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Can Digital Finance Enable China's Industrial Carbon Unlocking under Environmental Regulatory Constraints? Joint Tests of Regression Analysis and Qualitative Comparative Analysis

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Abstract: Sustainable development goals challenge the carbon lock-in dilemma of the industrial economy, and identifying the motivation and mechanism behind carbon unlocking has become an urgent priority. With its inclusive and precise advantages, digital finance (DF) provides a new impetus for the economy's low-carbon transformation, while reasonable environmental regulation (ER) acts as an important guiding constraint. We focus on the carbon unlocking performance of DF under ER constraints. After constructing and calculating the industrial carbon unlocking efficiency (ICUE), we observe the trends of ICUE fluctuating positively, clustering towards the eastern region, and polarization. Subsequently, based on theoretical analyses, we explore the marginal and configuration effects of DF and ER in improving ICUE using panel data from 30 Chinese provinces between 2011 and 2021 and adopt a mixed research method with regression analysis (Tobit hierarchical regression and quantile regression for panel data (QRPD)) and dynamic fuzzy-set qualitative comparative analysis (fsQCA). The regression analysis results show that DF can notably enhance China's provincial ICUE, with ER generally serving as a positive moderator; however, the unlocking potential of informal environmental regulations needs further exploration. As ICUE improves in a specific location or time, the positive contribution of DF to ICUE also increases, whereas the moderating effect of ER exhibits an optimal range and follows an inverted U-shape. The dynamic fsQCA results support the findings of the regression analysis and further emphasize that effective cooperation between DF and ER is crucial for high ICUE, while inadequate DF support and the absence of formal environmental regulations remain bottlenecks in industrial carbon lock-in. Moreover, configuration paths demonstrate clear path dependency in both time and space, indicating a prolonged unlocking endeavor.



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1. Introduction

Balancing environmental protection and economic development is a constant topic for the sustainability of human societies, especially within production systems. The heavy consumption of fossil fuels in production systems is a major contributor to CO₂ emissions, leading to global climate change, while extreme weather events also significantly impact these systems [1]. Therefore, it is imperative to break the bottleneck of endless resource extraction and disposal [2], which manifests itself in a carbon lock-in (CLI) dilemma, a techno-institutional complex (TIC) dependent on fossil fuels [3]. In response, the international community has actively explored low-carbon policies to impose environmental regulation (ER) constraints and regulate economic development. The Paris Agreement set the target of limiting global temperature increases to 2 °C [4]. China also proposed the dual carbon goal of reaching peak carbon emissions before 2030 and striving to achieve carbon neutrality by 2060 [5], implementing innovative policies such as carbon emissions trading. Concurrently, the financial sector, as the forerunner of economic development and change,

has been transformed by the rapid growth of digital finance (DF), disrupting traditional financial practices and profoundly influencing economic development and environmental quality. Therefore, our focus is on assessing the carbon unlocking performance of DF under ER constraints, which is a critical step towards facilitating low-carbon transition and fostering sustainable economic and social development.

Since its reform and opening up, China's economy has developed rapidly, and energy consumption and carbon emissions have increased significantly [6]. At present, China is still in an important historical period of deepening industrialization and urbanization. The industrial sector is not only an important pillar of rapid economic development but also a major source of fossil energy consumption and carbon emissions [7]. This area is key to achieving economic transformation. In 2020, China's industrial added value accounted for 32.6% of its GDP; however, its carbon emissions accounted for as much as 70% [8]. China's industry is facing serious CLI problems. As the world's largest energy consumer and greenhouse gas emitter, the carbon unlocking performance of China's industry is particularly important.

In the era of digitization, DF is known for its convenience, low cost, and low threshold [9], which simplifies the environmental financing process and rapidly narrows the environmental funding gap. Given powerful data support and technological orientation, DF also has unique advantages in terms of optimizing resource allocation, promoting renewable energy R&D, and enhancing green innovation efficiency. Thus, DF provides a good opportunity for industrial carbon unlocking. The United Nations Climate Change Conference [10] noted that finance and technology are critical factors in achieving a 40% reduction in greenhouse emissions by 2030, highlighting the positive role of DF in addressing climate change challenges and achieving low-carbon economic development.

ER is an effective means to address environmental externalities and improve industrial carbon emission efficiency [11]. China has implemented specific formal environmental protection laws and tools, such as pollution charges, low-carbon city pilots, and technology and finance integration pilot policies. Total investments in environmental pollution control have continued to grow, accounting for 1.48% of the GDP in 2018 [12]. This has significantly improved China's overall environmental situation [13]. In recent years, environmental protection organizations and other stakeholders have increasingly participated in the supervision of local environmental protection [14]. As China's economic growth shifts to the high-quality development stage, the environmental regulatory system will continue to evolve and impose crucial limitations on the ongoing influx of digital financial resources into environmental production.

Given the aforementioned realities, we focus on the realization paths of China's industrial carbon unlocking and aim to answer two questions: (1) Can DF break China's industrial fossil energy locking dilemma, thereby improving its efficiency of industrial carbon unlocking? (2) Can external ER work well with DF and play a binding role in the process of China's industrial carbon unlocking?

Therefore, referring to the technology–organization–environment (TOE) framework [15], which describes the process of technological innovation and application, we construct an industrial carbon unlocking efficiency (ICUE) index system and a theoretical framework. Subsequently, using a mixed methods approach, we place DF, ER, and ICUE in the same research framework and investigate the impacts of the drivers (DF and ER) on enhancing ICUE from the perspectives of the levels of marginal effects and the paths of configuration effects. Specifically, regression analysis, including Tobit hierarchical regression and quantile regression for panel data (QRPD), is used to identify the direct marginal effect of DF on ICUE and the moderating marginal effect of ER and to further analyze their evolutionary patterns. Dynamic fuzzy-set qualitative comparative analysis (fsQCA) is used to infer the combined effects of antecedent configurations and their spatial–temporal heterogeneity.

Possible marginal contributions of this paper are as follows: (1) Thematically, we creatively incorporate DF, ER, and ICUE into the same research framework, which not only expands the dual perspectives, financial and institutional, of carbon unlocking research but

also clarifies the direction of DF development. Meanwhile, we examine both formal and informal ERs and seek to comprehensively analyze the intrinsic contribution of regulatory constraints to DF in breaking the high CLI of the industrial economy. (2) Regarding measurement indicators, a more systematic and complete ICUE classification indicator is creatively constructed by combining classical TIC theory and applying the TOE framework to select carbon unlocking inputs. This is an important supplement to the existing index and theoretical systems of carbon unlocking. (3) Methodologically, we expand and apply the dynamic analysis of fsQCA to break the barrier between panel data and QCA, and then adopt a mixed research method to combine the advantages of regression analysis and dynamic fsQCA and conduct supplementary demonstrations. Regression analysis excels in quantifying marginal effect levels, whereas dynamic fsQCA has a unique advantage in identifying the configuration effect paths. The synergy of their findings allows for a holistic and nuanced exploration of the underlying mechanisms driving the achievement of industrial carbon unlocking objectives, including both effect levels and configurations. Therefore, our research results can provide a road map reference for leveraging industrial carbon unlocking through the collaboration of DF and ER, and they are of great theoretical value and practical significance for maintaining the sustainable high-quality development of the industrial economy.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on carbon unlocking, DF and ER. Section 3 establishes the theoretical framework and proposes research hypotheses. Section 4 details our research methodology, selected variables, and data sources. Section 5 analyzes the spatial–temporal characteristics of ICUE. Section 6 identifies the direct effect of DF on ICUE and the moderating effect of ER, as well as their evolutionary trends. Section 7 exploits the causal relationships of multiple concurrences between antecedent configurations and ICUE, along with their spatial–temporal heterogeneity. Section 8 presents main conclusions, practical suggestions, and research prospects.

2. Literature Review

2.1. Research on Carbon Unlocking and the TOE Framework

Carbon lock-in (CLI) is an inevitable challenge in the pursuit of global emissions reduction goals [16]. Unruh [3] first proposed the CLI concept based on the evolution of techno-institutional complex (TIC), arguing that it is a macrobarrier to the spread of low-carbon technologies and hinders the broad application of environmental protection technologies in industrial development due to the coevolution of technology and institutions [17,18]. Since then, scholars have attempted to interpret and expand this concept from different dimensions and perspectives, such as the development economics perspective of CLI [19], the social–technical landscape perspective of CLI [20], industry CLI [21], and regional CLI [22]. The definitions of CLI differ among scholars, but they are committed to deepening the understanding and discussion of the mechanism of CLI.

Based on this definition, how to alleviate the CLI dilemma and unlock the sustainable development of a high-carbon economy has become an important issue. Relevant research has focused mainly on two mainstream directions.

On the one hand, there is ongoing scholarly discourse on the causes of CLI, and diverse conclusions have been obtained from different perspectives. Some researchers have focused on single factors. Mattauch et al. [23] found that although a higher elasticity of substitution requires less proactive policies, insufficient policy supply will result in a deeper degree of carbon locking. Most scholars have explored the multiple motivations for CLI by dividing it into more detailed types, such as three, four, or even five types, to emphasize its deepened hierarchical structure and measurability [24–26]. The mainstream views are technical, institutional, industrial, and behavioral CLIs. In addition, based on QCA method and cross sectional data, Hong et al. [27] investigated some economic and policy factors, concluding that industrialization, urbanization, increasing consumption, and lack of ERs led to the high CLI in the construction industry.

On the other hand, studies on carbon unlocking paths have highlighted the critical role of technological innovation, industrial optimization, institutional frameworks, and energy considerations in driving the transition towards a low-carbon economy. First, scholars have emphasized the transformative potential of technology, such as enhancements in information and communication technology efficiency [28] and the application of smart transportation [29], as a key driver of carbon unlocking. Second, the impact of institutions and policies has attracted extensive attention. The current literature has confirmed the positive role of pilot policy innovations such as low-carbon cities [30] and innovative cities [31] in breaking economic CLI and empowering unlocking. Third, several articles have examined the energy factor using the IV-GMM model and have concluded that consuming renewable energy and eliminating energy poverty can help solve the CLI dilemma [28,32]. In addition, using spatial modelling and threshold modelling tools, Xu et al. [33] discussed the nonlinear relationship between industry transfer and CLI. By combining PLS-SEM and NCA methods, Chen et al. [34] used questionnaire data and revealed the necessary economic conditions for achieving carbon unlocking in transportation infrastructure beyond the currently accepted TIC lock-in.

Collectively, these studies underscore the multifaceted nature of carbon locking causes and carbon unlocking pathways, which has important reference value for exploring the direction of low-carbon and sustainable economic development.

To date, two quantitative methods have been commonly used for the measurement of CLI and carbon unlocking. One is the single index calculation [33,35], but this method is too simple to reveal technological and institutional characteristics. Therefore, another method, constructing a comprehensive index, is more widely used. However, as mentioned earlier, the components of the CLI indicator are still controversial, and the selection of relevant factors is somewhat random.

Carbon unlocking implies eliminating the barriers of low-carbon technology diffusion, which is highly consistent with the applicability of the TOE framework, which focuses on the innovation and adoption of technology and provides an integrated framework with multifactor linkages in the three systems [15]. Whereas the technology system mainly refers to the existing technological characteristics of organization and the relationship between technology and the organization, the organization system pertains to the organization's relevant characteristics, like its scale and resources, and the environment system encompasses the macroenvironment in which the organization's activities are situated, including political, economic, social, cultural, and other environments. This framework is flexible, practical, and operable, and has addressed complex governance issues [36,37]. However, few scholars have focused on and applied this framework to solve the carbon unlocking problem. Although Hong et al. [27] attempted to use the TOE framework initially, they only assessed the basic carbon emissions indicator and used cross sectional data, failing to capture the full impact of decarbonization. Therefore, based on the TOE framework, we can systematically construct a comprehensive index of carbon unlocking from three dimensions—technology, organization, and environment—and then carry out empirical analysis.

2.2. Research on the Carbon Effect of DF

Restricted by the construction of the carbon unlocking index, few historical studies on the relationship between DF and carbon unlocking have been published. However, academics have potentially discussed this issue with a range of composite objects, including, but not limited to, CLI, carbon decoupling, low-carbon transition, and high-quality development, leading to three different points.

Specifically, the majority of studies have praised the positive role of DF in reducing CLI and facilitating low-carbon energy transition in Chinese cities [38,39], as well as promoting the decoupling of carbon emissions from economic growth in the ECA region [40]. The asymmetric, threshold, and intermediary effects in the relationship between the two were examined in the above studies. However, some controversial voices have reflected the belief that financial development can increase carbon emissions. They considered that

improving financial openness led to rapid expansion of economic volume in the short term, increasing the urgent demand for energy, and the rebound effect increased carbon emissions, thus hindering the carbon unlocking process in economic development [41]. In addition, several articles have emphasized the nonlinear characteristics of the relationship between DF and carbon unlocking. Fu et al. [42] revealed an inverted U-shaped relationship between DF development and energy efficiency in China, and their further analysis confirmed the remarkable impacts of breadth coverage, depth use, and digitization degree of DF. The semi-parametric spatial lag model of Li et al. [43] also suggested an inverse U-shaped relationship between digital inclusive finance and high-quality economic growth.

Notably, a considerable number of studies have explored the effect of DF on single categorized indexes related to carbon unlocking, such as affecting technological innovation, industrial structure adjustment and macro and micro green environment formation, with a wealth of academic results.

Specifically, some studies have revealed that DF can directly or indirectly promote green technology innovation and industrial structure upgrading [44,45], which are necessary processes to achieve full carbon unlocking. Another study discussed the implications of green DF for green environment, noting that green DF and green agricultural growth contributed to the green economic recovery of the BRICS economies [46]. Moreover, regarding environmental awareness and behavior, related studies have confirmed the role of DF in promoting the corporate social responsibility of pollution-intensive industries and facilitating consumer online purchases [47,48].

Previous studies have not only highlighted the extensive and complex impact of DF on the low-carbon economic transition, but also thoroughly explored its effect on individual pathways for unlocking carbon, which sheds important light on the comprehensive carbon unlocking effects of DF.

2.3. Research on the Carbon Effect of ER

Studies on the carbon effect of ER can be divided into three categories. One is that the majority of studies have supported the Porter hypothesis and have argued that appropriate environmental policies can internalize environmental costs external to the firm, encouraging or forcing technological innovation and thus stimulating production efficiency [49–51]. Nevertheless, some researchers have claimed that strict environmental policies can produce a “green paradox” effect and hinder economic development and improvement in environmental quality [52]. Environmental policies aggravate pollution control costs, squeeze production resources, and lead to inefficient energy use [53,54]. Moreover, few studies have explored the specific environmental effects of different types of ER through both linear and nonlinear regression methods. Feng et al. [55] investigated the nonlinear effects of official and unofficial ER on environmental quality using a quantile regression model and stressed the stronger time lag effect of unofficial ER. In addition, the moderating roles of heterogeneous ERs have received increasing attention. Zhao et al. [56] suggested that in terms of the relationship between the energy dilemma and CO₂, the moderating effect of FER is greater than that of IER, and the higher the intensity of DER is, the more significant its threshold effect is.

In addition to the individual carbon effects of ER, appropriate ER can guide the funds released by DF into the environmental protection field, which helps realize low-carbon development. ER tends to signal environmental governance to the market, and industries with energy-saving, carbon-reducing, and green features are likely to be favored by the market or financial institutions and thus receive financial support [9]. Recent studies have confirmed the potential of ER in reinforcing the positive impact of DF on carbon emission efficiency [57] and green development efficiency [58]. Yan et al. [59] simultaneously examined the carbon-reducing capacities of DF and ER in the short and long run through multivariate regressions, and further identified a positive moderating effect of financial institution competition. These findings suggest that the full combination

of efficient markets and responsive governments can more effectively mitigate carbon emission pressure and achieve the purpose of carbon unlocking.

2.4. Research Gap

Current studies have provided valuable insights for our study; however, some limitations exist. (1) Scholars have focused on the low-carbon effects of DF or ER using various composite or single indicators related and reached the conclusion that DF, ER, or both had positive, negative, or non-linear impacts on low-carbon development. However, few have directly established a link between DF and carbon unlocking. More importantly, no articles have been found that combine DF, ER, and carbon unlocking to conduct analyses, and existing examinations have given more attention to FER, failing to highlight the binding power of IER. (2) Research on carbon unlocking has gradually shifted from the theoretical analysis of CLI conceptualization to the empirical testing of CLI causes and unlocking paths, while the construction of a carbon unlocking classification index, which is mostly the independent expansion of TIC theory, is still in the exploratory stage, leading to strongly subjective research indices and diversified research conclusions. (3) Traditional regression methods were mainly used to investigate the pathways of carbon unlocking or the carbon effects of DF and ER, which have advantages in estimating the net effect of a single factor or the interaction effect of binary factors on the outcome, *ceteris paribus*; however, determining the overall synergy of the motivating system (more than three factors) is difficult considering the complicated statistical interpretations and multicollinearity problems. Although individual studies have explored the necessary conditions and sufficient configurations for CLI or unlocking using QCA and NCA methods, they have been limited to cross-sectional data or questionnaire data on a single indicator, such as carbon emissions, and thus cannot provide a comprehensive grasp of the carbon unlocking issue.

In view of this, our study develops an ICUE indicator with a more complete framework structure, integrates DF, ER, and ICUE within a unified framework, and employs mixed research methods to thoroughly investigate the marginal and configuration effects of DF and ER on ICUE, with a view to enriching relevant research on carbon unlocking and providing reference paths for industrial economies to achieve sustainable development.

3. Theoretical Analysis and Research Hypotheses

3.1. The Direct Effect Mechanism of DF on ICUE

DF combines the advantages of traditional finance and digital technology, which not only enhances financial efficiency and sustainability [60], but also improves energy–environmental performance with digital technology support [61]. Therefore, DF serves as a crucial link between the real economy and low-carbon development. Further, compared to single digital technology, DF can meet the needs of ICUE for unlocking multiple systems of technology, organization, and environment, provide stable financial support, and optimize resource integration and information transfer through digital and intelligent methods [62], thus becoming a significant tool for supporting green transformation and enhancing ICUE of enterprises in a holistic manner.

From the perspective of theoretical mechanisms, DF development is conducive to promoting technological innovation, optimizing industrial resource allocation and structure layout, and creating low-carbon production environments, so as to give full play to the quality-enhancing effect of DF to comprehensively improve the integrated ICUE of industrial technology, organization, and environmental systems.

Specifically, regarding technology, DF breaks through geographical and information barriers, improves the intertemporal liquidity of funds, and absorbs long-tail funds in the financial market, which provides a wider source of funds and realization possibilities for technological innovation. Secondly, with its efficient information screening and risk assessment capabilities, DF can effectively reduce the information mismatch in the financing process [63], thus alleviating the enterprise financing constraints and realizing the win–win situation of reducing the cost and improving the efficiency of innovation financing. In

addition, the integrated and online mode of financial digitalization reduces non-essential capital and energy consumption, thus facilitating the use of saved resources to innovate technology and improve productivity. Therefore, through technical revolution and application, enterprises can realize low-energy production and simultaneously improve the carbon unlocking efficiency of their technology system.

Regarding industrial organization, DF establishes a direct matching mechanism between the supply and demand sides of capital, which contributes to achieving efficient resource allocation [64]. Simultaneously, the digital nature of DF effectively mitigates the information asymmetry in the capital market and reduces financial friction, thus helping to correct the cross-sectoral and intra-sectoral mismatches of production factors in a timely manner. Secondly, with the help of identification and screening mechanisms, DF can realize the accurate sinking of funds and help enterprises in low-carbon transformation. And through the agglomeration of productive services, DF can promote the optimization and upgrading of industrial structure [65], which indirectly improves the efficiency of a low-carbon economy. In a word, DF provides convenience and impetus for the optimal allocation of industrial resources and the upgrading of the industrial structure, which can help industrial organizations reach a higher level of carbon unlocking efficiency.

Notably, the macroenvironment has great importance for industrial production activities. On the one hand, DF favors expanded information disclosure and lower service costs, which facilitates government and market screening of high-quality firms and monitoring of the production process. Thus, DF can encourage the utilization of fiscal policies and market rules to guide the low-carbon transition of production, provide an external institutional environment for industrial carbon unlocking and help to improve the efficiency of carbon unlocking in terms of institutional environment. On the other hand, irrational consumption behavior significantly contributes to environmental degradation. DF embeds the principles of sustainable development within the financial service sector through decentralized transactions, continuously guides green consumption behavior [66], and provides timely feedback from changes in consumer demand to the supply side. Moreover, DF also encourages the public to participate in environmental protection activities through digital platforms [67], such as planting trees through “Ant Forest” and recycling resources through second-hand trading platforms such as “Idle Fish”, thus raising their environmental awareness. As a result, DF, with its innate advantage of environmental friendliness, cooperates well with the government, enterprises, and citizens, creating a favorable external environment for industries to enhance carbon unlocking efficiency.

Obviously, DF development still has negative impacts. The quantity-increasing effect of expanding production also expands emissions. When this effect outweighs the quality-enhancing effect resulting from improvements in firm technology, industry organization, and the production environment, DF has a negative net environmental impact on the economy, thus hindering its carbon unlocking. These two effects are in fact a reflection of the digital character and financial nature of DF. However, as technologies develop and laws improve, the ecological effect of DF is still positive in general.

Based on the above theoretical analysis, the following hypothesis is proposed:

Hypothesis 1. *DF can significantly enhance the comprehensive ICUE, which encompasses fully unlocking the three systems of industrial technology, industrial organization, and industrial environment.*

3.2. The Moderating Effect Mechanism of ER

ER refers to a range of measures aimed at safeguarding the environment from pollution, including administrative, financial, and ethical initiatives. Due to the negative externalities associated with energy consumption and environmental pollution, market failures often occur, necessitating external constraints to ensure sustainable productive activities. As governments and markets impose stricter ecological regulations and individuals seek a higher quality of life, the transition towards low-carbon industries has emerged as a

prominent trend. In this process, ER plays a crucial role in enhancing the ICUE by regulating the quantity-increasing effect and quality-enhancing effect of DF.

As for the quality-enhancing effect of DF, firstly, ER triggers the Porter effect [68], prompting enterprises to balance green technological innovation and energy consumption [69]. This necessitates enterprises to innovate for improved energy efficiency and to drive industrial green transformation, placing significant demands on their financial standing. During this period, DF meets the demand for scalable and stable capital supply for green technological innovation and industrial restructuring, thus accelerating the carbon unlocking from technologies and organizations in highly carbonized industries under ER constraints. Secondly, ER improves corporate environmental information disclosure, guides DF to allocate productive resources in green processes, and encourages environmentally friendly industries to seek development opportunities, thereby also expanding industrial carbon unlocking. Moreover, enhancing ER binding effectively curbs excessive resource consumption and pollution caused by externalities and fosters a fairer and more efficient economic landscape, which facilitates the improved communication and collaboration among the public, businesses, and government, reduces transaction costs and financial friction, and achieves the allocation effect of DF resource and the improvement in ecological environment [70]. In summary, ER constraints can enhance ICUE by promoting the quality-enhancing effect of DF.

Notably, in terms of the quantity-increasing effect of DF, heterogeneous ER tools play various roles. On the one hand, the environmental policies and documents promulgated by the central government and the corresponding market trading rules reflect the national will and market demand for decarbonization development. These formal ERs impose strict limits on industrial carbon emissions by introducing explicit regulations and implementing reward and punishment mechanisms, such as emission quotas, sewage charges, environmental taxes, and investments in environmental governance [71,72]. Therefore, they can effectively control the scale effect of DF and weaken the quantity-increasing effect of DF on ICUE. On the other hand, informal ERs, such as environmental awareness, ethical norms, and public opinion [73,74], impose softer constraints on carbon emission reduction in the real economy. Increased environmental awareness and promotion of sustainable practices may encourage firms to invest DF funds in environmentally friendly production. However, the gradual shift away from a high-carbon economy may lead to a resurgence of public support for carbon-intensive consumption patterns. As a result, informal ERs may prolong the dominance of fossil fuels in China's economic and social landscape in the foreseeable future, thus fostering the quantity-increasing effect of DF and hindering ICUE enhancement.

Therefore, this article proposes the following hypothesis:

Hypothesis 2. *ER can significantly regulate the DF-ICUE relationship. Formal ER tends to play a positive moderating role by strengthening the quality-enhancing effect and weakening the quantity-increasing effect of DF, while informal ER may have a negative moderating role by simultaneously strengthening these two effects of DF.*

3.3. The Evolution Mechanisms of Direct and Moderating Effects

At various stages of carbon unlocking, DF development causes dynamic shocks to ICUE. The comprehensive decarbonization of production can only be achieved when both are developed in a coordinated manner. When ICUE is low, economic activity is characterized by a predominant production process with high energy consumption and pollution, coupled with underdeveloped economic and financial systems. During this phase, the motivation for clean technology innovations and energy savings is lacking, and the climate investment and financing system are underdeveloped. Financial development has not reached the necessary scale, and financial institutions tend to favor investigations into risk. Consequently, DF is ineffective in addressing the contradiction represented by the financial imbalance in the supply of and demand for decarbonization, leading to relatively

high investment and financing costs for enterprise decarbonization governance. This, in turn, limits the real assistance effect of DF development on carbon unlocking at this stage. As the issue of industrial carbon locking becomes more prominent and the dual carbon goal deepens, the status of the green industry in the national economy gradually improves. The service function of DF becomes more refined, resulting in a more mature cooperative decarbonization mode throughout society. This leads to the low-carbon transformation of the industrial economy through the optimization of technology and production processes. During this phase, the quality-enhancing effect of DF dominates the quantity-increasing effect, fully leveraging the advantages of financial digitization to address the problem of carbon lock-in and promote the accelerated increase in ICUE. Importantly, due to economic interests, the investment strategies of enterprises and traditional financial institutions will not immediately change completely. Instead, a period of adjustment and adaptation will be necessary. Thus, the process of unlocking the carbon effect of DF will be long and arduous. Therefore, this article proposes the following hypothesis:

Hypothesis 3a. *The direct carbon unlocking effect of DF is not static. Given continuous improvements in ICUE, its positive contribution to ICUE will gradually increase.*

Given that the carbon unlocking effect of DF is horizontally asymmetric and economic carbon unlocking is a complex process that cannot be completed spontaneously, a dynamically evolving and systematically adjusted ER support environment should be attached to different stages of industrial carbon unlocking to maximize the decarbonization advantages of DF. Specifically, at specific stages of the development of carbon unlocking, the external binding force of ER effectively addresses the negative externality of environmental problems. Relevant incentives and regulatory policies have formed a systematic response to significantly improve the level of decarbonization resource allocation, enabling DF to provide more precise, targeted, and cost-effective support for industrial carbon unlocking over a wider range and longer period, causing a more obvious decarbonization effect. However, when the degree of carbon locking is greater, the promotion of green development in the industrial economy requires a higher resource endowment, technological foundation, production system, and social environment standards. During this phase, the DF empowerment and external ER constraints are more limited, and their joint unlocking role cannot be fully realized. Moreover, at this time, the environmental awareness of the entire population is relatively weak, and local governments often adopt the short-term economic growth strategy of “pollution for growth”. The positive effect of DF supply on industrial carbon unlocking is not only extremely limited but may also lead to the inflow of funds into polluting industries due to weak external constraints, exacerbating industrial carbon locking [75]. Similarly, in the late stage of industrial carbon unlocking development, as production and energy-saving technology become relatively perfect and the industrial scale approaches the optimal level, the push and pull of DF and ER on the development of industrial low-carbon has been fully realized. The space for external forces to play a role will be continuously reduced, that is, the regulating effect of ER will show a decreasing trend. Therefore, this article proposes the following hypothesis:

Hypothesis 3b. *The synergistic unlocking effect of DF and ER is not static. Given continuous increase in ICUE, the moderating effect of ER on the DF-ICUE relationship has an inverted U-shape.*

4. Methodology and Data

4.1. Methodology

4.1.1. Econometric Regression Models

(1) Tobit regression models

The ICUE value is nonnegative, which belongs to restricted data and is not suitable for conventional OLS linear regressions. The Tobit model [76], which is based on the maximum likelihood estimation method, has high estimation accuracy and reliability with continuous

and restricted dependent variables. By maximizing the joint probability density function of the observed data, the parameters that best fit the data characteristics can be determined, avoiding large deviations due to limited explained variables. Therefore, after conducting correlation tests, unit root tests, and cointegration tests to examine the multicollinearity of variables and the stationarity of panel data, the panel Tobit model is introduced to test the relationship between DF and ICUE.

Notably, it is usually difficult to obtain consistent and unbiased estimators for the fixed effects Tobit model, and provinces exhibit individual differences. Thus, the random effects panel Tobit model is adopted. After regression, the likelihood ratio (LR) test is performed to examine the applicability of random Tobit model. The Wald test was used to evaluate the model's reliability. To minimize the heteroskedasticity problem, the logarithmic form of the driving variables is used. The Equations are as follows:

$$ICUE_{it}^* = \beta_0 + \beta_1 \ln DF_{it} + \sum_{i=1}^n \beta_i \ln X_{it} + u_i + \varepsilon_{it} \quad (1)$$

$$ICUE_{it} = \begin{cases} ICUE_{it}^*, ICUE_{it}^* > 0 \\ 0, ICUE_{it}^* \leq 0 \end{cases} \quad (2)$$

where $ICUE^*$ is the latent and real industrial carbon unlocking efficiency level of province i in year t (not observable) and $ICUE$ is the measured dependent variable. When $ICUE^* > 0$, the actual observation is equal to the potential efficiency $ICUE$. When $ICUE^* \leq 0$, $ICUE = 0$. DF_{it} is digital finance and β_1 is the estimated coefficient, reflecting the marginal effect of digital finance on the latent industrial carbon unlocking efficiency. Vector X_{it} represents control variables. u_i is the individual effect and ε_{it} is the random error, which follow a normal distribution.

To further test the moderating role of ER constraints on the ICUE effect of DF, we introduce the interaction term of DF and ER into Equation (1):

$$ICUE_{it}^* = \gamma_0 + \gamma_1 \ln DF_{it} + \gamma_2 \ln ER_{it} + \gamma_3 \ln DF_{it} * \ln ER_{it} + \sum_{i=1}^n \gamma_i \ln X_{it} + v_i + \zeta_{it} \quad (3)$$

where ER_{it} is environmental regulation and $\ln DF_{it} * \ln ER_{it}$ is the interaction term of centralized digital finance and environmental regulation. γ_3 is the estimated coefficient of our interest, reflecting the marginal moderating effect of ER on DF affecting $ICUE^*$. v_i and ζ_{it} is the individual effect and random error, respectively. The remaining settings and tests are the same as in Equation (1).

(2) QRPD models

Although panel Tobit regression offers distinct advantages in handling limited dependent variables, it imposes strict assumptions on variable distributions. Environmental data frequently display skewed normal distributions with distinct peaks or heavy tails, which can undermine the Tobit estimation results. In view of this issue, panel quantile regression effectively treats the dependent variable as a functional distribution and minimizes the sum of the absolute weighted residuals; thus, it remains robust against the influence of regression error parameter distributions and outliers. Moreover, quantile regression provides a more comprehensive analysis by estimating the marginal effects of drivers at various conditional quantiles of the dependent variable.

However, the fixed effect term in the traditional panel quantile model divides the random disturbance term into different parts, which makes it difficult to interpret the estimated results for each quantile. Powell [77] proposed quantile regression for panel data with non-additive fixed effects (QRPD) model, which incorporates fixed effects into random perturbations. The intercept parameter is allowed to vary according to fixed effects and unknown functions, ensuring the indivisibility of the random perturbation term. Therefore, QRPD can obtain more accurate coefficients and more robust results than traditional quantile regression.

Considering our data characteristics, we conducted normal distribution tests, and then adopted the QRPD to further capture the asymmetric link between ICUE and drivers, that is, the dynamic evolution of the direct marginal influence of DF on ICUE and the moderating marginal influence of ER at different ICUE levels, as shown in Equations (4) and (5).

$$Q_{ICUE_{it}} = \theta(\tau) \ln DF_{it} + \sum_{i=1}^n \theta_i(\tau) \ln X_{it} \quad (4)$$

$$Q_{ICUE_{it}} = \varphi_1(\tau) \ln DF_{it} + \varphi_2(\tau) \ln ER_{it} + \varphi_3(\tau) \ln DF_{it} * \ln ER_{it} + \sum_{i=1}^n \varphi_i(\tau) \ln X_{it} \quad (5)$$

where τ is the quantile and $Q_{ICUE_{it}}$ is the conditional quantile result of ICUE. DF_{it} , ER_{it} and X_{it} represent digital finance, environmental regulation, and control variables at the corresponding quantiles, respectively. $\theta(\tau)$ and $\varphi_3(\tau)$ are functions of τ , reflecting changes in the direct effect of digital finance on industrial carbon unlocking efficiency and changes in the moderating effect of environmental regulation therein, respectively. The QRPD models can be estimated using adaptive Markov chain Monte Carlo optimization methods [77].

4.1.2. Dynamic fsQCA Method

Environmental problems such as carbon unlocking are characterized by complex causality, and the effects of carbon unlocking tend to vary across different types of DFs and ERs (the coverage breadth, usage depth, and digitization level of DF and the formal and informal ER). Although traditional econometric models have advantages in estimating the marginal effects of single or two factors, they have limitations such as more stringent modelling assumptions, potential variable multicollinearity, and difficulty in dealing with multifactor interaction effects. In this context, QCA, as a complementary approach, plays a crucial role in uncovering the driver configuration affects that lead to results. Therefore, we further introduce the QCA approach to reveal the different paths in enhancing ICUE, so as to provide an in-depth understanding of the complex patterns and causality that cannot be covered by econometric modelling.

In contrast to traditional econometric regression analysis, QCA is a case-oriented methodology that conceptualizes research conditions and results by utilizing set theory and identifies specific conditional configurations by analyzing subset relationships to unveil intricate causal connections [78]. In general, there are three main advantages of QCA compared to traditional regression analysis. First, QCA has superior performance in studying “joint effect” and “interactive relationship” of multiple factors [79]. Second, QCA is an asymmetric data analysis technique that can address multiple causes of concurrency, equifinality, and causal asymmetry. That is, QCA highlights the fact that diverse configurations of drivers can produce the same result, and they are distinct from configurations that do not lead to the same outcome, which is helpful to identify the bottlenecks of low unlocking efficiency while identifying the implementation paths of high unlocking efficiency. Third, QCA can assess the relative importance of elements in forming configurations by distinguishing between core and edge conditions. These tasks are challenging to accomplish using traditional econometric regression analysis.

In this study, five secondary indices of DF and ER serve as antecedent driving conditions, and ICUE functions as a result variable, to explore the linkage effect of DF and ER factors behind the differences in provincial ICUE. Moreover, according to different variable types, QCA methods can be divided into crisp-set QCA (csQCA) for binary data (1/0), multi-value QCA (mvQCA) for multiple discrete data, and fuzzy-set QCA, fsQCA) dealing for values between 0 and 1. The variables in this paper are continuous, which is suitable for the fsQCA method.

Traditional fsQCA analysis involves four main steps: calibrating data, constructing a fuzzy-set truth table for software calculations (using the R 4.3.0), evaluating the reliability of results, and presenting findings. The reliability assessment employs two key indices—consistency and coverage—calculated using the following equations:

$$\text{Consistency}(X_i \leq Y_i) = \frac{\sum \min(X_i, Y_i)}{\sum X_i} \quad (6)$$

$$\text{Coverage}(X_i \leq Y_i) = \frac{\sum \min(X_i, Y_i)}{\sum Y_i} \quad (7)$$

where X_i and Y_i refers to the membership of region i in condition (or condition configuration) X and outcome Y , respectively. Consistency is comparable with the correlation and coverage is analogous to the coefficient of determination. A higher value of judgement indices (nearer to 1) is associated with a more reliable result, and the consistency level is generally not less than 0.75 [80], but the coverage level has not yet reached a harmonized minimum threshold.

However, traditional fsQCA lags behind cross-sectional data. Drawing on Hong et al. [27], we extend traditional fsQCA to dynamic fsQCA for panel data, to explore the linkage effect of the DF and ER factors behind the differences in provincial ICUE from the spatial–temporal dimension. The relevant indices are shown in Equations (8)–(10).

$$\text{POCONS}(X_{it} \leq Y_{it}) = \frac{\sum_{i=1}^N \sum_{t=1}^T \min(X_{it}, Y_{it})}{\sum_{i=1}^N \sum_{t=1}^T X_{it}} \quad (8)$$

$$\text{BECONS}(X_{it} \leq Y_{it}) = \frac{\sum_{i=1}^N \min(X_{it}, Y_{it})}{\sum_{i=1}^N X_{it}} \quad (9)$$

$$\text{WICONS}(X_{it} \leq Y_{it}) = \frac{\sum_{t=1}^T \min(X_{it}, Y_{it})}{\sum_{t=1}^T X_{it}} \quad (10)$$

where *POCONS*, *BECONS*, and *WICONS* denote the pooled consistency, the between consistency and the within consistency, respectively, which are computed using all cases, all province cases in each year, and all year cases in each province to reflect the adequacy of the configuration paths in the overall, temporal, and provincial dimensions, respectively. N and T are the number of provinces and years, respectively. The rest of the settings and the judgement of consistency are the same as in traditional fsQCA.

Furthermore, the distances between *BECONS*s or between *WICONS*s can effectively gauge the variability of consistency across temporal or provincial dimensions, reflecting the stability of configuration relationships in the presence of space–time effects; see Equations (11) and (12). To facilitate a comparison, the two distances were normalized to take values in the range of 0 to 1 (see Equations (13) and (14)).

$$\text{BECONS}_{dis} = d(\text{BECONS}, \text{POCONS}) = \sqrt{\sum_{t=1}^T \left(\frac{\text{BECONS}_t}{\sum_{t=1}^T \text{BECONS}_t} - \frac{1}{T} \right)^2} \quad (11)$$

$$\text{WICONS}_{dis} = d(\text{WICONS}, \text{POCONS}) = \sqrt{\sum_{i=1}^N \left(\frac{\text{WICONS}_i}{\sum_{i=1}^N \text{WICONS}_i} - \frac{1}{N} \right)^2} \quad (12)$$

$$\text{BECONS}_{dis}^{adj} = \frac{\text{BECONS}_{dis}}{\sqrt{\frac{T}{T^2 + 3T + 2}}} \quad (13)$$

$$\text{WICONS}_{dis}^{adj} = \frac{\text{WICONS}_{dis}}{\sqrt{\frac{N}{N^2 + 3N + 2}}} \quad (14)$$

where all of the settings in the formulas are the same as above. When the adjusted distances after standardization, $\text{BECONS}_{dis}^{adj}$ and $\text{WICONS}_{dis}^{adj}$, are below 0.2 [81], the configuration relationship remains stable in the presence of space–time effects, making the *POCONS* a reliable criterion for consistency assessment. Conversely, if the distances exceed these

thresholds, indicating instability, it is imperative to investigate potential spatial–temporal variation more comprehensively.

4.2. Variable Selection

4.2.1. Explained Variable

ICUE serves as our explained variable to measure the performance of industrial carbon unlocking. Unlike effectiveness indicators, which focus on the degree of achievement of results, efficiency indicators measure the proportionality between inputs and outputs. Such indicators provide a more comprehensive reflection of resource utilization and can help assess the carbon unlocking potential of drivers, implying information about future trends in unlocking phenomena.

We use the super-efficiency SBM model with undesirable outputs (US-SBM model) to measure China’s provincial ICUE, which combines the advantages of the SBM model in considering variable slacks [82] and the super-efficiency model in realizing the case ranking [83]. The details of US-SBM model are added in Appendix A. The indicator selection of the US-SBM model should follow the principles of simplicity, relevance, and diversity. Based on the discussion in the literature review section, classical TIC theory proposes five aspects of carbon lock-in motives—technology, organization, industry, system, and society—which are also key elements of carbon unlocking. The TOE framework constructs an overall structure of technology diffusion barriers of three systems—technology, organization, and environment—which is relevant to carbon unlocking issues and more complete. Therefore, we match the five aspects with the three systems. Then, referring to the mainstream literature and based on data availability, we select representative industrial inputs related to each system. The comprehensive ICUE system is shown in Table 1 and its TOE framework diagram is shown in Figure 1.

Table 1. Industrial carbon unlocking efficiency (ICUE) index system.

Index	Category	Composition of Specific Indicators	Measurement	Data Source	Reference
Input index	Technology inputs	Technology funding	Ratio of industrial R&D expenditure to GDP	China Statistical Yearbook on Science and Technology	[31]
		Technology personnel	Industrial R&D personnel full time equivalent	China Statistical Yearbook on Science and Technology	[31]
		Technology patent	Industrial patent applications	China Statistical Yearbook on Science and Technology	[84]
		Technology market	Ratio of transaction value in the technical market to GDP	China Statistical Yearbook	[85]
	Organization inputs	Labor endowment	Average annual number of industrial employees	China Statistical Yearbook	[3,84]
		Capital endowment	Average annual balance of industrial net fixed assets	China Industrial Economy Statistical Yearbook	[3,84]
		Energy endowment	Total industrial energy consume ¹	China Energy Statistical Yearbook	[84]
		Industrial structure	Proportion of added value of industry in GDP	China Statistical Yearbook	[31,85]
	Environment inputs	Employment environment	Urban employment in mining industry	China Statistical Yearbook	[31]
		Fiscal environment	Proportion of fiscal expenditure on science and technology	China Statistical Yearbook	[31]
		Population environment	Ratio of regional population to regional area	China Statistical Yearbook	[31]
		Traffic environment	Total passenger turnover	China Statistical Yearbook	[31]

Table 1. Cont.

Index	Category	Composition of Specific Indicators	Measurement	Data Source	Reference
Output index	Desired output	Economic development level	Gross industrial output	China Statistical Yearbook	[84]
	Undesired output	Carbon emission intensity	Ratio of industrial carbon emissions ^{1,2} to industrial output	China Energy Statistical Yearbook	[31,84]

¹ Due to data availability, industrial energy endowment is calculated for 13 fossil energy sources for the whole industry, including raw coal, cleaned coal, other cleaned coal, coke, crude oil, gasoline, kerosene, diesel fuel, fuel oil, refinery dry gas, natural gas, liquefied natural gas, and other energy sources. Industrial carbon emissions corresponding to energy consumption have been converted to standard coal equivalents using the carbon emission factor method. The rest of the industry-related descriptions refer to industrial enterprises above the scale. ² IPCC Guidelines for national greenhouse gas inventories[R]. Intergovernmental Panel on Climate Change, 2006.

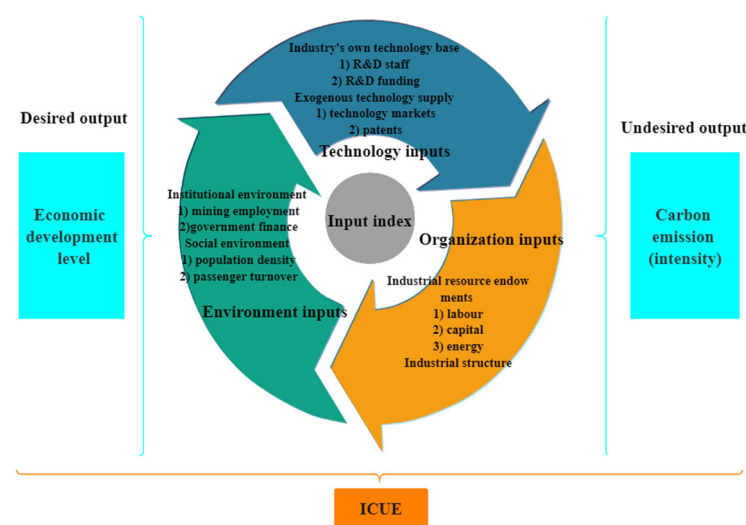


Figure 1. The TOE framework diagram of ICUE.

This index system involves more indicators, and potential correlations among technical indicators or environmental indicators could impact SBM results. To address this, the principal component analysis (PCA) using SPSS 25.0 software was conducted first on various inputs to reduce the dimensionality [86]. We obtained five new inputs. The advantages and results of the PCA method are shown in Appendix A. Then, the ICUEs were evaluated using the US-SBM model in MATLAB 2016a software with the five new inputs and two original outputs. To check the specific structures of provincial ICUE levels, we also measured the ICUE levels of the three systems using relevant inputs, namely, T-ICUE, O-ICUE, and E-ICUE.

4.2.2. Explanatory Variables

DF and its subindices are our explanatory variable. We used the digital financial inclusion index [87], which contains a composite index and three subindices: coverage breadth (BRE), usage depth (DEP), and digitization level (DIG). BRE is mainly reflected in the number of electronic accounts, such as internet payment accounts and their tied bank accounts. DEP is measured based on the actual usage of internet financial services, including payment, credit, insurance, credit investigation, investment, and money fund services. Regarding DIG support, convenience and cost are the main influencing factors.

4.2.3. Moderation Variables

ER and its subindices act as moderation variables. Considering the limitations of a single indicator and the structure of the ICUE, we refers to Zhao et al. [56] and Pargal and

Wheeler [88] to construct a comprehensive index of ER in terms of both formal environmental regulation (FER) and informal environmental regulation (IER). FER was measured using the amount of pollution control investment per unit of value added of industrial enterprises, reflecting mandatory constraints such as government policies and market rules. IER integrates four aspects—income level, education level, population density, and age structure—to reflect the soft constraints imposed by social environmental protection ideology on the environmental behavior of enterprises. The ER scores were calculated using the entropy weighting method with objective assignment.

4.2.4. Control Variables

Carbon unlocking is influenced by not only environmental factors but also political, economic, social, and cultural influences. Therefore, based on relevant studies, the following control variables were included in our study.

- (1) Government intervention (gov) was expressed as the ratio of government general public budget expenditure to GDP [33]. Higher budget expenditures ratios tend to indicate that local governments have stronger economic and environmental intervention capabilities.
- (2) Foreign direct investment (fdi) was measured as the actual utilization of foreign direct investment as a share of GDP [31,89]. The spillover and competition effects of foreign investment can have a significant impact on the regional ecological environment.
- (3) Human capital (stu) was calculated as the ratio of undergraduate and college students to the regional population [31,89]. Human capital is one of the important inputs for high-quality production activities, and the agglomeration of research practitioners can have a profound impact on regional low-carbon production capacity.
- (4) The industrial structure (inst) was represented by the ratio of the main business income of high-tech industries to the main business income of industrial enterprises above a certain size [84]. Generally, a higher ratio of high-tech industries is associated with a higher degree of carbon unlocking.
- (5) The energy structure (enst) was expressed as the proportion of industrial coal consumption to total energy consumption [33,84]. Coal is an important supply-side emission of CO₂, which is harmful to the carbon unlocking of production.

4.3. Data Source

Considering the availability time range of DF data and the poor performance of the QCA method in large samples, we selected panel data from 30 provinces in China from 2011 to 2021 as the research sample, excluding Hong Kong, Macao, Taiwan, and Tibet, where data are difficult to obtain. The data sources for the ICUE indicators include the China Statistical Yearbook on Science and Technology, China Industrial Economy Statistical Yearbook, China Statistical Yearbook, and China Energy Statistical Yearbook; for details, see Table 1. The DF, BRE, DEP, and DIG data were obtained from the Digital Finance Research Center of Peking University. The energy data were mainly obtained from the China Energy Statistical Yearbook. All of the data for calculating ER and the remaining control variables were obtained from the China Statistical Yearbook. A small amount of missing data were supplemented by Provincial Statistical Yearbooks, the EPS Database, and the national and local bureaus of statistics. In addition, we used linear interpolation to fill in the data gaps when necessary. All types of monetary indicators are price indices deflated using 2000 as the base period. The descriptive statistics of the main variables in this paper are shown in Table 2.

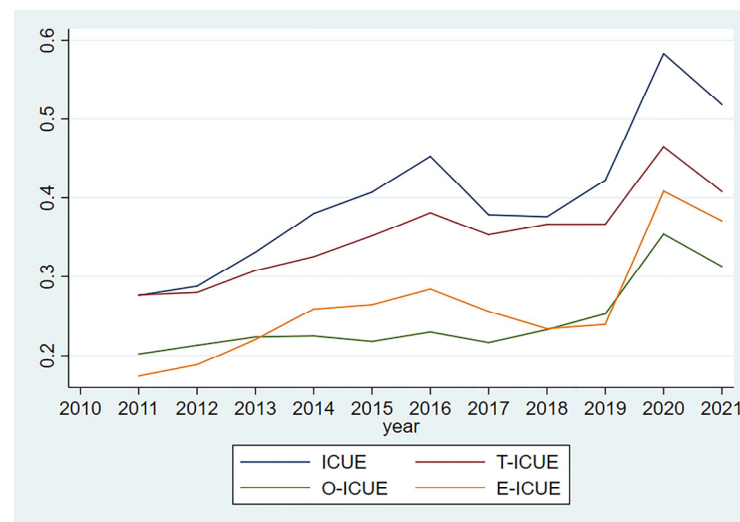
Table 2. Descriptive statistics of key variables.

Variable	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.	Jarque–Bera
ICUE	330	0.401	0.284	0.076	1.186	1.249	3.503	0.000
lnDF	330	5.283	0.669	2.909	6.129	−1.595	5.236	0.000
lnER	330	−1.884	0.397	−3.038	−0.448	−2.136	8.971	0.000
lnBRE	330	5.149	0.817	0.673	6.072	−1.612	6.549	0.000
lnDEP	330	5.266	0.652	1.911	6.236	−2.153	7.611	0.000
lnDIG	330	5.556	0.681	2.026	6.136	0.844	5.721	0.000
lnFER	330	−2.093	0.47	−3.374	−0.462	−0.368	3.877	0.000
lnIER	330	−3.993	0.876	−7.207	−1.391	0.700	4.949	0.000
lngov	330	3.141	0.374	2.367	4.164	0.378	2.902	0.018
lnfdi	330	0.173	1.182	−5.085	2.074	−1.322	4.851	0.000
lnstu	330	13.493	0.803	10.73	14.804	−1.267	4.785	0.000
lninst	330	2.003	0.858	−1.492	3.580	−0.914	4.553	0.000
lnenst	330	3.951	0.448	1.469	4.530	−2.675	12.905	0.000

5. Analysis of Evolution Characteristics of China's ICUE

5.1. Time Trend Analysis

Figure 2, obtained from StataSE-64 software, shows the time trends of ICUE for Chinese provinces from 2011 to 2021. ICUE generally shows a fluctuating upwards trend with similar subindicator trends. Among them, the T-ICUE level is the highest, indicating that the unlocking of technology is the most basic and has achieved some success in realizing industrial carbon unlocking, whereas the unlocking of organizations and the environment should receive more attention.

**Figure 2.** Temporal trends of China's annual average ICUE and its subindexes from 2011 to 2021.

From a specific perspective of years, ICUE and its subindicators experienced steady growth until 2017, possibly influenced by the 12th Five-Year Plan (2011–2015), which emphasized innovation in the real economy and environmental regulation, leading to enhanced resource efficiency across industries and a subsequent rise in ICUE. Notably, the ICUE decreased considerably in 2017, which is widely believed to be associated with the rebound in China's carbon emissions during the same period. Fang et al. [90] noted that China's carbon emissions rebounded from 2017 to 2019, ending the steady decline from 2013 to 2016. Furthermore, ICUE showed an abrupt change around 2020, which may be due to the shock of the COVID-19 pandemic that rapidly contracted the total carbon emissions of the society in the early period, while simultaneously slowing down the process of economic development and carbon unlocking in the aftermath.

5.2. Regional Distribution Analysis

ArcGIS 10.8 software was adopted to produce geographical distribution maps of ICUE in selected years (Figure 3) to visualize the evolutionary characteristics of the regional distribution of ICUE. We can see that the national ICUE levels vary significantly geographically, but are generally low, and provinces with high ICUE levels are gradually clustering in the eastern region. This may be because eastern China has relatively sophisticated technology and better industrial restructuring, allowing its industrial sector to use fossil energy more efficiently.

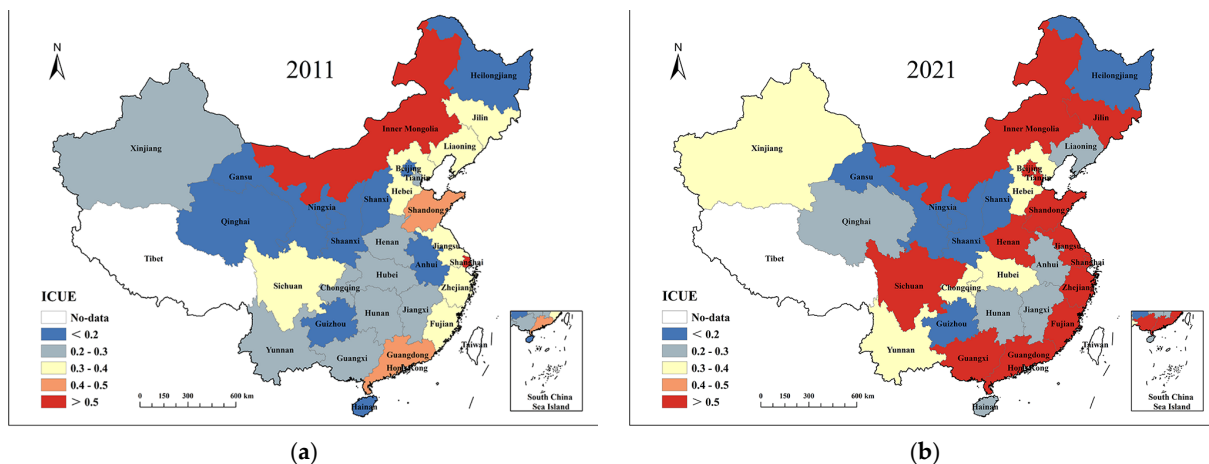


Figure 3. Spatial distributions of China's ICUE (subfigures (a,b) in 2011 and 2021, respectively).

Interestingly, the ICUE distribution in 2021 (Figure 3b) reveals a center–periphery pattern in the Beijing–Tianjin–Hebei region. On the one hand, this is directly related to the energy consumption of Hebei. On the other hand, as the political center of China, Beijing has occupied the highest quality high-tech industrial resources and has gradually relocated the environment-polluting and energy-intensive industries to the periphery. In contrast, the central and western provinces of Gansu, Ningxia, Shanxi, Shaanxi, Guizhou, and Heilongjiang have the lowest ICUE levels. In the process of low-carbon industrial transformation, they are usually disadvantaged by taking over the backward industries in the eastern region, which makes it difficult for them to improve industrial energy use efficiency. Moreover, the self-innovation capacity of these regions is not high, resulting in insufficient endogenous motivation to improve ICUE.

5.3. Kernel Density Analysis

The three-dimensional kernel density map of China's ICUE was generated using MATLAB 2016a software. Figure 4a shows little change in the peak value of the main peak and an upwards trend in the secondary peak's values, indicating a gradual deepening of the polarization of provincial ICUE. The “Matthew effect” between provinces is increasingly pronounced, with high ICUE provinces improving efficiency while low ICUE provinces are experiencing a decline, underscoring the need and urgency to improve ICUE.

Among the three dimensions of ICUE (Figure 4b–4d), low-carbon technologies dominate and play a stable role in industrial carbon unlocking, the external environment exerts a certain binding effect on high-carbon production, and the unlocking effectiveness of organizational factors declines annually. Therefore, China should focus on unclogging the utilization channels of environmental protection resources between upstream and downstream industries, creating a low-carbon industry chain and effectively promoting O-ICUE.

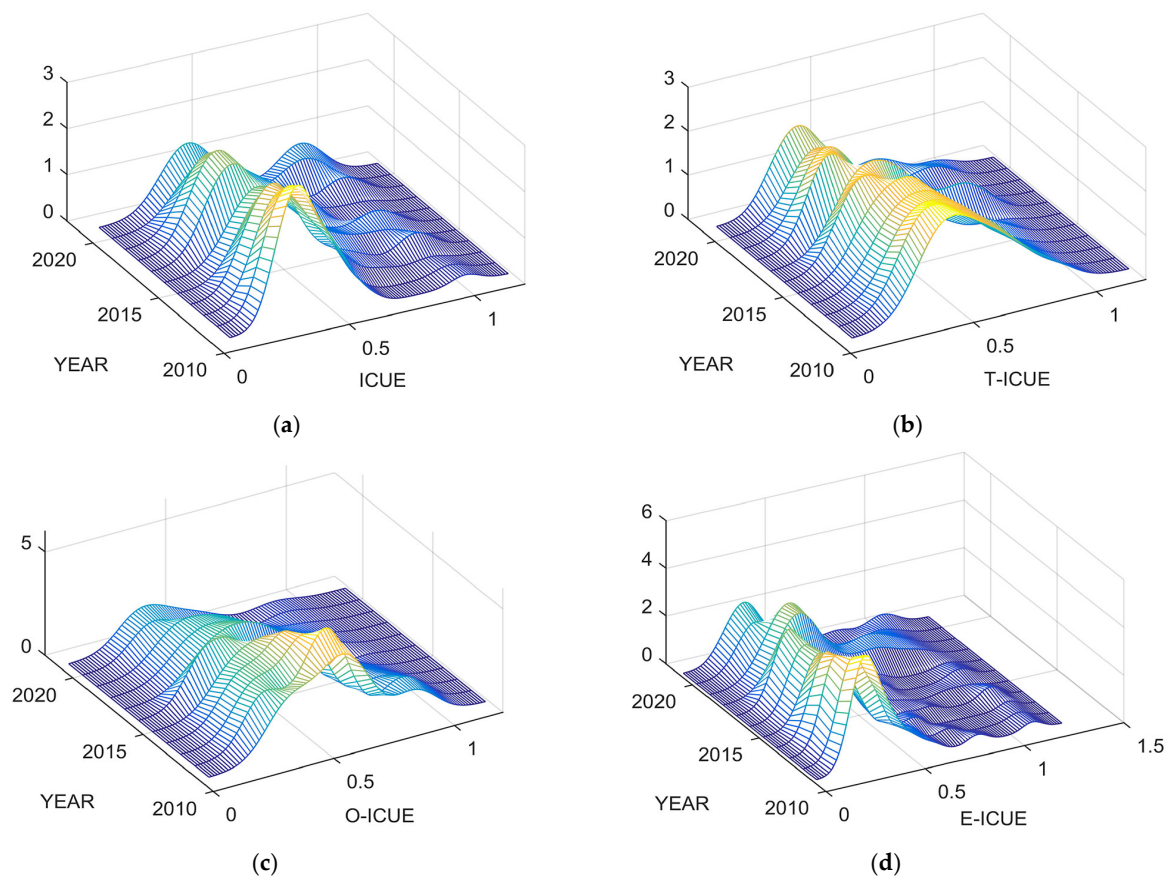


Figure 4. Kernel density of China's ICUE and its subindexes from 2011 to 2021 (Subfigures (a,b,c,d) for ICUE, T-ICUE, O-ICUE, and E-ICUE, respectively).

6. Regression Analysis

6.1. Tobit Hierarchical Regression Analysis

Before empirical regression analysis, a series of tests were conducted. The unit root tests (Table 3) show that all of the study variables are third-order monointegral variables, indicating that our variables are stable. Further cointegration tests (Table 4) show that all test statistics are significant at the 1% level, indicating that a long-term cointegration relationship between variables, that is, the influence of DF, ER, and other control variables on industrial carbon unlocking efficiency, is long-term and stable. The correlation tests (Table 5) reveal significant correlations between drivers and ICUE, which verify that our selection of variables is reasonable. All of the correlation coefficients between drivers are less than 0.8, and their variance inflation factor (VIF) values are far smaller than the empirical value of 10; thus, for the regression analysis here, multicollinearity is not a concern.

Table 3. Unit root test results.

Variable	LLC	IPS	ADF	PP	HT
ICUE	−5.4631 ***	−4.4113 ***	−3.8617 ***	2.1114	−4.4146 ***
lnDF	−5.3207 ***	−6.3260 ***	−12.0536 ***	−69.9927 ***	−2.0404 **
lnBRE	3.5984	−7.1307 ***	−11.7407 ***	−93.7432 ***	−4.2140 ***
lnDEP	−10.6453 ***	−6.1532 ***	−9.7544 ***	−54.5748 ***	−2.2438 **
lnDIG	−15.9088 ***	−7.0955 ***	−11.4886 ***	−53.3523 ***	−5.5492 ***
lnER	−11.7745 ***	−5.1146 ***	−8.6028 ***	−3.8234 ***	−6.1707 ***
lnFER	−6.7776 ***	−5.0699 ***	−5.3352 ***	0.3171	−0.8289
lnIER	−9.0723 ***	−4.8938 ***	−8.6308 ***	−8.1884 ***	−7.7390 ***

Table 3. Cont.

Variable	LLC	IPS	ADF	PP	HT
Ingov	−1.0674	−2.4781 ***	−5.6452 ***	1.9158	−1.6550 *
lnfdi	−4.1766 ***	−1.5829 *	−5.0637 ***	2.4014	−3.4559 ***
lnstu	−7.0004 ***	1.4785	−5.1395 ***	2.3648	4.8418
lninst	−5.7852 ***	−1.9313 **	−4.8518 ***	0.5436	−1.9186 **
lnenst	11.9632	−1.2148	−7.3530 ***	−2.1466 **	−2.8500 ***
ΔICUE	−3.8712 ***	−6.4256 ***	−8.7322 ***	−13.6383 ***	−9.5866 ***
ΔlnBRE	−3.0095 ***	−6.9236 ***	−14.2033 ***	−90.7762 ***	−3.4360 ***
ΔlnFER	−7.2495 ***	−6.8960 ***	−9.2303 ***	−13.9480 ***	−6.4729 ***
ΔIngov	−5.3297 ***	−6.0139 ***	−9.2673 ***	−11.2665 ***	−6.5083 ***
Δlnfdi	−4.8772 ***	−5.2332 ***	−8.3346 ***	−13.4698 ***	−7.9228 ***
Δlnstu	−9.4551 ***	−2.2569 **	−7.6353 ***	−2.6286 ***	5.6822
Δlninst	−9.0932 ***	−5.6556 ***	−8.8393 ***	−11.0604 ***	−5.0580 ***
Δlnenst	7.0117	−5.4897 ***	−7.9763 ***	−17.1479 ***	−4.6840 ***
Δ ² lnstu	−5.8981 ***	−5.1410 ***	−7.1749 ***	−13.2894 ***	−6.9912 ***
Δ ² lnenst	4.7907	−7.0253 ***	−11.1326 ***	−33.8872 ***	−11.2305 ***
Δ ³ lnenst	−7.3831 ***	−6.5838 ***	−11.8472 ***	−42.5715 ***	−11.8736 ***

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

Table 4. Cointegration test results.

Test	Statistic	Statistical Value	p Value
Kao	DF	−4.8859	0.0000
	ADF	−4.4605	0.0000
Pedroni	PP	−12.1827	0.0000
	ADF	−9.9481	0.0000

Table 5. Correlation test results.

	ICUE	lnDF	lnER	Ingov	lnfdi	lnstu	lninst	lnenst
ICUE	1.00	0.31 ***	0.24 ***	−0.53 ***	0.22 ***	0.36 ***	0.34 ***	−0.23 ***
lnDF	0.30 ***	1.00	0.43 ***	−0.06	−0.04	0.24 ***	0.40 ***	−0.17 ***
lnER	0.27 ***	0.37 ***	1.00	−0.14 **	0.21 ***	0.01	0.41 ***	−0.29 ***
Ingov	−0.40 ***	−0.04	−0.09	1.00	−0.49 ***	−0.69 ***	−0.48 ***	−0.02
lnfdi	0.13 **	−0.05	0.16 ***	−0.62 ***	1.00	0.30 ***	0.54 ***	−0.16 ***
lnstu	0.25 ***	0.20 ***	−0.06	−0.75 ***	0.43 ***	1.00	0.41 ***	0.29 ***
lninst	0.19 ***	0.37 ***	0.36 ***	−0.50 ***	0.50 ***	0.45 ***	1.00	−0.30 ***
lnenst	−0.18 ***	−0.19 ***	−0.37 ***	−0.08	−0.13 **	0.30 ***	−0.25 ***	1.00
VIF		1.56	1.45	3.30	1.94	3.30	2.02	1.51

Note: Besides the last row, Pearson and Spearman correlation coefficients are reported in the lower left and upper right, respectively. VIF values between endogenous variables are on the last row. *** and ** denote significance levels of 1% and 5%, respectively.

Then, we conducted a hierarchical regression analysis based on panel Tobit models to investigate the direct effect of DF on ICUE and the moderating effect of ER. Table 6 provides the results.

6.1.1. The Direct Effect of DF on ICUE

Columns (1)–(2) of Table 6 show that the LR test results are significant, indicating that the random panel Tobit model is suitable, and the Wald test is passed at the 1% level, indicating high reliability of the regression models. The regression coefficient of DF is significantly positive at the 1% level after controlling for relevant variables, indicating that DF effectively improves ICUE, supporting Hypothesis 1. More specifically, every 1% increase in DF can enhance expected ICUE by an average of 0.1156. Therefore, we can use the advantages of DF development to provide financing support for technological innovation, optimize resource allocation, and provide efficient services for carbonization

policy implementation and low-carbon consumption, thus accelerating the unlocking process of industrial technology replacement, industry transformation, and improvements in the environment.

Table 6. Tobit hierarchical regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ingov	0.0059 (0.0716)	−0.2205 ** (−2.4890)	−0.2033 ** (−2.3707)	−0.1806 ** (−2.1330)	−0.2049 ** (−2.3169)	−0.2282 *** (−2.6931)	−0.1893 ** (−2.2676)	−0.1540 * (−1.8206)	−0.2150 ** (−2.5335)
lnfdi	−0.0370 ** (−2.1245)	−0.0112 (−0.6503)	−0.0090 (−0.5322)	−0.0047 (−0.2792)	−0.0144 (−0.8231)	−0.0044 (−0.2527)	0.0026 (0.1529)	0.0044 (0.2627)	−0.0016 (−0.0954)
lnstu	0.2661 *** (4.3863)	0.1197 ** (2.0983)	0.1344 ** (2.4497)	0.1185 ** (2.2167)	0.1321 ** (2.2366)	0.0877 (1.6288)	0.0794 (1.5089)	0.0864 (1.6389)	0.0845 (1.5769)
lninst	−0.0589 * (−1.7381)	−0.1296 *** (−3.7327)	−0.1375 *** (−4.1000)	−0.1433 *** (−4.3294)	−0.1171 *** (−3.2873)	−0.1507 *** (−4.2794)	−0.1400 *** (−4.0298)	−0.1283 *** (−3.6593)	−0.1469 *** (−4.1438)
lnenst	−0.2401 *** (−5.1836)	−0.1841 *** (−4.0538)	−0.1557 *** (−3.4456)	−0.1141 ** (−2.4878)	−0.1753 *** (−3.8164)	−0.1420 *** (−3.1269)	−0.1029 ** (−2.2723)	−0.0872 * (−1.9053)	−0.1291 *** (−2.8088)
lnDF		0.1156 *** (5.2558)	0.0775 *** (3.2261)	0.1057 *** (4.2571)					
lnER			0.2347 *** (3.6624)	0.2507 *** (3.9411)					
lnDF*lnER				0.1310 *** (3.6267)					
lnBRE					−0.0169 (−0.4309)	−0.0080 (−0.2096)	0.0696* (1.6915)	0.0379 (0.9882)	0.0150 (0.3636)
lnDEP					0.0753 (1.4569)	0.0116 (0.2191)	0.0220 (0.4257)	0.0595 (1.1360)	0.0105 (0.1985)
lnDIG					0.0596 ** (2.0784)	0.0837 *** (2.8786)	0.0221 (0.7008)	0.0124 (0.3882)	0.0611 * (1.8562)
lnFER						0.1823 *** (2.8137)	0.1406 ** (2.1790)	0.1438 ** (2.2315)	0.1783 *** (2.7464)
lnIER						−0.0333 ** (−2.1492)	−0.0054 (−0.3273)	−0.0020 (−0.1214)	−0.0263 (−1.6148)
lnBRE*lnFER							0.0871 *** (2.8694)		
lnBRE*lnIER							−0.0485 *** (−2.8977)		
lnDEP*lnFER								0.0974 *** (2.9399)	
lnDEP*lnIER								−0.0627 *** (−3.0070)	
lnDIG*lnFER									0.0307 (1.2324)
lnDIG*lnIER									−0.0169 (−0.7702)
Constant	−2.1345 ** (−2.2954)	−0.1443 (−0.1662)	0.1510 (0.1823)	0.0096 (0.0119)	−0.4492 (−0.4981)	0.5622 (0.6576)	0.2637 (0.3147)	0.0088 (0.0104)	0.5342 (0.6272)
Log likelihood	74.1492	87.2620	93.9997	100.4423	87.8998	95.9528	105.4793	106.5438	97.3246
Wald test	52.14 ***	87.52 ***	104.04 ***	121.73 ***	88.93 ***	110.35 ***	136.43 ***	139.43 ***	114.04 ***
LR test	159.03 ***	152.67 ***	159.10 ***	157.71 ***	153.69 ***	156.42 ***	163.19 ***	161.87 ***	157.94 ***
N	330	330	330	330	330	330	330	330	330

Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. t statistics are in parentheses.

A similar finding was reported by Zhao et al. [38], who revealed that China's green financial inclusion development can effectively accelerate the process of CLI mitigation. This conclusion is also supported by other studies. By optimizing the industrial structure and promoting green technology, DF can also comprehensively reduce carbon intensity [91].

We further explored this relationship. Column (5) of Table 4 reveals that the digitization level of DF (DIG) has a significant positive carbon unlocking effect; however, the roles of its coverage breadth (BRE) and usage depth (DEP) are not obvious. Even BRE plays a negative role, which may be because the production-increasing effect of the continuous improvement in DF coverage has gradually exceeded the energy-saving effect [92]. Therefore, DF should shift from quantity to quality as quickly as possible.

6.1.2. The Moderating Effect of ER

In Columns (3)–(4) of Table 6, the coefficient of the interaction item between DF and ER is still significantly positive at the 1% level (0.1310) and even larger than the original regression coefficient of DF alone (0.1156), suggesting that the positive effect of DF on ICUE is effectively amplified when ER is at a high level, thus initially supporting Hypothesis 2.

Ding et al. [93] also found that the amalgamation of DF and ER can effectively enhance environmental performance such as carbon emission efficiency, which is an essential part of accelerating carbon unlocking and is internally in line with our conclusions. A possible explanation is that external environmental regulatory constraints can not only guide the funds released by DF into low-carbon production, but also affect corporate reputations. After weighing the cost of emission mitigation actions and illegal activities, enterprises tend to channel their resources towards green and environmentally friendly development, thus improving ICUE.

Similarly, to systematically assess the specific moderating effects of different types of environmental regulation, ER is decomposed and then cross-multiplied using the subdimensions of DF for regression. The results are reported in Columns (6)–(9) of Table 6. FER and IER markedly increase and decrease ICUE, respectively, leading to their interaction coefficients with the three decomposition variables of DF also being significantly positive and negative, respectively.

These findings are in line with those of several studies. FER can improve China's CLI by promoting green technology innovation, industrial structure upgrading, and public green behavior [94]. However, IER based on moral constraints is highly stochastic and compatible with China's current carbon-based energy consumption structure, thus negatively regulating the relationship between DF and ICUE [57]. In short, if we want to amplify the carbon unlocking effect of DF on the industrial economy, FER is an effective means of regulation, whereas the potential of IER needs to be further explored.

The findings discussed above support Hypothesis 2.

6.1.3. Robustness Tests

We performed a series of sensitivity tests for the effects of DF on ICUE and its subindicators: (1) Variable replacement: remeasuring the ICUE using absolute carbon emissions to replace relative carbon emission intensity, denoted as ICUE-A, and performing the Tobit regression. (2) Method change: using the ordinary least squares (OLS) method for estimations, including both random effects and fixed effects models. (3) Period adjustment: given that 2013 is generally regarded as the first year of DF development [38], regressions were conducted again using relevant data from 2014 to 2021. (4) Samples exclusion: considering that municipalities directly under the central government, in contrast to other provinces, have political specificity, we omitted the sample data of Beijing, Tianjin, Shanghai, and Chongqing, and then conducted a regression. The robustness test results are in Table 7; as we can see, the coefficient signs and significance levels of explanatory variables remain basically unchanged, indicating that our main conclusion, the positive impact of DF on ICUE, is reliable.

The possible reverse causality between DF and ICUE, as well as potential omitted variables and measurement errors in the models may trigger endogeneity problems. Thus, we adopted the following endogeneity tests: (1) Explanatory variables were lagged one period for regression. (2) Referring to Gu and Bian [95], the two-stage regression is conducted through the IV-Tobit model with mobile phone penetration as the instrumental variable of DF and taking its logarithm ($\ln\text{phone}$). The relevant data were obtained from the national bureau of statistics. The endogenous test results are shown in Table 8. Columns (1)–(2) indicate that the direction and significance level of the regression coefficients of lagged terms are consistent with those of the benchmark regression in Table 6. Columns (3)–(4) show that the impact of the instrumental variable on DF is significantly positive at the 1% significance level in the first-stage regression, and the impact of DF on ICUE remains significantly positive in the second-stage regression, which is also consistent with the

baseline regression results. Meanwhile, the results of exogeneity test and weak instrument robust test demonstrate that all instrumental variables are exogenous and correlated, so the instrumental variable selected in this paper are reasonable and valid. The above results prove again that the development of China's DF can contribute to carbon unlocking after mitigating endogeneity.

Table 7. Robustness test results.

Variable	(1) ICUE-A	(2) OLS-RE	(3) OLS-FE	(4) 2014 to 2021	(5) Samples Exclusion	(6) ICUE-A	(7) OLS-RE	(8) OLS-FE	(9) 2014 to 2021	(10) Samples Exclusion
lnDF	0.1153 *** (5.2326)	0.1161 *** (5.2608)	0.0916 *** (3.5921)	0.2644 *** (4.0184)	0.1006 *** (4.4532)					
lnBRE						−0.0191 (−0.4871)	−0.0165 (−0.4159)	−0.0431 (−1.0546)	−0.2008 (−1.1317)	−0.0232 (−0.5626)
lnDEP						0.0788 (1.5221)	0.0760 (1.4490)	0.0565 (1.0785)	0.2519 * (1.8628)	0.0382 (0.7277)
lnDIG						0.0590 ** (2.0529)	0.0593 ** (2.0371)	0.0762 *** (2.5931)	0.3147 *** (3.2151)	0.0913 *** (2.8007)
lngov	−0.2155 ** (−2.4175)	−0.2254 *** (−2.6330)	−0.1155 (−1.1745)	−0.4254 *** (−4.0370)	−0.1254 (−1.2802)	−0.1997 ** (−2.2416)	−0.2111 ** (−2.4793)	−0.1042 (−1.0744)	−0.4561 *** (−4.3185)	−0.1113 (−1.1331)
lnfdi	−0.0125 (−0.7239)	−0.0113 (−0.6473)	−0.0033 (−0.1634)	−0.0002 (−0.0077)	−0.0068 (−0.3853)	−0.0156 (−0.8898)	−0.0145 (−0.8159)	−0.0038 (−0.1831)	−0.0103 (−0.4480)	−0.0125 (−0.6964)
lnstu	0.1211 ** (2.1157)	0.1155 ** (2.1965)	0.3706 *** (3.3678)	−0.0016 (−0.0259)	0.1714 *** (2.7189)	0.1333 ** (2.2444)	0.1263 ** (2.3816)	0.4461 *** (4.0580)	−0.0024 (−0.0387)	0.1943 *** (2.9269)
lninst	−0.1228 *** (−3.5601)	−0.1278 *** (−3.7994)	−0.1998 *** (−4.5913)	−0.1429 *** (−3.0319)	−0.1381 *** (−3.7436)	−0.1107 *** (−3.1259)	−0.1152 *** (−3.3071)	−0.1840 *** (−4.1875)	−0.1480 *** (−3.1116)	−0.1261 *** (−3.3720)
lnenst	−0.1886 *** (−4.1589)	−0.1840 *** (−4.0195)	−0.1813 *** (−3.5871)	−0.1213 ** (−2.1048)	−0.1570 ** (−2.3497)	−0.1798 *** (−3.9208)	−0.1755 *** (−3.7819)	−0.1618 *** (−3.1683)	−0.1039 * (−1.7901)	−0.1400 ** (−2.0646)
Constant	−0.1670 (−0.1912)	−0.0781 (−0.0977)	−3.6043 ** (−2.4673)	1.1027 (1.1853)	−1.1700 (−1.1541)	−0.4744 (−0.5219)	−0.3583 (−0.4436)	−4.7824 *** (−3.2355)	0.5018 (0.5091)	−1.6756 (−1.5576)
Log likelihood/R-squared	87.2730	0.2057	0.2245	46.2217	85.9216	87.9800	0.2118	0.2377	49.4744	87.8571
Wald Chi ² /F	90.52 ***	85.99 ***	14.19 ***	43.74 ***	64.35 ***	92.09 ***	86.90 ***	11.38 ***	51.13 ***	68.50 ***
LR test/F test	144.88 ***		13.09 ***	103.51 ***	139.82 ***	145.80 ***		13.38 ***	103.64 ***	141.62 ***
N	330	330		240	286	330	330	330	240	286

Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. t statistics are in parentheses.

Table 8. Endogenous test results.

Variable	(1) ICUE	(2) ICUE	(3) lnDF	(4) ICUE
L.lnDF	0.1199 *** (5.4195)			
L.lnBRE		−0.0010 (−0.0238)		
L.lnDEP		0.0155 (0.2928)		
L.lnDIG		0.0947 *** (3.2797)		
lnphone			2.0347 *** (15.9008)	
lnDF				0.1993 *** (5.7160)
Controls	Yes	Yes	Yes	Yes
Constant	0.5385 (0.6016)	0.1073 (0.1138)	−13.088 (−11.02)	2.481 (5.09)
Wald Chi ² /F	74.07 ***	78.53 ***	80.23 ***	149.69 ***
LR test	135.30 ***	139.12 ***		
Exogeneity test (Wald)	135.30 ***	139.12 ***		6.65 ***
Weak instrument robust test (AR)				33.54 ***
Weak instrument robust test (Wald)				32.67 ***
N	330	330	330	330

Note: *** denote significance levels of 1%. t statistics are in parentheses.

6.2. The Dynamic Evolution of Direct and Moderating Effects

After analyzing the direct effect of DF on ICUE and the moderating effect of ER, we further explored the dynamic evolution of these marginal effects. Therefore, in this section, we applied the panel data quantile regression (QRPD) method for empirical analysis.

To confirm the applicability of the QRPD, we performed Jarque–Bera tests to check the normality of the data distribution. Table 2 shows that all variables have probability values of less than 1% based on the Jarque–Bera tests, indicating that these variables do not follow a normal distribution. Skewness and kurtosis portray the degree of asymmetry and dispersion of the data distribution, respectively. The skewness coefficients for all variables are nonzero, which also indicates an abnormal distribution. The test results demonstrated the necessity of QRPD analysis.

6.2.1. The Dynamic Evolution of Direct Effect

The QRPD results for DF at the 5th, 30th, 50th, 70th, and 95th quantiles of ICUE are reported in Columns (1)–(5) of Table 9, and the corresponding quantile plots are shown in Figure 5a.

Table 9. QRPD results based on direct effects of DF and its subdimensions.

	(1) 5th	(2) 30th	(3) 50th	(4) 70th	(5) 95th	(6) 5th	(7) 30th	(8) 50th	(9) 70th	(10) 95th
lnDF	0.0274 *** (3.3116)	0.0679 *** (9.9409)	0.1464 *** (6.5630)	0.0692 *** (3.1330)	0.3885 *** (6.0839)					
lnBRE						−0.0465 *** (−4.0 × 10 ²)	−0.0540 *** (−15.3051)	−0.0509 *** (−3.2523)	−0.0815 *** (−11.9876)	0.1387 *** (21.7592)
lnDEP						0.0496 *** (381.4075)	0.0535 *** (11.1103)	0.0714 *** (4.3404)	0.1930 *** (9.4595)	0.0055 (0.4275)
lnDIG						0.0452 *** (757.8095)	0.0494 *** (14.6747)	0.0464 *** (4.3585)	0.0249 (1.4108)	0.0715 *** (31.1177)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330	330	330	330	330	330

Note: *** denote significance levels of 1%. t statistics are in parentheses.

As shown in Columns (1)–(5) of Table 9 and Figure 5a, DF has a significant boosting effect on ICUE at different ICUE levels, and the coefficients fluctuate and increase from 0.0274 to 0.3885 with increased ICUE quantiles, which suggests that DF plays a stronger facilitating role on carbon unlocking activities in provinces with a higher ICUE, thus validating Hypothesis 3a.

Zhao et al. [38] reached a similar conclusion and reported that financial inclusion can significantly reduce CLI and is more effective in areas with aggravated CLI. This implies that the impact of DF development on ICUE has a cumulative effect and acts as a crucial driver for achieving comprehensive decarbonization. Thus, in areas with greater ICUE, more attention should be paid to the carbon unlocking function of the DF.

It is further analyzed in three dimensions of DF. The QRPD results are shown in Columns (6)–(10) of Table 9. BRE and DEP do not have a significant effect on industrial carbon unlocking activities in the full sample regressions; however, their roles are reflected in the context of dividing the ICUE levels. Specifically, BRE coefficients increase with the number of ICUE quantiles and turn from negative to positive at the 95th quantile (Figure 5b). This suggests that the broad coverage of DF can play a role in unlocking in the later stages of industrial carbon unlocking. A plausible reason is that the widespread use of DF to promote ICUE requires not only upgrading the industrial structure but also advancing technology and social practices, which take time and energy. DEP promotes ICUE to some extent at multiple quantile points. Its regression coefficients fluctuate upwards with increasing quantile points but are underpowered at high levels (Figure 5c), which may be due to some ceiling pressure on the expansion of digital financial products and services. In contrast, DIG has a significant positive impact at both the overall and most levels of ICUE, and its quantile plot approximately follows an inverted U-shaped curve trend (Figure 5d), suggesting that DF has a good track record of improving ICUE under means of digitization,

such as artificial intelligence and big data. Moreover, some potential outliers may interfere with the results.

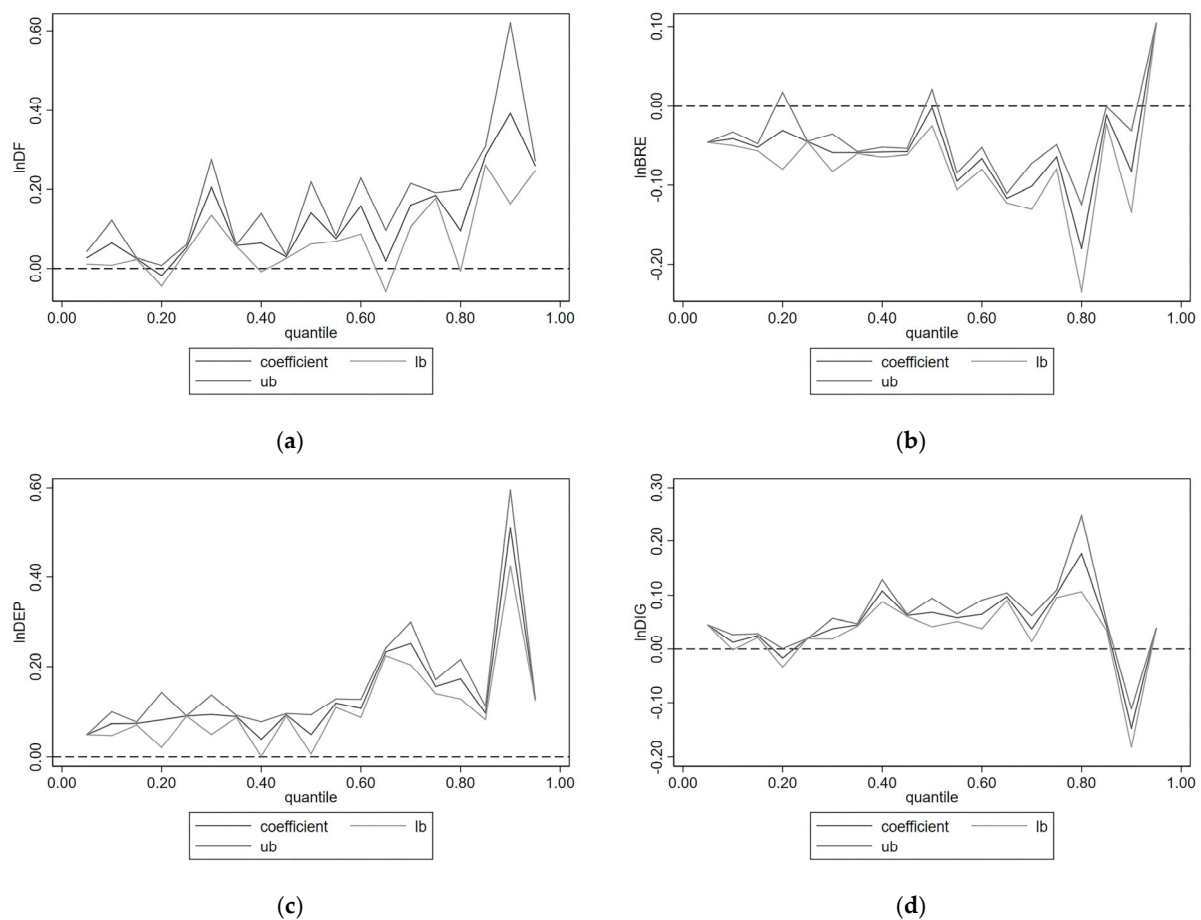


Figure 5. Variation of QRPD coefficients based on direct effects of DF and its subdimensions (subfigures (a,b,c,d) for DF, BRE, DEP, and DIG, respectively). Note: The X-axis represents the conditional quantiles of ICUE, and the Y-axis represents the coefficient values of various drivers. The middle curve depicts the quantile regression coefficients, and the areas between the upper and lower curves correspond to 95% confidence intervals of quantile estimation. Positive and negative effects are distinguished above and below the dotted line.

6.2.2. The Dynamic Evolution of the Moderating Effect

The moderating mechanism of ER is introduced into the QRPD model. The regression results are reported in Table 10, and the corresponding quantile plots are shown in Figure 6.

Table 10. QRPD results based on the moderating effect of ER.

	(1) 5th	(2) 30th	(3) 50th	(4) 70th	(5) 95th	(6) 5th	(7) 30th	(8) 50th	(9) 70th	(10) 95th
lnDF	−0.0202 (−0.9216)	0.0001 (0.0086)	0.0567 *** (2.8728)	0.1292 *** (23.3177)	0.1932 * (1.8552)	0.0359 *** (17.6816)	0.0782 *** (5.0737)	0.0575 *** (3.4614)	0.0186 (0.2764)	0.3038 *** (123.8570)
lnER	0.0963 *** (4.2715)	0.0922 *** (19.8908)	0.1665 *** (14.1320)	0.0726 *** (9.2125)	0.2781 (0.9544)	0.0684 *** (17.3475)	0.0949 *** (5.9248)	0.1618 *** (13.9730)	0.1620 * (1.6510)	0.0719 *** (24.1344)
lnDF*lnER						0.0048 (1.4778)	0.1167 *** (4.5944)	0.1604 *** (13.1076)	0.2528 *** (3.9785)	0.0762 *** (12.5395)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330	330	330	330	330	330

Note: *** and * denote significance levels of 1% and 10%, respectively. t statistics are in parentheses.

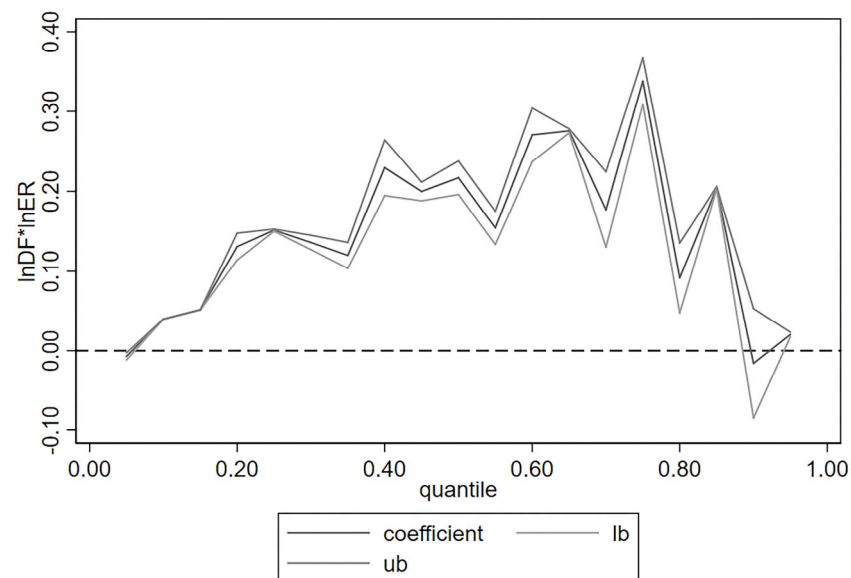


Figure 6. Variation of QRPD coefficients based on the moderating effect of ER. Note: The X-axis represents the conditional quantiles of ICUE, and the Y-axis represents the coefficient values of various drivers. The middle curve depicts the quantile regression coefficients, and the areas between the upper and lower curves correspond to 95% confidence intervals of quantile estimation. Positive and negative effects are distinguished above and below the dotted line.

In Table 10, except for the 5th quantile of ICUE, coefficients of the interaction term $\ln DF * \ln ER$ are significantly positive and follow an inverted U-shaped trend, increasing from 0.1167 to 0.2528 and then decreasing to 0.0762 (Figure 6). This finding illustrates that the moderating effect of ER on the DF-ICUE relationship must surpass a certain ICUE threshold to be visible. In the middle stage of industrial carbon unlocking, the synergistic effects of DF and ER are more favorable, as shown by the interaction term coefficients, which are significantly positive and higher than the coefficients of DF alone. At this point, environmental investment and financing activities are well organized and environmental regulation is in effect, allowing funds to actually flow into the industrial carbon unlocking areas. However, at a high level of ICUE, the interaction effect gradually weakens as the space for the role of finance and regulation gradually shrinks.

Lin et al. [96] also captured the potential asymmetry of the relationship between ER and industrial carbon emission efficiency (CEE). At low quantiles, a one-period lag in ER has a negative effect on CEE improvement, whereas the effect is positive at the middle and high quantiles. Thus, the targeting and assessment of the ER should be enhanced. ER policies need to be tailored to local conditions to control them to a reasonable degree and enhance their applicability.

The evolution trends of the moderating roles of different ERs were also examined next. The QRPD regression results and related quantile plots are shown in Table 11 and Figure 7, respectively.

Table 11. QRPD results based on moderating effects of FER and IER.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	5th	30th	50th	70th	95th	5th	30th	50th	70th	95th	5th	30th	50th	70th	95th
lnBRE*lnFER	0.0182 ***	0.0804 ***	0.1483 ***	0.1760 ***	0.1019 ***										
	(11.0053)	(5.7439)	(27.4838)	(22.8135)	(63.2939)										
lnBRE*lnIER	0.0050 ***	−0.0107 ***	0.0028	−0.0241 **	−0.0883 ***										
	(4.8242)	(−3.4616)	(0.6685)	(−2.0711)	(−1.2 × 10 ²)										
lnDEP*lnFER						0.0540 ***	0.1929 ***	0.1359 ***	0.1879 ***	0.1145 ***					
						(72.3717)	(11.4250)	(27.9269)	(17.6001)	(302.1873)					
lnDEP*lnIER						0.0174 ***	0.0311 ***	0.0027	−0.0260 ***	−0.1389***					
						(29.0682)	(7.6574)	(0.3881)	(−3.6872)	(−8.3 × 10 ²)					
lnDIG*lnFER											0.0163 ***	0.0395 ***	0.1203 ***	0.0516 ***	−0.0321 ***
											(80.3132)	(5.7702)	(20.5670)	(3.3609)	(−75.4685)
lnDIG*lnIER											0.0115 ***	−0.0100	−0.0137	−0.0154 ***	−0.0449 ***
											(23.4351)	(−1.6319)	(−1.1833)	(−3.1164)	(−5.4 × 10 ²)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330

Note: Limited to the table length, only the interaction term regression results are shown. *** and ** denote significance levels of 1% and 5%, respectively. t statistics are in parentheses.

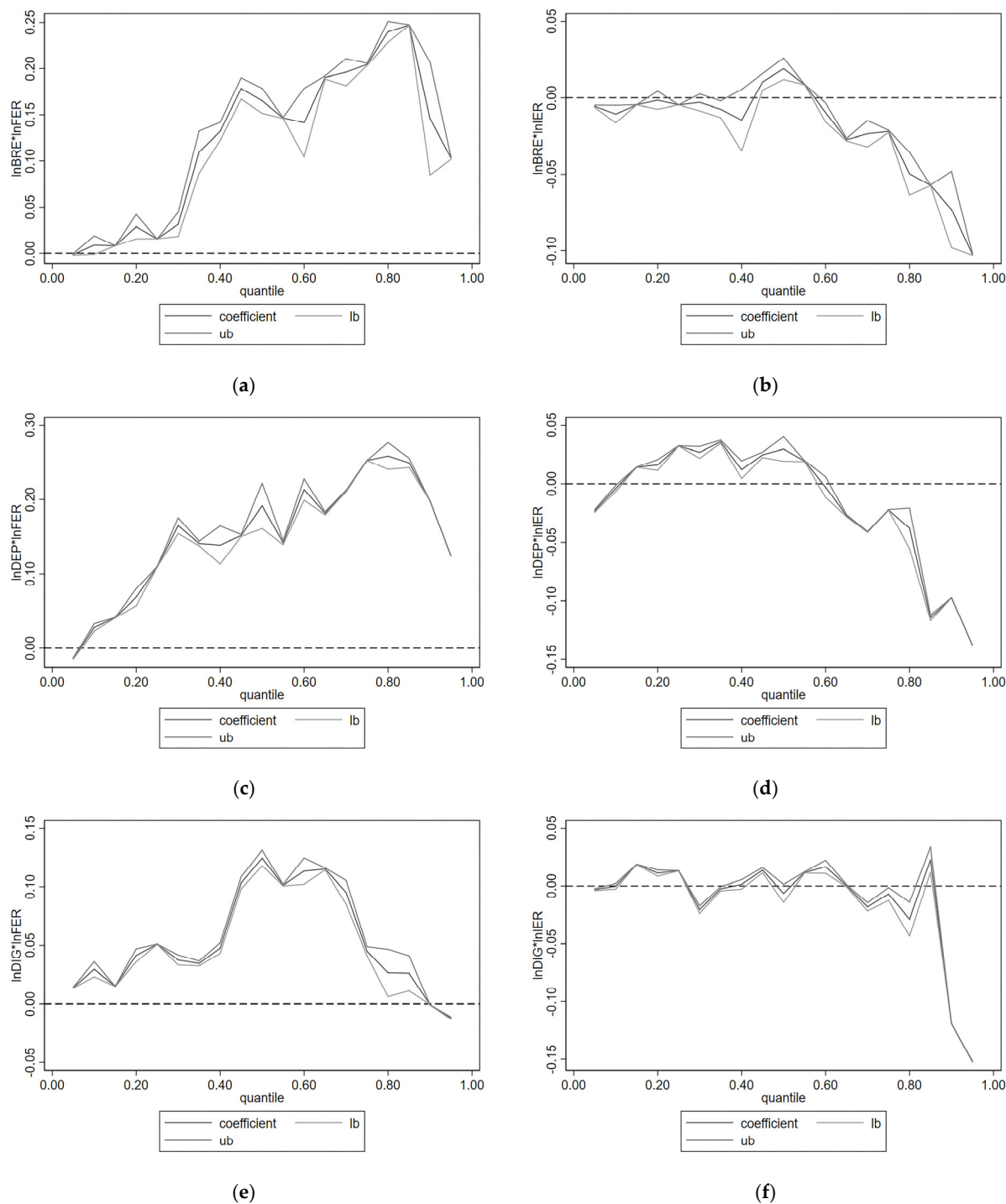


Figure 7. Variation of QRPD coefficients based on moderating effects of FER and IER (subfigures (a,c,e) for BRE*FER, DEP*FER, DIG*FER, respectively; and subfigures (b,d,f) for BRE*IER, DEP*IER, DIG*IER, respectively). Note: The X-axis represents the conditional quantiles of ICUE, and the Y-axis represents the coefficient values of various drivers. The middle curve depicts the quantile regression coefficients, and the areas between the upper and lower curves correspond to 95% confidence intervals of quantile estimation. Positive and negative effects are distinguished above and below the dotted line.

Table 11 shows that the coefficients of $\ln \text{BRE} * \ln \text{FER}$, $\ln \text{DEP} * \ln \text{FER}$, and $\ln \text{DIG} * \ln \text{FER}$ are significantly positive at the majority of ICUE quantile levels and follow an evolutionary pattern of first increasing and then decreasing (Figure 7a, 7c, 7e), displaying a similar

moderating trend as that of ER. This finding suggests that FER dominates the environmental constraint system in China and can strengthen DF to improve ICUE through its widespread popularization and the provision of personalized and digitized products and services. However, IER shows a negative moderating effect at most quantiles (Figure 7b, 7d, 7f), especially at the high ICUE level, which suggests that the moral soft constraint of China's IER has not yet produced the desired effect and even caters to the current high-carbonization growth model, thus negatively affecting DF's acceleration of carbon unlocking in the industrial economy. This finding is consistent with the Tobit regression results. Thus, the formation of higher-level environmental ideologies in China is imperative.

7. Configuration Analysis

As mentioned earlier, environmental problems, including carbon unlocking, have causal complexity caused by multiple factors. Traditional econometric regression analyses on the mechanisms of environmental pollution drivers tend to focus on the marginal effects of specific factors, while generally ignoring the multiple interactions between them (especially more than three factors) [97]. Therefore, after examining the binary interaction effects of drivers on ICUE and the asymmetry of effect sizes using Tobit hierarchical regression and QRPD in the previous section, we further explore the possible antecedent configurations and analyze the causal asymmetry of configuration effects. The empirical results were obtained through R 4.3.0 software.

7.1. Data Calibration

The original data should first be transformed into fuzzy-set membership scores ranging from 0 to 1 [78]. According to data characteristics and existing studies, we adopted the direct calibration method and used the 95%, 50%, and 5% quantiles of sample data as calibration anchor points, which represent the full membership anchor, crossover point, and full nonmembership anchor, respectively. The calibration results are shown in Table 12. Note that the cases with membership scores of 0.5 are difficult to categorize; therefore, we add 0.001 to 0.5 to make adjustments.

Table 12. Calibration thresholds of variables.

Variables		Full Membership Anchor	Cross-Over Point	Full Non-Membership Anchor
Outcome variables	ICUE	1.009	0.309	0.131
Condition variables	BRE	342.826	215.807	65.255
	DEP	365.561	228.735	89.576
	DIG	413.036	333.205	115.108
	IER	0.0556	0.018	0.007
	FER	0.198	0.123	0.070

7.2. Necessity Analysis of Single Conditions

According to the basic steps of fsQCA method, we first tested whether a single condition (in subdimensions of DF and ER) and its nonset constituted a necessary condition for the outcome (high and low ICUE), as determined by consistency. A single factor or its nonset is necessary for the outcome set when the consistency level exceeds 0.9 [78]. Table 13 shows the results.

Table 13 shows that the $BECONS_{dis}^{adj}$ and $WICONs_{dis}^{adj}$ of each factor are less than 0.2, indicating that the $POCONS$ s have high accuracy and can be used as a basis for judgement [81]. Moreover, the $POCONS$ levels of all of the condition sets and their nonsets are below 0.9. Thus, none of the single factors are necessary for an outcome of high or low ICUE. This finding echoes the complexity of industrial carbon unlocking in that no single element of DF and ER is a best practice.

Table 13. Necessity analysis results of single conditions.

Condition Variables	High ICUE				Low ICUE			
	POCONS	POCOV	BECONS ^{adj} _{dis}	WCONS ^{adj} _{dis}	POCONS	POCOV	BECONS ^{adj} _{dis}	WCONS ^{adj} _{dis}
BRE	0.724	0.635	0.143	0.036	0.574	0.610	0.167	0.034
~BRE	0.555	0.518	0.175	0.059	0.656	0.742	0.167	0.039
DEP	0.711	0.651	0.142	0.040	0.540	0.598	0.168	0.045
~DEP	0.561	0.502	0.173	0.060	0.685	0.742	0.151	0.034
DIG	0.738	0.610	0.146	0.031	0.603	0.604	0.162	0.026
~DIG	0.521	0.520	0.197	0.056	0.611	0.738	0.184	0.040
FER	0.733	0.069	0.057	0.065	0.538	0.610	0.078	0.088
~FER	0.583	0.510	0.093	0.084	0.724	0.767	0.053	0.070
IER	0.570	0.546	0.099	0.073	0.650	0.755	0.076	0.060
~IER	0.744	0.637	0.053	0.051	0.608	0.631	0.059	0.072

7.3. Sufficiency Analysis of Condition Configurations

Configuration analysis is the core of fsQCA and aims to test how different combinations of antecedent conditions affect the outcome. The criterion is the consistency level of adequacy, which is generally not less than 0.75 [80]. The consistency threshold and case frequency for high ICUE configurations in this paper are set to 0.8 and 3, respectively. The thresholds of raw consistency and case frequency for low ICUE configurations are set to 0.8 and 5, respectively. The results are reported in Table 14.

Table 14. Sufficiency analysis results of condition configurations.

Antecedent Variables	High ICUE			Low ICUE			
	C1	C2	C3	c1	c2a	c2b	c3
BRE	●	•	⊗	⊗	•	⊗	⊗
DEP	•	●	⊗	⊗	•	⊗	⊗
DIG	●		●	⊗			⊗
FER	●	●	●		⊗	⊗	⊗
IER		⊗	⊗	●	●	●	
Consistency	0.791	0.825	0.905	0.882	0.885	0.866	0.839
Raw Coverage	0.594	0.545	0.299	0.449	0.331	0.473	0.518
Unique Coverage	0.064	0.016	0.022	0.030	0.076	0.031	0.099
BECONS ^{adj} _{dis}	0.033	0.030	0.014	0.021	0.023	0.023	0.026
WCONS ^{adj} _{dis}	0.063	0.057	0.038	0.035	0.033	0.037	0.042
Configuration Type	DF-ER Total Synergy	DEP-FER Dual Synergy	DIG-FER Dual Synergy	DF Absence	ER Imbalance		DF-FER Total Absence
Solution Consistency		0.825			0.839		
Solution Coverage		0.545			0.518		

Note: “●” and “⊗” indicate core presence and absence, “•” and “⊗” indicate marginal presence and absence, and blank indicates “don’t care”.

Table 14 presents three high ICUE configuration paths and four low ICUE configuration paths. Both the single and the overall solutions exhibit a consistency level higher than 0.79, surpassing the acceptable minimum standard of 0.75. Additionally, the overall solution consistency exceeds 0.5. Therefore, the seven paths can be regarded as sufficient condition configurations for a specific level of ICUE. Notably, the overall solution consistency for high ICUE configurations is measured at 0.825, indicating an 82.5% probability of attaining a high ICUE level when meeting all three sets of conditional configurations. The

core conditions along each path can be categorized into three types: “DF-ER Total Synergy”, “DEP-FER Dual Synergy”, and “DIG-FER Dual Synergy”. In configuration C1, the core presence conditions included BRE, DIG, and FER, whereas the marginal presence conditions included DEPs with uncertain IERs. This demonstrates that the widespread adoption and digital development of DF, comprehensive synergy from FER, and marginal effects from deepening DF development can significantly improve the ICUE and accelerate the process of industrial low-carbon transition. Configuration C2 reveals that even with weak IERs present, achieving a high level of ICUE remains possible through a deeply developed DF coupled with strict FERs. Similarly, combining DIG development with FER constraints, as shown in configuration C3, compensates for deficiencies in IER and ultimately leads to a high level of industrial carbon unlocking, as shown in configuration C3.

Table 14 also shows an 83.9% probability of achieving a low level of ICUE of the four configurations. The findings from configuration c1 indicate that without DF, IERs alone can accomplish a limited degree of ICUE, which is called “DF Absence”. Similarly, configurations c2a and c2b show that the implementation of IERs with an absence of FERs is also insufficient to achieve a high level of ICUE, which is classified as “regulatory imbalance”. Obviously, the simultaneous absence of DF and ER cannot enable the realization of the full decarbonization of the industry, which is referred to as “DF-FER Total Absence”, as shown in configuration c3.

A comparison makes it evident that the paths leading to high and low levels of ICUE are asymmetrical. Therefore, it is crucial to not only infer the low level paths as the direct opposite of the high level paths, but to also carefully examine the configuration paths of low level ICUE. By identifying their shared influencing factors, it becomes clear that formal environmental regulation and financial digitization have a more widespread impact on ICUE. Both factors are exclusively present in high ICUE paths (e.g., configurations C1 and C3) and absent in nonhigh ICUE paths, indicating a strong correlation between these factors and high levels of ICUE, which significantly influences the process of full industry decarbonization.

7.4. The Spatial–Temporal Variation in Condition Configurations

All of the $BECONS_{dis}^{adj}$ and $WCONS_{dis}^{adj}$ in Table 13 are less than 0.2, indicating the high stability of configuration paths between years and provinces. However, considering that the WCONS distance of each path is always longer than its BECONS distance, the influence of province type may dominate in the seven paths. Hence, we further investigated the spatial–temporal heterogeneity of configurations by using the dynamic fsQCA panel data method. First, based on cases from different years, the BECONS diagram was obtained (Figure 8).

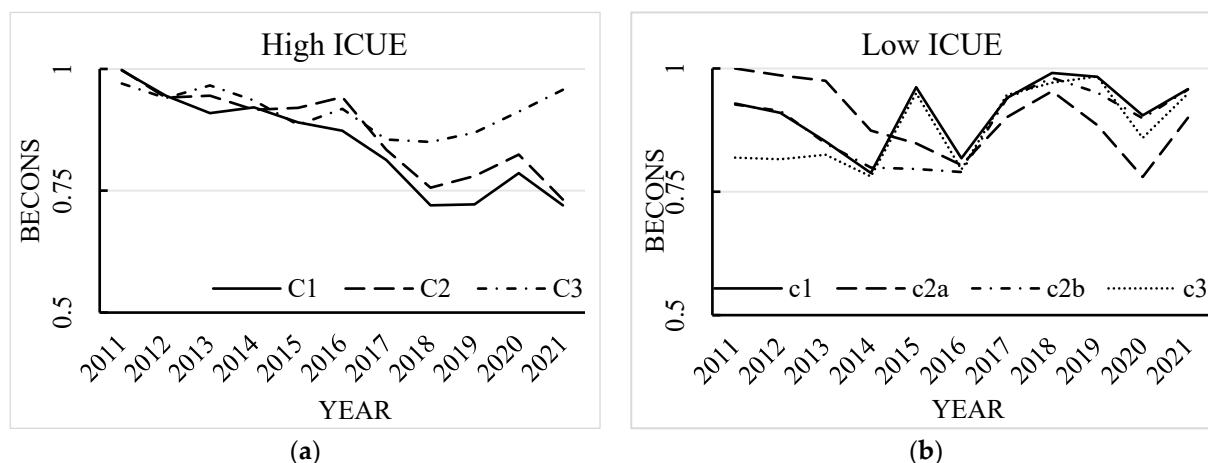


Figure 8. The BECONS results (subfigures (a,b) for high and low ICUE configurations, respectively).

Figure 8a and 8b depict the variations in BECONSs of the high and low ICUE configurations in the time series, respectively. Specifically, the high ICUE configurations C1 and C2 show a “turning trajectory”, and their carbon unlocking effectiveness has shown a weakening trend, even below the threshold of 0.75 in recent years. This may be related to the emergence of new elements and the update of new paths, which greatly reduces the comprehensive unlocking effect of existing configurations. The BECONS value of path C3 always fluctuates at a high consistency level, which not only indicates a temporal path dependence of the industrial carbon unlocking process, but also reveals that DIG development and FER constraints are the “leading path” of the sustainable low-carbon transformation of industry, which should be considered. In addition, although the BECONS of the four low ICUE configurations fluctuate greatly in different periods, they are always above the threshold value, showing the self-strengthening characteristics of industrial CLI. To overcome this dilemma, we need to start by unlocking the core bottleneck of the inefficient path, that is, strengthening the support of DF and ER for decarbonization work.

Second, based on cases of different provinces, the WICONS diagrams were obtained (Figure 9).

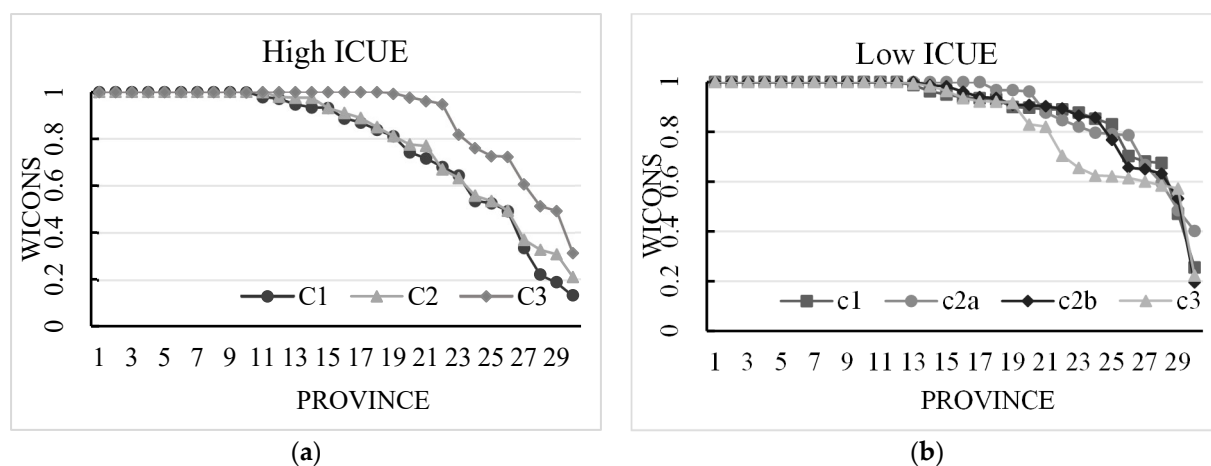


Figure 9. The WICONS results (subfigures (a,b) for high and low ICUE configurations, respectively).

Figure 9a and 9b show the WICONS plots of the variation in high and low ICUE configurations in different provinces, respectively. The analysis shows that configuration C1 is followed by the highest number of provinces with high ICUE, which proves that most industries use the combination of DIG and FER as the key drivers of carbon unlocking. Path c2a is the lowest ICUE configuration followed by the most provinces, indicating that the lack of strict FERs is still one of the root causes of the current predicament of carbon-based energy in the industrial economy. In general, more than half of the regions always follow the carbon unlocking path in the above analysis, showing the typical characteristic of regional path dependence.

7.5. Robustness Checks

Referring to existing studies, we tested the robustness of the results of high and low ICUE configurations by adjusting the consistency threshold and case frequency, respectively. (1) For high ICUE configurations, the raw consistency threshold first increased from 0.8 to 0.82, and the number of configurations obtained was reduced to 2, which had a clear subset relationship with the existing configuration results, and the core and edge conditions were unchanged. Second, when the case frequency threshold is increased from 3 to 4, the number of configurations, core conditions, edge conditions, and consistency and coverage of the overall solution do not change. (2) For low ICUE paths, the raw consistency threshold is increased from 0.8 to 0.85 and the case frequency is increased from 5 to 6. The test results are in complete agreement with the original conclusions. The above robustness tests show that the configuration conclusion of this paper has good robustness.

8. Conclusions and Policy Implications

At present, the industrial economy is in a critical period of low-carbon transformation. Finding the pain points of carbon locking in high-carbon-based industries and encouraging these industries to embark on the right track of carbon unlocking as soon as possible should be prioritized. As the largest carbon emitter, China's industrial carbon unlocking performance is particularly noteworthy. In this context, we calculate the ICUE of 30 provinces in China from 2011 to 2021, analyze its evolution characteristics, and discuss the marginal and configuration effects of DF and ER on ICUE, which has not only important significance for expanding the horizon of unlocking and configuration theories but also a far-reaching impact on global carbon unlocking practices. The key findings are as follows.

(1) China's provincial ICUE demonstrates a positive trend, peaking around 2020, with the eastern region hosting the majority of high-level ICUE provinces, and the polarization trend among provincial ICUEs stabilizing. (2) The results of the Tobit hierarchical regression show that DF can significantly improve provincial ICUE in China, while ER reinforces this effect in general. Whereas DF's coverage breadth tends to deepen the industrial CLI through quantity-increasing effects, DF's usage depth and digitization level are inclined to support industrial carbon unlocking through quality-enhancing effects. And formal environmental regulation plays a positive moderating role; however, informal environmental regulation has a negative moderating effect. (3) Dynamic evolution analysis emphasizes the asymmetry of marginal effect sizes. As the ICUE increases, the effect of DF on ICUE gradually increases, showing a cumulative effect, while the synergy with ER shows an inverted U-shape, in accordance with the law of diminishing marginal productivity. This indicates that the industrial carbon unlocking ability of DF is most prominent in years or regions with higher ICUE levels, while the combined unlocking effect of DF and ER is optimal in years or regions with moderate ICUE levels. (4) Dynamic fsQCA identifies the configuration path and its spatial-temporal dependencies for a specific ICUE target. The results emphasize that any single driver is not necessary for ICUE enhancement and that their configuration is causally asymmetrical. The effective cooperation between DF and ER is the key to achieving high ICUE, whereas informal environmental awareness rarely plays a dominant role, and insufficient support of DF, along with the absence of formal environmental regulations, remains the bottleneck in current industrial CLI. Furthermore, the configuration effects are characterized by a clear spatial-temporal path dependence.

Based on these results and conclusions, we propose several policy implications to give full play to the individual and integrated roles of DF and ER in the field of carbon unlocking.

Firstly, establish the regional monitoring and assessment system of ICUE, identify problems in a timely manner, and formulate corresponding policies to maintain the positive trend of ICUE. At the same time, strengthen inter-regional experience exchange and sharing to jointly address the challenges in industrial carbon unlocking energy efficiency. In addition, promote high-efficiency unlocking regions to drive low-efficiency unlocking regions, gradually eliminate the polarization of ICUE, and achieve comprehensive industrial carbon unlocking nationwide.

Secondly, it is essential to align the push of DF with the pull of ER to create a synergy for sustainable carbon unlocking in the real economy. On the one hand, utilize the inclusive nature of DF to absorb idle funds and facilitate the transition of high-carbon industries to low-carbon practices. Simultaneously, regulate the scalability of DF, promote its diversified development and digital integration in industrial processes to enhance its carbon reduction impact. On the other hand, strengthen ERs by improving the formulation and enforcement of local government regulations and market trading rules, enhance environmental education and awareness through media channels, so as to maximize the impact of both FERs and IERs, and finally guide the continuous development of DF towards green and sustainable growth.

Thirdly, continuous research on DF and ER should be conducted, financial policies and regulations should be tailored to suit the needs of different regions, and a one-size-fits-all approach should be prevented. Specifically, in the entire process of industrial carbon

unlocking, DF empowerment should always be placed in a prominent position to give full play to the cumulative effect. Meanwhile, in the early unlocking stage, the establishment of social environmental awareness and low-carbon consumption habits should be emphasized, combined with the constraints of environmental protection policies and market mechanisms, to ensure the smooth crossing of the initial threshold of environmental regulation in the DF empowerment of industrial decarbonization. At a later unlocking stage, the rebound effect of mandatory institutional constraints should be avoided, and regions should be given more autonomous decision-making power to promote flexible forms of low-carbon transformation.

Finally, establishing a coordinated mechanism between DF and ER is vital for sustainable development. High-efficiency carbon unlocking areas should maintain progress through technological innovation and environmental awareness. Low-carbon unlocking areas must expedite the balance between DF development and formal regulations to overcome industrial carbon constraints. In addition, technology collaboration, resource sharing, and knowledge exchange among regions should be encouraged, which will enhance unlocking efficiency and promote progress across all regions.

Although our empirical analysis of the link among DF, ER, and ICUE is significant, room for expansion still exists. First, our study involves many indicators and the measurement standard of the broad concept of ICUE is not unique. The data incompleteness and source uncertainty in this paper may affect the comprehensive understanding and accurate evaluation of the carbon unlocking phenomenon and the unlocking effect of DF and ER; thus, an effective measurement and analysis of all indicators needs to be further improved. Second, due to the focus of our research and the length of the paper, the nonlinear effects of drivers were not investigated. Therefore, DF or ER can be used as threshold variables to conduct regression analysis in the future to test the nonlinear characteristics of ICUE effects at different DF or ER levels. Third, in view of the possible spatial agglomeration and spatial spillover effects on DF development and ICUE levels in different regions of China, it is highly practical to expand the spatial perspective in future studies and use spatial methodology to test their spatial relationships.

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Appendix A

The slacks-based measure (SBM) model is quite suitable for estimating this relative efficiency, which can consider unexpected outputs and put input–output slacks directly into the objective function with the economic aim of maximizing actual profits rather than simply maximizing the efficiency ratio. As a nonparametric evaluation approach, the SBM model also lacks specific function form and treats indicators as dimensionless, which effectively promotes objectivity. The super-efficiency model can achieve an efficiency ranking among

the cases with efficiencies of 100%. Combining both methods, we obtained the super-efficiency SBM model with undesirable outputs (US-SBM model), defined as follows.

$$\rho^* = \min \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1 + s_2} (\sum_{r=1}^{s_1} \frac{s_r^{g+}}{y_{rk}} + \sum_{t=1}^{s_2} \frac{s_t^{b-}}{b_{tk}})} \quad (A1)$$

$$s.t. \begin{cases} x_{ik} \geq \sum_{j=1, j \neq k}^n \lambda_j x_{ij} + s_i^-, i = 1, \dots, m; \\ y_{rk} \leq \sum_{j=1, j \neq k}^n \lambda_j y_{rj} - s_r^{g+}, r = 1, \dots, s_1; \\ b_{tk} \geq \sum_{j=1, j \neq k}^n \lambda_j b_{tj} + s_t^{b-}, t = 1, \dots, s_2; \\ s_i^- \geq 0, \forall i; s_r^{g+} \geq 0, \forall r; s_t^{b-} \geq 0, \forall t; \lambda_j \geq 0, \forall j. \end{cases} \quad (A2)$$

where ρ^* represents the ICUE and its value is greater than 0, with higher values indicating greater efficiency. ρ^* less than 1 indicates inefficiency, and ρ^* greater than 1 represents efficiency. x_{ij} , y_{rj} , and b_{tj} denote the input, desirable output, and undesirable output values of DMU_j at time t , respectively. s_i^- , s_r^{g+} and s_t^{b-} are the corresponding slack improvements, respectively. m , s_1 , and s_2 denote the number of inputs, desirable outputs, and undesirable outputs, respectively. λ_j is the weight vector of DMU_j.

Appendix B

PCA explores the internal structure of the correlation or covariance matrices of original variables, deriving composite indicators through linear combinations. This approach reduces dimensionality, preserves key information and mitigates strong correlations, enhancing the scientific validity of SBM results. The results of PCA analysis in SPSS 25.0 software revealed that the Bartlett sphere test yielded KMO = 0.794 > 0.5 and a significance level of Sig = 0.0 < 0.5, which rejected the null hypothesis that the indicators were not correlated and proved that the inputs were suitable for PCA. According to the factor selection principle with feature roots greater than 1, five principal components were extracted, and their cumulative variance contribution rates were 36.006%, 57.439%, 67.367%, 74.935%, and 81.587%, which could represent most of the information of original inputs.

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