex_we*) as climate moderating variables helped strengthen the role of DFI in promoting RE firms' investment efficiency. As mentioned earlier, environmental problems such as acid rain and extreme weather brought about by sulfur dioxide emissions create localized panic, which helps to increase public trust in and acceptance of environmentally friendly RE products, and prompts more public investment in and consumption of RE products. This not only prompts enterprises to obtain more investment resources but also accumulates potential high-quality reputational resources, which makes enterprise managers more motivated and rigorous in formulating investment strategies.

By contrast, climate change has a significant weakening effect on the relationship between DFI and the investment efficiency of RE firms when extreme temperatures (*Ex_tem*) are used as the climate moderating variable. The explanations for this are as follows: First, DFI utilizes big data center cluster equipment, stores massive data, and relies on artificial intelligence technology for data identification and processing. Yu (2022) points out

Table 6 Moderating regression estimation results

Variables	Climatic environment			Policy environment	
	<i>SO2</i>	<i>Ex_we</i>	<i>Ex_tem</i>	<i>RE_po</i>	<i>FR_po</i>
	M(1)	M(2)	M(3)	M(4)	M(5)
<i>L</i>	0.1452* (1.78)	0.0565** (1.97)	0.5599*** (32.20)	0.0912* (1.89)	0.1354*** (18.49)
<i>DFI</i>	-0.0009*** (-4.57)	-0.0001* (-1.76)	-0.0003*** (-6.27)	-0.0002** (-2.15)	-0.0002*** (-2.60)
<i>DFI_Mod</i>	-6.3601** (-2.39)	-0.0001** (-1.97)	0.0001*** (7.10)	-0.0001** (-2.23)	-0.0062*** (-3.16)
<i>Mod</i>	-7.3568** (-2.39)	-0.0055*** (-2.68)	0.0001*** (3.07)	-0.0061*** (-3.98)	0.3693*** (3.34)
<i>Size</i>	0.1368*** (4.46)	0.0181*** (6.39)	0.0118*** (4.44)	0.1936*** (6.99)	0.0752*** (16.38)
<i>Age</i>	-0.0109*** (-5.88)	-0.0017*** (-7.12)	-0.0011*** (-8.50)	-0.0054*** (-2.78)	-0.0046*** (-37.30)
<i>Top</i>	-0.0006 (-0.89)	-0.0001 (-0.64)	-0.0001 (-1.22)	0.0013 (1.25)	0.0001 (0.70)
<i>Gro</i>	-3.6735*** (-6.85)	-0.3235*** (-5.64)	-0.0104*** (-4.25)	-3.2486*** (-5.85)	-0.0596*** (-12.77)
<i>Cap</i>	-0.3183 (-0.70)	-0.1583* (-1.71)	-0.0006 (-0.92)	-0.2007* (-1.73)	-0.0068*** (-5.24)
<i>Lev</i>	1.4700*** (3.02)	0.1634* (1.70)	0.0251*** (10.61)	0.0856 (0.74)	0.0622*** (10.84)
<i>FD</i>	0.0373* (1.94)	0.0027 (1.39)	0.0159*** (7.20)	0.0214* (2.36)	0.0123*** (6.58)
<i>Constant</i>	24.7012*** (6.98)	2.4449*** (6.37)	-0.0751*** (-2.67)	20.5738*** (5.63)	-0.3964*** (-11.72)
Firms fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
<i>AR (1)</i>	-2.72	-4.04	-4.21	-3.59	-4.02
<i>AR (2)</i>	-0.94	-1.13	0.32	0.43	-0.10
<i>Hansen test</i>	49.12	47.37	73.76	43.76	79.60

All z-statistics are shown under the estimated coefficient

*** 1% of significance level. **5% of significance level. *10% of significance level

that an increase in extreme temperatures reduces the operating efficiency of servers and storage equipment, and overreliance may even increase the risk of a capital chain breakage in enterprise investment projects. Enterprise managers cut various investment expenditures to reduce fluctuation losses and tend to use investments with low adjustment costs to smooth out investments with high adjustment costs, leading to passive deviation from the optimal level of investment, which in turn has an obvious negative impact on the efficiency of enterprise investment. Second, as an adaptive behavior to an extreme temperature rise, the public's most direct response is to increase the use of air conditioning and other temperature-control equipment (Davis & Gertler, 2015), thus generating public demand for energy-hungry traditional energy sources. This, in turn, inhibits the consumption demand for RE sources, causing RE firms to further deviate from their expectations for future investment.

M(4) and M(5) show the estimation results for the policy environment. With respect to the cross term regression results, it was found that the regression coefficient of the cross term between DFI and RE policy ($DFI \times RE_po$) and with financial regulatory policies ($DFI \times FR_po$) was significantly negative. This suggests that the continuous introduction of RE policies strengthens the role of DFI in promoting the investment efficiency of RE firms. This view is also supported by Qing et al. (2024). Meanwhile, DFI under financial regulation can play a stronger role in promoting the investment competitiveness and vitality of financial institutions to a certain extent (Treleven, 2015), reducing the barriers to capital and information flows, and thus effectively improving the investment efficiency of RE firms.

5 Conclusion and policy implications

5.1 Conclusion

This study comprehensively utilized micro-level enterprise data on the RE industry from the Cathay Pacific and Wind databases to empirically analyze the impact of DFI on RE firms' investment efficiency, and obtains several key conclusions: First, DFI can effectively improve RE firms' investment efficiency, but this effect is not significant in SOEs or the northern region. Second, in terms of the mechanism of action, DFI can improve enterprise investment efficiency by reducing external financing costs and increasing internal R&D expenditure on the supply side. On the demand side, however, DFIs cannot be promoted through consumption upgrades. Finally, in terms of moderating effects, an increase in Sulphur dioxide emissions, an increase in the number of extreme weather days, the introduction of RE policies, and the strengthening of financial regulation can help to strengthen the role of DFI in promoting the efficiency of RE firms' investments. Conversely, an increase in temperature extremes reduces equipment operating efficiency and weakens the promotional effect of DFI.

5.2 Policy implications

The policy implications of this study are both evident and significant. Initially, SOEs are more prone to improve their investment efficiency when motivated by DFI, and there is notably superior performance in the South area compared to the North area. These disparities indicate that the effects of DFI require reinforcement by other conditions. Consequently, differentiated incentives should be implemented to offer enhanced support and advantages to high-performing renewable energy firms, while diminishing the economic resources allocated to environmentally underperforming firms. This approach will facilitate coordinated development among renewable energy firms across various regions and enhance the overall efficacy of DFI.

Secondly, consumption behavior is a protracted process, and the method in which DFI can facilitate low-carbon consumption behaviors should be the focal point of policymakers' consideration. Specifically, on the one hand, the provision of price subsidies and financial services for low-carbon and clean RE products can increased the willingness to consume RE-related items. On the other hand, enabling residents to envision RE items through internet promotions and physical advertisements will facilitate effective RE demand. Finally, the government can encourage manufacture of specialized RE equipment to mitigate the

effects of extreme weather occurrences on RE firms. Increasing temperature extremes can diminish the operating effectiveness of big data devices, underscoring the vital necessity of resolving this issue for RE investment stability.

5.3 Limitations and future research

Two aspects of this paper require some caution. First, the role of DFI on the investment efficiency of RE firms is the focus of our attention. Nowadays, researchers communicate and share innovative ideas with the help of digital technology, and social network analysis can note the links between financial institutions and RE firms and analyze digital financial services characteristics in more depth. This methodology should be further applied in future studies. The second one is that the public availability of data is the fundamental reason for selecting RE listed firms as the sample object of this paper. Indeed, DFI may play a greater role in the growth of RE small and medium-sized enterprises (SMEs) in remote areas. However, at present, the data for this part is difficult to access, and subsequent research can overcome this limitation through questionnaires and interviews.

Appendix

See Table 7.

Table 7 Definition of variables

Variable	Variable name	Variable value
<i>INV</i>	Expected current year investment spending	Cash paid to construct fixed, intangible and other long-term assets (current year)
<i>INVlag</i>	Prior year investment expenditures	Cash paid to construct fixed assets, intangible assets and other long-term assets (previous year)
<i>Growth</i>	Enterprise Growth	Growth rate of main business
<i>Lev</i>	Gearing ratio	Total liabilities/total assets
<i>Cash</i>	Cash holdings	Cash to total assets
<i>Age</i>	Year of Listing	Current year—year of listing
<i>Size</i>	Firm Size	Natural logarithm of total assets
<i>Returns</i>	Stock Returns	Earnings per share growth rate

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Declarations

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