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The Impact of Foreign and Indigenous Innovations on the Energy Intensity of China's Industries

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Abstract: China's industrial sectors have an approximate consumption amounting to 70% of the aggregate power of the entire country. Investigating the driving forces of the decline in the energy intensity is essential for accelerating China's conversion into a low-carbon economy. Nowadays, there has been no agreement as yet when it comes to the impacts of China's industrial sectors on energy intensity. The current research work studies the impacts of key driving forces, in particular foreign as well as indigenous innovations, on China's industrial energy intensity in 34 industrial sectors between 2000 and 2010. Linear and nonlinear analysis methodologies are put to use. The linear empirical findings show that indigenous innovation primarily contributes to driving down the industrial energy intensity across the sampling duration. The foreign innovations, which take the shape of FDI as well as imports, are seen as benefiting the decline in industrial energy intensity; on the other hand, exports ramp up the industrial energy intensity. An additional investigation, on the basis of the panel threshold framework, indicates that the impact of foreign innovations by means of openness as well as industrial energy intensity has an association with the technological absorptive potential. The empirical evidence puts forward some pivotal inferences for policymakers with regard to China's declining industrial energy intensity—for instance, exploitation of the maximum benefit associated with the technology spillovers; in addition, it is important to take into consideration the attributes and scenarios that impact industrial energy intensity.

Keywords: indigenous innovation; foreign innovation; industrial energy intensity; panel threshold model

1. Introduction

Energy is regarded as a necessary input for economic development, besides serving as the foundation for material generation. China has attained rapid economic development in the last 40 years, but it has manifested reliance on power. According to *China Statistical Yearbook* (CSY), China showed a consumption of 4.36 billion tons of coal equivalent in the year 2016; this kind of usage accounted for almost 23% of the global aggregate. In addition, ecological issues caused by haze and acid rain, besides being a result of the elevated power usage, have emerged as an obstacle to sustainable economic growth in China. Accordingly, lowering the energy intensity (the power put to use in the production of one unit of gross domestic product (i.e., GDP)) has emerged as a key point of consideration among Chinese policy makers [1–4]. As the year 2016 ended, China's State Council emphasized the requirement that the country lower its energy intensity by 15% compared to the 2015 levels, by the year 2020. Subsequently, other accountable ministries or administrations, such as domestic governments, made announcements of associated platforms, employing a battery of policies as well as steps for the fulfilment of the national objective to control the energy intensity.

In this manner, analysis of the role various determinants play in the evolution of energy intensity will substantially benefits China by providing appropriate energy strategies to be put forward by the policy makers [5–10]. There are a number of researchers who have explored the driving forces behind China's energy intensity, and accordingly have put forward policy guidance for the reduction of energy intensity; in addition, they reached the conclusion that technological advancement constitutes one of the key determinants impacting energy intensity [11–16].

Owing to the fact that the technological advancement is pivotal to the transition to a low-carbon economy, foreign innovations in the shape of foreign direct investment (FDI) as well as trade are recognized as key channels of technological advancement apart from indigenous innovation (i.e., research and development (R&D)). The manner of the foreign innovation, whether in the form of FDI, imports, or exports, exerts an impact on the energy intensity by means of technology spillovers and thus has received a significant amount of attention [17–19]. Nevertheless, arriving at a consensus on the analytical framework of and mechanism behind the impacts of these kinds of factors on energy intensity is quite difficult. Three causes have been proposed. Firstly, there are observed differences in the proxy variables from different kinds of empirical research works that obscure the conclusions [3,5,8,15–20]. Considering the proxy variable of FDI as an example, Yan [1], Adom [15], and Elliott et al. [18] took the ratio of FDI to GDP as the proxy variable for the purpose of reflecting the FDI's impact on energy intensity. Hang and Tu [20] used the quantity of FDI for the reflection of its spillover impact on energy intensity. Zheng et al. [21] provided a definition of the ratio of FDI to fixed assets as the proxy variable to reflect the impact of FDI on energy intensity. In addition, different definitions of proxy variables of FDI naturally give rise to biased estimates in regression analyses. Moreover, the same types of issues can still be found in the case of trade. Secondly, FDI, together with exports and imports, are the channels for transferring state-of-the-art technology and management experience, so it requires consideration in the econometric model. Nevertheless, there are a few scholars who have carried out analyses of their effects on energy intensity simultaneously. For the purpose of determining the relative effect of indigenous as well as foreign innovations on energy intensity, there is a need to build a united framework. Thirdly, the impact of foreign innovations includes the technological absorptive capacity. For instance, enterprises with robust technological absorptive capacity are most likely to undergo a positive spillover impact from openness. By contrast, the ones with weak technological absorptive capacity are likely to undergo a negative spillover effect. Unfortunately, the majority of the existing research works have not attached sufficient significance to this issue, and there are just a few scholars who have carried out the relevant research [5,8,18]. For instance, Huang et al. [5] revealed that regional full-time equivalents (number of R&D staff recruited in accordance with their duty hours) are expected to help promote the positive spillover impact exerted by both FDI and trade, which are capable of contributing to the decline in the provincial energy intensity of China. Elliott et al. [18] further illustrated how FDI exerts different effects on the energy intensity of various countries. They also suggest that the differential technological absorptive capacity of the host country is responsible for these varying effects.

Furthermore, most existing studies dealing with the driving forces associated with the change in energy intensity are based on both the national and regional levels. For instance, Yan [1] made use of a fixed-effects model as well as China's interprovincial panel data between 2000 and 2012 for the analysis of the impacts of urbanization, economic structure, exports, and foreign direct investment (FDI) on energy intensity. As revealed by the research findings, China's rapid urbanization, industrialization, and exports have significantly increased energy intensity. In the meantime, increases in energy prices and FDI inflows have the potential of significantly lowering energy intensity. Through the use of the spatial econometrics and DEA-Malmquist index, Huang et al. [4] reached the conclusion that technological progress, together with its spillover effect, was the key to declining provincial energy intensity in China in 2000–2014. Huang et al. [5] applied the panel co-integration and panel threshold framework for the analysis of the variation factors of provincial energy intensity of China in 2000–2013. In accordance with their results, increasing indigenous R&D constitutes a productive methodology for lowering energy intensity, whereas the fast-paced process of industrialization and urbanization has the ability to significantly boost energy intensity. Yu [13] performed an analysis of the influencing factors of China's interprovincial energy intensity between 1988 and 2007 with the use of a spatial panel model. The empirical results showed that the increase made in the research and development (R&D) investment, marketization, in addition to GDP per capita, is capable of substantially lowering energy intensity of China and that the country's heavy dependence on industry and coal significantly hinders its energy reduction. Voigt et al. [16] made use of the World Input–Output Database for the analysis of the energy intensity factors of 40 major economies across the globe. The authors put forward that the technological advancement is counted among the pivotal reasons for the decline in energy intensity between 1995 and 2007, in addition to suggesting that the impacts of the structural change on energy intensity are comparatively minimal. Nevertheless, China's industries constitute key consumers of energy, with their consumption accounting for over 66% of the country's aggregate in the past few years (CSY, 2011–2017). Developing an understanding of the trend of China's industrial energy intensity, together with formulating scientific policy recommendations, is quite beneficial for China's transition to a low-carbon economy. Unfortunately, there are just a few scholars who have investigated the factors impacting the industrial energy intensity of China [21–25]. In these few research works, owing to data availability and consistency, the sampling period is limited to between 1999 and 2011. For instance, Zheng et al. [21] made use of a panel dataset covering 20 industrial sub-sectors of China between 1999 and 2007, together with a panel varying-coefficient regression model for investigating the impact of exports on the industrial energy intensity. They figured out that exports aggravate China's industrial energy intensity. Wang and Qi [22] distinguished different effects of the biased technological advancement as well as factor substitution on the industrial energy intensity for the period between 1999 and 2011. Through the application of the convergence theory originated in economics, Huang et al. [23] carried out an analysis of the convergence characteristics of industrial energy intensity of China from 2000 to 2010.

In summary, the current research work puts forward a united framework on the basis of a CH–LP model from Coe and Helpman [26] (referred to as CH) and Van Pottelsberghe de la Potterie and Lichtenberg [27] (referred to as LP) in a bid to illuminate the relative roles that different factors, especially indigenous innovations as well as foreign ones, played in industrial energy intensity between 2000 and 2010. Subjected to the united framework with a carefully designed econometric model, it is possible to compare and analyze the relative powers of both the indigenous and foreign innovations on industrial energy intensity. Furthermore, a further application of the panel threshold model is made for the purpose of investigating the roles different technological absorptive capacity influencing factors played in industrial energy intensity. The conclusions reached by this study will help decision makers clarify the relationship between indigenous innovations, foreign innovations, and energy intensity.

The structure of the current study is as follows. As highlighted in Section 2, the employed methodology is introduced. The findings and discussion are given in Sections 3 and 4, respectively. The final section concludes the major findings.

2. Materials and Methods

First, we derive a generalized model in which the technological progress and energy price are recognized as the key factors of the industrial energy intensity. Second, contrary to the majority of the earlier literature, a united framework based on the CH-LP model is developed for the assessment of the impact of foreign innovations—not just FDI, but also exports and imports—on industrial energy intensity. Third, subject to the united framework, the detailed roles the technological absorptive ability played in industrial energy intensity are also discussed. Figure 1 gives the theoretical analytical framework of our work.

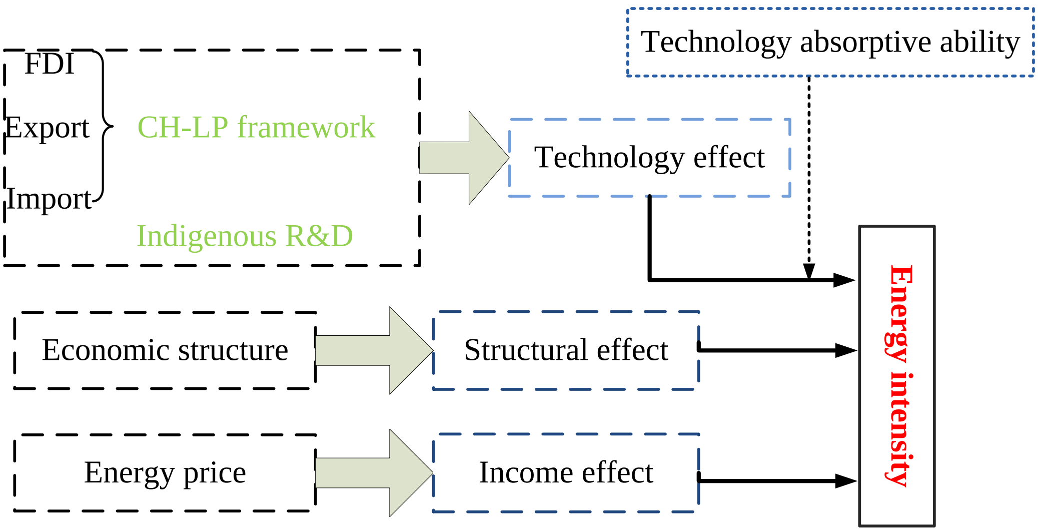

Figure 1. Theoretical analytical framework of this study.

2.1. Methods

2.1.1. Generalized Model

For the purpose of exploring the effects of both foreign and indigenous innovations on energy intensity, by following the prior work of Fisher-Vanden et al. [25], we make an assumption that the Cobb–Douglas cost function has the following form:

$$C(P_K, P_L, P_E, P_M) = T^{-1} P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} P_M^{\alpha_M} Q, \tag{1}$$

where Q represents production; P_K, P_L, P_E, and P_M are input factors of capital, labor, energy, and raw material price, respectively; $\alpha_X (X = K, L, E, M)$ is an indication of the elastic coefficient of the input factor; and T suggests the level of technological progress.

In accordance with the *Shephard* transformation, the factor demand for an input is equivalent to the derivative of its cost function. We derive the factor demand for energy as follows:

$$E = \frac{\alpha_E T^{-1} P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} P_M^{\alpha_M} Q}{P_E}, \tag{2}$$

where E is a representation of the energy demand. P_L, P_K, P_E, and P_M together with $(X = K, L, E, M)$ share the meanings presented in Equation (1).

We assume that

$$P_Q = P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} P_M^{\alpha_M}, \tag{3}$$

where P_Q denotes the output price index and $\alpha_K + \alpha_L + \alpha_E + \alpha_M = 1$. Subsequent to that, the energy intensity (defined as $EI = E/Q$) can be obtained through the substitution of Equations (3) into (2) as follows:

$$EI = \frac{\alpha_E T^{-1} P_Q}{P_E}, \tag{4}$$

where EI denotes energy intensity. $\frac{P_Q}{P_E}$ can be viewed as the relative price of energy. When the energy price increases, the actual income levels of consumers will decrease, lowering the demand for energy. This effect is called the income effect and has been captured by Hang and Tu [20].

The use of the logarithm of Equation (4) yields

$$\ln EI_t = \lambda + \alpha \ln T_t + \beta \ln \left(\frac{P_E}{P_Q}\right)_t + \varepsilon_t, \tag{5}$$

where λ represents a constant; α and β are the coefficients of technological progress and the relative price of energy, respectively; and ε_t denotes the error term.

With regard to an open economy, as suggested by an array of earlier research works, the technological progress is dependent not just on indigenous innovations but also on foreign innovations by means of openness [26–30]. Therefore, indigenous innovations as well as foreign innovations, in the shape of technology spillovers, are selected as the key factors impacting China's technological progress. (Theoretically, foreign innovation in the shape of the outward direct investment (ODI) also exerts an impact on the technological progress [3]. However, China's "going out strategy" was initiated in the year 2004 and is much smaller in comparison with FDI. Consequently, the technology spillover stemming from ODI has not been taken into consideration as a key means of the technological advancement in the case of China [30]) Hereafter, the technological progress can be expressed as follows:

$$\ln T_t = \alpha_0 + \alpha_1 \ln SRD_t + \alpha_2 \ln SFDI_t + \alpha_3 \ln SEX_t + \alpha_4 \ln SIM_t + u_t, \tag{6}$$

where α_0 denotes a constant; and *SRD*, *SFDI*, *SEX*, and *SIM* are the representations of the independent R&D stocks, in addition to the technology spillovers by means of not just FDI, but also exports and imports, respectively. Substituting Equation (6) into Equation (5) has the potential to express energy intensity as follows:

$$\ln EI_t = \alpha + \beta_1 \ln SRD_t + \beta_2 \ln SFDI_t + \beta_3 \ln SEX_t + \beta_4 \ln SIM_t + \beta_5 \ln\left(\frac{P_E}{P_Q}\right)_t + v_t, \tag{7}$$

In Equation (7), α stands for the constant, while β_i (i = 1, 2, . . . , 5) is the parameter requiring estimation.

2.1.2. Control Variables

The changing structure of the industrial sectors is also counted among the pivotal factors impacting energy intensity [21,23]. Moreover, the expansion of the industry scale is likely to lead to a rise in the number of companies with low technology levels entering the industry, accordingly lowering the energy efficiency and augmenting energy intensity [21]. Similar to Huang et al. [23], we employ the ratio of the assets in a sub-sector to the total assets in the overall industrial sectors as a reflection of the effect of relative modifications in the internal scale of the industry on energy intensity changes, which assumes that the industry expansion is going to increase energy intensity.

2.1.3. Empirical Model

We add the control variables into Equation (7), followed by estimating it as a panel data framework, presented as follows:

$$\begin{aligned} \ln EI_{it} &= \beta_0 + \beta_1 \ln SRD_{it} + \beta_2 \ln SFDI_{it} + \beta_3 \ln SEX_{it} + \beta_4 \ln SIM_{it} \\ &+ \beta_5 \ln\left(\tfrac{P_E}{P_Q}\right)_{it} + \beta_6 \ln ES_{it} + \varepsilon_{it} \end{aligned}, \tag{8}$$

In the above formula, the footnotes i (i = 1, 2, 3, . . . , M, N) and t (t = 1, 2, 3, . . . , S, T) represent the industry and year, respectively. *EI* stands for the energy intensity. *SRD* is an indication of the indigenous R&D capital stock. In addition to that, *SFDI*, *SEX*, and *SIM* respectively denote foreign innovations from FDI, exports, and imports. Moreover, P_E/P_Q is a representation of the relative energy prices. *ES* indicates the control variables, i.e., changes in industry scale. β_m (m = 0, 1, 2, . . . , 6) is the parameter to be approximated. In addition, the symbol "ln" means taking the natural logarithm. ε_{it} stands for the random interference term.

2.1.4. Estimation Method

Fixed effects (FE) and the random effects (RE) are among the most frequently used methodologies to perform the analysis of panel models. The Hausman test tool can be employed for the determination of the more appropriate model. Nonetheless, in a case where the FE model suffers from the serial correlation or heteroscedasticity, the estimated results are expected to have a bias. That is why the modified Wald test methodologies, put forward by Greene [31] and Wooldridge [32], are employed for the determination of whether there is autocorrelation and heteroscedasticity. For the purpose of addressing the issues of heteroscedasticity as well as autocorrelation, the Feasible Generalized Least Squares (FGLS) methodology has the potential to be a likely alternative methodology. Nonetheless, FGLS requires that the time dimension T be larger than or equal to the length N of the cross section; otherwise, the superiority of the FGLS is going to decrease. Accordingly, referring to Yan [1] and Huang et al. [33], the Driscoll–Kraay (DK) methodology is eventually employed for the purpose of re-estimating the model. The DK methodology has the potential to provide robust estimation results in the presence of autocorrelation as well as heteroscedasticity.

Companies have the opportunity of increasing the production efficiency and lowering the manufacturing costs through the digestion, absorption, and application of external knowledge stemming from openness. The technological absorptive capacity is one of the pivotal factors for the determination of the spillover effects of openness [5,15,28,34]. As indicated by Huang et al. [5] and Adom [15], the effect of FDI on energy intensity is dependent on the level of technology absorptive capacity, whereas the traditional linear analysis only shows the average effect of different explaining variables on the explained variable. This study also develops a nonlinear model for the investigation of the nonlinear impact of different technological factors on the industrial energy intensity of China.

Through the use of Hansen's endogenous threshold approach [35,36] (prior to proceeding with the nonlinear analysis, it is essential to determine the threshold impact using the null hypothesis: H_0 ($\beta_1 = \beta_2$). If this null hypothesis holds true, then no threshold impact exists, and the model is actually a linear model), we are capable of exploring the changes in impact that the technological factors exert on the industrial energy intensity at varied levels. Following Hansen [35] and Hansen [36], the panel threshold model with one threshold value is as follows:

$$\ln EI_{i,t} = \begin{cases} \alpha_i + X_{i,t}\beta_1 + u_{i,t} & q_{i,t} < \gamma \\ \alpha_i + X_{i,t}\beta_2 + u_{i,t} & q_{i,t} \geq \gamma \end{cases}, \tag{9}$$

where q_i refers to a cohort of threshold variables, which we have chosen as reflectors of the technology absorptive capability. γ stands for the threshold value. In addition, X denotes a vector of explaining variables that include the relative energy prices, together with the structural change, etc. When q_i exceeds the threshold value r, the threshold coefficient of q_i is β_2. If not, β_1 would be the threshold coefficient of q_i.

Subsequent to the verification of the single threshold, it is essential to check whether there are two thresholds in the model, expressed as follows:

$$\ln EI_{i,t} = \begin{cases} \alpha_i + X'_{i,t}\beta_1 + u_i & q_i < \gamma_1 \\ \alpha_i + X'_{i,t}\beta_2 + u_i & \gamma_1 \leq q_i < \gamma_2 \\ \alpha_i + X'_{i,t}\beta_3 + u_i & \gamma_2 \leq q_i \end{cases}, \tag{10}$$

where β_1, β_2, and β_3 refer to the coefficients of the threshold variables that are on the three sides of the threshold. Other variables share the same meaning as Equation (9). As highlighted in Huang et al. [5], Lai et al. [29], and Cohen and Levinthal [34], indigenous R&D is capable of not just serving as a key avenue for accelerating the technological progress, but of improving the technical absorptive capacity as well. Accordingly, indigenous R&D is typically considered to be a measure of absorptive capability [5,29,34]. In addition, the level of foreign enterprises entering China's industrial sub-sectors also exerts a significant impact on the spillover effects of the openness on industrial energy intensity. The deeper they enter into, the closer the relationship between foreign enterprises and local ones that would be expected. Consequently, foreign enterprises are more inclined to help local ones absorb their advanced technology as well as management experience. Accordingly, in the current research work, both the R&D intensity (as per definition, the share of R&D inputs to industrial added-value, unit: %) and the degree of foreign enterprises (LFC) entering China (defined as the ratio of assets in foreign-invested enterprises to the assets in large and medium enterprises, unit: %,) are chosen as the threshold variables. The data can be found in the *China Statistical Yearbook on Science and Technology* and CSY.

2.2. Data Collection and Processing

Considering that China's official statistical data on industrial segmentation were significantly different in 1999, and taking into consideration the availability as well as the comparability of statistics, the relevant data of 34 industrial sub-sectors from 2000 to 2010 are selected in our research (The codes and corresponding names of these 34 industries are presented in Appendix A (Table A1)) These data have been derived from the CSY, *China Science and Technology Statistical Yearbook*, and *China Energy Statistics Yearbook*. The comprehensive data sources and treatment methodologies for the associated variables are described hereafter.

The energy intensity of each industry (unit: tons of coal equivalent per 10,000 yuan) is calculated by the ratio of energy consumption to the industrial added value. Furthermore, the aggregate amount of the energy consumed by different kinds of sectors over the can be obtained from the *China Energy Statistical Yearbook* (various years). Value-added data between 2000 and 2010 were obtained from the "Main Indicators of Industrial Enterprises above Designated Size by Industrial Sector" in CSY (various years). These data require adjustment to the steady price in the year 2000 by the industrial product price index acquired from the CSY. Nevertheless, because there are no data available on the added value between 2008 and 2010, the data on the cumulative growth rate of the value added that are obtained from the National Bureau of Statistics of China are used for the purpose of estimating the value added between 2008 and 2010.

The indigenous R&D stock is represented by the internal R&D operations of large and medium-sized industrial entities in different sub-sectors. Similar to Huang et al. [5], the corresponding R&D expenditure data can be obtained from the *China Science and Technology Statistical Yearbook*, followed by converting to the base period with the GDP deflator. Subsequently, in accordance with the perpetual inventory theory, we are able to perform the calculation of the R&D capital stock formed by R&D activities in the industrial subsectors over the years to yield:

$$K_t = I_t + (1 - \sigma)K_{t-1}, \tag{11}$$

where σ indicates the capital depreciation rate that is consistent with the data put to use by Yan [1] and Huang et al. [5], where σ = 9.6% (For the purpose of testing the stability and verifying that our estimated empirical results are credible, the test with σ = 15% is repeated. The results have been presented in Appendix B (see Table A2). As suggested by the comparison carried out, the approximated findings are strong). Furthermore, the R&D capital stock of the base period is calculated in accordance with the method of Yan [1] for the creation of an entire time series of the capital stock:

$$K_{2000} = \frac{I_{2000}}{g_{2000-2010} + \sigma}, \tag{12}$$

where $g_{2000-2010} = \left[\frac{I_{2010}}{I_{2000}}\right]^{1/10} - 1$ is a representation of the annual growth rate of indigenous R&D in 2000–2010.

As a result of lacking direct investment, coupled with the trade data from most of China's industrial sub-sectors and foreign countries (regions), we make use of the CH–LP technology spillover analysis framework for the calculation of the total amount of technology spillovers that China has acquired by means of FDI and trade (FDI is expressed in terms of actual use of foreign investment. The data on imports from other nations (regions) are expressed with regard to the countries of origin and regions of China. The data on exports to other countries (regions) are expressed in terms of the destination countries and regions of China. Owing to the fact that Hong Kong is counted among the largest trade regions in entrepot trade with China's mainland, the goods exported from China to Hong Kong require adjustments. However, it is also quite difficult to calculate the re-exports accurately. For simplicity, we make an assumption that the total amount of goods that China imports from Hong Kong is equal to that exported to Hong Kong) In accordance with Coe and Helpman [26] and Van Pottelsberghe de la Potterie and Lichtenberg [27], the total amount of technology spillovers that China obtained by means of FDI, imports, and exports can be expressed as follows:

$$SFDI_t = \sum_{n=1}^{N} \frac{FDI_{nt}}{K_{nt}} S^d_{nt}, \tag{13}$$

$$SIM_t = \sum_{n=1}^{N} \frac{IM_{nt}}{Y_{nt}} S^d_{nt}, \tag{14}$$

$$SEX_t = \sum_{n=1}^{N} \frac{EX_{nt}}{Y_{nt}} S^d_{nt}, \tag{15}$$

Herein, the subscripts n (n = 1, 2, 3, ..., N) as well as t (t = 1, 2, 3, ..., T) represent the foreign country (region) and the year, respectively. Moreover, $SFDI$, SIM, and SEX are, respectively, the corresponding indications of the technology spillovers that China has acquired by means of the openness in the shape of FDI, imports, and exports. FDI_{nt} denotes the total direct investments foreign country (region) n invested in China in year t. IM and EX both are the aggregate import and export commodities between China and its trading partners (or areas). K, S, and Y are the aggregate fixed capital creation of foreign countries (regions), R&D capital stock, and gross domestic product, respectively. Taking into consideration that the major R&D activities worldwide are carried out in some developed countries and there are relationships between China and these countries in terms of investment and trade, the G7 countries, Hong Kong, Singapore, and Korea are selected as China's key technology spillovers. In addition, the perpetual inventory theory is again applied for the calculation of R&D capital stock for foreign countries (regions).

Subsequent to the calculation of the technology spillovers that China has acquired by means of openness, next we determine the technology spillovers obtained by each industrial sub-sector. We assume that China's industrial sub-sectors have gained technology spillovers on the basis of the ratio of their FDI, exports, and imports to China's total. However, only the FDI data on mining, production, power, gas and water generation, and supply sectors are available from the CSY, so we make use of the ratio of the assets in industrial sector m's foreign-funded enterprises to the total assets in all the industrial sectors to denote the percentage of their FDI versus the aggregate in China. Then we are able to present the technology spillovers attained by each industrial sub-sector originating from FDI as follows:

$$SFDI_{mt} = \frac{C_{mt}}{C_m} \frac{FDI_{It}}{FDI_t} SFDI_t, \tag{16}$$

where m (m = 1, 2, 3, . . . , M) is the industrial sub-sector and t (t = 1, 2, 3, . . . , T) stands for year. $SFDI_{mt}$ suggests the technology spillover by means of FDI received by the industrial sub-sector m. FDI_{It}/FDI_t denotes the share of FDI acquired by the whole industrial sector to the total FDI received by China in year t. C_{mt}/C_m stands for the ratio of the assets in industrial sector m's foreign-funded enterprises to the total assets in all industrial sectors. In the same manner, we are capable of expressing the technology spillovers obtained by different kinds of industrial sub-sectors in China by means of exports and imports as follows:

$$SIM_{mt} = \frac{IM_{mt}}{IM_t} SIM_t, \tag{17}$$

$$SEX_{mt} = \frac{EX_{mt}}{EX_t} SEX_t, \tag{18}$$

where IM_{mt} and EX_{mt} are the total amount of imports and exports of the industrial sector m at time t, respectively. The total imports and exports of each industrial sub-sector over the years are from the three-digit industry classification data of the UN Comtrade database in SITC Revision.3 standard and are merged in accordance with the industry classification standard data of the National Bureau of Statistics of China.

Structural change, as represented by the ratio of the assets in a sub-sector to the total assets in the aggregate industrial sectors, is selected as the control variable; the relevant data are from the CSY. Table 1 gives definitions of the variables put to use in the model and their data characteristics.

Table 1. Data definitions.

Variables	Definition (unit)	Max	Min	Mean	Std
lnEI	ln form of energy consumption divided by industrial added value of each industrial sub-sector (TCE/10^4 yuan)	2.7660	−2.7658	0.2780	1.1981
lnSRD	ln form of indigenous R&D capital stock: (10^8 yuan)	7.9420	−0.0758	4.6322	1.5966
ln$SFDI$	ln form of foreign innovation through FDI (10^8 yuan)	5.5718	−3.4882	2.4902	1.6736
lnSEX	ln form of foreign innovation through export (10^8 yuan)	7.3127	−2.2607	3.6848	1.8705
lnSIM	ln form of foreign innovation from import (10^8 yuan)	7.0766	−2.4728	3.5055	1.8692
lnP_e/P_q	ln form of the ratio of price index of purchasing fuel and power to price index for industrial product (%)	5.7004	4.1918	4.8070	0.2643
lnES	ln form the ratio of the assets in a sub-sector to the total assets in the overall industrial sectors (%)	2.8956	−2.1762	0.4738	1.1560

Note: TCE stands for ton of standard coal equivalent. The capital depreciation rate is 9.6%.

3. Results

3.1. Linear Regression Analysis

The application of the Hausman test tool is made for the determination of the appropriate estimator (RE or FE) for the model. The result rejects the RE model at the 1% significance level, which indicates that the FE model is expected to be suitable for the estimation. Nevertheless, heteroscedasticity and autocorrelation are identified by means of the modified Wald test method put forward by Greene [31] and Wooldridge [32], suggesting that the FE model is expected to have a bias. That is why the FGLS model is also put to use. Taking into consideration that the FGLS model is inefficient when cross-sectional dimension N is greater than time dimension T, we provide the estimation results on the basis of the DK methodology. Table 2 gives the linear estimated results, including the FE, FGLS, and DK models.

Table 2. The results based on the linear analysis.

Variables	FE	FGLS	DK
Constant	5.8635 ***	5.6245 ***	5.8635 ***
	(0.3398) [a]	(0.2554)	(0.3767)
ln*SRD*	−0.3417 ***[b]	−0.3694 ***	−0.3417 ***
	(0.0341)	(0.0267)	(0.0247)
ln*SFDI*	−0.1719 ***	−0.0775 ***	−0.1719 ***
	(0.0339)	(0.0257)	(0.0525)
ln*SEX*	0.0325	0.1461	0.0325
	(0.2075)	(0.2210)	(0.3253)
ln*SIM*	−0.0684	−0.1893	−0.0684
	(0.2122)	(0.2153)	(0.3344)
$\ln P_e/P_q$	−0.7544 ***	−0.5516 ***	−0.7544 ***
	(0.0849)	(0.0633)	(0.0929)
ln*ES*	0.3638 ***	0.2012 ***	0.3638 ***
	(0.0633)	(0.0387)	(0.0586)
Hausman (*p*)	42.8 ***		
Wald x^2	1140.05 ***		
Heteroscedasticity test [c]	4813.20 ***		
First-order autocorrelation test	60.19 ***		
Within-R^2	0.7906		0.7906
Observations	374	374	374

Notes: [a] Values presented in the parentheses are the stand errors. [b]***, **, and *are the indications of significance at the 1%, 5%, and 10% levels, respectively. [c] The null hypothesis for the heteroscedasticity test suggests that there is no heteroscedasticity and the null hypothesis for autocorrelation test indicates that there is no first-order autocorrelation. The capital depreciation rate is 9.6%.

The second column of Table 2 gives the findings on the basis of the FE estimator. Due to the serial correlation and heteroscedasticity in the FE model, the third and fourth columns give the results on the basis of FGLS and DK estimator, respectively. As shown, indigenous innovation (ln*SRD*) occupies the largest regression coefficient for energy intensity in all three models, which suggests that the indigenous innovation is the most effective tool for lowering China's industrial energy intensity. As shown, a 1% rise in the indigenous R&D capital stock is expected to result in a decrease in the industrial energy intensity of approximately 0.35% at the 1% significance level. Through a continuous increase in indigenous R&D expenditures, Chinese industrial enterprises are capable of directly creating and accumulating new technology, which aids the reduction of industrial energy intensity. With regard to foreign innovations, they also have the potential to exert impact on China's industrial energy intensity by means of FDI and imports. As shown, the technology spillovers that come from both FDI as well as imports positively and significantly impact the reduction of China's industrial energy intensity. The foreign-funded enterprises have made an excellent demonstration of competition against domestic enterprises in China, encouraging domestic enterprises to attain and absorb technology spillovers through FDI. In the meantime, the impact of foreign innovation in the form of imports on industrial energy intensity is also negative but insignificant, which suggests that imports exerted a positive spillover effect on China's industrial energy intensity. Local industrial enterprises have continuously innovated on the basis of learning for the imitation of imported products by means of the import of some capital goods and production equipment with excellent quality and high technology. This approach enhances local industrial enterprises' competitive advantage as well as the potential of innovation, accordingly augmenting the energy efficiency and lowering the energy intensity. Theoretically, industrial enterprises have an incentive to lower manufacturing costs and increase production efficiency for the enhancement of the international competitiveness of products. The learning-by-doing impact is also expected to promote progress in technology. Accordingly, exports are anticipated to lower the industrial energy intensity. However, as revealed by the results, foreign innovation through exports increases the industrial energy intensity.

In addition to the effects of indigenous and foreign innovations on China's industrial energy intensity, of the other variables, the empirical evidence presented in the earlier literature concerning the nexus between energy intensity and energy price is consistent with our findings in Table 2 [3,4,20,25]. In all three models, the increase in the relative energy price is conducive to lowering China's industrial energy intensity, suggesting that, in a fiercely competitive market, the increase in energy prices is expected to motivate entities to adopt energy-conserving technologies, together with lowering energy usage. Conversely, a decline in energy prices will reduce energy-saving consciousness. With regard to the economic structure, the empirical evidence is in line with the results presented by Zheng et al. [21], in which they put forward that the expansion in the industry scale is expected to encourage low production efficiency, in addition to increasing the energy intensity of the entire industry.

3.2. Nonlinear Analysis

For the purpose of comprehensively revealing the manner in which the technological absorptive capacity impacts the roles of foreign innovations in the shape of FDI as well as the industrial energy intensity, the panel threshold model is employed. Prior to carrying out the nonlinear analysis, there is a need to test the presence of a threshold impact between technology spillovers and industrial energy intensity with the use of the "bootstrap method" put forward by Hansen [35,36]. Table 3 gives the results of the threshold impacts. Subsequent to the application of the "bootstrap method" for testing if there is a threshold effect, the number of thresholds requires estimation in the following.

Table 3. Test of threshold effects for technology spillovers.

Threshold Variable	Independent Variable	Threshold Value	*F*	*p*-Value	5% Critical Value
LFC [b]	Single	0.8	21.0021 ***[a]	0.001	4.0874
	ln*SFDI* Double	0.8, 31.57	10.8609 ***	0.002	3.7766
	Triple	0.8,31.57, 57.78	9.0507 ***	0.004	4.0037
	Single	0.8	14.3437 ***	0.001	4.2870
	ln*SEX* Double	0.8,31.57	20.7860 ***	0.000	6.4628
	Trible	0.8,31.57, 57.78	18.6475 ***	0.000	3.9566
	Single	0.8	15.0719 ***	0.001	7.6137
	ln*SIM* Double	22.45	21.3923 ***	0.001	4.3234
	Trible	0.8, 22.45,57.78	15.4517 ***	0.000	3.9011
	Single	0.35	17.47 ***	0.001	3.7540
	ln*SFDI* Double	0.35, 0.83	7.6038 ***	0.007	4.1056
	Trible	0.35, 0.83, 1.79	5.5733 ***	0.009	1.6908
R&D intensity	Single	0.35	38.8761 ***	0.000	3.9233
	ln*SEX* Double	0.35, 1.10	14.7158 ***	0.002	4.330
	Trible	0.35, 1.10,1.73	6.5309 **	0.010	3.672
	Single	0.35	37.1671 ***	0.000	4.0123
	ln*SIM* Double	0.35, 1.10	13.9764 ***	0.000	3.6338
	Trible	0.35, 1.10,1.73	3.3071 *	0.06	3.5261

Notes: ***, **, and *are indications of significance at the 1%, 5%, and 10% levels, respectively. LFC denotes the level of foreign enterprises in China's industrial sub-sectors. The capital depreciation rate is 9.6%.

As is evident from Table 3, the effects of foreign innovations in the shape of FDI as well as trade on the industrial energy intensity are not linear but suffer from a structural break. When the level of foreign enterprises entering into China is chosen as the threshold variable, the triple threshold of *F*-statistics is termed as having significance at the 1% level, suggesting that the effect of foreign innovations in the shape of FDI as well as the trade are not linear. In addition, when R&D intensity is selected as another threshold variable, the test findings still clearly reject the linear structure of the model. The above empirical evidence reveals that foreign innovations in the shape of FDI, together with exports as well as imports, manifest high sensitivity towards changes in the level of foreign enterprises in China or the R&D intensity.

Table 4 provides the nonlinear estimation findings through the application of the panel threshold model when LFC and R&D intensity are at varied levels. Moreover, as presented, rows one to three are the estimated results while choosing LFC as the threshold variable. When LFC is relatively low (less than the first threshold value, i.e., 0.8), the effect of foreign innovation through FDI on industrial energy intensity is negative but insignificant even though FDI significantly lowers the industrial energy intensity. When LFC increases, together with exceeding the first threshold while still being under the second threshold (i.e., 31.57), the effect of foreign innovation by means of FDI on the industrial energy intensity not only experienced a rapid increase in significance, but the coefficient also increased from -0.0462 to -0.1634. When LFC continues rising, the positive impact (in terms of reducing energy intensity) of the technology spillover that comes from FDI is further enhanced.

Rows four to six show the manner in which the technology spillover from exports (ln*SEX*) exerts an impact on the energy intensity when LFC is taken as the threshold variable. When LFC is under the first threshold (0.8%), the technology spillover through exports increases the industrial energy intensity at the 5% significant level. Accompanied by a rise in LFC, the technology spillover that comes from exports drives up the industrial energy intensity, but the coefficient lowers from 0.4777 to 0.1506; in addition, the significance of the coefficient continues declining, which is an indication that increasing LFC is capable of alleviating the adverse impact of exports on the industrial energy intensity.

As suggested by rows seven to nine of Table 4, the manner in which the foreign innovation in the form of imports (ln*SIM*) exerts an impact on the industrial energy intensity when LFC is selected as the threshold variable. Even when LFC is low (below the first threshold, i.e., 0.8%) the technology spillover from imports still has the potential to lower the industrial energy intensity. With the increase in LFC, the positive spillover impact of imports on the reduction of the industrial energy intensity is expected to be further enhanced, increasing from 0.0335 to 0.3425. The above empirical results suggest that the increase in LFC has the ability to enhance the positive spillover impacts of FDI as well as of imports in terms of decreasing industrial energy intensity or reducing the adverse spillover impact of exports driving up the industrial energy intensity.

As the R&D input intensity is considered to be a threshold variable, the findings presented in rows 10 to 12 of Table 4 indicate that the effect of foreign innovation in the shape of FDI on the industrial energy intensity changes with the increase in the threshold variable. As presented, when the R&D intensity is below the first threshold (i.e., 0.35%), FDI reduces the industrial energy intensity at the 1% significance level. When R&D intensity increases, together with exceeding the first threshold, the spillover impact of FDI on industrial energy intensity is expected to stay positive irrespective of varying extents of R&D input; however, the positive impact of FDI on the industrial energy intensity is expected to decrease, together with a rise in R&D intensity.

Similar to the findings in rows 10 to 12, regardless of varying extents of R&D intensity, foreign innovation through exports has the potential to lower the industrial energy intensity despite this effect being insignificant. In addition, with the increasing R&D intensity, the positive spillover impact of exports on energy intensity continues lowering. The last three rows of Table 4 show the manner in which the effect of foreign innovation by means of imports on the industrial energy intensity changes with the increase of R&D intensity. As presented earlier, when R&D intensity is less than the first threshold value (i.e., 0.35%), a positive but insignificant spillover effect that comes from imports could be expected. Once the R&D intensity is in excess of the first threshold, a negative spillover impact through imports is expected to appear. When R&D keeps increasing and exceeding the second threshold, the negative spillover impact of the foreign innovation in the form of exports on the industrial energy intensity continues to increase, which suggests that the increasing R&D input intensity inhibits the positive spillover impact exerted by imports on energy intensity.

Table 4. Panel threshold estimation results.

Threshold Variable	Independent Variable	Threshold Value	Variables	Coefficient	Threshold Value	Variable	Coefficient	Threshold Value	Variable	Coefficients
			ln*SFDI*	−0.0462		ln*SFDI*	−0.1634 ***[a]		ln*SFDI*	−0.2029 ***
	ln*SFDI*	$\gamma < 0.8$	ln*SEX*	0.0950	$0.8 < \gamma < 31.57$	ln*SEX*	0.0950	$31.57 < \gamma < 57.78$ [b]	ln*SEX*	0.0950
			ln*SIM*	−0.1270		ln*SIM*	−0.1270		ln*SIM*	−0.1270
			ln*SFDI*	−0.1709 ***		ln*SFDI*	−0.1709 ***		ln*SFDI*	−0.1709 ***
LFC [c]	ln*SEX*	$\gamma < 0.8$	ln*SEX*	0.4777 **	$0.8 < \gamma < 31.57$	ln*SEX*	0.2510	$31.57 < \gamma < 57.78$	ln*SEX*	0.2115
			ln*SIM*	−0.2887		ln*SIM*	−0.2887		ln*SIM*	−0.2887
			ln*SFDI*	−0.1725 ***		ln*SFDI*	−0.1725 ***		ln*SFDI*	−0.1725 ***
	ln*SIM*	$\gamma < 0.8$	ln*SEX*	0.2035	$0.8 < \gamma < 22.45$	ln*SEX*	0.2035	$22.45 < \gamma < 57.78$	ln*SEX*	0.2035
			ln*SIM*	−0.0335		ln*SIM*	−0.2397		ln*SIM*	−0.2798
			ln*SFDI*	−0.2680 ***		ln*SFDI*	−0.1838 ***		ln*SFDI*	−0.1482 ***
	ln*SFDI*	$\gamma < 0.35$	ln*SEX*	0.0455	$0.35 < \gamma < 0.83$	ln*SEX*	0.0455	$0.83 < \gamma < 1.79$	ln*SEX*	0.0455
			ln*SIM*	0.1061		ln*SIM*	0.1061		ln*SIM*	0.1061
			ln*SFDI*	−0.1359 ***		ln*SFDI*	−0.1359 ***		ln*SFDI*	−0.1359 ***
R&D intensity	ln*SEX*	$\gamma < 0.35$	ln*SEX*	−0.2488	$0.35 < \gamma < 1.1$	ln*SEX*	−0.1464	$1.1 < \gamma < 1.73$	ln*SEX*	-0.1153
			ln*SIM*	−0.0446 **		ln*SIM*	−0.0446 **		ln*SIM*	−0.0446 **
			ln*SFDI*	−0.1426 ***		ln*SFDI*	−0.1426 ***		ln*SFDI*	−0.1426 ***
	ln*SIM*	$\gamma<0.35$	ln*SEX*	−0.0643	$0.35 < \gamma < 1.1$	ln*SEX*	−0.0643	$1.1 < \gamma$	ln*SEX*	−0.0643
			ln*SIM*	−0.0772		ln*SIM*	0.0271		ln*SIM*	0.0643

Notes: [a] ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. [b] The coefficient for $\ln SFDI$, $\ln SEX$, and $\ln SIM$ when $57.78 \leq \gamma$ are −0.28333, 0.1506, and −0.3425, respectively *. When $1.79 \leq \gamma$, the coefficient for ln*SFDI* is −0.1156 ***; when $1.73 < \gamma$, the coefficient for ln*SEX* is −0.0937. [c] LFC denotes the level of foreign enterprises in China's industrial sub-sectors. The capital depreciation rate is 9.6%.

In summary, the interesting results shown in Table 4 reveal that, with increasing LFC, the positive spillover impact exerted by FDI and imports on the industrial energy intensity is expected to keep increasing. Moreover, the negative spillover impact exerted by exports on the industrial energy intensity is expected to decrease; this evidence strongly supports the hypothesis that LFC helps promote the positive spillover impact of the openness on decreasing industrial energy intensity, together with alleviating the negative spillover impact of exports driving up industrial energy intensity. Inconsistent with the roles of LFC played in influencing the impact of technology spillovers on industrial energy intensity, R&D inputs do not enhance the positive spillover effect, but hamper the positive spillover impact of the openness on industrial energy intensity. This surprising result is in line with the study carried out by Zheng et al. [21] addressing the effect of indigenous R&D on exports affecting China's industrial energy intensity, as well as that of Huang et al. [5] on the impact exerted by indigenous R&D on the technology spillover. These results do not negate the classic theory, which suggests that R&D is conducive to digesting and absorbing foreign knowledge and technology. China's majority indigenous R&D activities are concentrated in original technology innovation and few are put to use for the digestion and absorption of foreign technology in the industry. R&D input intensity is increasing, but does not promote the absorption of overseas knowledge and technology.

4. Discussion

Technological progress has been counted among the most pivotal forces driving down energy intensity. Nevertheless, there is no consensus as to how indigenous and foreign innovations in the form of openness exert influence on industrial energy intensity. The application of the carefully designed econometric model, on the basis of the united framework, scientifically evaluates their relative strength. Moreover, how the technology absorptive ability exerts an impact on the role foreign innovations play in industrial energy intensity is also discussed. The objective of this discussion is more comprehensive, to provide policymakers with not only the causes responsible for the interesting empirical results but also a proposal for lowering industrial energy intensity.

In practice, with regards to an open economy such as China, both indigenous and foreign innovations are important means of technological progress; an important issue that we are facing involves the determination of whether indigenous or foreign innovations are more important to industrial energy intensity reduction. Theoretically, indigenous innovation directly gives rise to new technology, and has been identified as the most pivotal means of hastening technological progress. Consistent with our expectations, indigenous innovation should be employed as the most pivotal element for cutting down the industrial energy intensity of China.

When transnational entities of developed countries make investments in developing countries, such as China, they are typically equipped with advanced management experience and technology. This cutting-edge technology and management experience will transfer to local entities by means of the demonstration and competition effect. As per expectations, foreign innovation in the form of FDI positively impacts the decrease in industrial energy intensity. In the same manner, a developing country is capable of importing new and sophisticated equipment from developed countries, which is quite beneficial for gaining a positive spillover effect. Contrary to the impact of FDI and imports on the industrial energy intensity, exports negatively contribute tow industrial energy intensity. With regard to China, exports are considered to be key to the fast-paced economic development. For the purpose of maintaining that rapid economic development, China has introduced a series of fiscal policies that are deemed conducive to the growth of export-oriented enterprises. Lots of domestic enterprises are enticed into the production of high-energy-consuming export products. China's own advantages, characterized by cheaper energy and lower labor costs, are also quite evident, and provide encouragement for transnational entities transferring high-energy-consuming industrial sub-sectors (for instance, the chemical industry, textile industry, and et al.) to China for the purposes of production. Consequently, China is renowned as a "world factory." The substantial exports of these products actually intensified China's energy consumption, in addition to increasing the industrial energy intensity.

With the transfer of advanced technology or management experience to developing countries, we need an intricate mechanism for assimilating or absorbing the advanced technology or management experience. The technological absorptive ability plays a crucial role and requires consideration. As per expectations, the technological absorptive ability that impacts factors is likely to alleviate the negative spillover effects of foreign innovations exerted on the industrial energy intensity or promote the positive spillover impacts exerted by foreign innovations on the industrial energy intensity. In addition, the application of our empirical results benefits China's goal of controlling the energy intensity. First of all, China must make use of indigenous R&D as the most important element for lowering its industrial energy intensity, together with providing steady energy for sustainable economic growth among the four technological determinants. Secondly, the technology spillovers coming from the openness constitute a pivotal factor affecting industrial energy intensity. The technology spillover through exports is of immense significance. For the purpose of gaining a positive spillover effect from exports, the incorporation of policies dealing with ecological safeguards for preventing developed nations from transferring high-energy-using sectors to China, together with discarding policies that encourage the export of energy-consuming goods, is likely to be quite useful. Thirdly, the varying behaviors of the technology spillovers mean that solutions should be in accordance with the specific characteristics of each technology spillover. The increase in LFC is likely to strengthen the cooperation between foreign enterprises and local ones, which contributes to facilitating the positive spillover effects of the openness. On the contrary, the increasing R&D input intensity has not enhanced the technological absorptive capacity of industrial entities, which reveals that raising the R&D intensity is not going to be an effective means of lowering energy intensity.

The analysis framework and empirical conclusions of the current research help shed light on the influence of varying technological determinants on China's industrial energy intensity; however, owing to the data limitations, the study cannot fully reflect the impacts exerted by technological absorptive potential on the evolution of energy intensity. This constitutes a major drawback of this study.

5. Conclusions and Future Research

The current research work performs an analysis of the impacts of varying technological determinants on the industrial energy intensity, subjected to a united framework through the use of a panel dataset covering China's 34 industrial sub-sectors in the period between 2000 and 2010. The linear analyses, which include the fixed effects model in addition to the FGLS and DK models, are employed for the analysis and evaluation of the impacts of indigenous R&D and foreign innovations in the shape of not just FDI, but also imports and exports, on the industrial energy intensity. Taking into consideration the evident differences in the technological absorptive capacities of different industrial sub-sectors, the impacts of different kinds of technology spillovers on energy intensity are not likely to be consistent. Accordingly, the current research work further employs the panel threshold model for determining how they exert an impact on the industrial energy intensity.

The regression results, on the basis of the linear analysis, suggest that, between indigenous and foreign innovations, the indigenous R&D contributes more to lowering China's industrial energy intensity. Foreign innovations are still deemed quite important for the formation of a developing country's low-carbon economy. Other than exports, both FDI and imports give rise to a positive spillover impact reduction for the industrial energy intensity. In addition, the empirical evidence, which is based on the panel threshold model, reveals that foreign innovations through openness have a nonlinear impact on the industrial energy intensity, which has a close association with LFC and R&D inputs. As LFC is comparatively lower, it is tough to observe a positive and substantial spillover impact that stems from the openness. With the increasing LFC, the positive effect of the technology spillovers that comes from FDI as well as imports on the industrial energy intensity is expected to be improved substantially. Furthermore, the negative impact of the technology spillover by means of exports is expected to decline. This reveals that the entry of foreign-funded enterprises into China has the potential of empowering both the cooperation and synergy between them and local enterprises, followed by ultimately forming a community of interest for helping Chinese enterprises absorb foreign knowledge and technology. Inconsistent with the roles of LFC played in influencing the impacts exerted by technology spillovers on the industrial energy intensity, R&D input indeed hampers the positive impact exerted by the technology spillovers on industrial energy intensity.

China is a representative developing country that has low energy efficiency coupled with high carbon emissions, but the development of a green economy would benefit both China and the rest of the world. The current research works aims at analyzing the evolution of energy intensity, especially the functions of the indigenous innovations as well as the foreign innovations played in the industrial energy intensity. This scientific framework can be applied to other developing countries. Future research could focus on other developing countries.

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Appendix A

Table A1. Detailed information on the 34 industrial sub-sectors.

Code	Sub-Sectors
H01	Mining and Washing of Coal
H02	Extraction of Petroleum and Natural Gas
H03	Mining and Processing of Ferrous Metal Ores
H04	Mining and Processing of Non-Ferrous Metal Ores
H05	Mining and Processing of Non-metal Ores
H06	Processing of Food from Agricultural Products
H07	Manufacture of Foods
H08	Manufacture of Liquor, Beverages, and Refined Tea
H09	Manufacture of Tobacco
H10	Manufacture of Textile
H11	Manufacture of Textile, Wearing Apparel, and Accessories
H12	Manufacture of Leather, Fur, Feather and Related Products, and Footwear
H13	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products
H14	Manufacture of Furniture
H15	Manufacture of Paper and Paper Products
H16	Printing and Reproduction of Recording Media
H17	Manufacture of Articles for Culture, Education, Arts and Crafts, Sport, and Entertainment Activities
H18	Processing of Petroleum, Coking, and Processing of Nuclear Fuel
H19	Manufacture of Raw Chemical Materials and Chemical Products
H20	Manufacture of Medicines
H21	Manufacture of Chemical Fibers
H22	Manufacture of Non-metallic Mineral Products
H23	Smelting and Pressing of Ferrous Metals
H24	Smelting and Pressing of Non-ferrous Metals
H25	Manufacture of Metal Products
H26	Manufacture of General Purpose Machinery
H27	Manufacture of Special Purpose Machinery
H28	Manufacture of Railway, Ship, Aerospace, and Other Transport Equipment
H29	Manufacture of Electrical Machinery and Apparatus
H30	Manufacture of Computers, Communication, and Other Electronic Equipment
H31	Manufacture of Measuring Instruments and Machinery
H32	Production and Supply of Electric Power and Heat Power
H33	Production and Supply of Gas
H34	Production and Supply of Water

Appendix B

Table A2. Robust test for the estimated results.

Variables	FE	FGLS	DK
Constant	5.6610 *** (0.0402) [a]	5.5765 *** (0.3247)	5.6610 *** (0.4789)
ln*SRD*	−0.3714 ***[b] (0.0402)	−0.3866 *** (0.0352)	−0.3714 *** (0.0201)
ln*SFDI*	−0.1532 *** (0.0460)	−0.1038 *** (0.0683)	−0.1532 * (0.0852)
ln*SEX*	0.1139 (0.2146)	0.1374 (0.1866)	0.1139 (0.3577)
ln*SIM*	−0.1668 (0.2263)	−0.1972 (0.2059)	−0.1668 (0.3886)
$\ln P_e/P_q$	−0.6858 *** (0.0896)	−0.4774 *** (0.0531)	−0.6858 *** (0.0943)
ln*ES*	0.3867 *** (0.0687)	0.2064 *** (0.0322)	0.3867 *** (0.0655)
Hausman (*p*)	41.5742 ***		
Wald x^2	1079.25 ***		
Heteroscedasticity test [c]	4755.34 ***		
First-order autocorrelation test	61.71 ***		
Within-R^2	0.7793		0.7793
Observations	374	374	374

Notes: [a] Values presented in the parentheses are the standard errors. [b]***, **, and * are indicators of significance at the 1%, 5%, and 10% level, respectively. [c] The null hypothesis for the heteroscedasticity test suggests that there is no heteroscedasticity and the null hypothesis for autocorrelation test indicates that there is no first-order autocorrelation. The capital depreciation rate is 15%.

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