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When Green Accounting Fails to Drive Green Energy: Institutional Quality and China's Renewable Energy Transition

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Abstract: This study examines how institutional quality, government R&D expenditure, and SEEA-aligned environmental asset indicators are associated with renewable energy adoption in China from 1999 to 2023. It addresses the puzzle that environmental accounting signals and innovation investment do not automatically translate into renewable energy use. Annual data from the World Development Indicators and Worldwide Governance Indicators were analyzed using a hybrid empirical strategy. The Autoregressive Distributed Lag approach was applied to estimate short-run and long-run relationships, while Double Machine Learning, Random Forest, Gradient Boosting, and SHAP interpretability were used as supplementary tools for robustness and predictive importance. Given the limited sample size, machine-learning results are interpreted as orthogonalized associations and as predictive evidence rather than as definitive causal effects. ARDL results show that regulatory quality has a positive and statistically significant long-run association with renewable energy adoption. In contrast, government R&D expenditure and adjusted net savings show negative associations, suggesting that innovation spending and fiscal capacity may not support renewable energy adoption unless directed toward deployment and energy-system substitution. Energy resource depletion is statistically insignificant, while natural resource rents show a weak positive long-run association. Machine-learning results identify government R&D expenditure as the strongest predictor, although its direction remains negative. The findings indicate that China's renewable energy transition depends less on fiscal or technological inputs alone and more on the institutional capacity to convert these inputs into adoption outcomes. The study implies that SEEA-based indicators should be integrated with regulatory mechanisms, deployment-oriented innovation policy, and outcome-based evaluation of energy transition.

Keywords: Renewable Energy Adoption, Institutional Quality, SEEA, Environmental Accounting, Adjusted Net Savings, China

1. Introduction

Renewable energy adoption (REA) has become a central pillar of global climate governance, with direct implications for industrial competitiveness, energy security, geopolitical dependence, and ecological stability (Narang, 2025; Wu et al., 2025). As countries accelerate their decarbonization strategies, the expansion of renewable energy is increasingly viewed not only as an environmental necessity but also as an indicator of institutional capacity and long-term fiscal sustainability. Empirical evidence suggests that higher renewable energy penetration contributes meaningfully to emissions reduction, with a 1% increase in renewable penetration associated with a 1.14% decline in CO_2 emissions in emerging markets (Fernandes et al., 2025; Ayaz Atalan et al., 2025). In addition to its mitigation function, REA reflects the ability of national institutions to convert environmental constraints into structural economic transformation. In China, this relationship is particularly important because the scale and pace of renewable energy adoption directly affect the feasibility of the country's dual-carbon targets: reaching peak carbon emissions by 2030 and achieving carbon neutrality by 2060 (Zhang, Muhammad, Dai, Khan, & Ahmad, 2024). Moreover, China's renewable energy transition has broader international relevance, given its influence on green infrastructure investment and energy cooperation under the Belt and Road Initiative (Zhao, Ju, Xue, Ren, Ji, & Chen, 2022).

Despite China's position as one of the world's largest renewable energy investors and its substantial contribution to annual global renewable capacity additions (IEA, 2023), its renewable energy adoption pathway continues to reveal a gap between policy ambition and actual energy transition outcomes. Renewable energy consumption as a share of total final energy consumption reached 15.2% in 2023, remaining below the level required to support China's 2030 transition commitments (World Bank, 2023). This gap persists despite considerable fiscal investment, technological development, and public innovation expenditure. Therefore, the challenge does not appear to be merely a matter of the availability of financial or technological resources. Rather, it may reflect inefficient resource allocation toward fossil-intensive infrastructure, weak policy transmission mechanisms, and institutional constraints that limit the conversion of fiscal and technological inputs into measurable renewable energy outcomes (Zhao et al., 2023; Wang et al., 2025; Dawo & Khalifa, 2025). Understanding the structural drivers of this decoupling is consequently essential for strengthening China's national climate strategy.

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This policy puzzle remains insufficiently explained by existing theoretical and empirical frameworks. The System of Environmental-Economic Accounting (SEEA) provides a rigorous biophysical foundation for sustainability assessment by measuring natural capital depletion, resource rents, and adjusted savings as indicators of intergenerational welfare (United Nations, 2012). However, SEEA-based indicators do not automatically translate into energy transition outcomes (Goodland & Daly, 1996). Their policy relevance depends on whether environmental accounting signals are recognized, interpreted, and acted upon by effective institutions. Institutional Theory, therefore, provides a necessary complementary perspective by emphasizing the role of regulatory quality, enforcement capacity, and governance credibility in shaping whether environmental indicators become operational policy instruments (Ganda, 2022; Olaniyi & Odhiambo, 2024; Epis, 2025). Although previous studies have examined SEEA-related indicators, institutional quality, and innovation expenditure, these factors are often analyzed separately or through fragmented interaction models. Limited research has systematically integrated SEEA-aligned environmental asset indicators with institutional and innovation variables in a unified China-specific model of renewable energy adoption.

Methodological limitations further restrict the existing literature. Studies on China's energy transition frequently rely on ARDL, GMM, or related econometric approaches, which are useful for examining long-run relationships and mixed integration orders but may remain vulnerable to omitted-variable bias, nonlinear confounding, and complex policy interactions (Li et al., 2024; Zhang, Li& Zhang, 2023). Conversely, recent machine-learning applications often prioritize predictive accuracy while giving less attention to theoretical interpretability, long-run equilibrium relationships, and policy-relevant marginal associations (Tang et al., 2024; Tashbaeva et al., 2024). As a result, there remains a need for an integrated framework that combines econometric estimation with interpretable machine-learning tools. Such a framework can help assess long-run relationships, isolate orthogonalized associations, and evaluate the relative predictive importance of institutional, fiscal, innovation, and environmental accounting indicators.

To address these theoretical and methodological gaps, this study examines how institutional quality, government R&D expenditure, and SEEA-consistent environmental asset indicators shape renewable energy adoption in China from 1999 to 2023. Specifically, the study addresses the following research questions:

1. To what extent is regulatory quality associated with renewable energy adoption in China?
2. How do SEEA-aligned indicators, including adjusted net savings, energy resource depletion, and natural resource rents, relate to renewable energy adoption?
3. Does the integration of ARDL estimation with machine-learning-based interpretability provide additional insight into the relative importance of institutional, innovation, and environmental accounting indicators in China's renewable transition?

By addressing these questions, the study contributes to the literature in three ways. First, it links SEEA-based environmental accounting indicators to Institutional Theory to explain why environmental accounting signals may fail to generate renewable energy outcomes in the absence of effective governance channels. Second, it develops a China-specific empirical framework that considers institutional quality, government R&D expenditure, adjusted net savings, energy depletion, and natural resource rents within a single model. Third, it combines ARDL estimation with orthogonalized machine-learning diagnostics and SHAP-based interpretability to provide a more transparent assessment of the relationships among environmental accounting, governance, innovation, and renewable energy adoption. These contributions offer evidence that may inform governance-focused renewable energy policy in China and other emerging economies facing similar institutional and environmental transition challenges.

2. Literature Review

2.1. Literature Review and Hypothesis Development

Renewable energy adoption (REA) has become a central indicator of climate-policy effectiveness, energy security, and long-term sustainability. In China, this issue is particularly important because the country's dual-carbon targets require a substantial transformation of the energy structure and a gradual reduction in fossil-fuel dependence (Robinson & Acemoglu, 2012; Aboulajras et al., 2025). Although China has expanded renewable energy capacity and invested heavily in green technologies, renewable energy consumption as a share of total final energy consumption declined from 30.3% in 1999 to 15.2% in 2023 (World Bank, 2023). This trend suggests that investment and installed capacity do not automatically translate into effective renewable energy adoption. Therefore, the literature increasingly emphasizes the role of institutional quality, innovation expenditure, and environmental accounting indicators in explaining the uneven progress of energy transition.

Institutional quality is widely recognized as a key condition for renewable energy adoption. Regulatory quality, in particular, reflects the capacity of the state to design, implement, and enforce policies that support clean energy deployment. Berrich et al. (2024) show that institutional enforcement can accelerate renewable energy adoption by strengthening policy credibility and reducing implementation uncertainty. Similarly, Zhang, Godil, Badr, and Lu (2024) find that regulatory quality supports emissions reduction through renewable energy expansion, while Wu et al. (2025) link governance capacity to sectoral decarbonization in China. These studies indicate that institutions shape the extent to which energy policies become operational outcomes. However, most existing studies examine regulatory quality either as part of a broader governance index or as a moderating variable, rather than estimating its separate relationship with renewable energy adoption in China (Vasa et al., 2024; Tang & Zhou, 2025; Shang et al., 2025; Ayaz Atalan et al., 2025). This creates a gap in understanding whether regulatory quality independently explains renewable energy adoption in a state-led transition system.

Government R&D expenditure is another important driver of renewable energy transition, yet its effect remains empirically contested. In advanced economies, innovation expenditure often supports renewable deployment by improving technology development, commercialization, and energy efficiency (Adu et al., 2024). However, in emerging and state-led economies, the relationship may be weaker or delayed because public R&D can be allocated to fossil-fuel efficiency, grid modernization, or industrial upgrading rather than direct renewable substitution (Andriamahery & Qamruzzaman, 2022). Moreover, weak commercialization channels and fragmented regulatory systems can reduce the ability of innovation spending to generate measurable renewable energy outcomes. Therefore, although government R&D expenditure is theoretically relevant, its direct association with renewable energy adoption requires further examination in China's institutional context.

Hypothesis 1 (H1): *Regulatory quality is positively associated with renewable energy adoption in China, whereas the association between government R&D expenditure and renewable energy adoption is context-dependent.*

Environmental accounting indicators provide another important perspective on the renewable energy transition. The System of Environmental-Economic Accounting (SEEA) links economic activity with natural capital depletion, resource rents, and sustainability-adjusted saving (United Nations, 2012). Adjusted net savings (ANS), energy resource depletion (ERD), and natural resource rents (NRR) are therefore useful indicators for assessing whether economic development is environmentally sustainable. Nevertheless, the relationship between these indicators and renewable energy adoption remains unclear. Adjusted net savings may support renewable energy adoption when national savings are directed toward green investment and long-term sustainability (Kukharets et al., 2024). However, when fiscal resources are used to support conventional infrastructure or fossil-intensive development, higher savings may not lead to renewable energy expansion (Atuahene et al., 2025).

Similarly, natural resource rents may either support or delay renewable energy adoption. In countries with strong governance and transparent revenue allocation, resource rents can finance renewable subsidies, infrastructure, and green innovation (Sarosh & Yen, 2024). Conversely, in rent-dependent economies, resource rents may reinforce fossil-fuel lock-in by sustaining extractive industries and reducing incentives for energy diversification (Latif et al., 2025). Energy resource depletion also has an ambiguous role. Theoretically, higher depletion should encourage renewable substitution; however, depletion may remain only an accounting signal unless institutions convert it into effective policy action through regulation, pricing, or investment redirection (Sibanda et al., 2023; Chen & Usman, 2025). Existing studies often examine these SEEA-related indicators separately, and few studies jointly assess their association with renewable energy adoption alongside institutional quality and innovation expenditure (Tashbaeva et al., 2024; Hacıimamoğlu & Cengiz, 2024; Liu et al., 2025). This gap is important because environmental accounting indicators may have limited policy value unless they are connected to institutional and investment mechanisms.

Hypothesis 2 (H2): *SEEA-aligned indicators, including adjusted net savings, energy resource depletion, and natural resource rents, have heterogeneous associations with renewable energy adoption in China.*

Methodologically, existing studies on renewable energy transition in China commonly rely on ARDL, GMM, or related econometric approaches (Zhang et al., 2023; Li et al., 2024; Sarosh & Yen, 2024). These methods are useful for examining long-run relationships and mixed integration orders. However, they may be limited in capturing nonlinear patterns and shared variation among institutional, fiscal, and environmental variables. At the same time, recent machine-learning studies often emphasize prediction but provide limited theoretical interpretation (Rubanenko, 2024; Shang et al., 2025). Consequently, there remains a need for an integrated empirical approach that combines long-run econometric estimation with interpretable machine-learning diagnostics. Such an approach can help assess the relative importance of institutional quality, innovation expenditure, and SEEA-aligned indicators in explaining renewable energy adoption.

Hypothesis 3 (H3): *Regulatory quality, government R&D expenditure, adjusted net savings, energy resource depletion, and natural resource rents jointly explain renewable energy adoption in China, with institutional quality expected to play a central role.*

2.2. Theoretical Framework

This study is grounded in the integration of the System of Environmental-Economic Accounting and Institutional Theory. SEEA provides the environmental accounting foundation for understanding how natural capital depletion, resource rents, and adjusted savings reflect the sustainability of economic development. It expands conventional economic accounting by incorporating environmental stocks, resource flows, depletion, and degradation into national accounts (United Nations, 2012). From this perspective, adjusted net savings, energy resource depletion, and natural resource rents are not merely statistical indicators; rather, they signal whether economic growth is compatible with long-term environmental sustainability.

Institutional Theory complements SEEA by explaining why environmental accounting signals do not automatically lead to policy action. According to North (1990), institutions shape incentives, constraints, and economic behavior through formal and informal rules. In the context of energy transition, regulatory quality determines whether environmental indicators are translated into renewable energy policies, investment decisions, and enforcement mechanisms. Strong institutions can reduce policy uncertainty, improve compliance, limit rent-seeking, and direct fiscal resources toward renewable energy development. Conversely, weak institutional capacity can prevent environmental accounting indicators from influencing actual energy-transition outcomes.

The combined SEEA–Institutional framework is therefore appropriate for examining renewable energy adoption in China Lütkepohl, 2005; Megnidio-Tchoukouegno & Adedeji, 2023; Ozkan & Okay, 2024). SEEA explains what should be measured: adjusted net savings, energy depletion, and natural resource rents. Institutional Theory explains how these indicators may influence renewable energy adoption through regulatory quality, policy credibility, and implementation capacity (Qu et al., 2024). Within this framework, regulatory quality is expected to function as a key institutional condition, while government R&D expenditure represents the innovation channel through which technological capacity may support renewable energy deployment. At the same time, ANS, ERD, and NRR capture the environmental asset conditions that may either encourage or constrain the transition.

Based on this framework, renewable energy adoption is treated as the outcome of interaction between environmental accounting signals, institutional capacity, and innovation expenditure. ARDL estimation is used to examine short-run and long-run relationships, while machine-learning diagnostics are used to assess relative predictive importance and conditional associations. This theoretical structure allows the study to evaluate whether China's renewable energy adoption is driven primarily by environmental accounting indicators, innovation expenditure, or the institutional capacity needed to convert these factors into effective transition outcomes.

3. Methodology

This study employs a quantitative time-series design to examine the relationships among institutional quality, innovation expenditure, SEEA-aligned environmental asset indicators, and renewable energy adoption in China over the period 1999–2023. China is selected because its renewable energy transition is shaped by large-scale public investment, persistent fossil-fuel dependence, environmental accounting reforms, and dual-carbon policy commitments. Therefore, the Chinese case provides an appropriate setting for examining whether institutional quality and environmental accounting indicators are associated with actual renewable energy adoption. Annual data are obtained from the World Development Indicators and Worldwide Governance Indicators of the World Bank. Renewable energy adoption (REA) is used as the dependent variable and measured as the share of renewable energy consumption in total final energy consumption. The explanatory variables are regulatory quality (RQ), government R&D expenditure (GRE), adjusted net savings (ANS), energy resource depletion (ERD), and natural resource rents (NRR). These variables capture the institutional, innovation-related, and environmental asset dimensions of China's renewable energy transition.

Table 1: Variable Definitions and Data Sources

Variable	Proxy / Measurement	Code	Theoretical Rationale
Renewable Energy Adoption (REA)	Renewable energy consumption (% of total final energy consumption)	EG.FEC.RNEW.ZS	Captures the physical-flow dimension of renewable energy transition
Regulatory Quality (RQ)	Regulatory Quality: Percentile Rank	RQ.PER.RNK	Measures institutional capacity to formulate and implement effective policies
Government R&D Expenditure (GRE)	Research and development expenditure (% of GDP)	GB.XPD.RSDV.GD.ZS	Reflects public innovation investment that may support renewable technologies
Energy Resource Depletion (ERD)	Adjusted savings: energy depletion (% of GNI)	NY.ADJ.DNGY.GN.ZS	Measures the economic cost of fossil-energy stock depletion
Natural Resource Rents (NRR)	Total natural resource rents (% of GDP)	NY.GDP.TOTL.RT.ZS	Captures extractive income that may support or delay renewable transition
Adjusted Net Savings (ANS)	Adjusted net savings (% of GNI)	NY.ADJ.NNAT.GN.ZS	Represents sustainability-adjusted saving after accounting for depletion and environmental damage

REA, GRE, ANS, ERD, and NRR are transformed into natural logarithms to reduce skewness and improve coefficient interpretation. RQ is retained in its original percentile-rank form because it is already standardized.

The baseline empirical model is specified as follows:

$$lnREA_t = \beta_0 + \beta_1 lnANS_t + \beta_2 lnERD_t + \beta_3 lnGRE_t + \beta_4 lnNRR_t + \beta_5 RQ_t + \varepsilon_t$$

where $lnREA_t$ denotes renewable energy adoption, $lnANS_t$ denotes adjusted net savings, $lnERD_t$ denotes energy resource depletion, $lnGRE_t$ denotes government R&D expenditure, $lnNRR_t$ denotes natural resource rents, and RQ_t denotes regulatory quality. The term ε_t represents the error term, while t denotes the year. This specification is consistent with the study's SEEA–Institutional framework because it combines environmental accounting indicators, innovation expenditure, and institutional quality within a single empirical model.

The Autoregressive Distributed Lag approach is used to estimate the short-run and long-run relationships among the variables. ARDL is appropriate because it performs well in small-sample time-series studies and can be applied when variables are integrated at I(0), I(1), or a combination of both, provided that no variable is integrated at I(2) (Pesaran et al., 2001; Narayan, 2005). Before estimating the ARDL model, the Augmented Dickey–Fuller test is used to examine the stationarity properties of each variable (Dickey & Fuller, 1979). The optimal lag length is then selected using standard information criteria to ensure a parsimonious dynamic specification. After confirming the integration order of the variables, the ARDL bounds test is applied to assess the existence of a long-run relationship among them. Once cointegration is confirmed, the error-correction model is estimated to evaluate short-run adjustment toward the long-run equilibrium. The short-run error-correction specification is expressed as follows:

$$\Delta lnREA_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \Delta lnREA_{t-i} + \sum_{i=0}^{q_1} \beta_i \, \Delta lnANS_{t-i} + \sum_{i=0}^{q_2} \theta_i \, \Delta lnERD_{t-i} + \sum_{i=0}^{q_3} \lambda_i \, \Delta lnGRE_{t-i} + \sum_{i=0}^{q_4} \phi_i \, \Delta lnNRR_{t-i} + \sum_{i=0}^{q_5} \psi_i \, \Delta RQ_{t-i} + \delta ECT_{t-1} + \varepsilon_t$$

where Δdenotes the first-difference operator, $ECT_{t-1}$is the lagged error-correction term, $p$and $q$represent the selected lag orders, and $\varepsilon_t$is the error term. A negative and statistically significant coefficient of ECT_{t-1}indicates that short-run deviations from long-run equilibrium are corrected over time. In addition to the ARDL estimation, pairwise Granger causality tests are conducted to examine the predictive direction between renewable energy adoption and the explanatory variables. The Granger causality framework evaluates whether past values of one variable provide statistically significant information for predicting another variable (Granger, 1969). The general specification is expressed as follows:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, Y_{t-i} + \sum_{i=1}^{p} \beta_i \, X_{t-i} + \varepsilon_t$$

where $Y_t$represents the dependent variable, $X_t$represents the explanatory variable being tested, $p$denotes the selected lag length, and $\varepsilon_t$is the error term. The null hypothesis states that $X_t$does not Granger-cause Y_t. Rejection of the null indicates predictive precedence, meaning that past values of $X_t$help explain variations in Y_t. However, the test is interpreted as evidence of temporal predictability rather than structural causality. The full Granger causality results are reported in Appendix Table A2. Impulse response functions and variance decomposition are also used as supplementary dynamic tools. The impulse response function traces the response of renewable energy adoption to shocks to the explanatory variables, while variance decomposition identifies the proportion of the forecast error variance in renewable energy adoption explained by each variable over time (Lütkepohl, 2005). These analyses are used only as supplementary dynamic evidence and are reported in Appendix Tables A3 and A4.

Given the high correlations among some SEEA-aligned indicators, particularly adjusted net savings, energy resource depletion, and natural resource rents, multicollinearity is acknowledged as a potential concern. Therefore, the related coefficients are interpreted with caution, especially when statistical significance and theoretical expectations diverge. This is particularly important in a small-sample time-series setting, where highly correlated regressors may affect coefficient stability. Several diagnostic and stability tests are conducted to assess the model's reliability. The Breusch–Godfrey test is used to examine serial correlation, while the Breusch–Pagan-Godfrey test is used to detect heteroskedasticity (Breusch & Godfrey, 1978; Breusch & Pagan, 1979). The Ramsey RESET test is applied to assess functional-form misspecification, and the Jarque–Bera test is used to evaluate the normality of the residuals (Ramsey, 1969; Jarque & Bera, 1980). In addition, CUSUM and CUSUMSQ tests are used to examine parameter stability across the study period (Brown et al., 1975).

To complement the econometric analysis, machine-learning-based robustness and interpretability techniques are applied. Double Machine Learning is used to estimate orthogonalized associations between each explanatory variable and renewable energy adoption after accounting for shared variation among the remaining predictors (Chernozhukov et al., 2018). Gradient Boosting is used for nuisance function estimation, while cross-fitting is used to reduce overfitting. However, because the study relies on a small annual time-series sample, DML is not treated as definitive evidence of causality. Instead, it is used as a supplementary robustness tool. Random Forest and Gradient Boosting models are also used to assess predictive importance, while SHAP values are applied to interpret the relative contribution of each variable to model predictions (Breiman, 2001; Friedman, 2001; Lundberg & Lee, 2017). These outputs are interpreted as predictive and diagnostic evidence rather than direct causal effects. Finally, one-standard-deviation scenario simulations are used to compare the relative magnitude of changes associated with each explanatory variable. These simulations help illustrate how standardized changes in institutional quality, innovation expenditure, and SEEA-aligned indicators are associated with changes in renewable energy adoption. However, because the analysis is based on observational time-series data, the scenario results are interpreted as model-based associations rather than definitive policy effects.

4. Results and Findings

4.1. Descriptive Statistics and Correlation Analysis

Table 2 presents the descriptive statistics and correlation matrix for renewable energy adoption (REA), adjusted net savings (ANS), energy resource depletion (ERD), government R&D expenditure (GRE), natural resource rents (NRR), and regulatory quality (RQ). The mean value of REA is 16.812, with a standard deviation of 6.060, indicating substantial variation in renewable energy adoption across the study period. The wide range between the minimum value of 11.300 and the maximum value of 30.300 suggests that China's renewable energy adoption followed a non-linear pattern rather than a stable upward trajectory.

ANS records a mean value of 25.367, suggesting relatively high sustainability-adjusted savings during the sample period. However, its variation indicates that environmental savings were not stable across China's different phases of industrial and policy transformation. ERD has a mean of 1.564, while NRR records a mean of 3.277 and a relatively large standard deviation of 2.337. This indicates that natural-resource dependence fluctuated considerably across the sample period. GRE has a mean of 1.727, reflecting a gradual but relatively stable commitment to R&D expenditure. Meanwhile, RQ records a mean of 41.876, suggesting moderate institutional quality with limited variation compared with the economic and environmental variables.

Table 2: Descriptive Statistics and Correlation Matrix

Panel A. Descriptive Statistics

Variable	Mean	Median	Minimum	Maximum	Std. Dev.
REA	16.812	14.900	11.300	30.300	6.060
ANS	25.367	24.218	17.494	34.613	5.651
ERD	1.564	1.223	0.362	4.225	1.033
GRE	1.727	1.780	0.750	2.555	0.549
NRR	3.277	2.310	0.864	9.648	2.337
RQ	41.876	41.905	31.892	49.510	4.203

Panel B. Correlation Matrix

Variable	LN_REA	LN_ANS	LN_ERD	LN_GRE	LN_NRR	RQ
LN_REA	1.000					
LN_ANS	0.007	1.000				
LN_ERD	0.087	0.803***	1.000			
LN_GRE	-0.724***	-0.488**	-0.512***	1.000		
LN_NRR	-0.080	0.791***	0.824***	-0.354*	1.000	
RQ	-0.489**	0.454**	0.339*	0.194	0.419**	1.000

*Note: REA = Renewable Energy Adoption; RQ = Regulatory Quality; GRE = Government R&D Expenditure; ERD = Energy Resource Depletion; NRR = Natural Resource Rents; ANS = Adjusted Net Savings. LN denotes natural logarithmic transformation. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.*

The correlation matrix reveals several important patterns. REA is negatively correlated with GRE ($r = -0.724$, $p < 0.01$) and RQ ($r = -0.489$, $p < 0.05$). Although this may seem counterintuitive, these bivariate correlations should be interpreted with caution because they do not account for dynamic effects, lag structures, or shared variation among explanatory variables. The negative association between GRE and REA may reflect delayed commercialization, resource misallocation, or the possibility that innovation expenditure did not directly translate into renewable energy use during the study period. In addition, REA has a weak positive correlation with ERD and is almost unrelated to ANS, suggesting that environmental asset indicators alone may not automatically generate renewable energy adoption.

The high correlations among ANS, ERD, and NRR indicate that environmental asset indicators are closely connected. Specifically, ANS is strongly correlated with ERD (0.803, $p < 0.01$) and NRR (0.791, $p < 0.01$), while ERD is strongly correlated with NRR (0.824, $p < 0.01$). These relationships suggest that resource depletion, extractive rents, and sustainability-adjusted savings are structurally linked in China's development pathway. Therefore, the subsequent econometric and machine-learning analyses are necessary to assess their separate associations with renewable energy adoption. Variance inflation factors were examined to assess multicollinearity among the explanatory variables. The results indicate that multicollinearity does not materially alter the interpretation of the main ARDL estimates.

4.2. Pre-estimation Tests and Cointegration

Table 3 reports the pre-estimation tests. The Augmented Dickey–Fuller results indicate that ln_rea, ln_erd, ln_gre, ln_nrr, and rq are stationary at the level, whereas ln_ans becomes stationary after first differencing. Therefore, the variables are integrated at a mixture of I(0) and I(1). This supports the use of the ARDL approach, provided that no variable is integrated at I(2). The lag-selection results identify one lag as the optimal structure, which is appropriate given the limited sample size and the need to preserve degrees of freedom. In addition, the ARDL bounds test produces an F-statistic of 54.133, which exceeds the 1% upper critical bound of 4.15. This confirms the existence of a long-run relationship among renewable energy adoption, adjusted net savings, energy resource depletion, government R&D expenditure, natural resource rents, and regulatory quality. The full VAR lag-order selection results are reported in Appendix Table A1.

Table 3: Pre-estimation Tests: Unit Root, Lag Selection, and Cointegration

Panel A. ADF Unit Root Test

Variable	Level ADF Result	First-Difference ADF Result	Decision
ln_rea	-3.078 (0.005)	-2.620 (0.016)	I(0)
ln_ans	-0.169 (0.867)	-2.851 (0.010)	I(1)
ln_erd	-2.574 (0.018)	-5.635 (0.000)	I(0)
ln_gre	-4.155 (0.000)	-4.959 (0.000)	I(0)
ln_nrr	-2.107 (0.047)	-5.164 (0.000)	I(0)
rq	-2.215 (0.037)	-5.399 (0.000)	I(0)

Panel B. Lag Selection and ARDL Bounds Test

Test	Result	Decision
Optimal lag length	1	Selected by information criteria
ARDL bounds F-statistic	54.133	Cointegration confirmed
1% lower bound	3.06	
1% upper bound	4.15	F-statistic exceeds upper bound

Note: The mixed I(0)/I(1) integration order supports the use of ARDL. The full lag-selection table may be placed in the appendix.

4.3. ARDL Short-run and Long-run Findings

Table 4 reports the ARDL short-run and long-run estimates. The long-run results show that regulatory quality has a positive and statistically significant association with renewable energy adoption ($\beta = 0.012$, $p = 0.017$). This supports the argument that institutional capacity is important for translating energy-transition objectives into measurable renewable energy outcomes. Although the coefficient is relatively small, its positive direction and statistical significance indicate that improvements in regulatory quality are associated with higher renewable energy adoption over time. This finding is consistent with the institutional argument that credible regulation, policy enforcement, and administrative capacity facilitate clean energy transition (Berrich et al., 2024; Zhang, Wang, Qi, He, Yang, Cai, & Chai, 2024). Additional dynamic tests were conducted to examine predictive temporal relationships and adjustment patterns. The full Granger causality results are provided in Appendix Table A2.

By contrast, adjusted net savings have a negative and statistically significant long-run association with renewable energy adoption ($\beta = -1.530$, $p < 0.01$). This result is contrary to the expectation that higher sustainability-adjusted savings should support the renewable energy transition. A plausible interpretation is that savings and fiscal capacity may not have been consistently directed toward renewable energy deployment. Instead, they may have supported broader infrastructure, industrial expansion, or fossil-intensive activities at certain points in the sample period. Therefore, ANS appears to function as a sustainability accounting indicator rather than an automatic driver of renewable energy adoption. Government R&D expenditure also shows a negative and statistically significant long-run association with renewable energy adoption ($\beta = -0.976$, $p < 0.01$). This finding suggests that public innovation expenditure did not translate directly into renewable energy consumption during the period under study. The result may reflect commercialization delays, the allocation of R&D toward fossil-fuel efficiency or grid reliability, or weak conversion of innovation spending into actual renewable energy use. Therefore, the findings do not reject the importance of innovation; rather, they suggest that innovation expenditure requires effective institutional and market transmission channels.

Natural resource rents have a positive but marginally significant long-run association with renewable energy adoption ($\beta = 0.306$, $p = 0.061$). This result suggests that resource rents may have supported renewable energy adoption to some extent, possibly through fiscal capacity or state-led investment. However, the marginal significance suggests that this relationship should be interpreted with caution. Energy resource depletion is negative but statistically insignificant ($\beta = -0.277$, $p = 0.110$), indicating that depletion pressure alone does not appear to induce renewable substitution in the absence of effective policy transmission. In the short run, GRE and NRR have negative and statistically significant coefficients. This suggests that innovation expenditure and resource rent dynamics may generate adjustment costs before contributing to the renewable energy transition. RQ is also weakly negative in the short run, which may reflect temporary implementation frictions associated with regulatory reform. The error-correction term is negative and statistically significant ($\beta = -0.270$, $p < 0.01$), indicating that approximately 27% of short-run disequilibrium is corrected each year. This adjustment speed suggests that China's renewable energy transition is gradual and structurally sticky.

Table 4: ARDL Short-run and Long-run Estimates

Variable	Coefficient	Std. Error	t-Statistic	p-value
Short-run coefficients				
D(LN_ANS)	0.061	0.045	1.345	0.202
D(LN_ERD)	0.045	0.026	1.701	0.113
D(LN_GRE)	-0.263	0.040	-6.520	0.000
D(LN_NRR)	-0.086	0.028	-3.033	0.010
D(RQ)	-0.001	0.001	-2.029	0.064
CointEq(-1)	-0.270	0.015	-18.137	0.000
Long-run coefficients				
LN_ANS	-1.530	0.178	-8.611	0.000
LN_ERD	-0.277	0.161	-1.714	0.110
LN_GRE	-0.976	0.087	-11.180	0.000
LN_NRR	0.306	0.149	2.052	0.061
RQ	0.012	0.004	2.747	0.017
C	7.369	0.476	15.493	0.000

Note: The dependent variable is LN_REA. The negative and statistically significant error-correction term confirms adjustment toward the long-run equilibrium.

4.4. Diagnostic and Stability Tests

Table 5 reports the diagnostic and stability tests used to assess the reliability of the ARDL estimates. The Breusch–Godfrey F-statistic is not statistically significant (p = 0.133), indicating little evidence of serial correlation. However, the Obs*R-squared statistic is significant (p = 0.025), indicating some sensitivity to serial correlation in the diagnostics. Therefore, this result should be acknowledged cautiously rather than dismissed. The Breusch–Pagan-Godfrey test indicates no evidence of heteroskedasticity, while the Ramsey RESET test confirms that the model does not suffer from major functional-form misspecification. In addition, the Jarque–Bera test supports the approximate normality of the residuals. Supplementary dynamic evidence from the impulse response function and variance decomposition is reported in Appendix Tables A3 and Appendix Tables A4.

Figure 1 presents the residual normality plot. The distribution of residuals is approximately centered around zero, with a skewness of 0.384 and a kurtosis of 2.011. The Jarque–Bera p-value of 0.456 further supports the assumption of normality of the residuals. This indicates that the residual distribution does not substantially violate the assumptions required for valid ARDL inference.

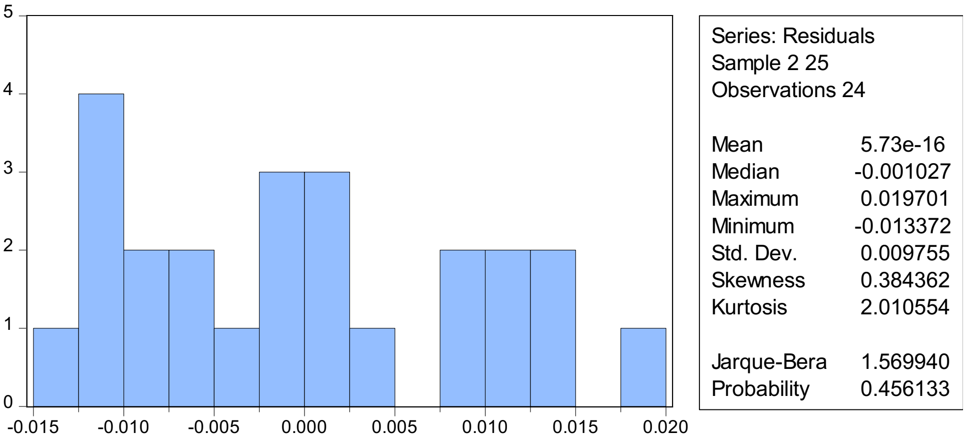

Figure 1: Residual Normality Test

Figure 2 reports the CUSUM and CUSUMSQ stability plots. The CUSUM line remains within the 5% critical bounds, indicating that the estimated coefficients are stable over the study period. Similarly, the CUSUMSQ plot remains within the critical boundaries, suggesting that the model does not suffer from major structural instability. This is important because the study period includes significant changes in China's energy policy, industrial structure, and environmental governance.

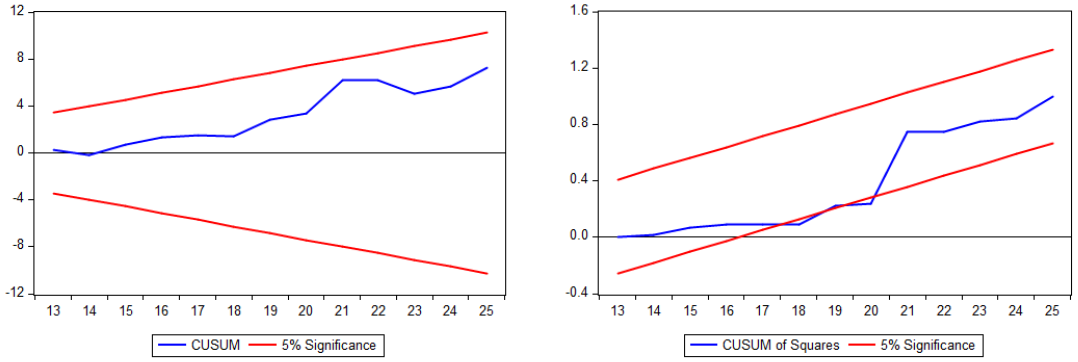

Figure 2: CUSUM and CUSUMSQ Stability Tests

Taken together, the diagnostic and stability results indicate that the ARDL model is broadly reliable. Nevertheless, the significant Obs*R-squared value in the Breusch–Godfrey test suggests that serial-correlation sensitivity should be reported as a limitation.

Table 5: Post-estimation Diagnostic and Stability Tests

Diagnostic Test	Statistic	p-value / Result	Decision
Breusch–Godfrey Serial Correlation LM Test	F = 2.433	0.133	No serial correlation based on F-test
Breusch–Godfrey Obs*R^2	7.360	0.025	Sensitive result; caution required
Breusch–Pagan-Godfrey Test	F = 0.738	0.680	No heteroskedasticity
Breusch–Pagan Obs*R^2	8.694	0.561	No heteroskedasticity
Ramsey RESET Test	F = 1.234	0.289	No functional-form misspecification
Jarque–Bera Normality Test	—	0.456	Residuals approximately normal
CUSUM / CUSUMSQ	—	Within 5% bands	Parameter stability supported

Note: The significant Obs*R^2 value in the Breusch–Godfrey test indicates some sensitivity in the serial-correlation diagnostics. Therefore, the diagnostic evidence is acceptable but should not be overstated.

4.5. Machine-Learning Robustness and Interpretability

To complement the ARDL results, machine-learning-based analyses of robustness and interpretability were conducted. Table 6 presents the DML orthogonalized association estimates. These estimates are interpreted as supplementary evidence rather than definitive causal effects, given the limited annual time-series sample. The results broadly support the ARDL findings. GRE has the largest negative estimate (-0.244), followed by ANS (-0.056) and NRR (-0.048). RQ shows a positive estimate (0.038), although the standard error suggests that this association is relatively weak. ERD has only a small negative estimate (-0.011), indicating limited explanatory relevance after controlling for shared variation among predictors.

Table 6: DML Orthogonalized Association Estimates

Variable	Estimate	Standard Error	Interpretation
LN_ERD	-0.011	0.031	Weak negative association
LN_ANS	-0.056	0.026	Negative association
RQ	0.038	0.036	Positive but weak association
GRE	-0.244	0.118	Strongest negative association
LN_NRR	-0.048	0.025	Negative association

Note: DML estimates are interpreted as orthogonalized associations, not definitive causal effects.

Table 7 combines the scenario simulation and machine-learning predictive-importance results. The one-standard-deviation scenario estimates indicate that GRE has the largest negative association with renewable energy adoption (-0.249), whereas RQ has a positive association (0.038). These results suggest that innovation expenditure was the most influential negative predictor in the sample, while regulatory quality remained the only positive predictor among the main institutional and SEEA-related variables.

The Random Forest and Gradient Boosting results also show that GRE has the highest predictive importance. In the Random Forest model, GRE records the largest SHAP importance value (0.219) and the highest permutation importance (1.254 ± 0.822). Similarly, in the Gradient Boosting model, GRE records the largest SHAP value (0.244) and the highest permutation importance (1.396 ± 0.898). Therefore, both machine-learning models identify GRE as the dominant predictor of renewable energy adoption, although its direction is negative. This should be interpreted as evidence of an innovation-adoption gap rather than of R&D expenditure being inherently harmful.

Table 7: Scenario Simulation and Machine-Learning Predictive Importance

Variable	1 SD Scenario $\Delta\ln(\mathrm{REA})$	RF SHAP	RF Permutation Importance	GB SHAP	GB Permutation Importance
LN_ERD	-0.012	0.004	-0.000 ± 0.002	0.008	0.002 ± 0.002
LN_ANS	-0.057	0.020	0.017 ± 0.014	0.026	0.023 ± 0.023
RQ	0.038	0.037	0.035 ± 0.031	0.010	-0.000 ± 0.006
GRE	-0.249	0.219	1.254 ± 0.822	0.244	1.396 ± 0.898
LN_NRR	-0.049	0.005	0.002 ± 0.003	0.011	0.003 ± 0.003

Note: RF = Random Forest; GB = Gradient Boosting; SHAP = Shapley Additive Explanations. Scenario values represent the estimated change in ln(REA) associated with a one-standard-deviation change in each explanatory variable. Machine-learning results are interpreted as predictive importance rather than causal effects.

Detailed machine-learning robustness results, including DML fold stability, Random Forest importance, Gradient Boosting SHAP values, and permutation importance, are reported in Appendix Table A5. Figure 3 presents the Gradient Boosting SHAP beeswarm plot. The plot shows that GRE has the strongest influence on model predictions, with higher GRE values generally associated with negative SHAP contributions to renewable energy adoption. This supports the interpretation that R&D expenditure did not translate efficiently into renewable energy use during the sample period. RQ shows a smaller but positive contribution, suggesting that stronger regulatory quality is associated with higher predicted renewable energy adoption. ANS, ERD, and NRR show weaker and more mixed contributions, indicating that SEEA-aligned indicators alone do not consistently explain renewable energy adoption in the absence of institutional transmission.

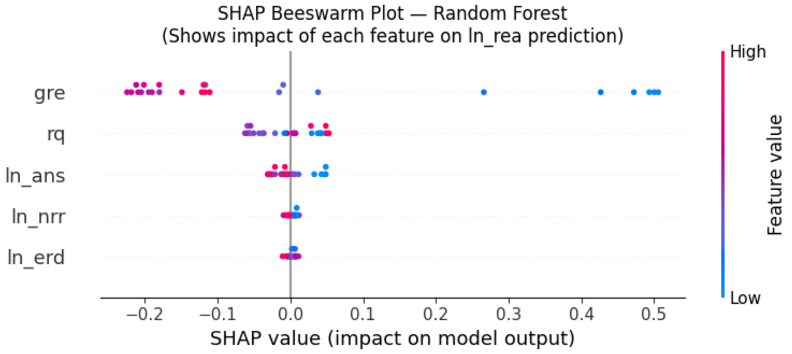

Figure 3: SHAP Beeswarm Plot for Gradient Boosting Model

Figure 4 presents the Random Forest SHAP beeswarm plot. The Random Forest results are broadly consistent with the Gradient Boosting model. GRE again appears as the dominant predictor, while RQ contributes positively but with a smaller magnitude. The consistency across the two models strengthens the interpretation that the negative GRE–REA relationship is not only an ARDL result but also a stable predictive pattern in the machine-learning analysis.

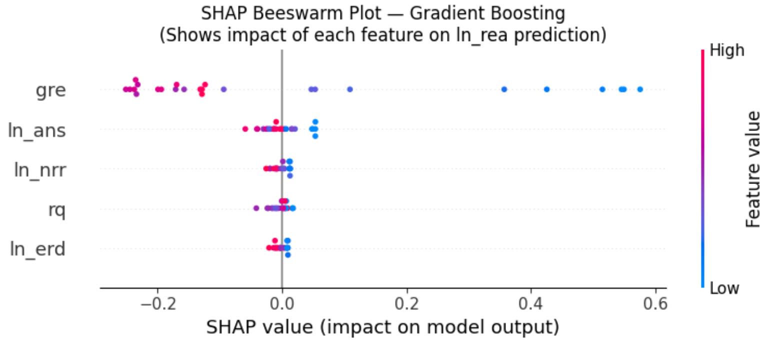

Figure 4: SHAP Beeswarm Plot for Random Forest Model

The SHAP visualizations are important because they clarify not only which variables are influential but also how they contribute to model predictions. In both models, GRE dominates predictive behavior but contributes negatively, while RQ contributes positively. This pattern supports the central argument of the study: China's renewable energy adoption is not constrained simply by the availability of innovation expenditure or fiscal resources; rather, the conversion of these inputs into renewable energy outcomes depends on institutional capacity, policy direction, and implementation effectiveness.

4.6. Interpretation of the Main Findings

The findings provide three important insights. First, regulatory quality is the only variable that shows a positive and statistically significant long-run association with renewable energy adoption in the ARDL model. This supports H1 with respect to the role of institutional quality. The finding suggests that governance capacity, policy credibility, and regulatory enforcement are important for converting climate-policy ambition into renewable energy adoption. However, H1 is only partially supported, as government R&D expenditure does not exhibit the expected positive association.

Second, the negative long-run associations between ANS and GRE indicate that fiscal and innovation-related resources do not automatically lead to renewable energy adoption. This finding is important because it challenges the assumption that higher savings or higher R&D expenditure necessarily accelerates the renewable transition. In China's case, the results suggest that these resources may require stronger institutional alignment, commercialization channels, and targeted deployment mechanisms. Therefore, the findings point to a possible implementation gap between financial or technological capacity and actual renewable energy use.

Third, the SEEA-aligned indicators show mixed results. ANS is negative and significant, ERD is insignificant, and NRR is positive but only marginally significant. Therefore, H2 is supported only insofar as SEEA-related indicators exhibit heterogeneous associations with renewable energy adoption. The results suggest that environmental accounting indicators are useful for measuring sustainability pressures, but they do not necessarily serve as direct drivers of transition unless supported by institutional mechanisms.

H3 receives partial support, as the combined results indicate that institutional quality, innovation expenditure, and SEEA-aligned indicators jointly explain the dynamics of renewable energy adoption. However, the direction of the effects differs from theoretical expectations. GRE is the strongest predictor in the machine-learning models, but its association is negative. RQ is consistently positive in the long-run ARDL model and in the DML results, yet its predictive importance is smaller than that of GRE. This indicates that institutional quality is theoretically central, whereas innovation expenditure is empirically dominant as a predictor due to its strong negative relationship with renewable energy adoption over the sample period.

The findings therefore support the study's SEEA–Institutional argument. SEEA indicators provide important measures of environmental sustainability, but their influence on renewable energy adoption depends on institutional capacity and policy transmission. Similarly, innovation expenditure may not accelerate renewable adoption unless it is directed toward deployment, commercialization, and energy-system substitution. In China's case, the main challenge appears not to be the absence of fiscal or technological resources, but the effectiveness with which these resources are converted into renewable energy use.

To keep the main results section concise, detailed supplementary outputs are provided in the appendix. Appendix Table A1 reports the full lag-order selection criteria, Appendix Table A2 presents the Granger causality tests, Appendix Tables A3 and A4 report the impulse response and variance decomposition results, and Appendix Table A5 provides the detailed machine-learning robustness and predictive-importance results.

5. Discussion

The results provide a nuanced explanation of renewable energy adoption in China by showing that institutional quality, innovation expenditure, and SEEA-aligned environmental asset indicators do not influence renewable energy adoption in the same direction or with the same strength. More importantly, the findings suggest that financial capacity, innovation spending, and environmental accounting signals do not automatically translate into higher renewable energy use. Instead, their relevance depends on the institutional and policy mechanisms through which they are converted into practical energy-transition outcomes.

First, regulatory quality emerges as the most theoretically consistent positive factor. The ARDL results show that regulatory quality has a positive and statistically significant long-run association with renewable energy adoption. Similarly, the DML estimates indicate a positive orthogonalized association, although the effect is weaker. This supports the institutional argument that governance capacity, policy credibility, and regulatory enforcement are central to the energy transition. In China's context, this means that renewable energy adoption depends not only on investment or technology availability but also on whether regulatory institutions can coordinate policy implementation, reduce uncertainty, and guide resources toward renewable deployment. This finding is consistent with prior studies showing that institutional quality strengthens the effectiveness of climate policy and renewable energy investment (Berrich et al., 2024; Zhang et al., 2024; Wu et al., 2025).

Second, the negative association between government R&D expenditure and renewable energy adoption is one of the most important and counterintuitive findings of the study. Both the ARDL and machine-learning results show that GRE is negatively associated with REA, while the SHAP and permutation-importance results identify GRE as the strongest predictor in the model. This does not mean that R&D expenditure is harmful in itself. Rather, it suggests that public innovation expenditure may not have been effectively translated into renewable energy consumption during the study period. Several explanations are possible. R&D spending may have been directed toward fossil-fuel efficiency, industrial upgrading, grid reliability, or technologies with long commercialization periods. In addition, innovation expenditure may require stronger deployment channels, market incentives, and institutional coordination before it can generate measurable renewable energy outcomes. Therefore, the finding points to an innovation-adoption gap rather than a rejection of innovation-led transition theory.

Third, the results show that SEEA-aligned indicators exhibit mixed, and in some cases unexpected, associations with renewable energy adoption. Adjusted net savings have a negative and statistically significant long-run association with REA. This finding challenges the assumption that higher sustainability-adjusted savings automatically support renewable energy adoption. In the Chinese context, fiscal capacity and national saving may have supported infrastructure expansion and industrial development without necessarily resulting in a proportional substitution of renewable energy. This interpretation is consistent with the argument that environmental accounting indicators require institutional transmission before they can influence actual policy outcomes (Adu et al., 2024; Tang & Zhou, 2025). Therefore, ANS should be viewed as a sustainability signal rather than a direct driver of renewable energy.

Energy resource depletion is statistically insignificant in the long-run ARDL model and weak in the machine-learning results. This indicates that depletion pressure alone does not appear to force renewable substitution. Although SEEA treats depletion as an important indicator of unsustainable resource use, the results suggest that depletion becomes policy-relevant only when it is linked to regulation, pricing mechanisms, or mandatory substitution policies. Without such channels, depletion may remain an accounting measure rather than a practical driver of renewable energy adoption.

Natural resource rents show a positive but marginally significant long-run association with renewable energy adoption. This result indicates that resource rents may have contributed to renewable deployment in some periods, possibly by expanding fiscal capacity for state-led investment. However, the weak significance also suggests that resource rents are not a stable or reliable driver of renewable energy adoption. Their effect depends on how resource revenues are governed and whether they are recycled into green infrastructure rather than used to sustain fossil-intensive sectors. This supports the view that natural resource rents can either enable or delay energy transition depending on institutional quality and policy allocation mechanisms (Szetela et al., 2022; Latif et al., 2025).

The findings also clarify the hypotheses. H1 is partially supported: regulatory quality has a positive long-run association with renewable energy adoption, whereas government R&D expenditure shows a negative rather than positive association. H2 is supported only with respect to heterogeneity, as the SEEA-aligned indicators do not move in a uniform direction: ANS is negative, ERD is insignificant, and NRR is marginally positive. H3 is supported because the combined model shows that institutional quality, innovation expenditure, and environmental asset indicators jointly explain renewable energy adoption dynamics. However, the direction of several effects differs from theoretical expectations.

Theoretically, the findings strengthen the value of integrating SEEA with Institutional Theory. SEEA provides important indicators for measuring environmental sustainability, but the results show that these indicators do not automatically produce renewable energy adoption. Institutional Theory explains this limitation by emphasizing that accounting signals require governance capacity, enforcement mechanisms, and policy credibility before they can influence real transition outcomes. Therefore, the study demonstrates that environmental accounting is necessary for sustainability measurement, but institutional quality is necessary for sustainability implementation.

The results also indicate that China's renewable energy transition is not constrained simply by a shortage of fiscal or technological resources. Instead, the central challenge appears to be the conversion of available resources into renewable energy use. Higher R&D expenditure, stronger fiscal capacity, and environmental accounting signals may fail to increase renewable energy adoption when they are not aligned with deployment-oriented policies. This has important implications for dual-carbon planning because it suggests that China should focus not only on increasing green investment but also on improving the institutional mechanisms that determine how investment is allocated, monitored, and translated into renewable energy consumption.

From a policy perspective, the findings suggest three priorities. First, strengthening regulatory quality should remain central to China's renewable energy strategy because institutions appear to provide the most consistent positive channel for renewable adoption. Second, government R&D expenditure should be more directly linked to renewable deployment, commercialization, and energy-system substitution rather than only upstream innovation or general industrial upgrading. Third, SEEA-aligned indicators such as ANS, ERD, and NRR should be embedded more explicitly into policy evaluation, fiscal planning, and renewable-energy investment decisions. Without such institutional integration, environmental accounting indicators may remain useful for monitoring sustainability but be limited in driving actual energy transition.

Taken together, the results show that renewable energy adoption in China is best understood as an institutional-transmission problem. Environmental accounting indicators identify sustainability pressures, and innovation expenditure provides technological potential, but regulatory quality determines whether these signals and resources are converted into renewable energy outcomes. This supports the central argument of the study: the missing link between green accounting and green energy is not merely measurement or investment, but the institutional capacity to translate sustainability information into effective energy-transition action.

5.1. Policy Implications

The findings suggest that China's renewable energy transition depends not only on investment and environmental accounting but also on the institutional capacity to convert these resources into actual renewable energy use. First, regulatory quality should be strengthened because it is the only variable with a positive and significant long-run association with renewable energy adoption. This implies that clearer regulations, stronger enforcement, better coordination between national and local authorities, and more credible policy implementation are necessary for achieving China's dual-carbon targets. Second, government R&D expenditure should be more closely linked to renewable energy deployment. The negative association between R&D expenditure and renewable energy adoption suggests that innovation spending may not automatically support energy transition. Therefore, public R&D should prioritize commercialization, grid integration, energy storage, and technologies that directly increase renewable energy consumption.

Third, SEEA-aligned indicators should be connected more directly to policy decisions. Adjusted net savings, energy depletion, and natural resource rents are useful sustainability indicators, but the results show that they do not automatically drive renewable energy adoption. These indicators should therefore be integrated into fiscal planning, infrastructure approval, and the evaluation of renewable energy investments. Fourth, resource rents should be redirected through transparent green-financing mechanisms. Since natural resource rents show only a weak positive association with renewable energy adoption, resource revenues should be strategically recycled into renewable infrastructure, storage systems, and grid modernization rather than supporting fossil-intensive activities. Finally, policy evaluation should shift from input-based measures to outcome-based measures. Higher R&D spending or stronger environmental accounting does not necessarily mean stronger renewable energy adoption. Policymakers should assess whether these inputs produce measurable increases in renewable energy consumption. These implications indicate that the key policy priority is to strengthen the institutional link between green accounting, innovation expenditure, and actual renewable energy adoption.

6. Conclusion

This study examined how institutional quality, government R&D expenditure, and SEEA-aligned environmental asset indicators are associated with renewable energy adoption in China from 1999 to 2023. By integrating SEEA with Institutional Theory, the study shows that renewable energy adoption is not driven by environmental accounting signals or innovation expenditure alone. Rather, these factors require effective institutional transmission to influence actual energy-transition outcomes. The findings indicate that regulatory quality has a positive and significant long-run association with renewable energy adoption. This confirms the importance of governance capacity, policy credibility, and regulatory enforcement in supporting China's renewable transition. In contrast, government R&D expenditure and adjusted net savings show negative associations with renewable energy adoption, suggesting that financial and innovation resources may not automatically translate into renewable energy use unless they are directed toward deployment, commercialization, and energy-system substitution. The SEEA-aligned indicators produce mixed results. Energy resource depletion is insignificant, while natural resource rents show only a weak positive association. These findings suggest that environmental accounting indicators are useful for measuring sustainability pressures, but they do not function as direct drivers of renewable energy adoption without institutional support. Therefore, the study concludes that the missing link between green accounting and green energy in China is institutional quality.

7. Limitations and Future Research

This study has several limitations. First, it uses annual national-level data for 1999–2023; therefore, the sample size is limited. Second, national-level data do not capture regional differences across Chinese provinces. Third, the machine-learning results should be interpreted as predictive and diagnostic evidence rather than definitive causal effects. Fourth, government R&D expenditure is measured broadly and does not distinguish between renewable-energy R&D, fossil-efficiency innovation, grid development, and other forms of technological investment.

Future research should use provincial-level data to examine regional differences in regulatory quality, resource dependence, and renewable energy adoption. Further studies should also separate renewable-specific R&D from general R&D expenditure to better explain the innovation–adoption relationship. In addition, future work may test regulatory quality as a mediator or moderator in the relationship between SEEA indicators and renewable energy adoption. Comparative studies across emerging economies would also help determine whether China's experience reflects a broader institutional challenge in translating environmental accounting into renewable energy outcomes.

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Appendix A: Supplementary Empirical Results

Appendix Table A1: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-16.653	NA	2.66e-07	1.888	2.182	1.966
1	160.614	251.127*	2.28e-12*	-9.884*	-7.823*	-9.338*

Source: Author's estimation.
*Note: * indicates the lag order selected by the criterion.*

Appendix Table A2: Pairwise Granger Causality Tests

Null Hypothesis	Obs.	F-Statistic	p-value
LN_ANS does not Granger Cause LN_REA	23	5.831	0.011
LN_REA does not Granger Cause LN_ANS	23	9.975	0.001
LN_ERD does not Granger Cause LN_REA	23	0.707	0.506
LN_REA does not Granger Cause LN_ERD	23	9.881	0.001
LN_GRE does not Granger Cause LN_REA	23	0.329	0.724
LN_REA does not Granger Cause LN_GRE	23	0.014	0.986
LN_NRR does not Granger Cause LN_REA	23	0.587	0.566
LN_REA does not Granger Cause LN_NRR	23	7.083	0.005
RQ does not Granger Cause LN_REA	23	1.085	0.359
LN_REA does not Granger Cause RQ	23	1.936	0.173
LN_ERD does not Granger Cause LN_ANS	23	1.579	0.233
LN_ANS does not Granger Cause LN_ERD	23	6.185	0.009
LN_GRE does not Granger Cause LN_ANS	23	7.999	0.003
LN_ANS does not Granger Cause LN_GRE	23	0.006	0.994
LN_NRR does not Granger Cause LN_ANS	23	1.411	0.270
LN_ANS does not Granger Cause LN_NRR	23	5.533	0.013
RQ does not Granger Cause LN_ANS	23	1.041	0.374
LN_ANS does not Granger Cause RQ	23	1.180	0.330
LN_GRE does not Granger Cause LN_ERD	23	0.918	0.417
LN_ERD does not Granger Cause LN_GRE	23	0.863	0.439
LN_NRR does not Granger Cause LN_ERD	23	1.658	0.218
LN_ERD does not Granger Cause LN_NRR	23	1.762	0.200
RQ does not Granger Cause LN_ERD	23	1.116	0.349
LN_ERD does not Granger Cause RQ	23	0.262	0.772
LN_NRR does not Granger Cause LN_GRE	23	0.808	0.461
LN_GRE does not Granger Cause LN_NRR	23	0.744	0.489
RQ does not Granger Cause LN_GRE	23	0.063	0.940
LN_GRE does not Granger Cause RQ	23	0.220	0.805
RQ does not Granger Cause LN_NRR	23	0.758	0.483
LN_NRR does not Granger Cause RQ	23	0.396	0.679

Source: Author's estimation.
Note: Granger causality indicates predictive precedence, not structural causality. REA = Renewable Energy Adoption; RQ = Regulatory Quality; GRE = Government R&D Expenditure; ERD = Energy Resource Depletion; NRR = Natural Resource Rents; ANS = Adjusted Net Savings.

Appendix Table A3: Impulse Response Function: Response of LN_REA

Period	LN_REA	LN_ANS	LN_ERD	LN_GRE	LN_NRR	RQ
2024	0.014	0.000	0.000	0.000	0.000	0.000
2025	0.009	-0.012	0.018	-0.014	-0.003	0.005
2026	0.000	-0.017	0.030	-0.010	-0.001	0.009
2027	-0.002	-0.024	0.020	-0.008	-0.002	0.006
2028	0.001	-0.024	0.016	-0.007	0.000	-0.001
2029	-0.001	-0.023	0.012	-0.008	0.000	-0.006
2030	-0.006	-0.020	0.014	-0.007	0.002	-0.010
2031	-0.011	-0.019	0.012	-0.007	0.006	-0.013
2032	-0.012	-0.015	0.010	-0.007	0.009	-0.015
2033	-0.011	-0.011	0.008	-0.007	0.010	-0.016

Source: Author's estimation.
Note: Values show the response of LN_REA to shocks in the model variables.

Appendix Table A4: Variance Decomposition of LN_REA

Period	S.E.	LN_REA	LN_ANS	LN_ERD	LN_GRE	LN_NRR	RQ
2024	0.014	100.000	0.000	0.000	0.000	0.000	0.000
2025	0.032	28.351	14.293	33.967	20.131	1.179	2.078
2026	0.049	11.893	18.463	52.471	12.478	0.555	4.140
2027	0.059	8.231	28.903	48.057	10.629	0.454	3.728
2028	0.066	6.623	36.238	44.217	9.559	0.365	2.998
2029	0.071	5.594	41.147	40.316	9.296	0.308	3.340
2030	0.077	5.462	42.554	38.175	8.929	0.371	4.510
2031	0.082	6.598	42.128	35.504	8.507	0.805	6.458
2032	0.087	7.871	40.467	32.925	8.188	1.703	8.846

Period	S.E.	LN_REA	LN_ANS	LN_ERD	LN_GRE	LN_NRR	RQ
2033	0.091	8.770	38.447	30.806	8.158	2.726	11.094

Source: Author's estimation.

Note: Values indicate the percentage contribution of each variable to the forecast-error variance of LN_REA.

Appendix Table A5: Machine-Learning Robustness and Predictive Importance Results

Variable	DML Stability Mean ± Std	RF SHAP Mean |SHAP|	RF Permutation Importance Mean ± SD	GB SHAP Mean |SHAP|	GB Permutation Importance Mean ± SD
LN_ERD	-0.027 ± 0.016	0.004	-0.000 ± 0.002	0.008	0.002 ± 0.002
LN_ANS	-0.068 ± 0.019	0.020	0.017 ± 0.014	0.026	0.023 ± 0.023
RQ	0.005 ± 0.003	0.037	0.035 ± 0.031	0.010	-0.000 ± 0.006
GRE	-0.200 ± 0.033	0.219	1.254 ± 0.822	0.244	1.396 ± 0.898
LN_NRR	-0.050 ± 0.052	0.005	0.002 ± 0.003	0.011	0.003 ± 0.003

Model note: Random Forest test-set $R^2 = 0.962$.

Source: Author's estimation.

Note: DML stability values represent fold-level robustness of orthogonalized associations. RF = Random Forest; GB = Gradient Boosting; SHAP = Shapley Additive Explanations. SHAP and permutation-importance values indicate predictive contribution, not causal effects. The high Random Forest R^2 should be interpreted cautiously because the analysis is based on a small annual macroeconomic time series.