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Toward Sustainability Through Carbon Neutrality: Predicting Innovation Quality in New Energy Firms from the Business Environment

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Abstract

Achieving sustainable development and carbon neutrality requires continuous technological upgrading in the new energy sector. Improvement of innovation quality in new energy firms therefore plays a significant role in sustainability transitions. However, whether and how the business environment supports the innovation quality in the new energy sector remains unclear. Using machine learning, our study assesses the predictive ability of the business environment for innovation quality in new energy firms, distinguishes the importance of different elements, and then portrays predictive patterns of critical elements. The results show that the business environment provides substantial predictive ability for innovation quality, increasing out-of-sample R^2 from 0.6200 to 0.7001, which represents an improvement of 0.0801. Among the focal explanatory variables, human resources, financial environment, and public services emerge as relatively important elements. Furthermore, we find that human resources and innovation quality exhibit an overall upward trend, whereas public services and financial environment have a complex relationship with innovation quality. Heterogeneity analysis reveals that the predictive ability of the business environment for innovation quality varies significantly across firms with different ownership and locations. Our study provides evidence for policy design and business environment optimization to strengthen the institutional foundations of sustainable development.

Keywords: institutional environment; clean energy firms; innovation quality; sustainable development; machine learning; predictive research

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1. Introduction

Developing new energy is crucial for driving energy transition and achieving carbon neutrality [1]. As the world's largest market for new energy investments, China is at the forefront of this movement and ranks first in installed new energy capacity and manufacturing [2–4]. However, the expansion in scale has not been accompanied by a corresponding improvement in innovation quality. Challenges such as low-end lock-in, insufficient core technologies, and long-term reliance on imported key components and equipment persist [5], hindering the development of the new energy industry and thereby impeding the achievement of energy transition and carbon neutrality. Therefore, it is imperative to improve the innovation quality of new energy firms.

Innovation in the new energy sector is characterized by high uncertainty, long cycles, and spillover effects, which expose firms to high costs and uncertain returns, thereby discouraging them from pursuing high-quality innovation [5]. The theory of new institutional

economics emphasizes that an effective institutional environment is critical for encouraging corporate innovation [6]. As an important institutional environment, a favorable business environment encourages high-quality innovation by reducing firms' non-productive costs, such as rent-seeking and agency costs [7,8], ensuring resource access neutrality and market competition neutrality [9], improving access to critical resources like credit financing and professional intermediaries [10,11]. The significant role of business environment in firm innovation has been confirmed in the existing literature, and these findings provide important theoretical guidance for our study. However, several limitations remain in the existing literature. Studies on Chinese companies or firms of other transition economies confirm that business environment significantly promotes firm innovation. However, these studies usually treat firms as a homogeneous group, without fully considering industry heterogeneity. Although few scholars have focused on the heterogeneity effects of business environment on high-tech firms [12,13], the impact of business environment on new energy firms' innovation quality remains underexplored. The new energy sector receives more subsidies, is more capital dependent, and has more severe market distortions [14], meaning that existing findings derived from other industries may not fully explain the institutional logic underlying high-quality innovation in this sector. Does the business environment constitute a key predictor of innovation quality in new energy firms? Do different elements of the business environment possess the same predictive ability? What patterns characterize the predictive relationship between critical business environment elements and innovation quality in this sector? Previous research has yet to provide systematic answers to these questions. Methodologically, much of the existing literature relies on traditional econometric methods, which are often constrained by limited variables and multicollinearity, making it difficult to assess the predictive contribution of each business environment element to innovation quality in new energy firms and capture the complex relationship between them. Thus, existing studies fail to provide effective responses to the above questions.

In order to complete these research limitations, we construct a forecasting model that includes the business environment and the innovation quality of new energy firms. Forecasting studies can address the limitations of traditional econometric methods. Through machine learning, the forecasting model can examine the predictive ability of the business environment on innovation quality, identify the predictive contributions of different business environment elements, and depict the predictive patterns of crucial elements for innovation quality [15]. Our results provide empirical evidence for the government to shape a business environment that is conducive to predicting the innovation quality of new energy firms.

The main contributions of our study are threefold. First, enhancing the innovation quality of new energy firms has long been a concern in academia. However, existing research fails to adequately consider the significant role of institutional environment in improving the innovation quality of new energy firms. We address the limitations of the current literature by incorporating the business environment into the research framework, thereby further exploring the predictors of innovation quality of new energy firms. Second, while the existing literature widely acknowledges the significant role of the business environment in innovation, there remains a lack of in-depth analysis focusing on the new energy sector. Consequently, the policy implications proposed in the literature often lack targeted relevance. By focusing on new energy enterprises, we reveal the critical role of the business environment in predicting their innovation quality, thereby yielding more targeted and actionable policy implications. Third, we move beyond the traditional econometric methods commonly used in the existing literature. By applying machine learning, we not only evaluate the predictive ability of the business environment for innovation quality

in new energy firms, but also identify the relative importance of its constituent factors and capture complex relationships. This approach effectively addresses the limitations of traditional econometric methods, which often struggle to accurately identify the importance of different business environment elements for corporate innovation because of multicollinearity. It provides more precise empirical evidence for understanding the role of the business environment and the relative importance of its various components.

The remainder of the paper is organized as follows. Section 2 presents the literature review and theoretical framework. Section 3 describes the methodology, data collection, and definition of variables. Results are summarized in Section 4, including those of descriptive statistics, predictive ability, relative importance, predictive model, and robustness tests. Section 5 provides the heterogeneity analysis. Section 6 discusses the conclusion, limitations and provides implications.

2. Literature Review and Theory Framework

2.1. Research on Innovation in New Energy Enterprises

New energy, with its low-carbon and sustainable attributes, has become a key pathway for countries around the world to address climate change and reduce carbon emissions. As the world's greatest carbon emitter, China has taken the lead in committing to carbon neutrality and is aggressively developing its new energy sector to achieve this commitment. Currently, China ranks among the global leaders in both installed new energy capacity and equipment manufacturing. However, challenges such as low-end lock-in, insufficient core technologies, and long-term reliance on imported key components and equipment continue to constrain the development of the new energy industry. As a result, scholars have grown increasingly interested in how to improve the innovation quality of new energy firms. As a capital- and technology-intensive industry, new energy firms face significant innovation financing constraints. Firms usually turn first to the government for resource support, given its role in allocating resources and shaping innovation through policies [16]. Research shows that both supportive and regulatory policies, along with their interplay [17] and environmental regulations [18], can foster innovation in renewable energy enterprises. However, Li et al. [19] find that the relationship between government subsidies, including both innovation and non-innovation subsidies, and innovation is complex and nonlinear. With subsidies declining, some scholars have begun to focus on the role of the market in stimulating corporate innovation. Lin and Xie [20] find that venture capital helps increase financial capital, alleviate financing constraints, and strengthen corporate R&D investment, thereby indirectly promoting green innovation in renewable energy. Wei et al. [21] use feasible generalized least squares to analyze how digital inclusive finance affects renewable energy development through both production and consumption channels. Amid the wave of emerging technologies and industrial revolution, digital transformation has emerged as a key driver of innovation in the new energy sector [22]. Additionally, some scholars argue that as the formulators and executors of corporate strategy, executives exert an important influence on corporate innovation. Zhu et al. [23] find that academic executives promote innovation within new energy vehicle enterprises by increasing basic research investment. The innovation drivers in new energy firms are shown in Table 1.

Table 1. Studies on the innovation drivers in new energy firms.

Explanatory Variables	Findings	Research
Government subsidies	Nonlinear effect on innovation	[19]
Government policies	Positive impact on innovation	[17]
Environmental regulations	Promote innovation	[18]
Venture capital	Indirectly promote green innovation	[20]
Digital inclusive finance	Positive effect on development	[21]
Digital transformation	Enhance innovation performance	[22]
Academic executives	Promote innovation	[23]

2.2. Business Environment and Firm Innovation

According to new institutional economics, the business environment can be understood as a set of formal institutional arrangements that influence firms' incentives and resource allocation efficiency. New institutional economics argues that a superior institutional environment reduces transaction costs, mitigates information asymmetry, and strengthens property rights protection, thereby strengthening firms' incentives to engage in high-quality innovation [6]. Since innovation activities involve substantial sunk costs, long investment cycles, and high uncertainty, they are particularly sensitive to the institutional environment. In this framework, the business environment, as an external institutional system, directly influences the innovation activities of firms within a region.

Existing research pays considerable attention to the connection between the business environment and corporate innovation. First, studies investigating the effect of the overall business environment on firm innovation show that optimization of the business environment promotes corporate innovation. For instance, based on data from small and medium-sized enterprises, Nam and Tram [24] find that a favorable business environment strengthens innovation persistence. Using firm-level data from 28 transition economies, Gogokhia and Berulava [25] provide cross-country evidence that the business environment promotes corporate innovation investment. Similarly, based on Chinese A-share listed companies, Sun et al. [11] report a positive relationship between the business environment and firms' R&D investment. Furthermore, Liang et al. [13] indicate that an improved business environment promotes sustainable innovation by alleviating perceived uncertainty, easing financing constraints, and attracting innovative talent, and this promotion of sustainable innovation is more significant in high-tech firms. Employing data of A-share listed companies in China's capital market, Dai and Xiao [12] reveal that business environment can promote firms' green innovation through digital transformation, innovation ability, and a willingness to pursue environmental management, and the positive impact is more pronounced in state-owned enterprises, high-tech enterprises, and low-polluting enterprises. Wang and Zhang [26] show that upgrading the business environment exhibits a more salient improvement in resilience for private enterprises, small and medium-sized enterprises and high-tech industries.

Second, another stream of the literature explores the impact of specific components within the business environment on firm innovation. For instance, using a stage-by-stage difference-in-differences approach and data of Chinese A-share listed firms, Xu et al. [27] find that information infrastructure upgrades positively influence corporate innovation investment and output. Han et al. [28] argue that the development of new digital infrastructure can indirectly enhance substantive green innovation by improving digital finance, entrepreneurial activity, and information technology indices. Lin and Zhang [29] and Osei [30] discover that human capital interacts with digital finance and digital infrastructure to drive innovation. Ji et al. [31] explore the complex relationship between external financing environments and corporate innovation, revealing that proximity to commer-

cial banks enhances innovation among non-state-owned enterprises. Table 2 presents the studies on business environment and firm innovation.

Table 2. Studies on business environment and firm innovation.

Research Question	Sample	Method	Research
Innovation persistence	Small and medium-sized firms	Dynamic random probit estimation	[24]
Innovation investment	Firms of transition economies	Regression model	[25]
Innovation investment and output	A-share firms	DID	[27]
R&D investment	A-share firms	Regression model	[11]
Sustainable innovation	A-share firms	Regression model	[13]
Green innovation	A-share firms	Fixed model	[12]

2.3. Machine Learning and Corporate Behavior

In recent years, machine learning has grown as a key methodology in corporate finance and governance research within the social sciences [32–34]. Wang et al. [35] employ a random forest algorithm to identify key elements impacting corporate misconduct, finding a strong relationship between corporate governance traits and misconduct. Bertomeu et al. [36] provide methodological evidence on the usefulness of machine learning for firm-level prediction by applying gradient-boosted regression trees to detect accounting misstatements. Leveraging a random forest regression model on 2815 local projects, He et al. [37] determine that autonomy, decision-making level, and funding scale are the most critical drivers for achieving budget coordination objectives in Chinese local governments. Zare [38] investigates the predictive power of machine learning in forecasting financial market returns using macro-finance variables and finds that random forest consistently outperforms alternatives in accuracy.

2.4. Research Gaps

The present studies have provided important insights into the drivers of innovation in new energy enterprises, such as policy, venture capital, digitalization, and corporate governance. While these factors undoubtedly influence firm innovation, they largely focus on firm-level or policy-level drivers.

Meanwhile, the important role of business environment in promoting firm innovation has received extensive attention. However, most studies examine the business environment in general firms or high-tech industries, without paying sufficient attention to the new energy industry. Given the capital intensity, technological complexity, and policy sensitivity of new energy enterprises, it remains unclear whether and how the business environment predicts their innovation quality.

Furthermore, traditional econometric methods, such as fixed effects models and regression models, are widely used to examine the nexus between the business environment and firm innovation. These methods are effective in addressing unobserved heterogeneity and potential endogeneity. However, the relationship between the business environment elements and innovation quality may be nonlinear and complex. The traditional regression models impose assumptions and may suffer from multicollinearity when multiple business environmental elements are included simultaneously. In recent years, machine learning methods have gained prominence in economics and management research. Machine learning algorithms allow for the capture of complex associations without requiring prior assumptions. Moreover, variable importance analysis ranks different elements of the business environment, thereby providing additional insights into their relative contributions. The comparison between traditional methods and machine learning are displayed in Table 3.

Table 3. Comparison between traditional econometric methods and machine learning.

Dimensions	Traditional Econometric Methods	Machine Learning
Assumption	Require pre-specified assumptions	Without pre-specified assumptions
Nonlinearity	Limited ability to model nonlinear relationships unless explicitly specified	Naturally capture complex nonlinear relationships
Multicollinearity	Sensitive to multicollinearity among explanatory variables	More robust to multicollinearity
Interpretability	Coefficient-based interpretation	Feature importance ranking and predictive performance
Research Focus	Causal inference under structural assumptions	Prediction accuracy and variable importance

Therefore, following the paradigm suggested by Shah et al. [39], our study leverages institutional theory and the resource-based view to construct a conceptual framework including the business environment and innovation quality of new energy firms, and employs machine learning to evaluate the predictive ability of the business environment for innovation quality in new energy firms. It further identifies critical business environment elements predicting innovation quality and reveals their complex interrelationships. Our paper not only broadens the research perspective but also provides empirical evidence to help governments build a business environment that supports high-quality innovation in new energy firms.

2.5. Theoretical Framework

Previous studies have established a diversified evaluation system for the business environment. For example, drawing on the World Bank's business environment evaluation system, certain scholars develop a five-dimensional analytical framework encompassing investment and financing environment, enterprise market environment, government intervention environment, population consumption environment and public service environment [40]. Guo et al. [41] solely employ the marketization index to measure the Doing Business environment. Li et al. [42] construct a six-dimensional analytical framework including public services, human resources, market environment, innovation environment, financial environment, and governmental environment. Given that the indicator system developed by Li et al. [42] is more comprehensive, scientific, practical, and quantifiable, it can assess the business environment of each city across multiple dimensions, and its integration of governmental and market logics better reflects China's situation. Therefore, our study draws on the research of Li et al. [42] to construct a business environment evaluation system covering public services, human resources, market environment, innovation environment, financial environment, and governmental environment.

The resource-based view suggests that firms' innovation activities are closely related to the resources they possess [43]. Meanwhile, institutional theory points out that firms' behaviors and performance are embedded in institutional contexts. A favorable institutional environment can reduce uncertainty, improve regulatory efficiency, and create superior conditions for firms' innovation. External environments, such as public services, governmental environment, human resources, innovation environment, financial environment, and market environment, play a crucial role in facilitating firms' access to innovation resources, including human capital, financial capital, technological infrastructure, and innovative talents. Therefore, a favorable business environment not only provides institutional support for firm innovation but also enhances firms' ability to accumulate innovation resources, thereby supporting high-quality innovation in new energy firms. The theoretical relationships between different business environment elements and the innovation quality of new energy firms are as follows.

(1) Public services:

Public services refer to various basic services provided by the government. High-quality public services not only facilitate business operations, but are also crucial for attracting and retaining innovative talents in companies [44]. First, high-quality public services offer superior work and living conditions, strongly attract talent, and provide a talent pool for high-quality corporate innovation [13]. Second, as a technology-intensive sector, new energy innovation relies on high-tech equipment and precision instruments, requiring stable basic services like water, power, and gas supply. Well-developed public services provide essential support for high-quality innovation in new energy firms.

(2) Governmental environment:

Government corruption has been examined as a deterrent to innovation in the regional renewable energy sector [45]. A favorable governmental environment can minimize firms' incentives to seek rents from the government and alleviate the adverse effects of government corruption on corporate innovation. Meanwhile, a good governmental environment helps lower institutional transaction costs and tax burdens for enterprises, enhances social resource allocation, and encourages firms to increase R&D investment, thereby contributing to predict innovation quality in new energy firms [46].

(3) Human resources:

Human capital is a major predictor of high-quality innovation in new energy firms [46]. Therefore, attracting prominent talent is crucial for supporting innovation quality in new energy firms. A city's human resources environment significantly impacts talent concentration. First, a top-tier urban human resources environment improves talent attractiveness, attracting more exceptional individuals to companies [47,48]. Second, labor costs reflect the human resources conditions of the business environment. Higher salaries not only signal firms' recognition of talent but also improve employees' quality of life, thereby increasing firms' attractiveness to skilled workers. Finally, a well-developed human resources environment promotes continuous career development and contributes to the improvement of the workforce's overall skill level [49]. Therefore, our paper asserts that an improved urban human resource environment fosters high-quality innovation in new energy firms.

(4) Financial environment:

Due to the high investment, substantial risk, and uncertain returns associated with high-quality innovation, new energy firms often face financial exclusion and discrimination in traditional financial markets, making it difficult for them to acquire sufficient bank financing [50,51], thereby constraining the deployment of high-quality innovation [52]. Improving the financial environment offers a solution to this issue. Optimizing the financial environment enhances credit allocation efficiency, facilitates capital mobility, lowers financing costs, and ensures capital for enterprise innovation, thereby mitigating the adverse effects of capital market flaws on new energy firms' innovation quality. Benavides-Franco et al. [53] find that a developed financial system is a key factor affecting the financing efficiency of renewable energy projects.

(5) Market environment:

Resource scarcity limits innovation quality in new energy firms [5]. Markets are the cornerstone of resource allocation [54]. A favorable market environment enables the cross-regional and cross-industry flow of resources, which improves the efficiency of resource allocation and utilization [55]. Thus, a favorable market environment helps firms acquire resources more efficiently, mitigating resource scarcity's adverse effect on innovation quality in new energy firms.

(6) Innovation environment:

As a technology-intensive industry, the new energy sector relies heavily on technological innovation for its survival and growth. Coad et al. [56] state that boosting R&D investment and fostering a conducive R&D environment are important for driving firm innovation. In a favorable innovation environment, new energy firms can efficiently integrate innovation resources, increase R&D investment, and then enhance innovation quality. Conversely, an unfavorable innovation environment raises innovation costs and discourages firms from investing in innovation.

To facilitate understanding, a conceptual model is presented in Figure 1 to illustrate the framework of our study. Within this theoretical framework, our study aims to achieve the following research aims.

RA1: To explore the predictive ability of business environment on innovation quality in new energy firms.

RA2: To identify the relative importance of the six business environment elements in predicting the innovation quality of new energy firms.

RA3: To reveal the predictive model between the crucial business environment elements and innovation quality of new energy firms.

RA4: To examine the heterogeneous predictive associations across firm ownership and location.

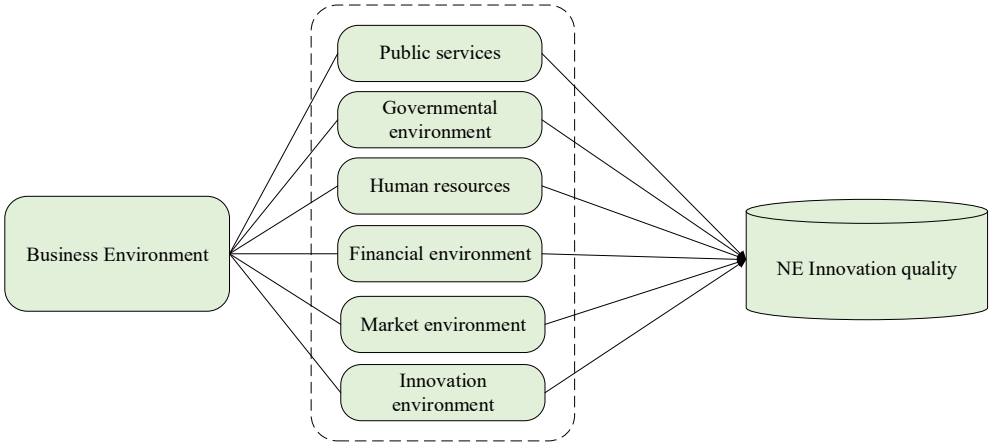


Figure 1. Conceptual model.

3. Research Design

3.1. Research Method

Model performance is evaluated by explanatory power and prediction accuracy in our study. Explanatory power reflects the model's goodness of fit in predicting innovation quality. In our study, the out-of-sample goodness-of-fit R^2_{OOS} is used to examine the forecasting ability of the model on the test set. The larger the R^2_{OOS}, the stronger the predictive ability of the model on innovation quality. Predictive accuracy reflects the accuracy of the model in forecasting the innovation quality. The out-of-sample MSE_{OOS} (mean square error) is chosen to measure the degree of deviation between the predicted and actual values of the model [57]. In addition, considering that the mean square error may be affected by outliers, leading to a large deviation of its estimate from reality, we also use the MAE_{OOS} (mean absolute error) to assess the accuracy of the model in predicting innovation quality.

Following He et al. [37], we use IncNodePurity to evaluate the relative importance of variables. IncNodePurity represents the average reduction in model node impurity,

which measures the total amount of reduction in node impurity due to splits caused by this variable. A larger IncNodePurity value indicates greater variable importance.

Additionally, we use partial dependence plots to portray the pattern by which explanatory variables predict the response variable. Partial dependence plots are an important tool for analyzing the predictive pattern of the explanatory variable on the response variable, revealing the relationship between the response variable and the explanatory variable [37].

Hyperparameters were tuned over mtry $\in$ seq (2, 10, by = 1) and min.node.size $\in$ seq (1, 10, by = 1) using an exhaustive grid search with 5-fold cross-validation in caret. The selected parameters were applied to retrain the final model (ntrees = 500). Model robustness was evaluated across 30 re-estimations with different random seeds.

3.2. Data Collection

Considering the continuity, consistency, and availability of data at the city level, the sample period of our study is 2008–2019. Additionally, our study screens the sample according to the following conditions: (1) excluding companies that had been ST, *ST, PT; (2) excluding firms with significant missing variables.

The data used in the business environment evaluation system are mainly derived from the China Urban and Rural Construction Database, the China Urban Database and the China Urban Statistical Yearbook. For cities with less extensive missing data, we use interpolation to fill in the gaps. Additionally, patent data and enterprise-related data are collected from the China Research Data Service Platform (CNRDS) and the CSMAR database.

3.3. Variable Definitions

3.3.1. Explanatory Variable

Business environment. Drawing on Li et al. [42], we construct an evaluation index system for the urban business environment in China, as shown in Table 4. It should be noted that our study adjusts some indicators of the original evaluation system in response to the research questions. First, given that the response variable in our study is the innovation quality of new energy firm, the original innovation output indicator is excluded to prevent potential endogeneity problems. Second, following Xue et al. [58], the digital foundation is incorporated into the public services evaluation index system.

Table 4. Business environment evaluation system.

Dimensions	Primary Indicators	Secondary Indicators
Public services	Hydraulic supply (0.3)	Public water supply capacity
	Natural gas supply (0.4)	Gas supply capacity
	Electricity supply (0.1)	Industrial electricity supply capacity
	Digital infrastructure (0.2)	Cell phone penetration (0.4)
		Internet penetration (0.6)
Human resources	Human resources pool (0.7)	Number of enrolled students in regular higher education institutions (0.5)
		Number of employees (0.5)
	Labor costs (0.3)	Average wage level

Table 4. *Cont.*

Dimensions	Primary Indicators	Secondary Indicators
Market environment	Economic indicator (0.2)	Regional per capita GDP (0.3)
		Regional gross domestic product (0.7)
	Import and export (0.5)	Actual utilization of foreign investment in the current year (0.4)
		Number of newly signed projects in the current year (0.6)
	Enterprise organization (0.3)	Number of large-scale industrial firms
Innovation environment	Innovation input	Science expenditure
Financial environment	Practitioner size (0.7)	Financial practitioners
	Financing service (0.3)	Ratio of balance of loans from financial institutions at the end of the year to GDP (0.5)
		Ratio of total deposits in financial institutions at the end of the year to GDP (0.5)
Governmental environment	Government intervention (0.2)	Ratio of local fiscal expenditure to GDP (0.2)
		Value-added tax payable by enterprise (0.8)
	Government efficiency (0.8)	Ratio of local fiscal revenue to local fiscal expenditure

Furthermore, we apply the utility coefficient method to nondimensionalize the indicators, adopt the coefficient of variation (CV) method to determine the weights of indicators, and then hierarchically weight the indexes to derive the business environment index. The CV method measures the amount of information contained according to the degree of variation in the indicators. The greater the coefficient of variation, the larger the weight. The CV method is often used to determine the index weight of a comprehensive evaluation system that includes multiple aspects, such as new-type urbanization [59]. The business environment evaluation system constructed in our paper contains six dimensions, each of which reflects an essential feature of the business environment and together captures the comprehensive environment in which Chinese enterprises operate. Hence, it is reasonable to use the CV method.

3.3.2. Response Variable

Innovation quality. Drawing on Acharya and Xu [60] and Liu et al. [61], we use the number of forward citations of a company's authorized invention-type patents to measure innovation quality. The reasons can be explained from two aspects. On the one hand, patent data is an essential indicator to measure innovation performance, because it can objectively reflect the progress of innovation [62]. However, the quality of patents is highly heterogeneous. Hence, the number of patent citations is widely used as a proxy for innovation quality [63,64]. Forward citation counts refer to the number of citations of a patent by subsequent patents, indicating that these newer patents are technologically based on the cited patent [65]. A larger number of citations implies that the patent is more valuable and has a higher technical impact on the underlying invention [64]. On the other hand, the Chinese patent system grants three types of patents: invention, utility, and design patents. The invention-type patent refers to new technical schemes proposed

for a product, method, or the product's improvement. This type of patent represents the core technical achievements of an enterprise and is regarded as the innovation of high technical level. According to the data of the National Intellectual Property Administration, the grant rate for invention-type patent in 2019 was only 44.3%, the lowest among the three types [61]. This further indicates that invention-type patents involve higher examination standards and stronger novelty requirements than other patent types. Furthermore, firm innovation output is commonly proxied by authorized patent counts [66]. Authorized patents indicate that a firm submits high-quality well-prepared patent applications likely to meet the patentability requirements [67]. Hence, the innovation quality is measured by the forward citations of a company's authorized invention-type patents. In addition, since our study aims to explore the predictive ability of the business environment for innovation quality, the data for year t + 1 are employed. Meanwhile, the indicator is processed by taking the natural logarithm after adding one to mitigate the effect of right-skewed distribution.

3.3.3. Control Variable

Following Shan et al. [68], we set the control variables as follows. Net interest rate on total assets (*Roa*) measured using net profit divided by total assets. Ratio of current assets (*Car*) measured the ratio of current assets to total assets. Current ratio (*Cr*) is measured by dividing current assets by current liabilities. Cash flow from operating activities (*Cfl*) measured the ratio of cash flow from operating activities to total assets. Asset collateralization capability (*Acc*) measured the ratio of net fixed assets to total assets. Firm size (*Size*) is measured by the natural logarithmic of total assets. Leverage (*Lev*) is measured by dividing total liabilities by total assets. Ratio of independent directors (*Idr*) is measured by the ratio of the number of independent directors to the number of board members. Board size (*Bs*) is represented by the total number of board members. Chairman's shareholding ratio (*Csr*) is measured by the percentage of company shares held by the chairman of the board of directors. Firm age (*Age*) is measured using the natural logarithm of the difference between the number of years counted during the period minus the number of years the business was established. Ownership (*Own*): state-owned enterprises are assigned a value of 1, non-state-owned enterprises are assigned a value of 0.

4. Empirical Results

4.1. Descriptive Statistics

Table 5 shows the descriptive statistics for the response, explanatory, and control variables. As seen in Table 5 for the response variable, the maximum value of innovation quality is 8.2300, the minimum value is 0.0000, the mean is 2.4450, and the standard deviation is 1.5710, indicating considerable heterogeneity across new energy firms. Meanwhile, there are large differences in public services (PS), market environment (ME), governmental environment (GE), financial environment (FE), innovation environment (IE), and human resources (HR) in different cities, indicating that the development of urban business environment in China is unbalanced.

Table 5. Descriptive statistics for variables.

Variables	Mean	S.D.	Min	Max
Iq	2.4450	1.5710	0.0000	8.2300
PS	22.7840	18.7310	1.7580	65.8700
HR	30.3310	17.5430	4.3210	74.0020
ME	19.6010	14.0080	1.3140	64.2300
IE	19.2910	25.1980	0.0770	100.0000

Table 5. *Cont.*

Variables	Mean	S.D.	Min	Max
FE	16.8100	16.4450	1.7260	80.0260
GE	53.3400	8.0680	26.5600	95.3500
Roa	0.0340	0.0590	−0.5110	0.7620
Car	0.4590	0.2050	0.0240	0.9440
Cr	2.7060	6.1060	0.1210	87.8190
Cfl	0.0190	0.0830	−0.9790	0.5550
Acc	0.0760	0.1300	0.0000	0.8490
Size	22.1900	1.1850	18.8800	25.7400
Lev	0.3900	0.1910	0.0020	0.8400
Idr	0.3690	0.0500	0.3330	0.6000
Bds	8.7680	1.7470	5.000	15.000
Csr	8.5470	14.2990	0.0000	56.9200
Age	2.7520	0.3960	0.6930	3.5840
Own	0.3360	0.4730	0.0000	1.0000

4.2. Predictive Ability of Business Environment on Innovation Quality

First, we construct the benchmark model and the business environment model by including the variables shown in Table 6. Then, based on the sample of Chinese new energy listed companies, we utilize the random forest method to examine whether the inclusion of business environment can significantly improve the model's prediction of innovation quality. Table 7 presents the "Random Forest–Benchmark Model", which includes only control variables, and the "Random Forest–Business Environment Model", which additionally adds business environment variables. By comparing the predictive performance of the two models in predicting innovation quality, we assess the contribution of the business environment to the innovation quality of new energy firms. Meanwhile, the "OLS–Benchmark Model" and "OLS–Business Environment Model" are used as the control groups to examine whether the random forest method can notably improve the forecasting ability of the model compared with the OLS method.

Table 6. Model construction.

Response Variable	Model	Explanatory Variable
Innovation quality	Benchmark model	Net interest rate on total assets (*Roa*); Ratio of current assets (*Car*); Current ratio (*Cr*); Cash flow from operating activities (*Cfl*); Asset collateralization capability (*Acc*); Firm size (*Size*); Leverage (*Lev*); Ratio of independent directors (*Idr*); Board size (*Bs*); Chairman's shareholding ratio (*Csr*); Firm age (*Age*); Ownership (*Own*)
	Business environment model	In addition to the variables of the benchmark model, the business environment is also included. Public services (*PS*); human resources (*HR*); market environment (*ME*); innovation environment (*IE*); financial environment (*FE*); governmental environment (*GE*)

Table 7. Model fit results.

Model		R^2_{OOS}	MSE_{OOS}	MAE_{OOS}
Random forest	Benchmark model	0.6200	0.9149	0.7536
	Business environment model	0.7001	0.7882	0.7048
OLS	Benchmark model	0.1630	1.9709	1.1344
	Business environment model	0.1715	1.9554	1.1178

Note: MSE_{OOS} is the mean square error and MAE_{OOS} is the mean absolute error, both of which measure the degree of deviation between the true and predicted values. The smaller the values of the MSE_{OOS} and MAE_{OOS}, the higher the accuracy of the predictive model in describing the data.

We can find from Table 7 that the random forest model performs substantially better than the OLS model. Specifically, the "Random Forest–Business Environment Model" improves upon the "OLS–Business Environment Model" by 0.5286 in terms of R^2_{OOS}, and the "Random Forest–Benchmark Model" outperforms the "OLS–Benchmark Model" by 0.4570 on the same metric. This result indicates that the random forest model has stronger out-of-sample predictive ability than the OLS model.

Moreover, the values of MSE_{OOS} (0.7882) and MAE_{OOS} (0.7048) of the "Random Forest– Business Environment Model" are smaller than the values of MSE_{OOS} (1.9552) and MAE_{OOS} (1.1178) of the "OLS–Business Environment Model". Therefore, the superiority of the random forest model over the OLS model is further confirmed by the lower MSE_{OOS} and MAE_{OOS}.

Compared with the benchmark model, the business environment model exhibits significantly better predictive performance for corporate innovation quality. Concretely, relative to the "Random Forest–Benchmark Model", the "Random Forest–Business Environment Model" increases R^2_{OOS} from 0.6200 to 0.7001, representing an absolute improvement of 0.0801. This indicates that the random forest model is significantly more effective in predicting the innovation quality of enterprises after considering the business environment. This may be because the machine learning model is evaluated based on out-of-sample predictive performance. Unlike the in-sample R^2 obtained by conventional measures, whether the out-of-sample R^2 obtained by machine learning improves with the increase in the number of variables added depends on the explanatory power of the added variables on the response variable. If the newly added variables have inadequate explanatory power, the out-of-sample R^2 may decline because of overfitting; if they have strong explanatory power, the out-of-sample R^2 may increase. In our study, the R^2_{OOS} of the "Random Forest–Benchmark Model" is 0.6200, and the R^2_{OOS} of the "Random Forest–Business Environment Model" is 0.7001. This improvement indicates that business environment provides substantial incremental explanatory power for enterprise innovation quality.

4.3. Variable Relative Importance

Table 8 depicts the relative importance of the variables in the "Random Forest–Business Environment Model" for forecasting the innovation quality of new energy firms. It should be noted that the variable importance results should be interpreted from two distinct perspectives. First, in the overall ranking across all variables, several control variables exhibit greater importance than the business environment elements, indicating that conventional determinants remain the dominant predictors of innovation quality. Second, the purpose of our study is not to argue that business environment variables are the most important predictors among all variables, but rather to examine whether they retain predictive power after controlling for traditional variables, and whether their relative importance differs across dimensions. The findings suggest that, although business environment variables do not occupy the highest positions in the overall ranking, they still contribute incremental

predictive power, with substantial heterogeneity in importance across different dimensions. Within focal explanatory variables, human resources (HR), financial environment (FE), and public services (PS) are ranked higher, indicating that they are important business environment elements for predicting the innovation quality of new energy firms.

Table 8. Importance ranking of variables.

Variable Types	Variables	Relative Importance
Explanatory variable	HR	83.9393
	FE	60.9346
	PS	56.5651
	IE	51.8488
	GE	51.2366
	ME	46.2395
Control variable	Size	241.4148
	Car	121.4483
	Bds	89.3103
	Acc	70.8109
	Age	63.6690
	Lev	57.4313
	Csr	53.4384
	Idr	52.2824
	Cfl	51.6496
	Cr	44.4557
	Roa	43.9372
	Own	7.1137

4.4. Predictive Model of Crucial Business Environment Elements on Innovation Quality

The random forest algorithm can effectively identify the predictive pattern of the explanatory variable for the response variable through partial dependence plots. Partial dependence plots indicate the predictive contribution of a change in a specific variable on the response variable, while all other variables remain constant. This method is well suited to identifying the complex association between the explanatory variable and the response variable [37]. As a result, our study uses partial dependence plots to illustrate the predictive patterns of human resources, financial environment, and public services for the innovation quality of new energy firms.

Figure 2 illustrates the partial dependence plot for human resources and firm innovation quality. It seems obvious that the relationship between human resources and innovation quality in new energy firms is generally positive, indicating that a better human resource environment is more conducive to the prediction of innovation quality. This result is not only consistent with the resource-based view arguments regarding the strategic importance of valuable and difficult-to-imitate resources, but also consistent with the conclusions of existing research [29]. As a technology-intensive industry, high-quality innovation in the new energy sector is closely associated with the recombination of specialized knowledge and the integration of multi-skilled talent. A developed human resource environment, characterized by the availability and mobility of skilled labor and sound training systems, expands firms' access to knowledge inputs and strengthens their absorp-

tive capacity [69]. Specifically, the high level of human resources can create a competitive income and service environment, implying that the city has a great potential to attract skilled talents, thereby mitigating the negative association of brain drain on the innovation quality of new energy firms. In addition, high-level human resources create sustained career development opportunities, enabling enterprise innovators to continuously upgrade their technical expertise and knowledge reserves, and thus better predict the innovation quality of new energy firms.

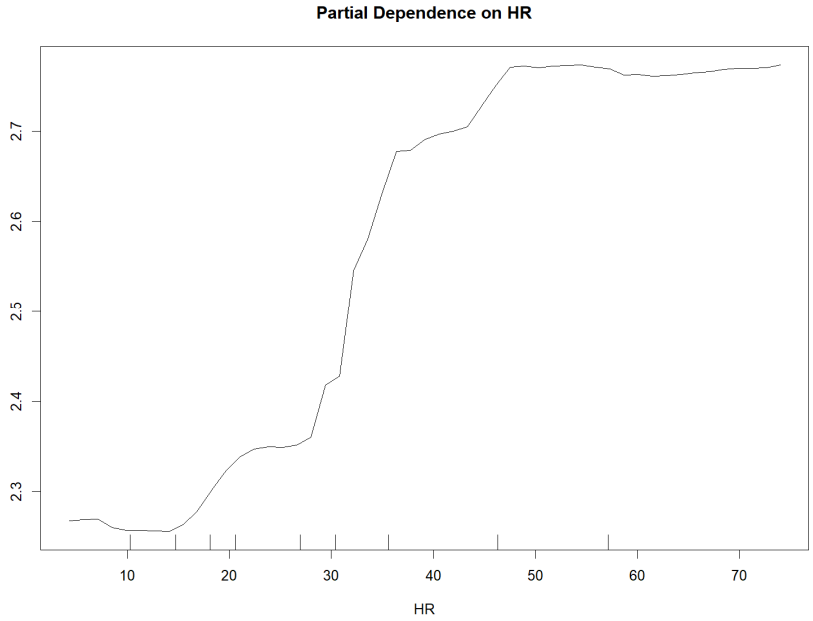


Figure 2. Human resources and innovation quality. Note: The horizontal axis is human resources, and the vertical axis is innovation quality.

Figure 3 presents the partial dependence plot for the financial environment and innovation quality of new energy firms. Different from prior research that emphasized the monotonic positive relationship between financial environment and innovation, our results suggest that the predictive association between financial environment and innovation quality varies across stages of financial environment development. The resource-based view emphasizes that access to strategic resources enhances competitive positioning, yet the value of strategic resources depends on complementary institutional conditions. Institutional theory further suggests that formal structures and market-supporting institutions evolve over time, and their effectiveness varies across developmental stages. Therefore, our results align with the arguments of the resource-based view and institutional theory.

The downward segment observed in the partial dependence plot may be interpreted in light of financial market immaturity. Compared with fossil energy, new energy technologies remain relatively immature and are characterized by high initial fixed asset investment, long investment cycles, and uncertain R&D returns [70]. Such technological and market characteristics increase capital intensity and risk exposure. However, in the early stages of financial development, financial institutions with limited risk assessment capabilities and a short-term profit orientation may exhibit cautious investment behavior toward the new energy sector. Meanwhile, underdeveloped financial markets typically provide limited financial instruments, resulting in narrow financing channels.

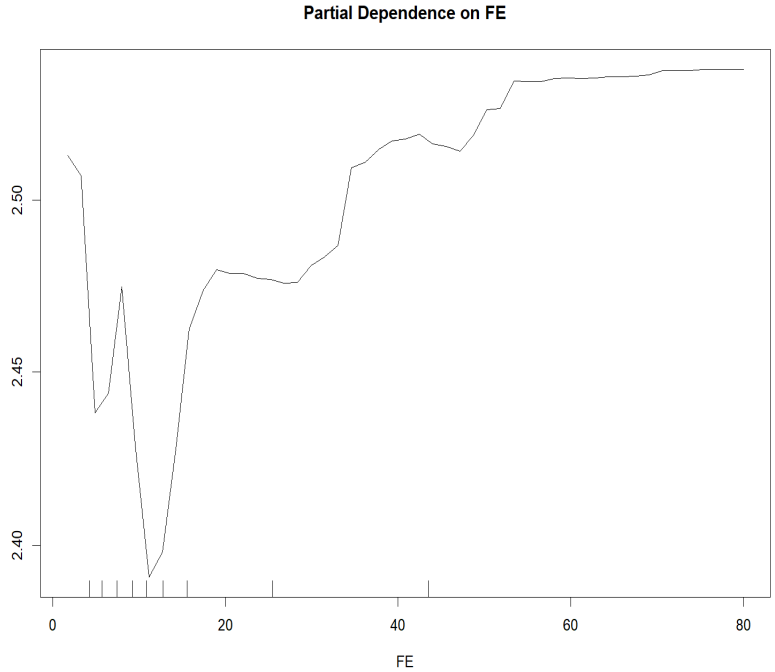


Figure 3. Financial environment and innovation quality. Note: The horizontal axis is financial environment, and the vertical axis is innovation quality.

As the financial environment improves, more diverse financial products and more professional financial services make it easier for new energy firms to acquire financing [71]. With the formation of the dual-carbon strategy, policy instruments such as green finance, carbon finance, and pilot carbon emissions trading programs have been introduced and developed. Particularly, green finance has been continuously refined, forming a diversified product system that includes green credit, green bonds, green funds and green insurance. Green finance not only broadens financing channels for the new energy industry through targeted loans, green bonds, and industrial funds, but also directs capital toward green industries. It effectively leverages finance to connect the capital, information, and talent essential for new energy development, accelerating breakthroughs in new energy technologies. In addition, in an excellent financial environment, the financial system provides a more efficient mechanism for project evaluation. Owing to their professional expertise and informational advantages, financial intermediaries can scientifically evaluate the prospects of new energy projects and enterprise capabilities. By identifying innovative projects with development potential, they can allocate funds more precisely to provide long-term financial support for high-quality initiatives, thereby enhancing access to financing for new energy firms [72].

Furthermore, government intervention may partly moderate the predictive role of the financial environment. In the early stages of industry development, extensive subsidy policies were introduced to stimulate innovation and promote industry growth. Such policy-driven resource allocation may weaken the predictive ability of the financial environment. As subsidies gradually decline and market-oriented financing becomes more prominent, the financial environment is more closely associated with the innovation quality of new energy firms.

Figure 4 displays the partial dependence plot for public services and the innovation quality of new energy firms. It is clear that there is an overall upward trend between public services and innovation quality; nevertheless, after a certain point, the predictive contribution of public services to the innovation quality of new energy firms begins to decrease.

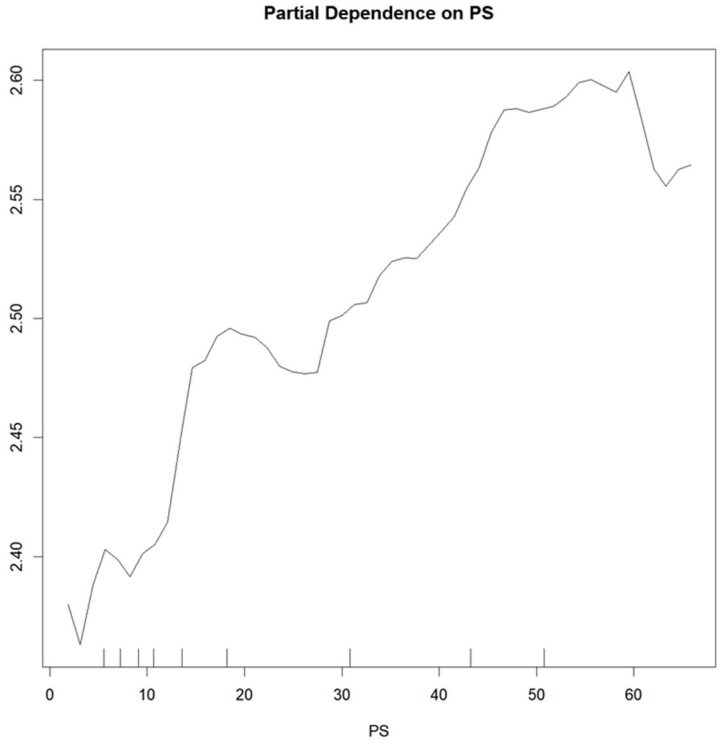


Figure 4. Public services and innovation quality. Note: The horizontal axis is public services, and the vertical axis is innovation quality.

First, high-quality innovation in new energy firms is associated with the provision of public services. As a technology-intensive industry, the new energy industry relies on high-tech equipment and precision instruments for its innovation and therefore requires stable public services. Previous research highlights that public infrastructure is positively associated with innovation [27,28]. Consequently, by optimizing public services, firms can secure a foundational guarantee for their innovation investments, thereby minimizing losses from energy disruptions and sustaining high-quality R&D activities.

Second, given their inherent resource constraints, new energy firms frequently encounter substantial limitations in pursuing high-quality innovation through internal resources alone. From a resource-based perspective, external institutional environments constitute important complementary assets that shape firms' access to knowledge and collaborative networks. Public services provide a platform for collaboration and knowledge exchange among new energy firms, thereby mitigating the constraints on high-quality innovation arising from limited internal resources. In particular, regional digital infrastructure reduces the cost of information transmission and improves its efficiency. At the same time, urban digital infrastructure shortens the temporal and spatial distance of information flows among diverse innovation actors, strengthening interorganizational knowledge exchange and collaboration, and thereby stimulating innovation emergence [73,74]. However, institutional theory argues that formal structures simultaneously enable and constrain organizational behavior. While moderate institutional support reduces coordination costs and uncertainty, excessive public expenditure or administrative expansion may alter incentive structures. Previous research indicates that a higher level of public services may be accompanied by increased tax burdens, which are negatively associated with innovation quality [75].

4.5. Robustness Test

In order to ensure that the results are robust, we conduct the following robustness tests.

4.5.1. Changing the Measurement of Response Variable

In the main test, we use the number of forward citations of a company's authorized invention-type patents to measure innovation quality. In this section, we measure the innovation quality using the number of forward citations of a company's authorized invention-type patents (including self-citations) to examine robustness. We retain self-citations in the robustness measure because they may reflect cumulative technological development within firms and internal knowledge reinforcement, which are also important dimensions of innovation quality. The results are presented in Tables 9 and 10. It can be found that the results are consistent with those of the main test.

Table 9. Model fit results after changing the measurement of response variable.

Model		R^2_{OOS}	MSE_{OOS}	MAE_{OOS}
Random forest	Benchmark model	0.6281	0.9559	0.7688
	Business environment model	0.7039	0.8303	0.7211
OLS	Benchmark model	0.0966	2.2772	1.1962
	Business environment model	0.1248	2.2280	1.2005

Table 10. Importance ranking of variables after changing the measurement of the response variable.

Variable Types	Variables	Relative Importance
Explanatory variable	HR	71.2784
	FE	66.9610
	PS	64.0318
	GE	53.2272
	ME	49.7540
	IE	48.5037
Control variable	Size	285.5148
	Car	118.7119
	Bds	105.8589
	Acc	73.1202
	Lev	62.8307
	Csr	58.1491
	Age	55.4255
	Cr	53.1452
	Idr	53.0229
	Cfl	47.5969
	Roa	46.4157
	Own	5.8658

4.5.2. Changing the Method of Sample Division

In the main test, we randomly divide the samples into a training set and a testing set without accounting for potential future information leakage. To avoid biased results due to the sample partitioning method, we follow the study of Chen et al. [76] and thus divide the sample into training and testing sets using a rolling forecast split. The results are shown in Tables 11 and 12. It can be seen that the results remain robust.

Table 11. Model fit results after changing the sample division method (rolling forecast).

Model		R^2_{OOS}	MSE_{OOS}	MAE_{OOS}
Random forest	Benchmark model	0.5484	1.1638	0.8605
	Business environment model	0.5686	1.1116	0.8341
OLS	Benchmark model	0.1620	2.1596	1.1572
	Business environment model	0.1676	2.1448	1.1688

Table 12. Importance ranking of variables after changing the sample division method (rolling forecast).

Variable Types	Variables	Relative Importance
Explanatory variable	HR	56.4739
	PS	37.7430
	FE	32.7829
	IE	29.1429
	ME	22.7716
	GE	19.3288
Control variable	Size	94.8003
	Car	48.4035
	Bds	35.4156
	Cr	33.6561
	Lev	32.8578
	Acc	29.9591
	Age	28.8848
	Csr	28.7164
	Idr	26.7279
	Cfl	23.7030
	Roa	22.2973
	Own	2.7595

4.5.3. Changing the Number of Decision Trees

In the main test, the number of regression trees in the random forest model is set to 500. In this robustness test, the number of regression trees is changed to 600. The results are shown in Tables 13 and 14.

Table 13. Model fit results after changing the number of decision trees.

Model		R^2_{OOS}	MSE_{OOS}	MAE_{OOS}
Random forest	Benchmark model	0.6242	0.9054	0.7516
	Business environment model	0.7043	0.7818	0.7026
OLS	Benchmark model	0.1630	1.9707	1.1344
	Business environment model	0.1715	1.9552	1.1178

Table 14. Importance ranking of variables after changing the number of decision trees.

Variable Types	Variables	Relative Importance
Explanatory variable	HR	83.5437
	FE	60.4352
	PS	56.4774
	GE	51.7413
	IE	51.4639
	ME	46.4664
Control variable	Size	240.2114
	Car	120.3352
	Bds	90.868
	Acc	69.9681
	Age	63.1445
	Lev	57.5248
	Csr	54.3184
	Idr	52.0292
	Cfl	51.6153
	Roa	43.8563
	Cr	43.7900
	Own	6.9766

4.5.4. Considering Year Fixed Effects

To capture common macroeconomic and policy shocks across cities, we incorporate a year indicator into the random forest model as a predictive feature. This specification allows the model to flexibly absorb time-specific heterogeneity, and thus to enhance the accuracy of the predictive model. The results are presented in Tables 15 and 16. These results certify that the main findings are robust.

Table 15. Model fit results after considering year fixed effects.

Model		R^2_{OOS}	MSE_{OOS}	MAE_{OOS}
Random forest	Benchmark model	0.5359	1.1313	0.8540
	Business environment model	0.6360	0.9543	0.7897
Fixed model	Benchmark model	0.0969	2.1960	1.1979
	Business environment model	0.1050	2.2008	1.1862

Table 16. Importance ranking of variables after considering year fixed effects.

Variable Types	Variables	Relative Importance
Explanatory variable	HR	77.1369
	PS	51.5444
	FE	49.5161
	GE	48.8340
	IE	42.3870
	ME	42.3154
Control variable	Size	230.1029
	Car	114.4494
	Bds	81.8654
	Acc	65.2701
	Idr	54.9986
	Csr	53.8977
	Lev	52.4442
	Age	50.2290
	Cfl	46.0948
	Cr	43.7032
	Roa	39.8249
	Own	6.3867

4.5.5. Adding ALE Plots and ICE Plots

Partial dependence plots are conditional expectations that assume feature independence and break under correlated predictors. To address the concern that high correlation among predictors may affect the reliability of the partial dependence plots (PDPs), we further add accumulated local effects (ALE) plots and individual conditional expectation (ICE) plots to examine the predictive association. The results are shown in Figures 5–10. We can find that both ALE plots and ICE plots exhibit predictive patterns consistent with the original partial dependence plots. These additions further support the robustness of our results.

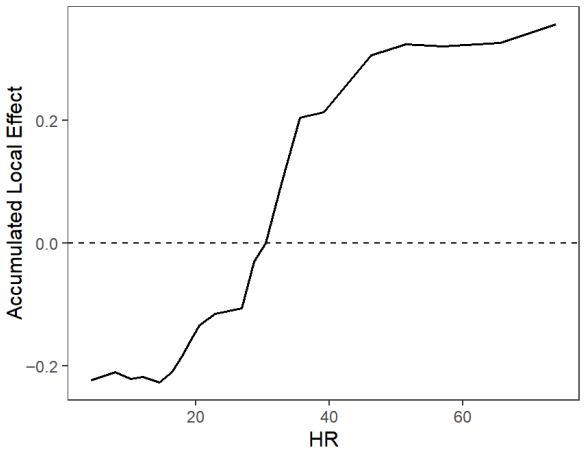


Figure 5. Accumulated local effects plot for human resources.

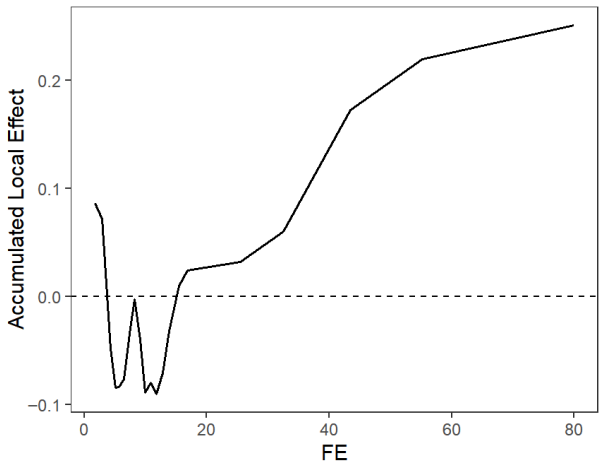


Figure 6. Accumulated local effects plot for financial environment.

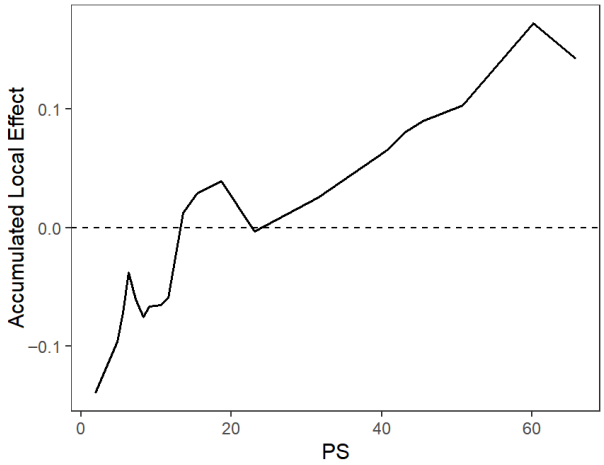


Figure 7. Accumulated local effects plot for public services.

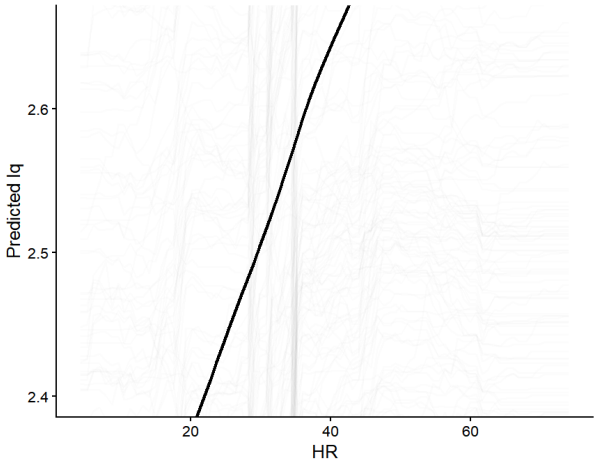


Figure 8. Individual conditional expectation plot for human resources. Note: The grey lines represent individual ICE curves, while the bold line shows the average trend.

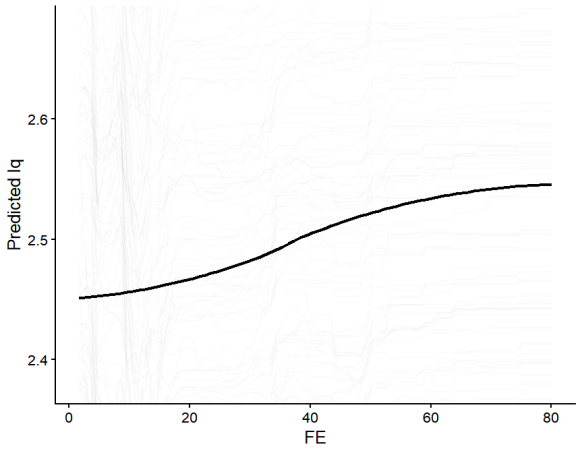


Figure 9. Individual conditional expectation plot for financial environment. Note: The grey lines represent individual ICE curves, while the bold line shows the average trend.

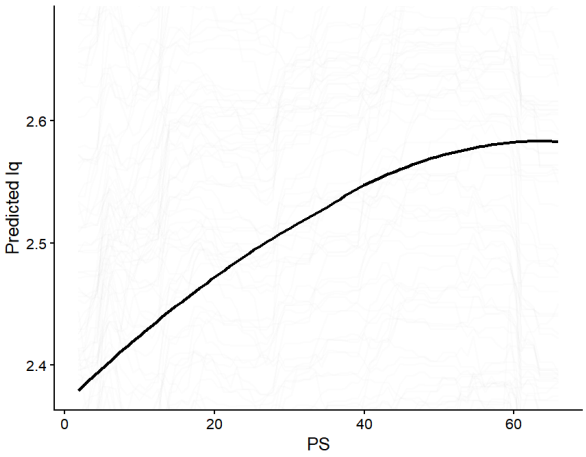


Figure 10. Individual conditional expectation plot for public services. Note: The grey lines represent individual ICE curves, while the bold line shows the average trend.

5. Heterogeneity Analysis

(1) Firm's ownership

To further examine the predictive ability of the business environment for innovation quality across firms with different ownership, we divide the sample into state-owned and non-state-owned firms. The results are shown in Tables 17 and 18. It can be found that the business environment has a greater predictive ability for the innovation quality of state-owned firms than that of non-state-owned firms. A comparison of variable importance between state-owned and non-state-owned firms reveals notable heterogeneity. Human resources and the financial environment rank more prominently for state-owned firms, whereas their relative importance is lower for non-state-owned firms. In contrast, the governmental environment emerges as the primary determinant for non-state-owned firms. This divergence may be explained by differences in resource endowments and institutional support. The new energy industry is characterized by strong capital and technology intensity, and high-quality innovation in this sector relies heavily on financial resources and human capital investment. Owing to their political attributes, state-owned firms are generally better to acquire support from financial institutions and attract high-quality talent. Consequently, in cities with a well-developed financial environment and favorable human resources, state-owned firms tend to possess more abundant innovation resources, which in turn enhances their predictive capability. In contrast, non-state-owned firms face relative disadvantages in resource acquisition and institutional protection, making them

more sensitive to the quality of the governmental environment. A favorable governmental environment can reduce transaction costs and enhance their competitive advantage. As a result, human resources and the financial environment are more significant for state-owned new energy firms, whereas the governmental environment is more significant for non-state-owned new energy firms.

Table 17. Importance ranking of variables in state-owned firms.

Variable Type	Variables	Relative Importance
Explanatory variable	HR	65.1655
	FE	42.7259
	PS	36.3151
	GE	33.3855
	ME	20.4471
	IE	16.9601

Table 18. Importance ranking of variables in non-state-owned firms.

Variable Type	Variables	Relative Importance
Explanatory variable	GE	43.5559
	PS	37.3029
	ME	28.7187
	FE	25.8296
	IE	23.7732
	HR	19.9070

(2) Firm's location

We divide the region into three sections: East, Central, and West, to investigate the predictive ability of the business environment for innovation quality among firms in different regions. The results are shown in Tables 19–21. It can be discovered that the business environment is more important in predicting the innovation quality of new energy firms in the central region. Comparing the relative importance of variables across firms in different regions, the results indicate that public services and the governmental environment consistently rank highly across all three regions. In contrast, human resources and the financial environment assume the highest importance for firms in the eastern region, the second highest for firms in the central region, and comparatively lower importance for firms in the western region. This may be due to the uneven distribution of financial and human resources in different regions. The financial environment in the eastern region is more developed, which can significantly contribute to the innovation quality of new energy firms by reducing financing costs and improving financing efficiency. Simultaneously, the eastern and central regions, characterized by their advanced economic development and abundant job opportunities, tend to attract a large number of excellent talents, thereby enabling new energy firms in these regions to more easily recruit individuals possessing innovative capabilities. Conversely, the western region experiences severe brain drain, posing challenges in recruiting an adequate number of talents to support the innovative activities of new energy firms. Furthermore, the R&D and manufacturing activities of new energy firms in China are predominantly situated in the eastern and central regions, thereby placing a greater reliance on the financial environment and human resources of these cities.

Table 19. Importance ranking of variables for firms in the western region.

Variable Type	Variables	Relative Importance
Explanatory variable	PS	28.3621
	GE	12.4831
	ME	7.1461
	IE	5.9297
	HR	2.6710
	FE	1.4566

Table 20. Importance ranking of variables for firms in the central region.

Variable Type	Variables	Relative Importance
Explanatory variable	GE	14.4914
	HR	9.0342
	PS	6.6295
	IE	5.8680
	FE	4.8971
	ME	2.0471

Table 21. Importance ranking of variables for firms in the eastern region.

Variable Type	Variables	Relative Importance
Explanatory variable	HR	69.7738
	PS	51.8226
	GE	48.9735
	FE	48.4500
	ME	42.9192
	IE	32.9650

6. Conclusions and Implications

6.1. Conclusions

Improving the innovation quality of new energy firms is an important pathway for reducing carbon emissions and achieving sustainable development. In order to explore the predictors of innovation quality in new energy firms, our study assesses the predictive ability of the business environment for innovation quality in new energy firms, distinguishes the relative importance of different business environment elements, and then portrays the predictive patterns of critical elements. We derive the following conclusions.

First, the business environment is a significant predictor of innovation quality in new energy firms. Incorporating the business environment substantially improves the predictive ability compared with the benchmark model, increasing the out-of-sample R^2 from 0.6200 to 0.7001, which represents an improvement of 0.0801. This predictive ability remains robust across several tests, confirming the stability of the results.

Second, among the focal explanatory variables, human resources, the financial environment, and public services emerge as relatively important elements. The variable importance results within the focal explanatory variables show that human resources have the highest importance value (83.9393), followed by the financial environment (60.9346)

and public services (56.5651). These findings suggest that, although business environment variables are not the top-ranked predictors in the full model, they continue to provide incremental predictive value beyond conventional controls, with substantial heterogeneity across elements.

Third, the predictive patterns between important variables and innovation quality are different. Specifically, the predictive pattern between human resources and the innovation quality of new energy firms is generally upward. The financial environment shows a nonlinear relationship, initially downward but turning upward at higher levels, suggesting that the predictive association between the financial environment and innovation quality varies across stages of financial environment development. Public services also show a nonlinear relationship, but while the predictive association between public services and innovation quality is initially upward, after a certain point, the association becomes downward.

Fourth, heterogeneity analysis reveals variation in the predictive ability across ownership and regions. For state-owned firms and those located in the eastern and central regions, the financial environment and human resources remain important predictors, whereas public services are important across all firm types and regions.

6.2. Practical Implications

The findings of our study indicate that human resources, public services, and the financial environment are key factors predicting the quality of innovation in new energy firms. Therefore, priority should be given to optimizing human resources, public services, and the financial environment, which exhibit a relatively significant association with firms.

For the optimization of human resources, the government should refine talent recruitment policies and enhance training opportunities. It is essential to fully leverage the distinctive strengths of energy-focused universities in cultivating talent, strengthen the talent system within the low-carbon energy sector, and ensure a robust talent supply to support high-quality innovation in new energy firms.

Regarding the financial environment, financial institutions could innovatively develop financing products with flexible maturity structures and preferential interest rates, tailored to the new energy sector's characteristics of substantial capital requirements and extended investment recovery. At the same time, governments should encourage financial institutions to integrate their operations with digital technologies and establish new energy data platforms. Financial institutions can use such platforms to conduct comprehensive credit assessments of enterprises, opening up diversified financing channels for new energy companies.

Regarding public services, when they are underdeveloped, governments should prioritize strengthening infrastructure to ensure the provision of essential public services. Once a foundational level of service has been achieved, however, the focus should shift toward enhancing service efficiency and quality. Governments can leverage digital technologies such as artificial intelligence and big data to redesign service processes, foster cross-departmental resource integration and collaboration, and lower the cost of public service delivery. This would not only improve operational efficiency but also create a more supportive environment for innovation in new energy firms.

The government should fully consider the technological innovation needs of enterprises with different ownership and the distinct regional environments they operate in, then tailor the business environment accordingly to promote high-quality innovation in new energy firms. For state-owned firms and those located in the eastern and central regions, the government should prioritize improving urban financial environment and human resources. This includes supporting the development of green bonds, venture

capital, and industrial funds in these regions to attract capital investments into new energy industries. Additionally, the eastern and central regions should be encouraged to formulate specialized talent plans for the new energy industry and establish mechanisms for talent exchange. Policy measures such as government digitalization and tax preferences can be utilized to provide non-state-owned firms with essential government support.

6.3. Limitations

First, considering data completeness and availability, we chose 2019 as the cutoff point of our data. In future research, extending the timeframe of our data is an important direction. We will instantly extend the timeframe with updated data.

Second, our study adopts a predictive framework. Therefore, the results should be interpreted as predictive associations and variable importance rather than causal effects or mechanisms. Future research could employ causal inference or causal machine learning methods to further explore the causal relationships between the business environment and innovation quality.

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