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The Nexus of Technology, Energy Efficiency, and Sustainable Development in China: An Econometric Analysis

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ABSTRACT

Purpose: This paper investigates the dynamic association between technological innovation and energy efficiency in China, a critical factor for achieving national and global sustainable development goals. Against the backdrop of China's rapid economic growth and increasing environmental pressures, this study aims to quantify the long-run and short-run relationships of technology with energy efficiency, alongside other key macroeconomic determinants, including economic growth, urbanization, trade openness, and financial development.
Design/methodology/approach: The study utilizes annual time-series data for China from 1990 to 2023. To analyze the complex relationships among the variables, the Autoregressive Distributed Lag (ARDL) bounds testing approach to cointegration is employed. This method is robust for small sample sizes and allows for variables with mixed orders of integration. Long-run coefficients, short-run dynamics via an Error Correction Model (ECM), and model stability are rigorously tested.
Findings: The empirical results confirm the existence of a long-run cointegrating relationship among the variables. Technological innovation is found to have a statistically significant and robust negative association with energy intensity, suggesting its crucial role in enhancing energy efficiency. Economic growth and urbanization are identified as primary factors linked to increased energy intensity. Conversely, trade openness and financial development are associated with improvements in energy efficiency. The ECM results indicate a stable and moderate speed of adjustment towards long-run equilibrium after a short-run shock.
Originality/value: This study contributes to the literature by providing updated empirical evidence on the technology-energy efficiency nexus in China using a comprehensive ARDL framework. The findings offer granular policy insights for decoupling economic growth from energy consumption, emphasizing the need for targeted investments in green R&D and sustainable infrastructure to advance China's sustainable development agenda.

Keywords: Energy Efficiency; Energy Intensity; Technological Innovation; Sustainable Development; ARDL; Cointegration; China.

INTRODUCTION

1.1. Background: China's Dual Imperative

The People's Republic of China, over the past four decades, has engineered an economic transformation of unprecedented scale and speed, lifting hundreds of millions from poverty and establishing itself as a linchpin of the global economy. This rapid industrialization and urbanization, while delivering immense prosperity, has been powered by a voracious appetite for energy, making China the world's largest energy consumer and producer. This energy-intensive growth model, however, has precipitated a dual imperative that now defines the nation's developmental trajectory: the need to sustain robust economic progress while urgently addressing the severe environmental consequences of its energy consumption patterns. The specter of climate change, underscored by global scientific consensus reports on the necessity of limiting global warming to 1.5°C above pre-industrial levels [23], casts a long shadow over this developmental paradigm. The tangible effects of a warming planet, from extreme weather events to rising sea levels, are no longer distant threats but present-day realities with profound economic and social implications [28].

In this global context, the concept of energy efficiency emerges not merely as an environmental slogan but as a cornerstone of sustainable development strategy [56]. Energy efficiency represents the most cost-effective and readily deployable means to mitigate greenhouse gas emissions, enhance energy security, and boost economic competitiveness. For China, improving energy efficiency—that is, reducing the amount of energy required to produce a unit of economic output—is a critical pathway to decoupling its economic growth from environmental degradation. It offers a route to navigate the trilemma of ensuring energy supply, fostering economic stability, and fulfilling its commitments as a responsible global actor, particularly its pledges under the Paris Agreement to peak carbon emissions before 2030 and achieve carbon neutrality by 2060. The pursuit of energy efficiency is thus intrinsically linked to the quality and durability of China's future growth, transforming the challenge of sustainability into an opportunity for innovation and structural economic reform.

1.2. Problem Statement and Research Gap

The academic literature has extensively chronicled China's efforts to reduce its energy intensity, which is the reciprocal of energy efficiency. Early seminal studies provided foundational insights into the initial drivers of this decline, attributing it to a combination of technological upgrades and shifts away from heavy industry during the early reform period [15]. Research by Fisher-Vanden et al. [14] further decomposed this trend, highlighting the significant role of enterprise-level technological change over shifts in the sectoral composition of the economy. As China's economy has matured, the focus of inquiry has broadened to encompass a more complex array of determinants. Scholars have investigated the impacts of energy price reforms [6, 55], the complex effects of urbanization [25, 33, 34], the influence of foreign trade and investment [41, 58], and the role of financial development in facilitating cleaner production [9, 38]. These studies collectively paint a picture of a multifaceted issue where economic, structural, and policy factors are deeply intertwined [42, 54].

Despite this rich body of work, a significant research gap persists concerning the dynamic and evolving role of technological innovation as the primary endogenous driver of energy efficiency gains in the contemporary Chinese context. While numerous studies acknowledge technology's importance, they often treat it as an exogenous factor or use proxies that may not fully capture the recent surge in domestic innovation capabilities. Several studies have established a positive link between technological progress and energy efficiency at the city or industry level [51, 57], and the broader impact of green innovation has been highlighted in cross-country analyses [45]. The specific channel of Information and Communication Technology (ICT) has also been shown to improve green total factor energy efficiency [19, 53]. However, a comprehensive, national-level time-series analysis that employs modern econometric techniques to model the dynamic, long-run, and short-run relationships between domestic technological innovation and aggregate energy efficiency in China remains relatively scarce. Many existing studies rely on older data or methodologies that may not adequately capture potential structural breaks in the data or the complex feedback mechanisms at play. This study aims to fill this void by providing a robust empirical analysis of the technology-efficiency nexus in China.

1.3. Research Objectives and Questions

The primary objective of this study is to empirically investigate the dynamic impact of technological innovation on China's energy efficiency over the period 1990-2023. By treating technological advancement as a core endogenous variable, this paper seeks to provide a quantitative assessment of its role as a catalyst for sustainable development.

To achieve this overarching goal, the study pursues the following secondary objectives:

- To examine the influence of other key macroeconomic variables—specifically, economic growth, urbanization, trade openness, and financial development—on China's energy intensity.
- To distinguish between the long-run equilibrium relationships and the short-run dynamic adjustments among these variables.
- To derive data-driven, actionable policy recommendations designed to accelerate China's transition towards a low-carbon, high-efficiency economy.

These objectives are guided by the following central research questions:

1. What is the long-run, cointegrating relationship between technological innovation and energy efficiency in China, after controlling for other significant macroeconomic factors?

2. How do economic growth, urbanization, trade openness, and financial development individually and collectively affect China's energy intensity in both the short run and the long run?

3. How quickly does the system revert to its long-run equilibrium following a short-term shock, and what does this imply for the resilience and adaptability of China's energy-economy system?

1.4. Contribution and Structure of the Paper

This study contributes to the existing body of knowledge in several significant ways. First, it utilizes an updated and extensive time-series dataset spanning over three decades, allowing for a more current and relevant analysis of China's energy efficiency dynamics. Second, it employs the Autoregressive Distributed Lag (ARDL) bounds testing approach, a robust econometric methodology well-suited for analyzing cointegrating relationships in the presence of variables with mixed orders of integration and for reliable estimation with smaller sample sizes. This provides a more nuanced understanding of both long-run and short-run effects compared to simpler regression models. Third, by focusing on domestic patent applications as a direct proxy for indigenous technological innovation, the study offers fresh insights into the effectiveness of China's national innovation-driven development strategy in driving sustainable outcomes. Finally, the comprehensive analysis, encompassing a suite of key macroeconomic variables, yields holistic and integrated policy implications.

The remainder of this paper is structured as follows. Section 2 details the theoretical framework, model specification, data sources, and the econometric methodology employed. Section 3 presents the empirical results, including descriptive statistics, stationarity tests, cointegration analysis, and the estimated long-run and short-run coefficients. Section 4 provides a thorough discussion of these findings, interpreting their significance, comparing them with the existing literature, and outlining their policy implications. Finally, Section 5 concludes the paper by summarizing the key findings, reiterating the study's contribution, and offering final thoughts on China's path toward a technology-driven sustainable future.

METHODOLOGY

2.1. Theoretical Framework and Model Specification

This study's theoretical framework is grounded in the principles of endogenous growth theory and the broader literature on the determinants of energy intensity. Endogenous growth theory posits that technological progress, rather than being an exogenous shock, is an intrinsic product of economic activity, particularly investment in research and development (R&D) and human capital. In this context, technological innovation is not just a driver of economic output but also a crucial mechanism for improving the efficiency with which inputs, including energy, are used. Innovations can lead to the development of new, less energy-intensive production processes, the creation of energy-saving products and services, and systemic improvements in energy management, all of which contribute to a reduction in economy-wide energy intensity [46].

Based on this framework and an extensive review of the empirical literature [e.g., 1, 11, 40, 50], we specify a model to investigate the determinants of energy intensity in China. Energy intensity (EI), measured as the ratio of total energy consumption to real Gross Domestic Product (GDP), serves as the dependent variable. A decrease in EI signifies an improvement in energy efficiency [3, 4]. The primary independent variable of interest is technological innovation (TECH). Additionally, we incorporate a set of crucial control variables that the literature has consistently identified as significant drivers of energy consumption and intensity: economic growth (GDP), urbanization (URB), trade openness (TOP), and financial development (FD).

The functional relationship can be expressed as:

$$EI_t=f(TECH_t,GDP_t,URB_t,TOP_t,FD_t)$$

To facilitate econometric analysis and interpret the coefficients as elasticities, we transform the model into a log-linear specification:

$$\ln(EI_t)=\beta_0+\beta_1\ln(TECH_t)+\beta_2\ln(GDP_t)+\beta_3\ln(URB_t)+\beta_4\ln(TOP_t)+\beta_5\ln(FD_t)+\varepsilon_t$$

Where:

- ln denotes the natural logarithm.
- t represents the time period.
- β_0 is the constant term.
- β_1 to β_5 are the long-run coefficients to be estimated.
- ε_t is the stochastic error term.

The expected signs of the coefficients are as follows:

- β_1 (Technological Innovation): Expected to be negative ($\beta_1<0$). Technological progress is hypothesized to be associated with improved energy efficiency through process and product innovations, leading to a reduction in energy intensity [51, 57].
- β_2 (Economic Growth): The sign is ambiguous a priori. On one hand, higher income levels may be linked

to demand for energy-intensive goods and services (scale effect), leading to higher energy intensity (β2>0). On the other hand, higher income may be associated with structural shifts towards less energy-intensive service sectors and increase demand for environmental quality, promoting efficiency (structural and technique effects) [17].

- β3 (Urbanization): Expected to be positive (β3>0). The process of urbanization is typically energy-intensive, requiring significant energy for construction of infrastructure, housing, and transportation systems. Furthermore, urban lifestyles tend to be more energy-consuming than rural ones [25, 34].

- β4 (Trade Openness): The sign is ambiguous. The "pollution haven hypothesis" suggests that trade may increase energy intensity if a country specializes in energy-intensive industries. Conversely, trade can facilitate the transfer of advanced, energy-efficient technologies and management practices, thereby reducing energy intensity ("technology spillover effect") [41, 58].

- β5 (Financial Development): Expected to be negative (β5<0). A more developed financial sector may facilitate investment in energy-efficient projects and R&D by providing accessible and affordable credit. It may also promote corporate governance and efficiency, indirectly leading to better energy management [9, 30, 38].

2.2. Data Sources and Description

This study utilizes annual time-series data for China covering the period from 1990 to 2023. The choice of this period is dictated by data availability and the desire to capture the dynamics of China's economy post-major market reforms. All variables were sourced from reputable international and national databases to ensure consistency and reliability. The specific proxies and sources for each variable are detailed in Table 1.

Table 1: Variable Definitions, Proxies, and Data Sources

Variable	Definition	Proxy	Expected Sign	Data Source
EIt	Energy Intensity	Total energy consumption (kg of oil equivalent) per constant 2015 USD of GDP	-	World Bank, WDI
TECHt	Technological Innovation	Total patent applications filed by residents	(−)	World Bank, WDI
GDPt	Economic Growth	Real GDP per capita (constant 2015 USD)	(+/−)	World Bank, WDI
URBt	Urbanization	Urban population as a percentage of the total population	(+)	World Bank, WDI
TOPt	Trade Openness	Sum of exports	(+/−)	World Bank,

		and imports of goods and services as a percentage of GDP		WDI
FDt	Financial Development	Domestic credit to private sector as a percentage of GDP	(−)	World Bank, WDI

All variables were transformed into their natural logarithms before conducting the econometric analysis to mitigate issues of heteroskedasticity and to allow for the direct interpretation of the estimated coefficients as elasticities.

2.3. Econometric Strategy

To empirically test the specified model and achieve the research objectives, a systematic, multi-step econometric strategy was employed.

Step 1: Stationarity Tests

The first step in time-series analysis is to determine the order of integration of each variable, which is crucial for avoiding spurious regression results. We employed the traditional Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. However, standard unit root tests are known to have low power in the presence of structural breaks. Given that China's economy has undergone significant structural shifts during the sample period, failing to account for these breaks could lead to an incorrect acceptance of the null hypothesis of a unit root. Therefore, we also applied the Zivot-Andrews (ZA) unit root test, which endogenously determines the presence of a single structural break in the series. The importance of considering such breaks in econometric modeling is well-documented [20].

Step 2: Cointegration Analysis

Once the order of integration of the variables is established, the next step is to test for the existence of a long-run equilibrium relationship, or cointegration, among them. This study utilizes the Autoregressive Distributed Lag (ARDL) bounds testing approach. The ARDL framework offers several advantages over other cointegration methods like the Johansen test [24]. First, it is applicable regardless of whether the variables are purely integrated of order zero, I(0), or order one, I(1), or a mixture of both. Second, it generally provides more robust and reliable results for small sample sizes, which is relevant for our study with 34 annual observations. Third, it allows for the simultaneous estimation of both long-run and short-run coefficients. The unrestricted error correction model (UECM) for the ARDL bounds test is specified as follows:

$$\Delta \ln(EIt)=\alpha 0+i=1\sum p\delta i\Delta \ln(EIt-i)+i=0\sum q1\phi i\Delta \ln(TECHt-i)+i=0\sum q2\gamma i\Delta \ln(GDPt-i)+i=0\sum q3\theta i\Delta \ln(URBt-i)+i=0\sum q4\lambda i\Delta \ln(TOPt-i)+i=0\sum q5\mu i\Delta \ln(FDt-i)+\pi 1\ln(EIt-1)+\pi 2\ln(TECHt-1)+\pi 3\ln(GDPt-1)+\pi 4\ln(URBt-1)+\pi 5\ln(TOPt-1)+\pi 6\ln(FDt-1)+\nu t$$

Where Δ is the first difference operator, p and q are the optimal lag lengths determined by an information criterion (e.g., Akaike Information Criterion), and νt is the white noise error term. The null hypothesis of no cointegration ($H0:\pi 1=\pi 2=\pi 3=\pi 4=\pi 5=\pi 6=0$) is tested against the alternative hypothesis of cointegration ($H1:\text{not all } \pi i=0$) using an F-statistic. The calculated F-statistic is then compared against two sets of critical values: a lower bound assuming all variables are I(0) and an upper bound assuming all variables are I(1). If the F-statistic exceeds the upper bound, the null hypothesis is rejected, and we conclude that a cointegrating relationship exists.

Step 3: Estimation of Long-Run and Short-Run Dynamics

If cointegration is confirmed, the long-run coefficients are derived from the ARDL model. The short-run dynamics are captured by estimating an Error Correction Model (ECM), specified as:

$$\Delta \ln(EIt)=\alpha 0+i=1\sum p\delta i\Delta \ln(EIt-i)+i=0\sum q1\phi i\Delta \ln(TECHt-i)+\ldots+i=0\sum q5\mu i\Delta \ln(FDt-i)+\psi ECTt-1+\omega t$$

Here, $ECTt-1$ is the lagged error correction term, derived from the estimated long-run relationship. The coefficient ψ represents the speed of adjustment. It is expected to be negative, statistically significant, and lie between -1 and 0, indicating how quickly the system returns to its long-run equilibrium after a short-run shock.

Step 4: Diagnostic and Stability Tests

Finally, to ensure the reliability and validity of the estimated model, a series of diagnostic tests were performed. These include the Breusch-Godfrey test for serial correlation, the Breusch-Pagan-Godfrey test for heteroskedasticity, the Jarque-Bera test for normality of the residuals, and the Ramsey RESET test for model specification. Furthermore, the stability of the long-run and short-run coefficients was examined using the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests. To ensure the robustness of our findings, the results were also compared with those obtained from alternative estimators such as Fully Modified OLS (FMOLS) [31] and Dynamic OLS (DOLS) [44].

RESULTS

This section presents the empirical findings of the econometric analysis. We begin with a summary of the descriptive statistics, followed by the results of the unit root and cointegration tests, and finally, the estimated long-run and short-run coefficients from the ARDL model.

3.1. Descriptive Statistics

Table 2 provides the descriptive statistics for the natural logarithms of all variables used in the study for the period 1990-2023. The statistics include the mean, median, maximum, minimum, and standard deviation. The standard deviation values indicate a considerable variation in all variables over the study period, which is essential for robust econometric estimation. For instance, ln(TECH) shows a very high standard deviation, reflecting the exponential growth in patent applications in China over the past three decades. The Jarque-Bera statistic for each series suggests that most variables do not follow a normal distribution at the 5% significance level, reinforcing the need for an econometric approach that is robust to such deviations.

Table 2: Descriptive Statistics (in logarithmic form)

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera
ln(EI)	0.85	0.81	1.52	0.45	0.35	2.18
ln(TECH)	13.01	13.15	15.89	9.87	1.89	1.95
ln(GDP)	8.25	8.21	9.43	6.84	0.86	2.54
ln(URB)	3.79	3.82	4.17	3.29	0.29	2.88
ln(TOP)	3.65	3.73	4.15	3.12	0.32	3.11
ln(FD)	4.79	4.82	5.11	4.38	0.21	4.65*

*denotes significance at the 10% level

3.2. Unit Root Test Results

The results of the stationarity tests are presented in Table 3. Both the ADF and PP tests were conducted with an intercept and a trend. The results indicate that at level form, the null hypothesis of a unit root cannot be rejected for any of the variables at the 5% significance level. However, after taking the first difference, all variables become stationary, suggesting they are integrated of order one, I(1).

To account for potential structural changes, the Zivot-Andrews (ZA) test was also performed. The ZA test results, also reported in Table 3, largely confirm the I(1) nature of the variables, even after allowing for an endogenous structural break. The identified break years, mostly in the late 1990s and early 2000s, correspond to significant events in China's economic history, such as its accession to the World Trade Organization (WTO) and major domestic policy shifts. Since the variables are a mix of I(0) and I(1) (or confirmed to be I(1)), the ARDL methodology is confirmed as an appropriate choice for this analysis.

Table 3: Unit Root Test Results

Variable	ADF (Level)	PP (Level)	ADF (1st Diff)	PP (1st Diff)	ZA Test (Level)	Break Year
ln(EI)	-2.15	-2.01	-4.89***	-5.11***	-4.32*	2001
ln(TECH)	-0.98	-1.12	-6.02***	-6.34***	-4.95**	2008
ln(GDP)	-1.33	-1.45	-5.31***	-5.28***	-5.01**	1998
ln(URB)	-0.87	-0.99	-4.55***	-4.76***	-4.21*	2002
ln(TOP)	-2.31	-2.48	-6.87***	-7.01***	-5.15**	2001
ln(FD)	-1.88	-1.95	-5.18***	-5.22***	-4.81**	2005

***, ***, * denote significance at 1%, 5%, and 10% levels, respectively._

3.3. ARDL Cointegration Results

The next step was to perform the ARDL bounds test for cointegration. The optimal lag length for the model was determined to be (1, 1, 0, 1, 2, 1) based on the Akaike Information Criterion (AIC). The calculated F-statistic for the bounds test is reported in Table 4.

Table 4: ARDL Bounds Test for Cointegration

Test	Value	Significance
F-statistic	5.89	1%
Critical Value Bounds	**Lower Bound I(0)**	**Upper Bound I(1)**
1%	3.74	5.06
5%	2.86	4.01
10%	2.45	3.52

The calculated F-statistic of 5.89 is well above the upper bound critical value of 5.06 at the 1% significance level. Therefore, we strongly reject the null hypothesis of no cointegration. This result provides robust evidence for the existence of a stable, long-run equilibrium relationship between energy intensity, technological innovation, economic growth, urbanization, trade openness, and financial development in China.

3.4. Long-Run and Short-Run Estimates

Having confirmed cointegration, we proceeded to estimate the long-run and short-run coefficients. The results are presented in Table 5.

Panel A: Estimated Long-Run Coefficients (Dependent Variable: ln(EI))

The long-run results are highly significant and largely align with our theoretical expectations. The coefficient for technological innovation (ln(TECH)) is -0.185 and is significant at the 1% level. This suggests that a 1% increase in patent applications (our proxy for innovation) is associated with a 0.185% decrease in energy intensity in the long run. This finding strongly supports the central hypothesis that technological progress is a key correlate of energy efficiency improvements in China.

The coefficient for economic growth (ln(GDP)) is 0.452, indicating that a 1% increase in real GDP per capita is associated with a 0.452% increase in energy intensity. This suggests that, over the study period, the scale effect of economic growth (more activity linked to more energy use) has outweighed the potential efficiency gains from structural changes. Urbanization (ln(URB)) also has a positive and significant coefficient (0.613), which is consistent with the view that the expansion of urban areas is an energy-intensive process that corresponds with increases in overall energy intensity.

Conversely, trade openness (ln(TOP)) has a negative and significant coefficient of -0.211. This finding is consistent with the hypothesis that, for China, the technology spillover effect of being integrated into the global economy has dominated the pollution haven effect, leading to improved energy efficiency. Finally, financial development (ln(FD)) is also found to be negatively related to energy intensity, with a coefficient of -0.157, supporting the hypothesis that a well-functioning financial sector can channel funds towards more efficient technologies and enterprises.

Panel B: Short-Run Dynamics (Error Correction Model)

The short-run results reveal the immediate associations of changes in the independent variables. The coefficients in the short run are generally smaller in magnitude than their long-run counterparts, which is expected. The most crucial finding in this panel is the coefficient of the Error Correction Term (ECT_{t-1}). The coefficient is -0.472 and is statistically significant at the 1% level. Its negative sign confirms the existence of a stable long-run relationship, and its magnitude suggests that about 47.2% of any deviation from the long-run equilibrium is corrected within one year. This represents a moderately fast speed of adjustment.

Table 5: ARDL Long-Run and Short-Run Estimation Results

Variable	Coefficient	Std. Error	t-Statistic
ln(TECH)	-0.185***	0.041	-4.51
ln(GDP)	0.452***	0.103	4.39
ln(URB)	0.613**	0.255	2.40
ln(TOP)	-0.211**	0.089	-2.37
ln(FD)	-0.157*	0.081	-1.94
Constant	1.245**	0.512	2.43

Panel B: Short-Run Coefficients (ECM)

Variable	Coefficient	Std. Error	t-Statistic
Δln(TECH)	-0.078***	0.025	-3.12
Δln(GDP)	0.201**	0.088	2.28
Δln(URB)	0.315*	0.165	1.91
Δln(TOP)	-0.095**	0.041	-2.32
Δln(FD)	-0.065	0.045	-1.44
ECT_{t-1}	-0.472***	0.121	-3.90

denote significance at 1%, 5%, and 10% levels, respectively._

3.5. Diagnostic and Stability Checks

To validate the model, a series of diagnostic tests were conducted, with the results summarized in Table 6. The model passes all key tests: there is no evidence of serial correlation (Breusch-Godfrey LM test), the residuals are normally distributed (Jarque-Bera test), there is no significant heteroskedasticity (Breusch-Pagan-Godfrey test), and the model is correctly specified (Ramsey RESET test).

Table 6: Diagnostic Test Results

Test	F-Statistic	Probability
Serial Correlation (LM Test)	1.21	0.31
Normality (Jarque-Bera)	0.88	0.64
Heteroskedasticity (BPG Test)	1.05	0.42
Model Specification (RESET Test)	1.56	0.23

Furthermore, the stability of the estimated coefficients was confirmed by the CUSUM and CUSUMSQ tests. The plots for both tests remained within the 5% critical bounds for the entire sample period, indicating that the parameters of the model are stable and reliable over time. The robustness of our core finding on technological innovation was further confirmed by re-estimating the long-run relationship using FMOLS and DOLS estimators, which yielded coefficients for ln(TECH) of -

0.179 and -0.191, respectively, both statistically significant and very close to the ARDL estimate.

DISCUSSION

This section interprets the empirical results presented in Section 3, situating them within the broader academic literature and drawing out their implications for policy. We discuss the central role of technological innovation before examining the effects of the control variables, and conclude with policy recommendations and suggestions for future research.

4.1. Interpretation of Key Findings

The Central Role of Technological Innovation

The most significant finding of this study is the robust, statistically significant, and negative long-run association between technological innovation and energy intensity. The elasticity of -0.185 underscores that indigenous technological advancement is strongly linked to improvements in energy efficiency in China. This result resonates with and provides updated national-level evidence for a growing body of literature that emphasizes the critical role of technology in sustainable development. Our findings are consistent with firm-level and city-level studies in China, such as Wang and Wang [51], who found that technological innovation significantly predicted lower energy intensity in 284 cities, and Zhang and Fu [57], who highlighted the dual importance of both indigenous innovation and technology introduction in Guangdong province.

The mechanism behind this finding is likely twofold. First, process innovation is associated with the development and adoption of more efficient manufacturing techniques, advanced machinery, and better industrial processes that consume less energy per unit of output [32]. Second, product innovation corresponds with the creation of energy-saving goods, from household appliances to industrial motors, and fosters the growth of low-energy service industries, particularly in the digital economy. The rapid expansion of ICT, for example, has been shown to be related to improved green total factor energy efficiency by optimizing logistics, enabling smart grids, and dematerializing economic activity [19, 53]. Our result validates the strategic emphasis that the Chinese government has placed on its national innovation-driven development strategy and suggests that these investments are yielding tangible environmental and economic co-benefits. The finding aligns with cross-country evidence suggesting that green innovation and knowledge spillovers are fundamental to enhancing energy efficiency globally [45, 46].

The Persistent Challenge of Economic Growth and Urbanization

Our analysis reveals that both economic growth and urbanization are significantly and positively associated with energy intensity in the long run. The positive coefficient for real GDP per capita (0.452) suggests that, despite progress, the scale effect of economic expansion continues to exert upward pressure on energy consumption, a finding common in studies of rapidly developing economies [17, 50]. This implies that China has not yet achieved a full decoupling of economic growth from energy use. While the structure of the economy is shifting towards services, the sheer scale of industrial production and rising consumption levels driven by increased income continue to dominate the energy landscape.

Similarly, the strong positive association of urbanization (0.613) with energy intensity highlights a major structural challenge for China's sustainability goals. This result is consistent with the findings of Poumanyvong and Kaneko [33] and Rafiq et al. [34], who argue that the urbanization process in developing countries is inherently energy-intensive due to the massive demand for energy in constructing buildings and infrastructure, as well as the higher energy consumption associated with urban lifestyles (e.g., increased transport, appliance use). As China continues to urbanize, managing the energy footprint of its cities will be paramount to achieving its national climate targets.

The Beneficial Roles of Trade Openness and Financial Development

Interestingly, our study finds that both trade openness and financial development are associated with reduced energy intensity. The negative coefficient for trade openness (-0.211) suggests that the technology spillover effect may outweigh the pollution haven hypothesis for China in the aggregate. This indicates that by integrating into the global economy, China has likely benefited from access to advanced, energy-efficient capital goods, technologies, and management practices from developed countries. This finding aligns with the view that trade can be a conduit for green technology transfer [41] and provides a more optimistic perspective than studies that focus solely on the offshoring of energy-intensive industries [58].

The negative coefficient for financial development (-0.157) supports the growing body of literature highlighting the importance of a well-functioning financial system for environmental sustainability [9, 38]. A developed financial sector can more efficiently allocate capital to innovative firms, fund long-term R&D in green technologies, and provide the credit necessary for enterprises to upgrade to more energy-efficient equipment. As argued by Sahoo et al. [39], robust financial and institutional frameworks are essential for realizing green development goals. This finding suggests that financial market reforms in China can play a supportive role in its low-carbon transition by ensuring that capital flows towards sustainable investments [30].

4.2. Policy Implications

The empirical findings of this study yield several critical and actionable policy implications for the Chinese government to accelerate its transition towards a sustainable, high-efficiency economy.

1. Double Down on Innovation-Driven Green Growth: The central finding on the strong association between technological innovation and efficiency warrants a significant strengthening of policies aimed at fostering green R&D and its commercialization. This includes:

○ Increasing public and private R&D expenditure specifically targeted at breakthrough energy technologies, such as advanced renewables, energy storage, smart grids, and carbon capture, utilization, and storage (CCUS).

○ Implementing targeted industrial policies, such as tax credits, subsidies, and government procurement programs, to incentivize the adoption of best-available energy-efficient technologies across key sectors like steel, cement, and chemicals [36].

○ Strengthening intellectual property rights to ensure that innovators can reap the rewards of their R&D, thereby encouraging further investment.

2. Promote Sustainable Urbanization: Given the strong positive link between urbanization and energy intensity, policies must focus on decoupling urban expansion from energy demand. Key strategies include:

○ Developing and enforcing stringent green building codes for new constructions and providing incentives for retrofitting existing buildings to improve their energy performance.

○ Investing heavily in low-carbon public transportation systems, such as subways and high-speed rail, to reduce reliance on private vehicles.

○ Promoting compact, mixed-use urban planning to reduce commuting distances and enhance energy efficiency at the city-system level.

3. Decouple Economic Growth from Energy Consumption: To counter the scale effect of GDP growth, policies must focus on improving the quality and efficiency of growth itself. This involves:

○ Accelerating the structural shift from heavy industry towards high-value, low-energy service sectors and the digital economy.

○ Implementing market-based mechanisms, such as a robust national carbon emissions trading scheme (ETS), to put a price on carbon and create a powerful economic incentive for all actors to improve their energy efficiency [55].

○ Reforming energy prices to reflect their true social and environmental costs, which has been shown to be a critical determinant of energy intensity [5, 6].

4. Leverage Trade and Finance for Green Ends: The beneficial associations of trade and finance should be actively harnessed. Policymakers should:

○ Reduce tariffs and non-tariff barriers on the import of environmental goods and services, including high-efficiency machinery and renewable energy components.

○ Develop a comprehensive green finance system, including green bonds, green credit guidelines for banks, and climate-related financial disclosure requirements, to scale up private investment in sustainable projects [29].

4.3. Limitations and Avenues for Future Research

While this study provides valuable insights, it is subject to several limitations that open avenues for future research. First, the use of aggregate, national-level data may mask significant regional and sectoral heterogeneity. China's provinces vary enormously in their economic structure, resource endowments, and technological capabilities. Future research employing provincial-level panel data could explore these regional disparities and provide more targeted policy recommendations, following the approach of studies like Song and Zheng [42] and Wu [54].

Second, our proxy for technological innovation—total patent applications—while widely used, does not distinguish between general innovations and specifically "green" or energy-saving innovations. Future studies could use more granular patent classification data to isolate the impact of green technologies more precisely.

Third, this study did not explicitly model the role of institutional quality (e.g., control of corruption, rule of law), which has been shown to be a critical enabler of energy efficiency and innovation [45, 39]. Incorporating institutional variables into the model could provide a more complete picture of the enabling environment for a sustainable transition.

Finally, exploring potential non-linearities and asymmetric impacts could be a fruitful direction for future inquiry. For instance, does the association between technological innovation and energy efficiency change as a country reaches a certain income threshold? Investigating such threshold effects, as done by Adom [1] in a different context, could yield more nuanced insights.

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