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Research Article

Relationship between Urban Innovation Capability and Energy Utilization Efficiency: An Empirical Study of 281 Prefecture-Level Cities in China

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Following a dynamic nonlinear perspective, this study explores the relationship between urban innovation capability and energy utilization efficiency by employing the Panel Vector Autoregression (PVAR) and Dynamic Panel Threshold Regression (DPTR) methods. Using the 2003–2020 panel data of 281 prefecture-level cities in China, this study confirms that energy utilization efficiency improves owing to the improvement of urban innovation capability. Depending on the characteristics of the city, such as population density, industrial structure, and environmental pollution, high energy utilization efficiency in the early stages of city development may help or hinder the improvement of energy utilization efficiency in the later stages. The enhancement in urban innovation capability has failed to improve energy utilization efficiency and has adversely affected cities with a low population density or weak secondary industrial foundation. However, in cities with a high population density or proportion of secondary industry, the improvement in innovation capability significantly increases the efficiency of energy utilization. In addition, the positive effect that urban innovation capability has on energy utilization efficiency is higher in low-pollution cities than in high-pollution cities.

1. Introduction

Energy consumption is an important factor in the economic development and social progress of China. Given the increasing total economic scale, the demand for and dependence on energy in China are rising [1]. The latest data from the BP World Energy Statistics Yearbook highlights that in 2018, the total primary energy consumption in China is equivalent to 3273.5 million tons of oil, the highest in the world. Moreover, according to the "China Energy Supply and Demand Report," the total energy consumption of China amounts to 4.64 billion tons of standard coal, accounting for 23.6% of the total global primary energy consumption, and has ranked first worldwide for 10 consecutive years. The environmental deterioration in China owing to excessive energy consumption coexists with the energy tension caused by economic development. In

addition, the increasingly severe energy situation entails a greater need for energy utilization efficiency, and improving the efficiency of energy utilization has become the focus of economic development in China at this stage [2]. However, compared with the top countries regarding economic aggregate, energy consumption per unit of the Gross Domestic Product (GDP) is 2.14 times in the United States, 2.63 in Japan, 2.97 in Germany, 3.53 in the United Kingdom, and 2.75 in France. This implies that the economy in China is still supported by a large amount of energy consumption, and there is still a large gap between China and the developed countries regarding energy utilization efficiency [3].

The exponential growth of the economy and the limited development of resources have elevated the transformation of the "factor-driven" to the "innovation-driven". Thus, technological innovation has become a vital means for countries and cities to solve economic problems and occupy

development opportunities under the wave of the new technological revolution [4, 5]. Recent findings have confirmed that the city serves as the main location for scientific and technological innovation activities, and the increase in innovation capability is helpful in improving energy efficiency [6]. Improving energy utilization efficiency can also improve urban innovation capabilities [7]. However, does this conclusion apply to Chinese cities? Does energy utilization efficiency affect urban innovation capability in China? Does urban innovation capability affect energy utilization efficiency? Or do they interact? Is the relationship between the two forced or driven? Will this relationship change with the changes in urban population density, industrial structure, environmental pollution, and other factors? There are numerous questions that are not yet settled. Against this background, clarifying the dynamic relationship and mechanism between urban innovation capability and energy utilization efficiency in China is not only beneficial to ensuring national energy security and transforming the mode of economic growth, but also conducive to the sustainable and coordinated development of scientific and technological innovation and new urbanization.

As an important issue in the field of energy economics, energy utilization efficiency has been widely concerned by numerous scholars [8]. The connotation of energy utilization efficiency gradually extends, from the initial single-factor energy utilization efficiency to the total-factor energy utilization efficiency based on the traditional DEA model [9], from the static energy utilization efficiency to the dynamic total-factor energy utilization efficiency based on the Malmquist index model [10], and from only focusing on economic development to considering environmental pollution [11] and energy utilization efficiency at the enterprise level [12]. Similarly, urban innovation capability, as an important issue in regional economics, also attracts attention. Previous studies have discussed the definition and related concepts of urban innovation capability from the perspectives of innovation environment and resource integration [13, 14]. Moreover, the measurement standards and evaluation systems of urban innovation capability are extensively and fully discussed [15, 16], which triggers a dispute between a single indicator and an indicator system. However, Huang et al. [17] put regional innovation capability and energy utilization efficiency in China into a research framework and examined the coupling relationship between them from the perspective of spatial and temporal coordination. However, following the extant literature, most discussions on energy utilization efficiency and urban innovation capability exist independently, and few studies have investigated the relationship between the two, especially the dynamic nonlinear relationship.

The main contribution of this study is reflected in the following three aspects: first, from the perspective of dynamic nonlinearity, the dynamic correlation and mechanism between urban innovation capability and energy utilization efficiency are discussed. Second, the combined method of the Panel Vector Autoregression (PVAR) and the Dynamic Panel Threshold Regression (DPTR) is helpful in accurately identifying the dynamic causal relationship between urban innovation capability and energy utilization efficiency and clarifying the mechanism of action, as well as examining the dynamic nonlinear relationship between urban innovation capability and energy utilization efficiency under different constraints. Finally, this study uses nighttime lighting data, which have been widely used in the field of economic research recently; it measures the energy consumption of various prefecture-level cities following the idea that the brighter the night light is, the greater the total energy consumption is, solving the shortcomings of existing research in time span and urban measurement.

The remainder of the paper is structured as follows: Section 2 explains the research design and method; Section 3 introduces the data source and variable definition; Sections 4 and 5 discuss the PVAR system and DPTR analyses, respectively; and Section 6 concludes the study.

2. Methodology

2.1. PVAR System. PVAR can treat all variables as endogenous systems and examine the lagged terms of each variable, reflecting the interaction between variables. This method can capture individual differences and common shocks to different cross-sections by introducing individual effect and time-point effect variables, respectively, adding to the advantages of Vector Autoregression (VAR) models and panel data models. It can not only solve the problem of endogeneity but also effectively characterize the shock response and variance decomposition among system variables. We can explore the dynamic relationship between urban innovation capability and energy utilization efficiency as well as the direct, strengthening, feedback, and other dynamic interaction effects by constructing the PVAR system.

The PVAR system for analysis comprises the following main steps: (1) construct a Generalized Method of Moments (GMM) estimation to obtain the regression relationship between variables; (2) determine the influence of orthogonalization on other variables in the system by analyzing the impulse-response function; and (3) obtain the variance decomposition results in the prediction period and measure the contribution of each variable using the variance analysis. Because the estimation of the PVAR system is based on the fixed-effect dynamic panel model, the intragroup mean difference method should be used before the GMM estimator to eliminate the time effect. Subsequently, to eliminate the individual effect, the onward mean difference method should be employed. The PVAR system is expressed as follows:

$$
\begin{aligned}
Y_{it} = {} & Y_{it-1}A_1 + Y_{it-2}A_2 + \cdots + Y_{it-p+1}A_{p-1} + Y_{it-p}A_p \\
& + X_{it}B + f_i + \mu_t + \varepsilon_{it},
\end{aligned}
\tag{1}
$$

where $i \in \{1, 2, \ldots, N\}$ represents the prefecture-level cities in China; $t \in \{1, 2, \ldots, T\}$ indicates the year; Y_{it} is a $(1 \times k)$ vector of dependent variables; X_{it} is a $(1 \times l)$ vector of exogenous covariates (control variables); f_i represents an unobservable intercept effect, and this fixed effect can be eliminated using the forward difference Helmert transformation method (the forward difference Helmert

transformation method avoids the orthogonality between the lag regression and difference terms of the instrumental variable by removing the forward mean, so that the measurement test results can be more accurate); μ_t denotes the time effect; and ε_{it} is the random error term, which has the following characteristics: $E(\varepsilon_{it}) = 0$ and $E(\varepsilon_{it}'\varepsilon_{it}) = \Sigma$, and $E(\varepsilon_{im}'\varepsilon_{in}) = 0$.

2.2. DPTR.

Traditional panel threshold regression focuses on static effects and requires strong exogenous control variables [18]. However, strong exogenous conditions are often difficult to meet in the real world. Therefore, Seo and Shin [19] extended the traditional panel threshold model to the dynamic model, and the First Difference Generalized Method of Moments (FD-GMM) is employed to estimate it in solving the endogenous problem in the DPTR model. The specific form of the DPTR model is as follows:

$$y_{it} = (1, x_{it}')\phi_1 \cdot I\{q_{it} \leq \gamma\} + (1, x_{it}')\phi_2 \cdot I\{q_{it} > \gamma\} + \varepsilon_{it}. \quad (2)$$

The first-order difference form of (2) can be expressed as follows:

$$\Delta y_{it} = \beta' \Delta x_{it} + \delta' X_{it} 1_{it}(\gamma) + \Delta\varepsilon_{it}, \quad (3)$$

where $\underset{k_1 \times 1}{\beta} = (\phi_{12}, \ldots, \phi_{1,k_1+1})'$, $\underset{(k_1+1)\times 1}{\delta} = \phi_2 - \phi_1$, $\underset{2\times(1+k_1)}{X_{it}} = \begin{pmatrix} (1, x_{it}') \\ (1, x_{i,t-1}') \end{pmatrix}$, and $\underset{2\times 1}{1_{it}(\gamma)} = \begin{pmatrix} 1\{q_{it} > \gamma\} \\ -1\{q_{i,t-1} > \gamma\} \end{pmatrix}$. Making $\theta = (\beta', \delta', \gamma')$, and supposing θ is a compact set, $\Theta = \Phi \times$

$\Gamma \subset \mathbb{R}^k$, where $k = 2k_1 + 2$. Making $\Gamma = [\underline{\gamma}, \overline{\gamma}]$, $\underline{\gamma}$ and $\overline{\gamma}$ represent two percentiles of the threshold variables, respectively. Owing to the correlation between the regression element and individual effect, the parameter estimation obtained using the ordinary least squares regression directly on (3) is biased. Therefore, we need to find a $l \times 1$ dimensional tool variable $(z_{it_0}', \ldots, z_{iT}')\prime$ that satisfies $E(z_{it_0}'\Delta\varepsilon_{it_0}, \ldots, z_{iT}'\Delta\varepsilon_{iT})\prime = 0$ for any $2 < t_0 \leq T$ and $l \geq k$.

Because the model allows the endogeneity of threshold variable q_{it}, it is $E(q_{it}\Delta\varepsilon_{it}) \neq 0$. Therefore, q_{it} does not belong to the set of instrumental variables $\{z_{it}\}_{t=t_0}^T$, and the sample moment conditions of the following one-dimensional column vectors are considered:

$$\overline{g}_n(\theta) = \frac{1}{n}\sum_{i=1}^n g_i(\theta), \underset{l\times 1}{g_i(\theta)}$$

$$= \begin{pmatrix} z_{it_0}(\Delta y_{it_0} - \beta'\Delta x_{it_0} - \delta' X_{it_0}'1_{it_0}(\gamma)) \\ \vdots \\ z_{iT}(\Delta y_{iT} - \beta'\Delta x_{iT} - \delta' X_{iT}'1_{iT}(\gamma)) \end{pmatrix}. \quad (4)$$

Suppose that if and only if $\theta = \theta_0$, $E(g_i(\theta)) = 0$. Thus, making $g_i = g_i(\theta_0) = (z_{it_0}'\Delta\varepsilon_{it_0}, \ldots, z_{iT}'\Delta\varepsilon_{iT})\prime$ and $\Omega = E(g_i g_i')$, where Ω is assumed to be a positive definite. For a positive definite matrix W_n and $W_n \overset{p}{\longrightarrow} \Omega^{-1}$, making $\overline{J}_n(\theta) = \overline{g}_n(\theta)\prime W_n \overline{g}_n(\theta)$, where

$$W_n = \begin{pmatrix} \frac{2}{n}\sum_{i=1}^n z_{it_0} z_{it_0}' & \frac{-1}{n}\sum_{i=1}^n z_{it_0} z_{i,t_0+1}' & 0 & \cdots \\ \frac{-1}{n}\sum_{i=1}^n z_{i,t_0+1} z_{it_0}' & \frac{2}{n}\sum_{i=1}^n z_{i,t_0+1} z_{i,t_0+1}' & \ddots & \ddots \\ 0 & \ddots & \ddots & \frac{-1}{n}\sum_{i=1}^n z_{i,T-1}z_{iT}' \\ \vdots & \ddots & \frac{-1}{n}\sum_{i=1}^n z_{iT}z_{i,T-1}' & \frac{2}{n}\sum_{i=1}^n z_{iT}z_{iT}' \end{pmatrix}, \quad (5)$$

θ estimates can be derived from $\hat{\theta} = \arg\min_{\theta\in\Theta} \overline{J}_n(\theta)$. For fixed γ, let $\overline{g}_{1n} = 1/n\sum_{i=1}^n g_{1i}$, $\overline{g}_{2n}(\gamma) = 1/n\sum_{i=1}^n g_{2i}(\gamma)$, where $\underset{l\times 1}{g_{1i}} = \begin{pmatrix} z_{it_0}\Delta y_{it_0} \\ \vdots \\ z_{iT}\Delta y_{iT} \end{pmatrix}$, $\underset{l\times(k-1)}{g_{2i}(\gamma)} = \begin{pmatrix} z_{it_0}(\Delta x_{it_0}, 1_{it_0}(\gamma)\prime X_{it_0}) \\ \vdots \\ z_{iT}(\Delta x_{iT}, 1_{iT}(\gamma)\prime X_{iT}) \end{pmatrix}$, then for given γ, β, and δ, the estimators are expressed as the following equation:

$$\left(\hat{\beta}(\gamma)', \hat{\delta}(\gamma)'\right)' = (\overline{g}_{2n}(\gamma)'W_n\overline{g}_{2n}(\gamma))^{-1}\overline{g}_{2n}(\gamma)'W_n\overline{g}_{1n}$$

$$W_n = \left(\frac{1}{n}\sum_{i=1}^n \hat{g}_i\hat{g}_i' - \frac{1}{n^2}\sum_{i=1}^n \hat{g}_i\sum_{i=1}^n \hat{g}_i'\right)^{-1} \quad (6)$$

$$\hat{g}_i = \left(\Delta\hat{\varepsilon}_{it_0} z_{it_0}', \ldots, \Delta\hat{\varepsilon}_{iT} z_{iT}'\right)\prime.$$

Returning $\hat{\beta}(\gamma)$ and $\hat{\delta}(\gamma)$ to the objective function yields an estimate of θ: $\hat{\gamma} = \arg\min_{\gamma \in \Gamma} J_n(\gamma)$, $(\hat{\beta}, \hat{\delta})' = (\hat{\beta}(\gamma)', \hat{\delta}(\gamma)')\prime$.

3. Data

This study uses panel data from 281 prefecture-level cities in China from 2003 to 2020. The relevant data on the regional economy, industrial structure, and urban environmental pollution in various prefecture-level cities stem from the annual "China Statistical Yearbook" and "China Urban Statistical Yearbook." The data on the invention patent authorization in various prefecture-level cities are obtained from the official websites of the State Intellectual Property Office. The energy consumption of prefecture-level cities is calculated based on the nighttime light data that have been widely used in recent economic research [20–22]. The idea is that the brighter the night light is, the greater the total energy consumption. The nighttime lighting data are obtained from the "Global Night-time Light Database." This database was developed based on the Defense Meteorological Satellite Program (the DMSP global nighttime lighting data are available at "https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html"). The nighttime light data include cloudless observation frequency, average light image, and stable light image. Because the stable lighting image data contain relatively stable lighting in cities and towns, this study selects the stable lighting image data as the basic data night-light image data and the Visible Infrared Imaging Radiometer Suite (VIIRS night lighting data are available at "https://ncc.nesdis.noaa.gov/VIIRS/"). night light image data of the National Oceanic and Atmospheric Administration of the United States. These data reflect the nighttime lighting data of the cities and counties in China (The National Geophysical Data Center (NGDC) of the United States conducts a series of noise processing on the basic data, such as eliminating the influence of nighttime clouds, short-term fires, aurora, and lightning, so the processed data can truly reflect the energy consumption of human beings). We average the nighttime light data for each year in the research window period to ensure that nighttime light data cover all prefecture-level cities in China from the time and space dimensions. In addition, we convert the brightness of the light into a digital number (DN). The DN value range of each raster is 0–63 (63 is the saturation value of the data). The spatial dimension covers the longitude from 135°degrees east to 73°degrees west and the latitude from 3°degrees north to 54°degrees north.

The core variable energy utilization efficiency (energy) is measured by the logarithm of the per capita GDP of a prefecture-level city divided by the total energy consumption of the prefecture-level city (i.e., the reciprocal of energy consumption per unit GDP). The higher the value is, the higher the energy utilization efficiency is. The main variable, urban innovation capability (inno), is measured by the total number of invention patents in the prefecture-level cities. Moreover, the urban population density (density) is obtained by dividing the population of the prefecture-level cities by administrative area, thereby characterizing the differential impact of the scale of urban human activities. The industrial structure (struc) is measured by the proportion of the added value of the secondary industry in the regional GDP, thereby characterizing the overall industrial structure of the city. The degree of urban environmental pollution (pollu) is measured by the sulfur dioxide emissions of the prefecture-level cities. The descriptive statistics of the aforementioned variables are presented in Table 1.

4. PVAR Analysis

4.1. Model Estimation. The nonstationary problem of the variables often leads to the phenomenon of "pseudoregression" in the analysis, making the regression results deviate or even invalid. Therefore, we use Levin–Lin–Chu (LLC), Harris–Tzavalis (HT), and Fisher-ADF methods to examine whether the core variables have panel unit roots to ensure the robustness of the test results. Table 2 reports that the test results of the three methods reject the hypothesis that the variables are nonstationary, and it can be considered that the two core variables of energy utilization efficiency and urban innovation capability are stationary, which is suitable for the PVAR system analysis.

The orthogonal transformation between variables and lagged regression coefficients with the help of the Helmert method and the optimal lag order of the PVAR system is selected according to the information criteria, including the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the quasi-information criterion (QIC). When the lag term is 1, the BIC reaches the minimum, and when the order of the lag term is 2, the AIC and QIC reach the minimum (Table 3). Following the principle of "minority obeys majority," a PVAR system with lag order 2 is constructed.

In Table 3, the energy equation estimation results (Column 1) suggest that the early energy utilization efficiency significantly affects the later energy utilization efficiency, and the early urban innovation capability is also conducive to improving the later energy utilization efficiency. However, the estimation results of inno equation (Column 2) reveal that the estimation coefficient of energy utilization efficiency lagging one period is negative and does not exhibit aboriginality, indicating that the urban energy utilization efficiency of the previous period cannot significantly improve the urban innovation capability of the latter period and may even inhibit the urban innovation capability. The early urban innovation capability will be beneficial to the later innovation capability, which has certain "inertia" characteristics.

4.2. Impulse Response and Variance. The stability of the PVAR (2) model is first tested before analyzing the impulse response function and variance decomposition. Table 4 and Figure 1 demonstrate that the absolute values of the real and imaginary parts of the eigenvalues are all within the range of [0, 1]. Therefore, the PVAR model is considered stable.

TABLE 1: Descriptive statistics of variables.

Name	Symbol	Mean	SD	Min	Max	Obs
Energy utilization efficiency	energy	0.1259	0.8483	−2.1271	4.1374	5058
Innovation capability	inno	3.7893	1.9326	0	10.7377	5058
Population density	density	572.1839	313.0527	5.2016	2666.9483	5058
Industrial structure	struc	0.4850	0.1099	0.0900	0.9097	5058
Environmental pollution	pollu	56458.8437	58015.8401	1.9756	683170.7138	5058

TABLE 2: Unit root test for core variables.

Variable	Method			Conclusion		
	LLC	HT	ADF	LLC	HT	ADF
energy	−9.1795 ***	0.5182 **	1140.7838 ***	Steady	Steady	Steady
inno	−9.3768 ***	0.7563 ***	684.5540 ***	Steady	Steady	Steady

Note. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

TABLE 3: Estimated results of the PVAR system.

	(1) energy	(2) inno
Coefficients		
L.energy	0.5594*** (0.1523)	−0.4483 (0.5282)
*L*2.energy	0.3021*** (0.1031)	0.2933 (0.2772)
L.inno	0.0010*** (0.0002)	0.7452*** (0.0273)
*L*2.inno	0.0036* (0.0020)	0.0409*** (0.0154)
Control variables	Yes	Yes
Lag order	AIC	BIC	QIC
1	19.2748	−101.4501	−18.1671
2	16.5196	−80.0603	−24.0836
3	19.3278	−53.1073	−6.6874

Note. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively; "L" and "L2" represent lag order 1 and lag order 2, respectively; standard error is presented in parentheses.

TABLE 4: Stability test of the PVAR (2) model.

Eigenvalue		Module
Real	Imaginary	
0.6744	0	0.6744
0.2816	0.4673	0.5456
0.0.2816	−0.4673	0.5456
0.0670	0	0.0670

FIGURE 1: Roots of the companion matrix.

The impulse response function describes the response of an endogenous variable to an error; that is, the trajectory of the impact of a standard deviation of the random disturbance term on the current and future values of other variables. It can intuitively describe the dynamic interaction between energy utilization efficiency and urban innovation capability and determine the time lag relationship between variables. To intuitively describe the dynamic delay relationship between the variables in the system, we give each variable a standard deviation of the impact and use the Monte Carlo method to simulate 300 times, obtaining the impact of each variable on the 0–20 periods after each variable. The curve of the impulse response function of two variables is illustrated in Figure 2. The horizontal axis represents the response period of the shock response, and the maximum lag period is 20. The vertical axis represents the corresponding degree of the variable to the shock. The shadow part represents the 95% confidence interval, and the middle real line represents the size of the shock response in each period.

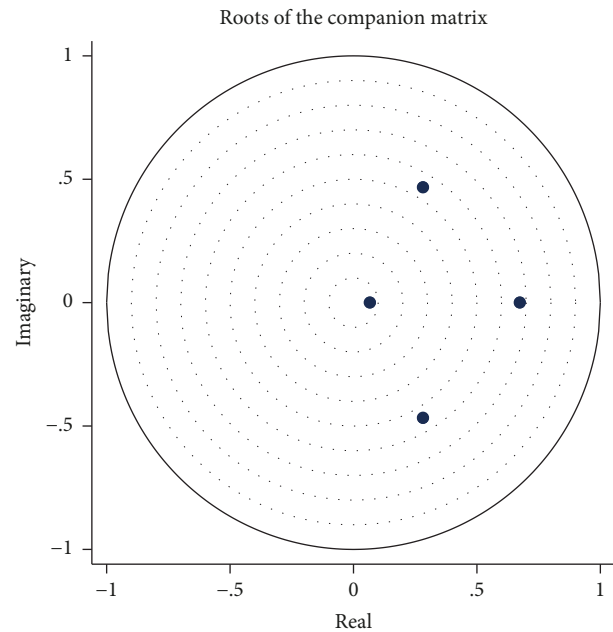There are three kinds of dynamic interaction effects in the PVAR system: direct, reinforcement, and feedback effects. First, the direct effect, which is the lag term of urban innovation capability variables on energy efficiency, can be concerned with the first line and the second column of the impulse response in Figure 2. In the face of an orthogonal impact of urban innovation capability (inno), the overall response of energy utilization efficiency shows an inverted "U-shaped" trend. In the first three periods, improving urban innovation capability can quickly improve energy utilization efficiency, whereas, from the fourth period, the positive effect gradually decreases and approaches 0. This implies that urban innovation capability has a positive effect on energy utilization efficiency, and it will significantly improve energy utilization efficiency in the early stages. However, its effect will gradually weaken with the continuous renewal of urban development and technological innovation. Second, the strengthening effect is the
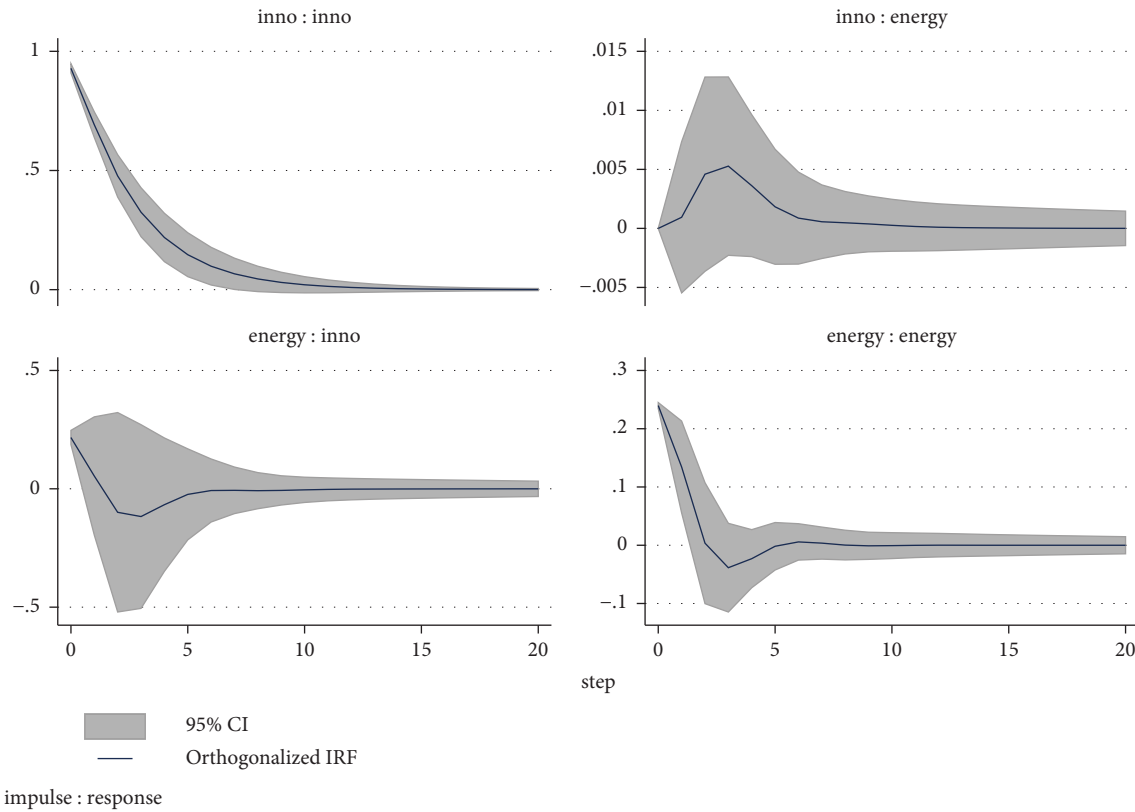
FIGURE 2: Impulse response. Note: the transverse axis represents the lag period of the impact; the middle curve is the impulse response function curve; and the shadow part is the 95% confidence interval.

lag effect of two variables on the current period. Although the strengthening effect of energy utilization efficiency displays a "U-shaped" trend of "positive first and then negative" and gradually converges to zero, the impulse response diagram on the diagonal can be observed. Finally, the feedback effect is the lag of energy utilization efficiency on urban innovation capability. The impulse response in Figure 2 (Row 2 and Column 1) describes the response of the urban innovation capability to energy utilization efficiency's orthogonal impact. Given an orthogonal impact on energy utilization efficiency, urban innovation capability presents a "U-shaped" change of "positive first and then negative" and converges to zero in the 10th phase.

Variance decomposition means the decomposition of the prediction mean square error of any endogenous variable into the contribution made by random shocks to each variable in the system. It calculates the percentage size of the contribution made by shocks to each variable shock, evaluating the impact of one variable on another. On the basis of the analysis of impulse response (Figure 2), we use variance decomposition to further examine the degree of interaction between urban innovation capability and energy utilization efficiency and obtain the contribution of the impact response of each equation to the fluctuation of each variable in the PVAR (2) system. The error variance decomposition results of the two core variables of energy utilization efficiency and urban innovation capability in the 1st–20th forecast periods are

reported in Table 5. The test results prove that the variance decomposition of the 8th period is basically stable, and the conclusion is meaningful.

Moreover, it can be inferred that the variance of the prediction error of energy utilization efficiency comes from itself in the first period, which is unrelated to urban innovation capability (Table 5). However, the contribution rate of urban innovation capability to the change in energy use efficiency has increased over time and finally been maintained at approximately 9.09%, whereas the contribution rate of energy use efficiency to the change in urban innovation capability remains at approximately 4.28%. Compared with the contribution rate of energy utilization efficiency to the change of urban innovation capability, the latter has a greater explanation than the former.

4.3. Granger Causality Analysis. A Granger causality test is conducted on the two core variables in the PVAR system to examine whether there is an obvious causal relationship between urban innovation capability and energy utilization efficiency. The results are reported in Table 6.

Combining the Granger causality analysis results in Table 6 and the variance decomposition results in Table 5, it can be observed that the improvement of urban innovation capability is the reason for the improvement of energy utilization efficiency. The increase in energy utilization efficiency is not the reason for the increase in urban

TABLE 5: Variance decomposition of the prediction error of core variables.

	Variance decomposition			
	energy		inno	
	energy	inno	energy	inno
1st	100%	0%	5.17%	94.83%
2nd	95.99%	4.01%	3.59%	96.41%
3rd	93.27%	6.73%	3.67%	96.33%
4th	91.56%	8.44%	4.20%	95.80%
5th	90.92%	9.08%	4.33%	95.67%
6th	90.91%	9.09%	4.31%	95.69%
7th	90.90%	9.10%	4.29%	95.71%
8th	90.91%	9.09%	4.28%	95.72%
9th	90.91%	9.09%	4.28%	95.72%
10th	90.91%	9.09%	4.28%	95.72%
11th	90.91%	9.09%	4.28%	95.72%
12th	90.91%	9.09%	4.28%	95.72%
13th	90.91%	9.09%	4.28%	95.72%
14th	90.91%	9.09%	4.28%	95.72%
15th	90.91%	9.09%	4.28%	95.72%
16th	90.91%	9.09%	4.28%	95.72%
17th	90.91%	9.09%	4.28%	95.72%
18th	90.91%	9.09%	4.28%	95.72%
19th	90.91%	9.09%	4.28%	95.72%
20th	90.91%	9.09%	4.28%	95.72%

TABLE 6: Granger causality test.

Variable	Granger test (null hypothesis)	χ^2 value	Degree of freedom	P value
Energy	The increase in urban innovation capability is not the reason for the increase in energy utilization efficiency.	14.131	2	0.001
Inno	The increase in energy utilization efficiency is not the reason for the increase in urban innovation capability.	1.167	2	0.558

innovation capability, and whether it is energy utilization efficiency or urban innovation capability, the fluctuation of its prediction error is mainly due to itself. This conclusion provides a basis for using the dynamic threshold regression model to test the nonlinear effect of urban innovation capability on energy utilization efficiency.

5. DPTR Analysis

The threshold variables are set as the population density, industrial structure, and environmental pollution of the prefecture-level cities, and the DPTR model is established in this section to analyze the differences in the impact of urban innovation capability on energy utilization efficiency under different population density, industrial structure, and environmental pollution levels. The specific forms can be expressed as follows:

$$
\begin{aligned}
\text{energy}_{it} = c_0 &+ \left(\phi_1 \text{energy}_{i,t-1} + \theta_1 \text{inno}_{it}\right) \text{I}\{q_{it} \leq \gamma\} \\
&+ \left(\phi_2 \text{energy}_{i,t-1} + \theta_2 \text{inno}_{it}\right) \text{I}\{q_{it} > \gamma\} + \alpha_i + v_{it},
\end{aligned}
\tag{7}
$$

where energy_{it} is a time-varying dependent variable; inno_{it} and lag-dependent variable $\text{energy}_{i,t-1}$ are explanatory variables; $\text{I}\{\cdot\}$ represents an indicator function, which is equal to 1 when the conditions in brackets are satisfied, otherwise 0; q_{it} denotes the three threshold variables that describe the urban population density, industrial structure, and environmental pollution; γ represents the threshold value; ϕ_1, ϕ_2, θ_1, and θ_2 represent the relevant slope parameters corresponding to the different intervals. Because the explanatory and threshold variables in the model may have endogenous problems, the error term of the model is set to $\varepsilon_{it} = \alpha_i + v_{it}$, which is composed of two parts by Seo and Shin [19]; α_i is an unobservable individual fixed effect; and v_{it} is a zero mean heterogeneous random disturbance term (v_{it} is assumed to be a martingale difference sequence, namely, $\text{E}(v_{it}|\chi_{t-1}) = 0$, where χ_{t-1} is the natural filtering in period t, and it is not assumed that inno_{it} or q_{it} is measurable relative to χ_{t-1}, namely, $\text{E}(v_{it}\text{inno}_{it}) \neq 0$ or $\text{E}(v_{it}q_{it}) \neq 0$. This setting allows the endogeneity of the explanatory variable inno_{it} and the threshold variable q_{it} in the model). The estimation results of the impact of urban innovation capability on energy utilization efficiency based on DPTR are summarized in Table 7. Population density, industrial structure, and environmental pollution level are used as threshold variables to represent the population, industry, and environmental constraints of the city to a certain extent.

We use the bootstrap method proposed by Hansen [23] to simulate the asymptotic distribution and p value of the statistics to test the validity of the estimation results of the DPTR model shown in Table 7. The nonlinear test results show that p values are close to zero and the model does have a nonlinear relationship (Table 7). Consequently, a dynamic threshold model with population density, industrial structure, and environmental pollution level as threshold variables can be established. First, from the parameter estimation results with population density as the threshold variable, the threshold value is 263.9851, which divides the sample into two intervals of low population density ($q_{\text{pop}} \leq 263.9851$) and high population density ($q_{\text{pop}} > 263.9851$), and the coefficients of variables in these two intervals are significantly different. When the urban population density is lower than approximately 264 people/km^2, the estimated value of the coefficient passes the 1% aboriginality test and demonstrates a positive "inertia" effect. This indicates that early energy utilization efficiency has a positive role in promoting later energy utilization efficiency under this threshold. The estimated value of the coefficient θ_1 is significantly negative, which indicates that the improvement of the innovation capability of cities with a low population density cannot improve their energy utilization efficiency but will inhibit it. However, in the urban population, the density is higher than 264 people/km^2, and the result is exactly the opposite. The energy utilization efficiency in the early stage is not conducive to improving energy utilization efficiency in the later stage, and improving

Table 7: Estimated results based on DPTR.

			Explained variable: energy		
			Model 1	Model 2	Model 3
Threshold variable			Population density (density)	Industrial structure (struc)	Environmental pollution (pollu)
Threshold value	γ		263.9851*** (13.3842)	0.4026*** (0.0004)	36285.2104*** (2190.5583)
	Explanatory variable	Coefficient			
Low					
	energy$_{i,t-1}$	ϕ_1	0.9086*** (0.0019)	0.9665*** (0.0045)	0.9794*** (0.0046)
	inno$_{it}$	θ_1	−0.0528* (0.0281)	−0.0029*** (0.0007)	−0.0095*** (0.0022)
High					
	energy$_{i,t-1}$	ϕ_2	−0.2038*** (0.0201)	−0.0241*** (0.0032)	−0.0408*** (0.0068)
	inno$_{it}$	θ_2	0.0275*** (0.0032)	0.0044*** (0.0007)	0.0005 (0.0024)
	Constant c_0		0.5829*** (0.0554)	−0.1812*** (0.0069)	−0.1540*** (0.0108)
Nonlinear test (p value)			0.00	0.00	0.00
Percentage of samples in high interval (%)			65.27%	59.84%	56.71%

Note. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively; standard error is presented in parentheses.

urban innovation capability will significantly promote the improvement of urban energy utilization efficiency. Second, from the parameter estimation results with industrial structure as the threshold variable, the threshold value is 0.4026 and is significantly indigenous at the level of 1%, which indicates that when the proportion of the added value of the secondary industry in the GDP of a prefecture-level city is higher than this threshold, the improvement of urban innovation capability is conducive to the improvement of its energy utilization efficiency. On the contrary, it will damage the improvement of energy utilization efficiency. Finally, from the results of parameter estimation with environmental pollution as the threshold variable, the threshold value is 36285.2104 and shows aboriginality at 1% level. The threshold value divides the samples into high-pollution (pollu > 36285.2104) and low-pollution (pollu ≤ 36285.2104) cities. However, the improvement of urban innovation capability is beneficial to the improvement of energy utilization efficiency for high- and low-pollution cities. Notably, compared with high-pollution cities, the improvement of innovation capability in low-pollution cities will have a stronger effect on improving energy utilization efficiency.

6. Conclusion

From the dynamic nonlinear perspective, this study discusses the relationship between urban innovation capability and energy utilization efficiency by using the PVAR and DPTR methods. Using the 2003–2020 panel data samples of 281 prefecture-level cities in China, we discussed the dynamic correlation and mechanism of energy utilization efficiency and urban innovation capability. The results reveal that the improvement in urban innovation capability is the reason behind the improvement in urban energy utilization efficiency, and the improvement in energy utilization efficiency is not the reason behind the improvement in urban innovation capability. The level of energy utilization efficiency in the early stages of the city may be both a boost and an obstacle

to the improvement of energy utilization efficiency in the later stages, depending on the situation of the city in terms of population density, industrial structure, and environmental pollution. For cities with low levels of population density, industrial structure, and environmental pollution, energy utilization efficiency has certain "inertia" characteristics. By contrast, for cities with high levels of population density, industrial structure level, and environmental pollution, the high efficiency of early energy utilization will hinder the improvement in energy utilization efficiency in the later period. From the perspective of urban innovation capability, enhancing urban innovation capability can not only improve energy utilization efficiency but also adversely affect cities with a low population density or weak secondary industrial base. Whereas for cities with a high population density or proportion of secondary industry, improving innovation capability will significantly improve urban energy utilization efficiency. Furthermore, the promoting effect of urban innovation capability on energy utilization efficiency in low-pollution cities is significantly stronger than that in high-pollution cities.

Some shortcomings remain in this study, which is unavoidable. First, the measurement of urban innovation capability is rather rough without considering the differences in patents (for example, patents for invention, patents for utility models, and patents for industrial design). The follow-up research can make a more detailed division of innovation capability according to Chinese patent classification standards so as to reflect the difference in quantity and quality of urban innovation capability. Second, this paper only considers the influence of urban population density, industrial structure, and environmental pollution on the relationship between urban innovation ability and energy utilization efficiency. A future study can further investigate the possible nonlinear relationship between urban innovation ability and energy utilization efficiency caused by economic development, urban infrastructure, policy implementation efficiency, etc.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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