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Analysis of Beijing's Energy Intensity Changes Based on an Input–Output Structural Decomposition Model from 2007 to 2020

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Abstract

As China's capital and a global megacity, Beijing has experienced sustained and rigid growth in energy demand driven by rapid population and economic expansion, rendering the analysis of energy intensity critically imperative for optimizing its energy system, alleviating resource and environmental pressures, and advancing toward carbon neutrality. By constructing a long-term comparable-price series, this study applies multi-period comparative structural decomposition analysis (SDA) across five benchmark years, spanning major policy cycles. It disaggregates changes in energy intensity into energy technology, production technology, and final demand structure effects across six sectors and five energy categories. The principal findings are threefold. First, Beijing's aggregate energy intensity exhibited a consistent downward trajectory, declining from 0.33699 tons of standard coal equivalent (tce) per 10,000 yuan in 2007 to 0.16393 tce per 10,000 yuan in 2020 (at constant 2012 prices). Second, the direct, indirect, and total energy consumption coefficients for all six sectors exhibited a broadly downward trend, with the largest reduction in the freight and postal sector, followed by industry. Third, energy technology change was the predominant driver of the decline in both aggregate energy intensity and consumption intensity across the five energy categories. Production technology and final demand structure changes exhibited heterogeneous effects across sectors and sub-periods. These findings provide policy-relevant insights for optimizing Beijing's energy structure, and several targeted recommendations are proposed.

Keywords: structural decomposition analysis; Beijing; comparable prices; energy intensity

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1. Introduction

Growing attention to energy transition has led governments worldwide to focus more on improving energy efficiency. A nation's energy consumption is primarily influenced by its Gross Domestic Product (GDP), the level of advancement in energy technologies, and industrial structure [1]. With the booming economy and accelerating urbanization, energy demand has been rising steadily, resulting in continued growth in energy consumption [2]. Energy intensity is a vital measure for analyzing the balance between energy efficiency and economic output [3]. For many nations, energy intensity not only provides an intuitive understanding of the economic benefits of energy use, but also serves as a valuable tool for long-term tracking [4]. Additionally, energy intensity serves as a key indicator for assessing the vulnerability of energy supply [5], which explains its widespread use. Index Decomposition Analysis (IDA), Structural Decomposition Analysis (SDA), and Production

Decomposition Analysis (PDA) are the primary methods for decomposing energy-related factors [6]. Each method has its specific applicability. IDA is relatively simple to calculate and requires minimal data, decomposing energy intensity into accumulative or multiplicative factors by aggregating departmental output and energy utilization data. However, IDA is unable to directly quantify the indirect impacts of factors such as technological advancements and efficiency changes on energy intensity, which restricts its applicability. PDA is an energy productivity decomposition method based on production theory, which reflects the contributions of technological changes and production efficiency improvements. Although it provides useful economic interpretations and policy implications, PDA has limitations in measuring industrial structural effects and energy substitution effects [7,8]. In contrast, SDA decomposes changes in the research object into the effects of various known influencing factors, allowing for an examination of the impact of a single factor while keeping others constant. This approach helps to identify the root causes of changes and clarify the contributions of each factor. SDA is particularly useful for considering factors such as industrial structure and consumption structure from a demand-side perspective and is a key tool for decomposing energy intensity and carbon emission driving forces [1,3,9,10].

China's rapid urbanization and industrialization have significantly increased energy consumption [11]. The structure of energy consumption and per capita GDP are key factors that influence energy efficiency [12]. By decomposing China's energy intensity from 1995 to 2015, it has been found that economic growth has been a significant driver of energy consumption [13]. An empirical analysis of China's provincial energy intensity reveals that urbanization, per capita income, and industrialization positively affect energy intensity [14]. The fossil-dominated energy structure has exerted considerable pressure on China's environment. Achieving the goal of energy transition poses significant challenges [15].

As China's capital and a global megacity, Beijing has long faced dual pressures from rigid growth in energy demand and increasingly tight resource and environmental constraints. From 2007 to 2020, Beijing's permanent population grew from 16.76 million to 21.89 million, its GDP increased from 1042.55 billion yuan to 3594.33 billion yuan, and its total energy consumption rose from 62.85 million tons of standard coal equivalent to 67.62 million tons. This sustained growth in energy demand poses severe challenges to the city's resource security and low-carbon transition. An in-depth analysis of the evolution of energy intensity and its driving factors is therefore of great practical significance for optimizing Beijing's energy system, alleviating resource and environmental pressures, and advancing the ''dual-carbon'' goals.

The period 2007–2020 fully covers the 11th, 12th, and 13th Five-Year Plan periods for Beijing and represents a critical transition stage in which the capital's industry shifted from ''incremental expansion'' to ''reduction and intensification.'' During the 11th Five-Year Plan period, Shougang initiated its relocation, Zhongguancun was upgraded to a national independent innovation demonstration zone, and the technological content of Beijing's industry increased significantly. During the 12th Five-Year Plan period, Beijing defined its strategic positioning as the ''four centers,'' launched the relocation of non-capital functions, and transformed Shougang from a ''steel giant'' into a high-end comprehensive industrial service area [16]. During the 13th Five-Year Plan period, Beijing implemented the first national ''Catalogue of Industries Prohibited and Restricted from New Development,'' carried out the ''Relocation, Rectification, and Improvement'' initiative, accelerated the clustering of high-precision and advanced industries, and initially formed the Beijing–Tianjin–Hebei collaborative model of ''R&D in Beijing, transformation in Tianjin and Hebei.'' These policy and industrial changes have profoundly altered Beijing's energy consumption patterns, providing a unique policy experiment for examining the stage-specific driving mechanisms of energy intensity.

However, existing studies still have notable shortcomings in characterizing the long-term evolution of Beijing's energy intensity. Most studies end in 2012 or earlier and thus fail to reflect the latest effects of non-capital function relocation and energy transition. In particular, a structural decomposition analysis of Beijing's energy intensity for 1997–2012 was conducted using a physical–monetary input–output table [17], but the analysis ended in 2012, focused on aggregate trends, and did not disaggregate energy categories or industrial sectors. Moreover, the existing literature tends to focus on aggregate trends, rarely conducting systematic decomposition from both energy category and sectoral dimensions simultaneously, nor aligning decomposition intervals precisely with major policy windows, which weakens the policy attribution capacity of their conclusions. In addition, due to the lack of long-term comparable-price input–output series, existing studies are also limited in terms of price comparability and temporal continuity.

To address these gaps, this study constructs a comparable-price energy input–output series for Beijing covering five time points—2007, 2010, 2012, 2017, and 2020—and applies multi-period comparative SDA across five benchmark years to systematically examine changes in aggregate energy intensity, intensity across five energy categories, and intensity across six sectors. The four decomposition intervals (2007–2010, 2010–2012, 2012–2017, and 2017–2020) are aligned with major policy windows during the 11th to 13th Five-Year Plan periods. The contributions of this study lie mainly in extending and deepening the application of existing methods. First, by integrating input–output tables with energy balance tables, it constructs a comparable-price energy input–output series covering five time points from 2007 to 2020, thereby addressing the limitations of existing studies in temporal continuity and price comparability and providing a data foundation for long-term dynamic tracking and policy-stage assessment. Second, it extends the application of SDA to a two-dimensional analysis of ''energy categories–industrial sectors,'' decomposing energy intensity changes at both the energy category and sectoral levels and further disaggregating final demand structure into consumption, investment, and net output, thereby identifying heterogeneous drivers across different dimensions. Third, it aligns the decomposition intervals with major policy windows during the 11th to 13th Five-Year Plan periods, enabling the decomposition results to serve policy-stage attribution analysis and enhancing the policy relevance of the conclusions. It should be noted that the single-region input–output framework used here captures changes within Beijing's territorial production structure; conclusions regarding supply chain or embodied energy reductions should be interpreted with this accounting boundary in mind. The remainder of this paper is organized as follows: Section 2 reviews the literature on energy intensity decomposition; Section 3 describes the modeling methods and data sources; Section 4 presents the empirical results; and Section 5 concludes the study and provides policy recommendations.

2. Literature Review

Initially emphasizing inter-sectoral dependencies, the input–output framework has evolved substantially, enabling a more precise capture of the extensive and profound impacts of non-economic factors—such as energy consumption patterns and environmental changes—on various sectors [18]. SDA has proven effective in decomposing the evolution of energy intensity into its driving factors over time. Methodological refinements in SDA [1,10] have further improved its accuracy and applicability, and recent research has coupled SDA with sensitivity analysis to identify the sectoral hotspots driving emission intensity changes [19]. The existing literature can be broadly categorized into three strands: national-level studies, cross-country comparative analyses, and regional- or city-level investigations.

(1) National-level research. Energy intensity characteristics vary significantly across countries and stages of development [20]. A decomposition of U.S. energy intensity

(1997–2002) reveals that economic structural changes exerted a greater impact on reducing energy intensity than improvements in energy efficiency [21]. Over the four decades following the mid-20th century, the decline in U.S. energy intensity resulted from both industrial structural changes and technological advancements [22]. Energy prices and per capita income further affect energy intensity by influencing energy efficiency [23]. Notably, even within the same country, the driving factors may differ across periods. China's energy intensity decline from 1981 to 1987 is mainly attributed to production technology innovation rather than shifts in final demand [24]. However, from 2002 to 2007, China's rising energy intensity was associated with changes in final demand—particularly a higher export share—and a shift toward energy-intensive industries [25]. From 1992 to 2010, investment was the main driver of China's energy consumption, while technological progress helped reduce it by approximately 5% annually [26]. Between 1997 and 2016, both technological progress and industrial restructuring jointly contributed to reducing China's energy intensity [27]. Furthermore, structural decomposition analysis based on constant-price and non-competitive input–output tables has been used to analyze the drivers of China's CO_2 emissions, highlighting the significant roles of energy intensity reduction and final demand expansion [28]. A recent SDA study found that between 2007 and 2019, imports significantly influenced China's energy consumption, with the import input effect increasing energy consumption by about 15% and the demand import effect reducing it by 5% [29]. Foreign direct investment has also been regarded as a channel for transferring highly energy-consuming technologies from developed to developing countries, thereby increasing their energy intensity [30]. Similar investigations have been conducted for Canada [31], Japan [32], and Thailand [33]. International trade is likewise considered a key factor, stemming from differences in the energy intensity of consumption goods and investment.

(2) Cross-country comparative studies. Energy intensity exhibits significant heterogeneity across countries, with large variations between economies and regions. Cross-national studies offer valuable insights into the underlying causes of these disparities. An analysis of energy use in 40 economies revealed that technological advancements are the key drivers of reductions in energy intensity [34]. Between 2003 and 2014, the energy intensity of EU member states generally decreased, but differences between countries were substantial, with varying rates of change [35]. A detailed analysis of the factors behind energy intensity differences among EU member states identified direct energy intensity effects and final demand effects as the main contributors [36]. A comparison of energy intensity between China and the U.S. in 1997, 2002, and 2007 highlighted technological factors and industrial structure as key contributors to their differences [37]. Using SDA, a comparison of developed countries (U.S., Germany, U.K.) with developing countries (China, Brazil, India) showed that both final demand and production structure significantly affect energy use, with varying contributions across countries [2].

(3) Regional- and city-level studies. A production theory-based decomposition of energy intensity in Chinese cities shows that technological changes and capital–energy substitution can effectively reduce energy intensity. An analysis of regional factors influencing Japan's energy intensity indicated that population agglomeration increases energy intensity [38]. Despite significant progress in reducing energy intensity, a study of provincial energy intensity in China between 1995 and 2017 revealed that disparities were gradually widening [39]. An analysis of data from 86 prefecture-level cities in China between 2006 and 2017 showed a significant reduction in energy intensity in eastern and central cities, while western cities saw increases [40]. Changes in energy input coefficients and final demand were the primary drivers of the reduction in Beijing's energy intensity from 1997 to 2012 [17]. More recently, energy intensity reduction has been shown to be the primary driver of carbon emission reduction in Beijing, with significant spatial spillover effects [41].

An LMDI analysis indicated that economic output and population growth were significant drivers of carbon emission increases in Beijing from 2010 to 2017. Additionally, panel data regression has been utilized to investigate provincial-level energy intensity in China [42], its influencing factors [43], and its energy-saving potential [44]. Although these studies examined various factors influencing energy intensity from different perspectives, few have focused on its long-term evolution at the city level. The structural decomposition analysis of Beijing's energy intensity (1997–2012) examined factors such as energy consumption coefficients, total demand coefficients, final demand, demand structure coefficients, and total energy consumption, but its focus on aggregate trends left limited room for the detailed analysis of energy categories and industrial sectors [17].

Research gap and positioning of this study. Existing studies extend only to 2012 and thus fail to capture the latest trends in Beijing's energy intensity, limiting the timeliness and applicability of their results. The period 2007–2020, however, encompasses key policy cycles for Beijing's energy transition and industrial adjustment—including the 2007 Olympic preparations, the 2012 coal-to-gas and clean air actions, the 2014 initiation of functional decentralization, and the 2017 ''Relocation, Rectification, and Improvement'' initiative—which profoundly shaped energy intensity changes and provide clear policy windows for stage-specific decomposition. To address these gaps, this study constructs a comparable-price energy input–output table for Beijing (2007, 2010, 2012, 2017, and 2020) and develops structural decomposition models for four intervals (2007–2010, 2010–2012, 2012–2017, and 2017–2020), exploring the driving factors behind Beijing's overall energy intensity, energy intensity by energy category, and energy intensity across six major industrial sectors. Compared with Ref. [17], this study extends the analysis to 2020, constructs comparable-price tables for additional benchmark years, introduces energy-type disaggregation, and further provides a more detailed decomposition of final demand components.

3. Model Construction

3.1. Basic Input–Output Model

Aphysical value-type energy input–output table is established, as shown in Table 1.

Table 1. Physical value-based energy input–output table.

		Inter Demands	**Final Demands**			**Total Output**
		Industrial Sector	**Final Consumption**	**Capital Formation**	**Net Exports**	
Inter-put	Industrial Sector	z_{ij}		Y_i		x_j
Primary Input		v_j				
Total Input		x_j				
Energy Consumption	1 2 3 ... m	e_{k_j}		e_{k_f}		e_k

This table extends the standard input–output table by incorporating the physical quantities of energy consumption. As shown in Table 1, z_{ij} represents the demand from sector j for products of sector i; Y_i indicates the final demand for the products of sector i; x_i is the total output of sector i; x_j is the total input of sector j; v_j refers to the initial input of

sector j; e_{kj} denotes the demand for energy type k by sector j; e_{kf} represents the final use of energy type k; and e_k indicates the total output of energy type k.

The direct consumption coefficient is defined as:

$$a_{ij} = \frac{z_{ij}}{x_j} \tag{1}$$

The total consumption coefficient, denoted as b_{ij}, represents the combined direct and indirect consumption of products from sector j:

$$b_{ij} = a_{ij} + \sum_{k=1}^{n} b_{ik} a_{kj} \tag{2}$$

The total consumption coefficient matrix B is composed of the total consumption coefficients b_{ij}, i.e., $B = [b_{ij}]$. In matrix form, it is expressed as:

$$B = (I - A)^{-1} - I \tag{3}$$

where $A = [a_{ij}]$ is the direct consumption matrix and I is the identity matrix of the same order as A. The basic input–output model is:

$$X = (I - A)^{-1} Y = LY \tag{4}$$

where X is the total output vector, Y is the final demand vector, and $L = (I - A)^{-1}$ is the Leontief inverse matrix.

3.2. Energy Intensity and Structural Decomposition Model

Following the approach used by the IEA and other international organizations, this study measures energy efficiency using energy intensity, defined as energy consumption per unit of GDP (I_e), expressed in tons of standard coal per 10,000 yuan.

(1) Energy consumption intensity

$$I_{ek} = \frac{E_k}{GDP} \tag{5}$$

where I_{ek} represents the energy consumption intensity of energy type k. E_k is the total consumption of k types of energy, and GDP is gross domestic product.

(2) Direct energy consumption coefficient

$$a^e_{k_j} = \frac{E_{k_j}}{x_j} \tag{6}$$

where E_{kj} is the consumption of energy type k in sector j. x_j is the total output of sector j, $a^e_{k_j}$ represents the direct consumption of energy type k per unit of output in sector j. The matrix A_e denotes direct energy consumption per unit of total output across sectors. Based on Equations (5) and (6), the following holds:

$$E = A_e X \tag{7}$$

Let $M = Y/GDP$ and substitute $X = (I - A)^{-1} Y$ into Equation (7):

$$I = \frac{E}{GDP} = \frac{A_e X}{GDP} = \frac{A_e (I - A)^{-1} Y}{GDP} = A_e LM \tag{8}$$

where $L = (I - A)^{-1}$ is the Leontief inverse matrix, and $M = Y/GDP$ is the final demand structure vector, whose components sum to 1.

The SDA model generally has four variations: (1) retaining cross-terms; (2) excluding cross-terms and assigning different weights to each variable; (3) using a weighted average

method; and (4) employing a bi-polar decomposition method. Among these, the bi-polar method provides a more accurate approximation and is therefore widely used in energy intensity decomposition [1,10]. In this study, the bi-polar method is adopted to decompose changes in energy intensity. This choice rests on three considerations.

$$\begin{aligned} \Delta I_e = & \quad I_e^1 - I_e^0 = A_e^1 L_1 M_1 - A_e^0 L_0 M_0 \\ = & \quad \tfrac{1}{2}(\Delta A_e L_1 M_1 + \Delta A_e L_0 M_0) \\ & + \tfrac{1}{2}(A_e^0 \Delta L M_1 + A_e^1 \Delta L M_0) \\ & + \tfrac{1}{2}(A_e^0 L_0 \Delta M + A_e^1 L_1 \Delta M) \end{aligned} \tag{9}$$

where superscript 0 denotes the base period and 1 the reporting period. $\Delta A_e = A_e^1 - A_e^0$, $\Delta L = L_1 - L_0$, and $\Delta M = M_1 - M_0$. The three terms represent the effects of energy technology change, production technology change, and final demand structure change, respectively.

Similarly, let I_{ei} represent the energy intensity of sector i, then:

$$I_{ei} = (\sum_{j=1}^{n} a_{ej} l_{ji}) N_i \tag{10}$$

where a_{ej} is the direct energy consumption coefficient of sector j, l_{ji} is the element in the j-th row and i-th column of the Leontief inverse matrix L, and $N_i = Y_i / V_i$ is the ratio of final demand to value added for sector i. Thus, the change in sectoral energy intensity can be decomposed as:

$$\begin{aligned} \Delta I_{ei} = & \quad I_{ei}^1 - I_{ei}^0 = \sum_{j=1}^{n} a_{ej}^1 l_{ji}^1 N_i^1 - \sum_{j=1}^{n} a_{ej}^0 l_{ji}^0 N_i^0 \\ = & \quad \frac{1}{2}(\sum_{j=1}^{n} \Delta a_{ej} l_{ji}^1 N_i^1 + \sum_{j=1}^{n} \Delta a_{ej} l_{ji}^0 N_i^0) \\ & + \frac{1}{2}(\sum_{j=1}^{n} a_{ej}^0 \Delta l_{ji} N_i^1 + \sum_{j=1}^{n} a_{ej}^1 \Delta l_{ji} N_i^0) \\ & + \frac{1}{2}(\sum_{j=1}^{n} a_{ej}^0 l_{ji}^0 \Delta N_i + \sum_{j=1}^{n} a_{ej}^1 l_{ji}^1 \Delta N_i) \end{aligned} \tag{11}$$

To further analyze how changes in demand structure affect energy intensity, the final demand for sector i is divided into three parts: $Y_i = W_i + K_i + P_i$. Here, W_i represents final consumption, K_i stands for capital formation, and P_i denotes net output. Thus, final demand changes can be divided into three effects: consumption structure, capital formation, and net output.

$$\begin{aligned} & \frac{1}{2}(\sum_{j=1}^{n} a_{ej}^0 l_{ji}^0 \Delta N_i + \sum_{j=1}^{n} a_{ej}^1 l_{ji}^1 \Delta N_i) \\ = & \frac{1}{2}(\sum_{j=1}^{n} a_{ej}^0 l_{ji}^0 \Delta N_{Wi} + \sum_{j=1}^{n} a_{ej}^1 l_{ji}^1 \Delta N_{Wi}) \\ & + \frac{1}{2}(\sum_{j=1}^{n} a_{ej}^0 l_{ji}^0 \Delta N_{Ki} + \sum_{j=1}^{n} a_{ej}^1 l_{ji}^1 \Delta N_{Ki}) \\ & + \frac{1}{2}(\sum_{j=1}^{n} a_{ej}^0 l_{ji}^0 \Delta N_{Pi} + \sum_{j=1}^{n} a_{ej}^1 l_{ji}^1 \Delta N_{Pi}) \end{aligned} \tag{12}$$

3.3. Data Source

(1) Sector Classification

This study employs Beijing's input–output tables for 2007, 2010, 2012, 2017, and 2020, all sourced from the Beijing Municipal Bureau of Statistics. The four decomposition intervals (2007–2010, 2010–2012, 2012–2017, and 2017–2020) align closely with Beijing's major policy windows. To clarify trends in Beijing's economic structure, the original sectors are consolidated into six main categories: Agriculture; Industry (covering sub-sectors such as coal mining and metal ore mining); Construction; Freight and Postal Services (covering transport, storage, postal, and information technology services); Commercial and

Catering Services (encompassing wholesale, retail, accommodation, and catering); and Other Services (including finance, real estate, leasing, and business services). The original input–output tables contain 42 sectors (including 24 industrial sub-sectors) in 2007 and 2010 and 43 sectors (including 25 industrial sub-sectors) in 2012, 2017, and 2020 due to statistical adjustments. To ensure strict comparability across all benchmark years, the data are harmonized into 43 unified sectors (including 25 industrial sub-sectors). The division into six sectors is a trade-off among data matching, policy relevance, analytical feasibility, and readability. The detailed concordance between the original 43 sectors and the six aggregated sectors is provided in Supplementary Table S1.

(2) Energy Consumption Data

This study uses data from energy balance tables for each year to construct the physical part of the energy input–output table. The focus is on measuring energy consumption in each sector for accuracy and comparability. Consumption is measured in tons of standard coal equivalent (tce) per 10,000 yuan. The consumption of each energy type is calculated in standard units and then adjusted using the corresponding conversion factor for standard coal. The original energy categories and their aggregation rules are documented in Supplementary Table S3, while the standard coal conversion coefficients are provided in Supplementary Table S2. Electricity and other secondary energy forms are treated using the terminal consumption approach. The sectoral concordance used to allocate energy consumption to the six sectors is provided in Supplementary Table S1.

(3) Price Index Adjustment

To ensure comparability across input–output tables from different years, this study converts current-price tables into comparable-price tables using 2012 as the base year and deflates each sector with its corresponding price index. The specific price indices used for each aggregated sector are based on the closest available proxies from the Beijing Statistical Yearbooks (various years): the Producer Price Index for Agricultural Producers for Agriculture; the Producer Price Index for Industrial Producers for Industry; the Price Index for Investment in Fixed Assets for Construction (the 2019 value is used as a proxy for 2020 due to data discontinuation); the Consumer Price Index for transport and communication for Freight and Postal Services; the Retail Price Index for Commercial and Catering Services; and the Consumer Price Index for services for Other Services. Due to adjustments in sectoral classifications during the study period and the unavailability of complete sub-sector price indices, a single index is applied to each aggregated sector. The intermediate transaction matrix, final demand, output, and value-added components were deflated consistently using the same sectoral price indices. After converting to constant prices, no additional balancing procedures were required to ensure the accounting balances of the input–output tables. A full sensitivity analysis using alternative deflators was not conducted due to data limitations and conceptual mismatches. However, for the industrial sector, the alternative Purchasing Price Index for Industrial Producers yields a cumulative factor of approximately 0.929, very close to 0.9122, indicating that the decomposition results are robust to this alternative choice. This is acknowledged as a limitation. It should be noted that this paper adopts a single-region input–output framework, whose accounting scope is limited to changes within Beijing's local production structure; therefore, conclusions regarding supply chains or embodied energy reduction should be interpreted cautiously within this accounting boundary.

The definitions of the main symbols used in this paper are shown in Table 2.

Table 2. Symbol Definitions.

Symbol	Definition
A	Direct consumption coefficient matrix
a_{ij}	Element of A, $a_{ij} = z_{ij/}x_j$
L	Leontief inverse matrix, $L = (I - A)^{-1}$
l_{ji}	Element of L
A_e	Matrix of direct energy consumption coefficients
a_{ej}	Direct energy consumption coefficient of sector j
M	Final demand structure vector, $M = Y/GDP$
N_i	Ratio of final demand to value added for sector i, $N_i = Y_i/V_{\mathrm{i}}$
W_i, K_i, P_i	Final consumption, capital formation, and net output of sector i
Δ	Difference between reporting and base periods

4. Empirical Analysis

4.1. Energy Consumption Coefficient

This study computes the direct, indirect, and total energy consumption coefficients for six sectors in Beijing in 2007, 2010, 2012, 2017, and 2020 (Table 3). Figures 1 and 2 illustrate the dynamic trends of the direct and indirect energy consumption coefficients for these sectors, respectively, from 2007 to 2020.

Table 3. Energy consumption coefficients for six sectors in Beijing from 2007 to 2020. Unit: tce/10,000 yuan.

Industry Sector	Year	Direct Energy Consumption Coefficient	Indirect Energy Consumption Coefficient	Total Energy Consumption Coefficient
Agriculture	2007	0.19406	0.29002	0.48407
	2010	0.18361	0.1996	0.38322
	2012	0.17063	0.20128	0.37192
	2017	0.13459	0.11482	0.24941
	2020	0.13142	0.11113	0.24256
Industry	2007	0.20281	0.52867	0.73149
	2010	0.11643	0.31610	0.43253
	2012	0.07500	0.26553	0.34053
	2017	0.04299	0.12693	0.16993
	2020	0.04263	0.10007	0.14270
Construction	2007	0.02193	0.28231	0.30424
	2010	0.03377	0.27278	0.30655
	2012	0.02437	0.25954	0.28391
	2017	0.02436	0.25573	0.28009
	2020	0.01415	0.20006	0.21421
Freight and Postal Industry	2007	0.24634	0.47716	0.72350
	2010	0.18068	0.27386	0.45454
	2012	0.16271	0.18866	0.35137
	2017	0.07867	0.09502	0.17368
	2020	0.03308	0.05754	0.09061

Table 3. *Cont.*

Industry Sector	Year	Direct Energy Consumption Coefficient	Indirect Energy Consumption Coefficient	Total Energy Consumption Coefficient
Commercial and Catering Services	2007	0.13026	0.21693	0.34718
	2010	0.05044	0.16438	0.21482
	2012	0.05552	0.12347	0.17899
	2017	0.04523	0.06973	0.11496
	2020	0.05095	0.05186	0.1028
Other Services	2007	0.06515	0.26722	0.33237
	2010	0.03934	0.18482	0.22415
	2012	0.04961	0.13115	0.18077
	2017	0.02822	0.09261	0.12083
	2020	0.02636	0.07257	0.09893

Note: Price factors are excluded with 2012 as the base year. Data are rounded to five decimal places. The same procedure is applied to subsequent tables.

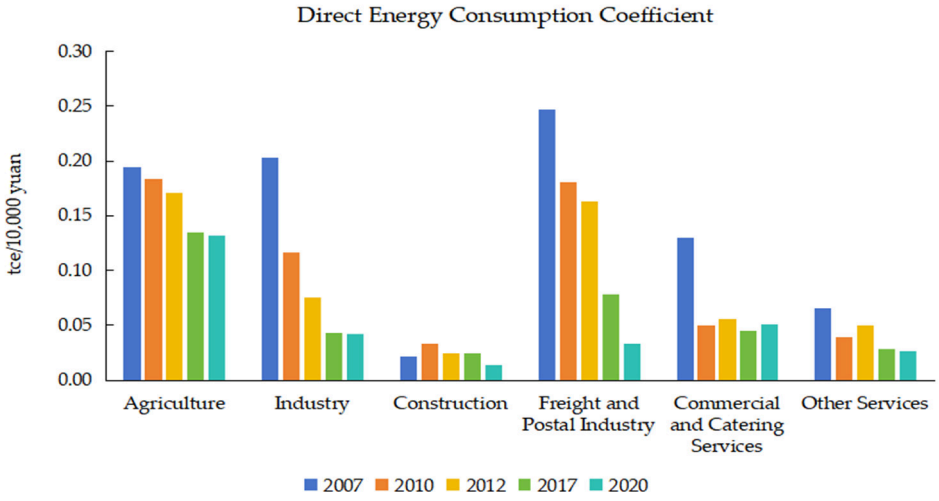


Figure 1. Changes in direct energy consumption coefficients of six sectors in Beijing from 2007 to 2020.

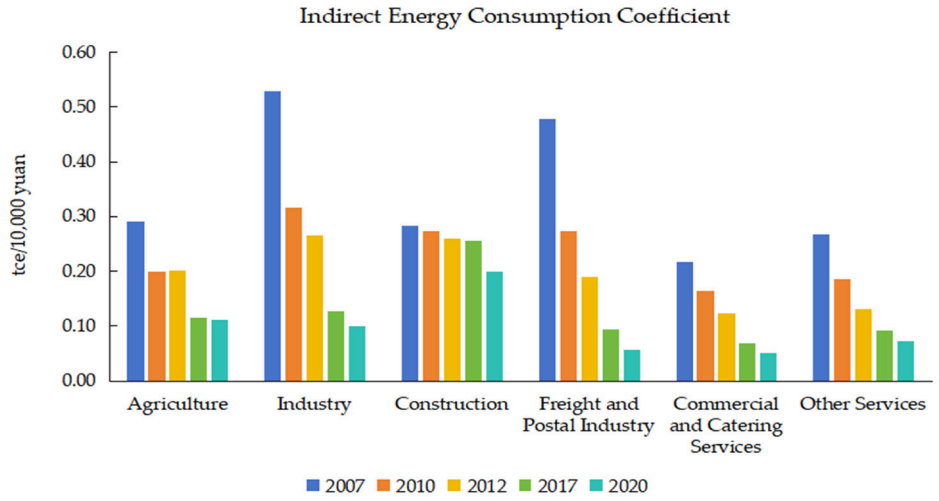


Figure 2. Changes in indirect energy consumption coefficients of six sectors in Beijing from 2007 to 2020.

(1) Direct versus indirect energy consumption patterns. Agriculture, industry, and freight and postal services exhibited relatively low direct energy consumption coefficients

but markedly higher indirect coefficients. In particular, the indirect coefficient of industry has persistently exceeded twice its direct coefficient, while that of freight and postal services approached twice its direct coefficient. For industry, the direct coefficient declined from 0.20281 in 2007 to 0.04263 in 2020, and the indirect coefficient fell from 0.52867 to 0.10007; nevertheless, indirect consumption consistently accounted for approximately 70% of total consumption. For freight and postal services, the direct coefficient decreased from 0.24634 to 0.03308, and the indirect coefficient fell from 0.47716 to 0.05754. Construction and other services had very low direct coefficients (construction was merely 0.01415 in 2020), yet indirect consumption remained dominant (the indirect coefficient of construction was 0.20006, about 93% of its total; for other services, the indirect share declined from approximately 80% in 2007 to about 73% in 2020, still representing the majority). This pattern indicates that the energy consumption of most sectors in Beijing is concentrated not in direct production but is embedded in the upstream supply chain. The high indirect coefficients arise because these sectors rely heavily on energy-intensive intermediate inputs—such as electricity, heat, steel, cement, and chemical materials—whose embodied energy is incurred upstream but attributed to the consuming sector through input–output linkages. Notably, the reduction in local direct energy consumption is consistent with the relocation of energy-intensive segments rather than an absolute decline in whole-chain energy consumption. As Beijing has phased out or relocated high-energy industries such as petroleum processing and metal smelting, local direct energy use has fallen, but the city's demand for energy-intensive intermediate goods produced elsewhere persists.

(2) Sectoral ranking by consumption type. With respect to direct consumption, freight and postal services ranked highest in most years, followed by industry, agriculture, and then construction and commercial and catering services. In terms of total consumption, industry ranked first in 2007 (0.73149), followed by freight and postal services (0.72350) and agriculture (0.48407). By 2020, the ordering had shifted to agriculture (0.24256) > construction (0.21421) > industry (0.14270) > commercial and catering services (0.10280) > other services (0.09893) > freight and postal services (0.09061). This reordering reflects not only differences in production structures and supply chain dependencies across sectors but also the differentiated effects of industrial relocation: the pronounced decline in industry's total coefficient is consistent with the net output effect of relocating energy-intensive segments rather than solely with local efficiency improvements, whereas the relatively high total coefficients and modest reductions in agriculture and construction are related to the energy intensity rigidity of their upstream supply chains (e.g., fertilizers and building materials).

(3) Declining trends and driving forces. When ranked by the magnitude of reduction in the total coefficient from 2007 to 2020, the sectors are: freight and postal services (0.72350 → 0.09061, about 87.5%) > industry (0.73149 → 0.14270, about 80.5%) > commercial and catering services (0.34718 → 0.10280, about 70.4%) > other services (0.33237 → 0.09893, about 70.2%) > agriculture (0.48407 → 0.24256, about 49.9%) > construction (0.30424 → 0.21421, about 29.6%). The freight and postal sector achieved the largest reduction, while construction saw the smallest. This ranking indicates that the pace of energy intensity reduction varied considerably across sectors, which is consistent with differences in production structure, supply chain dependencies, and the timing of policy interventions. It also suggests that no single factor can fully explain the sectoral heterogeneity; rather, the relative importance of energy technology, production technology, and final demand structure differs across sectors and sub-periods. A detailed decomposition of these driving forces is therefore provided in Section 4.4, following the aggregate and energy category analyses in Sections 4.2 and 4.3.

4.2. Structural Decomposition Analysis of Total Energy Consumption Intensity

As shown in Figure 3, Beijing's total energy consumption intensity declined across all four sub-periods examined. During 2007–2010, aggregate energy intensity declined by 0.00937 tce/10,000 yuan—the smallest reduction among the four sub-periods—with energy technology change contributing a reduction of 0.14291 tce/10,000 yuan and final demand structure change slightly reducing intensity by 0.00326 tce/10,000 yuan, while production technology change increased intensity by 0.13679 tce/10,000 yuan, almost entirely offsetting the energy-saving gains. This pattern is consistent with the combined effects of energy technology improvement and final demand restructuring. As shown in Table 4, similar decomposition dynamics can be observed across the subsequent sub-periods.

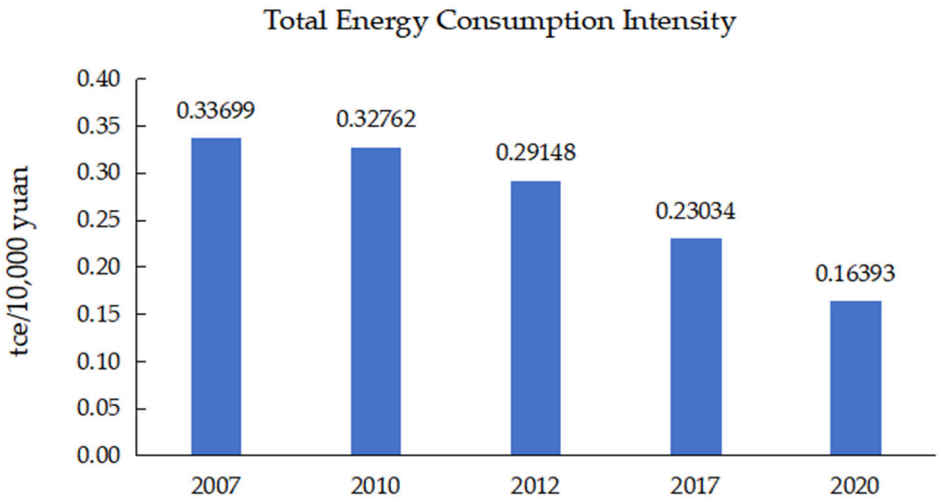


Figure 3. Trends in total energy consumption intensity in Beijing from 2007 to 2020.

Table 4. Structural decomposition of changes in Beijing's total energy consumption intensity. Unit: tce/10,000 yuan.

Contribution VALUE	Energy Technology Change	Production Technology Change	Final Demand Structure Change	Total Effect
2007–2010	−0.14291	0.13679	−0.00326	−0.00937
2010–2012	−0.03712	−0.00520	0.00618	−0.03614
2012–2017	−0.10402	0.04073	0.00215	−0.06114
2017–2020	−0.03572	−0.03689	0.00620	−0.06641

From 2010 to 2012, aggregate intensity fell by 0.03614 tce/10,000 yuan, with energy technology change contributing 0.03712 tce/10,000 yuan and production technology change turning negative for the first time (−0.00520 tce/10,000 yuan), forming a synergistic reduction. However, final demand structure change increased intensity by 0.00618 tce/10,000 yuan, partially offsetting the gains. This synergistic pattern reflects the combined effects of energy technology improvement and final demand restructuring during the early 12th Five-Year Plan period.

During 2012–2017, aggregate intensity decreased by 0.06114 tce/10,000 yuan; energy technology change contributed 0.10402 tce/10,000 yuan, whereas production technology change raised intensity by 0.04073 tce/10,000 yuan, offsetting nearly 40% of the technological savings. Final demand structure change added a small increase of 0.00215 tce/10,000 yuan. This indicates that adjustments in intermediate input composition during industrial relo-

cation imposed short-term constraints on energy conservation, though cumulative policy effects substantially expanded the total reduction compared with 2010–2012.

From 2017 to 2020, aggregate intensity declined by 0.06641 tce/10,000 yuan, with energy technology and production technology contributing 0.03572 and 0.03689 tce/10,000 yuan, respectively, marking another instance of a dual-driven synergistic reduction. Final demand structure change again slightly increased intensity (0.00620 tce/10,000 yuan). This dual-driven pattern reflects breakthroughs in both energy use efficiency and intermediate chain optimization under the ''Relocation, Rectification, and Improvement'' initiative.

Over the full 2007–2020 period, energy technology change consistently served as the primary driver (cumulative reduction of 0.31977 tce/10,000 yuan), while production technology change followed a pattern of alternating opposition and alignment (obstacle–facilitator–obstacle–facilitator), and final demand structure change exerted varying effects across sub-periods. The magnitude of reduction expanded progressively over time (from 0.00937 to 0.06641), suggesting that the energy-saving effects of non-capital function relocation and industrial transfer policies are characterized by significant cumulativeness and phase-specific characteristics: the deeper and more extensive the policy implementation, the weaker the structural drag against technological progress, and the stronger the synergy between the two forces.

4.3. Decomposition of Energy Intensity Structure by Energy Type

Table 5 reports the structural decomposition results of changes in energy consumption intensity by energy category in Beijing from 2007 to 2020, covering five categories—coal, oil, natural gas, electricity, and other energy—and decomposing them into three driving factors: energy technology change, production technology change, and final demand structure change. Overall, the consumption intensity of all five energy categories exhibited a declining trend, yet the magnitude of reduction, volatility, and dominant factors displayed pronounced heterogeneity across categories, indicating that Beijing's energy transition did not proceed synchronously or linearly across all categories but rather followed a differentiated pathway characterized by coal and oil declining first, natural gas and electricity fluctuating in stages, and synergistic reduction in the later period.

Energy technology change constituted the primary driver of the decline in intensity across all five categories, contributing negatively in the vast majority of categories and sub-periods. Moreover, this factor is not an abstract ''technological progress'' but comprises a series of identifiable specific technological measures and policy interventions: in the coal sector, it primarily benefited from clean energy retrofitting of coal-fired boilers, coal-to-electricity conversion, and coal-to-gas conversion; in the oil sector, it relied on fuel quality upgrading, the electrification of transportation, and fuel substitution in industrial kilns; in the natural gas sector, it was driven by pipeline network optimization and efficient utilization; and in the electricity sector, it stemmed from end-use efficiency improvement, the promotion of high-efficiency motors, and substitution by imported green electricity.

By category, the total effects for coal intensity across the four sub-periods were −0.01353, −0.02669, −0.02851, and −0.00362, respectively; the reduction peaked in 2012–2017 and then narrowed. Energy technology change consistently dominated the reduction (−0.05883, −0.02789, −0.02879, and −0.00228), underpinned by the continuous promotion of coal-fired boiler retrofitting, coal-to-electricity conversion, and coal-to-gas conversion. Production technology change was positive in 2007–2010 and 2012–2017 (+0.04105 and +0.00318), indicating that the intermediate input structure once tilted toward higher energy intensity, but later turned negative (−0.00145), suggesting a gradual optimization of the supply chain structure. The total effects for oil intensity were −0.01403, −0.00814, −0.01969, and −0.04224, respectively, with the reduction expanding significantly in 2017–2020. Energy

technology change was negative in all stages (−0.05533, −0.01362, −0.05196, and −0.03326), with fuel quality upgrading, transportation electrification, and industrial fuel substitution constituting the core forces of sustained reduction. Production technology change fluctuated considerably, and final demand structure change was positive in some sub-periods, indicating that demand-side structural shifts exerted a certain upward pressure on oil intensity.

Table 5. Decomposition results of factors influencing changes in energy intensity for five types of energy from 2007 to 2020. Unit: tce/10,000 yuan.

Type of Energy	Time Period	Energy Technology Change	Production Technology Change	Final Demand Structure Change	Total Effect
Coal	2007–2010	−0.05883	0.04105	0.00425	−0.01353
	2010–2012	−0.02789	0.00460	−0.00340	−0.02669
	2012–2017	−0.02879	0.00318	−0.00289	−0.02851
	2017–2020	−0.00228	−0.00145	0.00011	−0.00362
Oil	2007–2010	−0.05533	0.05127	−0.00997	−0.01403
	2010–2012	−0.01362	−0.00575	0.01122	−0.00814
	2012–2017	−0.05196	0.01981	0.01245	−0.01969
	2017–2020	−0.03326	−0.01842	0.00943	−0.04224
Natural Gas	2007–2010	−0.01089	0.00370	0.00092	−0.00627
	2010–2012	0.00413	−0.00256	−0.00059	0.00098
	2012–2017	−0.01157	0.00716	−0.00243	−0.00684
	2017–2020	0.00115	−0.00560	−0.00150	−0.00596
Electricity	2007–2010	−0.01776	0.04083	0.00155	0.02462
	2010–2012	−0.00063	−0.00147	−0.00101	−0.00311
	2012–2017	−0.01220	0.01024	−0.00489	−0.00685
	2017–2020	−0.00194	−0.01115	−0.00168	−0.01477
Other Energy	2007–2010	−0.00010	−0.00006	0	−0.00016
	2010–2012	0.00089	−0.00004	−0.00003	0.00082
	2012–2017	0.00050	0.00033	−0.00009	0.00074
	2017–2020	0.00062	−0.00027	−0.00017	0.00018

Natural gas intensity fluctuated markedly, with total effects of −0.00627, +0.00098, −0.00684, and −0.00596, respectively. Energy technology change was positive in 2010–2012 (+0.00413), which was the main contributing factor to the increase in that sub-period, consistent with the additional energy consumption brought about by pipeline construction and facility retrofitting in the early stage of natural gas substitution. Thereafter, energy technology change turned negative, and the clean and efficient advantages of natural gas were gradually released, indicating that natural gas substitution exhibits a phased characteristic of increasing consumption first, then reducing it, with the degree of infrastructure completeness being the key. Electricity intensity was positive in 2007–2010 (+0.02462), the only category with a substantial increase during the study period, possibly related to post-Olympic economic stimulus, surging electricity demand, and the structure of imported electricity. In the subsequent three sub-periods, it turned to reduction (−0.00311, −0.00685, and −0.01477), with the magnitude of reduction gradually expanding. Energy technology change was negative in all stages (−0.01776, −0.00063, −0.01220, and −0.00194), and the improvement of end-use electricity efficiency, the promotion of high-efficiency motors and variable frequency technologies, smart grid construction, and the increase in the share of imported green electricity (14.56 TWh in 2020, accounting for 12.5% of total society electricity consumption) jointly contributed to the substantial later decline in electricity intensity.

Regarding the "Other Energy" category, although its annual fluctuations were relatively small, its cumulative total effect over the study period was slightly positive (+0.00158), indicating a minor upward pressure on the overall energy intensity.

In sum, energy technology change was the largest contributing factor across all five categories, while production technology and final demand structure effects varied by category and sub-period.

4.4. Structural Decomposition of Energy Intensity Across Industry Sectors

This section presents the structural decomposition results for six sectors in Beijing from 2007 to 2020, identifying the contributions of energy technology, production technology, and final demand structure (further decomposed into consumption, investment, and net output).

In the agricultural sector (Figure 4), energy intensity declined continuously across all four sub-periods, with total effects of −0.35608, −0.03870, −0.27122, and −0.01969, respectively. The net output structural effect was the core driver of reduction, notably contributing −1.13288 in 2007–2010 and −1.62328 in 2012–2017, reflecting a shift in agricultural output composition toward products with lower embodied energy. Energy technology change consistently reduced intensity across all stages, owing to the diffusion of water-saving irrigation, precision fertilization, and optimized insulation and ventilation in facility agriculture. However, the consumption structure effect exerted marked upward pressure in 2012–2017 (+1.47032) and 2017–2020 (+0.17848), which is consistent with the upgrading of household food consumption structurally elevating agricultural energy use.

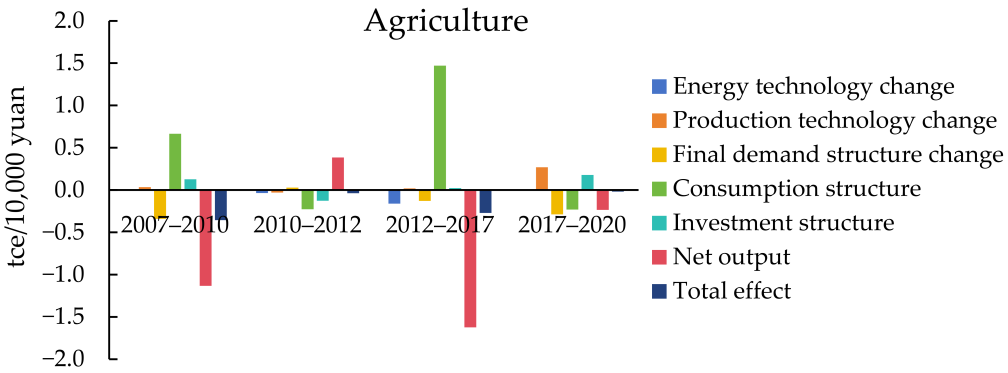


Figure 4. Decomposition of factors driving changes in agricultural energy intensity in Beijing from 2007 to 2020.

Turning to the industrial sector (Figure 5), total effects were negative in all four sub-periods (−0.47994, −0.06362, −0.35889, and −0.03074), indicating a continuous decline in total energy intensity. Energy technology change reduced intensity in all stages (−0.17252, −0.07759, −0.07714, and −0.00158), associated with industrial boiler retrofitting, high-efficiency motors, waste heat recovery, and digital energy efficiency management. Production technology change contributed to reduction in 2007–2010 (−0.07431) and 2010–2012 (−0.02597) but shifted to an increasing effect after 2012 (+0.03465 and +0.09504), which is consistent with the disruption of local supply chains during industrial relocation increasing purchased intermediate inputs and thus embodied energy consumption. The net output structural effect became a sustained and significant reducing force from 2010 onward (−0.33213 in 2012–2017 and −0.16230 in 2017–2020), consistent with output structure optimization brought about by the relocation of energy-intensive industries. While the net output effect dominated, the consumption and investment structure effects were relatively minor across the four sub-periods.

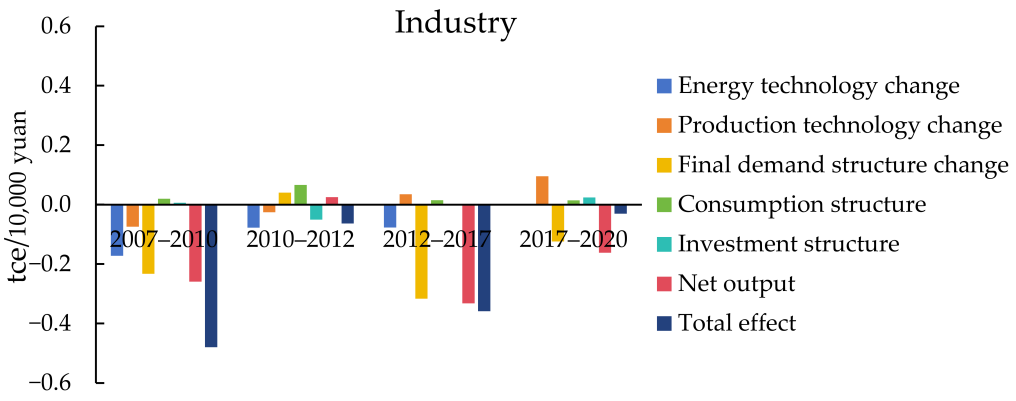


Figure 5. Decomposition of factors driving changes in industrial energy intensity in Beijing from 2007 to 2020.

The construction sector (Figure 6) saw a slight increase in total effect in 2007–2010 (+0.07027), followed by continuous declines (−0.15021, −0.03392, and −0.37934). Investment structure change played a dominant reducing role in 2012–2017 (−1.61223), reflecting growing demand for energy-efficient building investment; however, this reduction was largely offset by a substantial increase in the net output effect (+1.65329) during the same period. Energy technology change also continued to reduce intensity after 2010, consistent with mandatory green building standards and energy-saving retrofitting of existing buildings.

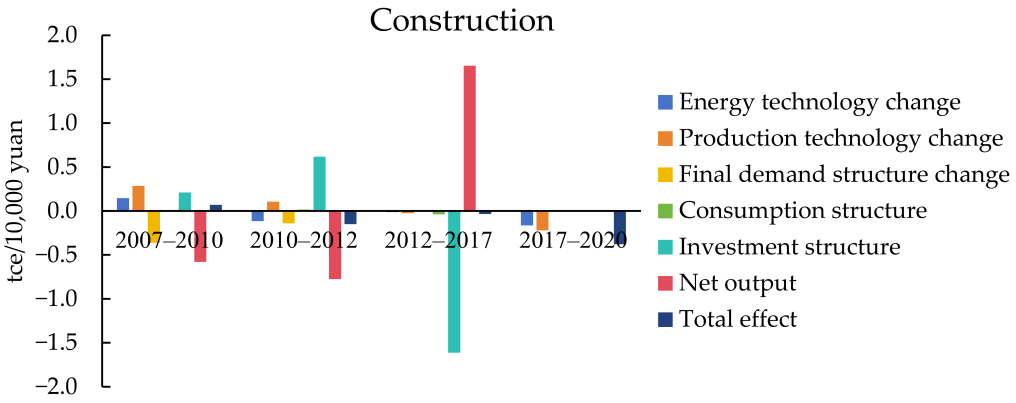


Figure 6. Decomposition of factors driving changes in construction energy intensity in Beijing from 2007 to 2020.

In the freight and postal sector (Figure 7), energy intensity declined steadily, with total effects of −0.85362, −0.33717, −0.59102, and −0.26141 across the four sub-periods. Energy technology progress (−0.33880, −0.09398, −0.39319, and −0.08244) and production technology change (−0.26805, −0.17170, −0.21689, and −0.18756) formed a dual-driven pattern, consistent with the promotion of new-energy trucks, railroad intermodal transport, and green logistics park construction.

For the commercial and catering sector (Figure 8), total effects remained negative (−0.10123, −0.01229, −0.03277, and −0.00320), with energy technology progress (e.g., efficient lighting, kitchen equipment, and intelligent temperature control) as the main contributor, while production technology and final demand structure changes increased intensity in some sub-periods.

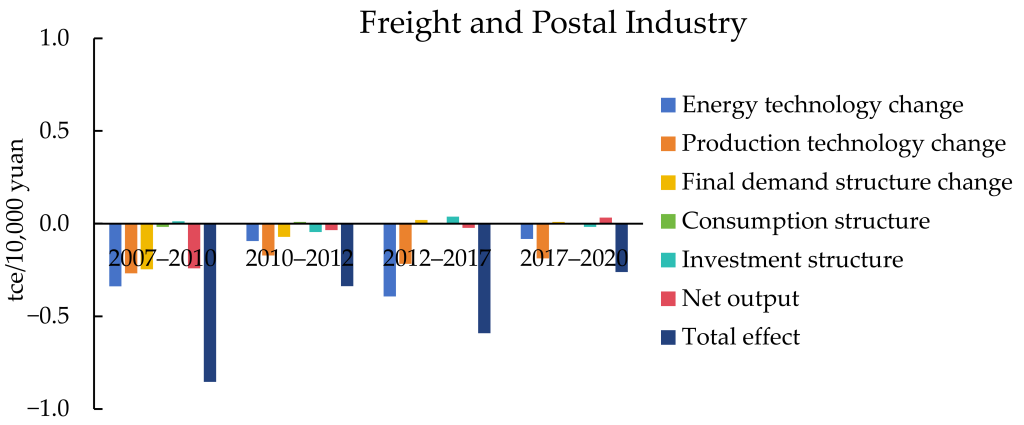


Figure 7. Decomposition of factors driving changes in freight and postal energy intensity in Beijing from 2007 to 2020.

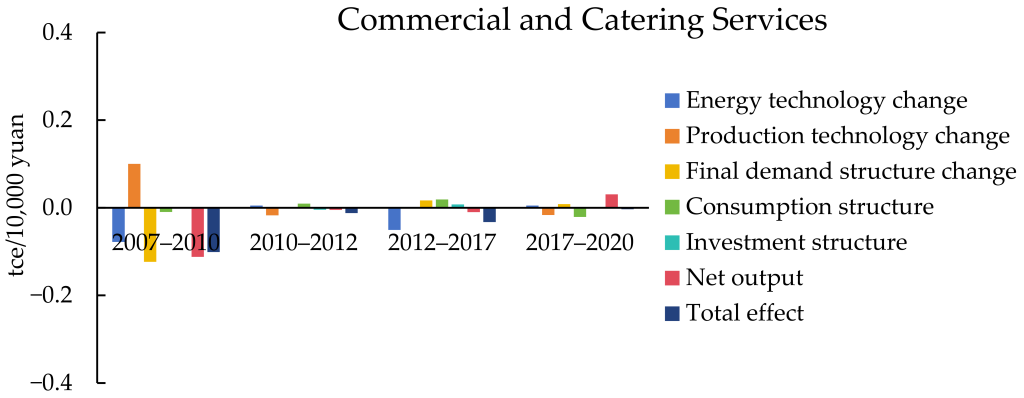


Figure 8. Decomposition of factors driving changes in commercial and catering energy intensity in Beijing from 2007 to 2020.

In other services (Figure 9), total effects also declined continuously (−0.26983, −0.10086, −0.07078, and −0.07978), with energy technology progress and the net output structural effect jointly contributing to the reduction; however, energy technology change increased intensity in 2010–2012 (+0.07401), possibly related to the expansion of emerging energy-intensive service formats such as data centers.

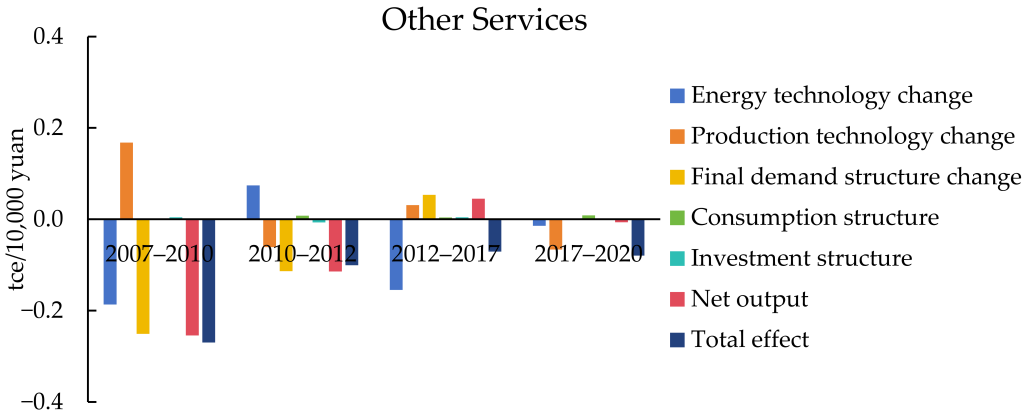


Figure 9. Decomposition of factors driving changes in other service industries' energy intensity in Beijing from 2007 to 2020.

These sectoral differences underscore the need for differentiated policy interventions, which are discussed in Section 5.

5. Conclusions

This study constructs a comparable-price energy input–output table for Beijing covering 2007–2020 and applies multi-period comparative structural decomposition analysis to examine changes in aggregate energy intensity, intensity across five energy categories, and intensity across six sectors. The principal findings are as follows.

Beijing's aggregate energy intensity declined consistently from 0.33699 tce/10,000 yuan in 2007 to 0.16393 tce/10,000 yuan in 2020, with reductions expanding progressively across the four sub-periods (0.00937, 0.03614, 0.06114, and 0.06641 tce/10,000 yuan, respectively). Energy technology change was the largest contributing factor to this decline, while production technology and final demand structure effects varied across sectors and sub-periods.

By energy category, coal intensity fell consistently, but its reduction narrowed in 2017–2020, leaving limited room for further cuts. Oil intensity dropped sharply in 2017–2020, consistent with the effects of transport electrification and fuel quality upgrading. Natural gas intensity exhibited an increase-then-decrease pattern, as early pipeline construction raised energy use before efficiency gains materialized. Electricity intensity rose in 2007–2010 due to post-Olympic demand stimulus, then declined steadily with end-use efficiency improvements and expanded green electricity imports.

By sector, agriculture's net output effect was the core contributing factor to reduction, but consumption structure upgrading created notable upward pressure after 2012. Industry saw negative total effects in all four sub-periods, with energy technology consistently reducing intensity and the net output effect contributing strongly after 2012; however, production technology turned to an increasing effect after 2012, which is consistent with embodied energy in purchased intermediate inputs due to supply chain disruption. Construction's investment structure change dominated reduction in 2012–2017, but the net output effect increased substantially in the same period, offsetting some investment-driven savings. Freight and postal services benefited from dual contributing factors—energy technology and production technology—and achieved the largest reduction among the six sectors. Commercial and catering services benefited mainly from energy technology progress, while production technology and demand structure increased intensity in some sub-periods. Other services saw significant energy technology reductions, but an increase in 2010–2012 possibly associated with data center expansion.

These findings suggest that sector-specific and energy-specific strategies are needed to sustain energy intensity reduction. The decomposition results directly support the conclusion that energy technology change is the dominant contributing factor and that production technology and final demand structure effects are heterogeneous across sectors and sub-periods. Based on these findings and broader policy considerations, possible directions include consolidating coal reduction, deepening transport electrification and fuel quality upgrading, expanding green electricity imports, promoting green supply chain coordination in the Beijing–Tianjin–Hebei region, and incorporating whole-chain embodied energy into energy-saving target assessment. It should be noted that the effectiveness of these broader policy measures is not directly evaluated by the single-region SDA framework used in this study, and future research could further examine them with multi-regional or extended analytical frameworks.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en19215135/s1, Table S1: Classification and name of sectors; Table S2: Reference coefficients for converting various energy sources to standard coal equivalent; Table S3: Aggregation of original energy types into five categories.

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X.X.: Writing—review & editing, Investigation, Data curation, Formal analysis, Visualization. L.F.: Writing—review & editing, Funding acquisition, Resources, Supervision. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

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