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Forecasting Energy Efficiency in Manufacturing: Impact of Technological Progress in Productive Service and Commodity Trades

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ABSTRACT

This paper employs the theory of biased technological progress to assess the effects of technological advancements across diverse trades, with a particular emphasis on predicting energy efficiency. A translog cost function model is developed, integrating five critical types of energy inputs. The empirical analysis is conducted using a comprehensive panel dataset comprising 26 major sub-sectors within China's manufacturing industry. The results indicate that diesel exhibits the highest own-price elasticity, whereas electricity the lowest. Further analysis highlights the factor substitution relationships and the bias of technological progress through productive service trade and commodity trade channels, providing insights into shifts in energy consumption patterns. Changes in energy efficiency are decomposed into factor substitution effects and technological progress effects via trade channels. The findings reveal the presence of Morishima substitution among three factors. Specifically, productive service trade and commodity imports show a bias towards the combination of energy with labor and energy with capital, while commodity exports are characterized by labor- and capital-biased technological progress. The contributions of factor substitution and the three trade channels demonstrate divergent impacts on energy efficiency improvements across the overall manufacturing sector, as well as within high-energy-consuming and high-tech sub-sectors. Overall, our study enhances the understanding of energy efficiency trends and technological progress in trade-related manufacturing activities, offering a robust foundation for future forecasting.

1 | Introduction

China is currently striving to peak carbon emissions (Qiu et al. 2023, Yao et al. 2023), with the government pledging to reduce carbon dioxide emissions per unit of GDP by more than 65% by 2030 relative to 2005 levels (Dinga and Wen 2022, Shi et al. 2019). However, its heavy reliance on coal as the main energy source presents a challenge to this end (Solarin et al. 2019, Shaheen and Luo 2023, Wang et al. 2013). To balance economic development with environmental benefits, technological progress is crucial and improved energy efficiency has shown to be a promising solution (Chang et al. 2018, Chen et al. 2019, Chien et al. 2022, Xu et al. 2015). In particular, techno-economic theory suggests that technological progress can enhance the utilization efficiency of production factors, leading to improved energy efficiency, and reduce pollution

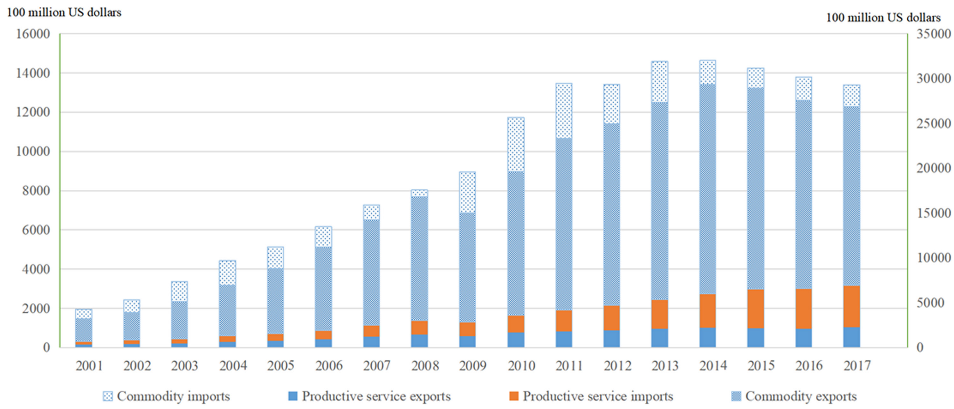

FIGURE 1 | Volumes of productive service and commodity trades within China's manufacturing sector.

(Elfarra et al. 2024). Biased technological progress, focusing on the substitution relationship between energy and non-energy factors, can further contribute to energy efficiency by reducing energy inputs (Chen et al. 2015, Dong et al. 2014, Dong and Chen 2014, Li and Li 2018). Previous studies have examined biased technological progress at national and sectoral levels using standardized constant elasticity substitution production functions. Additionally, researchers have investigated specific sources of technological progress (Wang and Qi 2021, Wei et al. 2019, Shah et al. 2022a).

In recent years, energy efficiency has emerged as a focal point of research, with particular attention given to its relationship with other key variables. Forecasting technologies can effectively identify critical influencing factors, thereby enabling the enhanced utilization of technological opportunities (Salo et al. 2003). A substantial body of research employs Data Envelopment Analysis (DEA) and its non-parametric derivatives. Noteworthy contributions in this field include Shah et al. (2022b), Yao et al. (2021a), and Yao et al. (2021b). Some studies focus on specific country groups, such as those by Shah et al. (2024) and Ul Hassan Shah et al. (2024). Others, including Yasmeen et al. (2022) and Yasmeen et al. (2023), based on the classic environmental-economic IPAT model, and its extended version, the STIRPAT model, emphasize the role of technology in environmental impact. Additional key research with respect to bias focuses on the substitution relationship between energy and other factors, including the relationship between energy and non-energy factors as well as the relationship between types of energy factors. At present, most research works employ the transcendental logarithmic cost function and the price of exogenous factors as their independent variable; however, a unified conclusion has not been reached yet with different studies showing heterogeneous results (see Bello et al. 2018, Jouhara et al. 2017, Opeyemi 2021, Welsch and Ochsen 2005, Wong and Chong 2010). The factor substitution elasticity has also been measured at the sectoral level in China, including general industry (Lin and Liu 2017, Lin and Tian 2016, Lu and Zhou 2008), manufacturing (Fan et al. 2010), and specific industries such as mining, agriculture, etc. (Li and Lin 2016), transportation (Li and Lin 2016, Lin and Xie 2014, Xie and Hawkes 2015), iron and steel (Wang and Lin 2017), and building construction (Wang and Lin 2017). Although these studies provide a rich perspective for understanding the performance of China's energy factors, an in-depth exploration of the sub-sectors of manufacturing and the substitution relationship between types of energy factors is still scarce.

The integration of China's manufacturing industry into global trade has been crucial for its development. International trade serves as a major source of technological progress, allowing for the exchange of information and the introduction of advanced technologies and intermediate products from abroad. This promotes learning, imitation, and secondary innovation in countries with less advanced technologies. Additionally, international trade fosters competition between domestic and foreign enterprises, driving local industries to upgrading their technological and management capabilities. Commodity trade, in particular, facilitates the flow of production factors and the technological diffusion through value exchange. The importance of service trade as a new driver for the transformation and upgrade of international trade has also grown (Yang 2016): its total volume has increased nearly tenfold from 2000 to 2018, with an average annual growth rate of 7.8% in the past five years. For manufacturers, productive service trade plays a key role in technological progress. Importing advanced productive services helps address domestic shortages and diversify the input and supply of intermediate services in the manufacturing sector. It strengthens connections between domestic and foreign industries, enabling access to specialized production services and enhancing the efficiency of intermediate services. Productive service imports allow advanced productive service factors to enter the manufacturing production process and create spillover of service technologies. Overall, integrating into world trade facilitates the technological advancement and competitiveness of China's manufacturing industry, paving the way for the achievement of the goals set out in the “Made in China 2025” initiative. Figure 1 depicts the volumes of productive services and commodity trades within China's manufacturing sector (the left vertical axis represents commodity trade, while the right axis the productive services trade).

From a trade perspective, existing research on international technological progress splits in two main streams. The first considers the process of trade activities of non-materialized form of research and development (R&D) spillovers. Helpman (1995) first examined the R&D spillovers based on import trade and found that domestic and import-based foreign R&D were both important sources of productivity growth. Amongst others, Frantzen (2010), Lumenga-Neso et al. (2005) and Klette et al. (2000) found that R&D relying on import-based trade led to prominent productivity spillovers. The second direction focuses on technological progress in the concrete form of commodities and services and is integrated in the host countries' production processes. Traded commodities embedded with advanced technology offer technologically lagging regions opportunities to adopt and emulate cutting-edge innovations. By mastering the application of this knowledge for imitative innovation, these regions enhance their technological capabilities and competitiveness via a "learning-by-doing" process. Technological spillovers from import trade are primarily concentrated in three areas: intermediate inputs, capital equipment, and manufactured products. Conversely, export trade generates technological spillovers through technological learning and competition. Recent research often measures trade channels by the scale of commodity trade, using import and export volumes. For example, Wan et al. (2015) tested the effect of technological progress from trade channels on the convergence of energy productivity across 16 European Union countries. Han et al. (2018) explored the impacts of technological progress from trade channels and regional cooperation on energy efficiency convergence across countries in the Belt and Road Initiative.

Technological progress in trade channels impacts energy efficiency through several distinct mechanisms. Productive service trade imports directly accelerate the rate of technology spillovers. By purchasing advanced foreign productive services, the limitations of domestic services are addressed in terms of efficiency and variety. This leads to a short-term increase in the productivity of the productive service sector, which in turn drives upwards spillovers in the overall technological level. For commodity exports, technological progress in trade is driven by the "learning-by-exporting" effect. Exporters improve manufacturing processes to meet the environmental and energy-efficiency standards of importing countries, thereby promoting gains in energy efficiency. Regarding commodity imports, technological progress occurs as the importing country relies on the introduction of high-quality products. Through reverse engineering and adaptation, domestic firms transform local technologies and indirectly absorb production management experience embedded in the imported products, thus achieving improvements in energy efficiency.

Against the backdrop of China's carbon neutrality imperatives and the intricate interplay among trade, technology, and energy efficiency, this study delivers four theoretically robust and empirically nuanced contributions. First, transcending the commodity trade-centric focus of the extant literature, it systematically integrates productive service imports, that is, a critical yet underexplored channel of cross-sectoral knowledge diffusion, into the analytical framework. It disentangles how intermediate service inputs (e.g., R&D, logistics) and commodity trade jointly influence energy efficiency through service-technology spillovers and embedded technological adoption. Second, addressing the aggregate-level oversights of prior research, the study models the heterogeneous composition of five energy factors (coal, electricity, diesel, gasoline, natural gas), quantifying their specific price elasticities to provide a microfoundation for granular energy policy design. Third, departing from static methodologies, it develops a dynamic translog cost system with error correction modeling, capturing both short-term factor adjustment dynamics (e.g., responses to energy price shocks) and long-term biased technological progress, thereby revealing time-varying efficiency mechanisms. Finally, through a comparative analysis of high-energy-consuming and high-tech sub-sectors, the study identifies divergent pathways of technological progress and sector-specific heterogeneities. Collectively, these insights enhance theoretical understanding of trade-technology-energy linkages and equip policymakers with targeted levers for intervention.

The remainder of the paper is arranged as follows. Section 2 briefly presents the model framework and the identification rules of technological progress bias. Section 3 analyzes the empirical results of the alternative relationship between various energy types and other factors, and identifies the bias of the trade technological progress. It focuses on the decomposition of the energy efficiency and the corresponding contributions. Section 4 summarizes our main conclusions and provides policy recommendations.

2 | Methodology

2.1 | The Static Feature Model

The current literature on energy demand elasticity commonly employs the translog cost function derived from the translog production function. In contrast with the Cobb-Douglas and constant elasticity substitution (CES) models, the translog is more versatile and does not impose prior parameter restrictions. Estimating the substitution elasticity between factors also directly affects the biased technological progress assessment. Within the cost function framework, the technological progress effects on energy efficiency can be simplified as changes in energy input given a certain level of output, making it easier to analyze the direction of biased technological progress.

The total cost function C is generally given as

$$C = f(P_k, P_L, P_E, Y, T, A), \tag{1}$$

where P_k, P_L, and P_E correspond to capital, labor, and energy prices; Y and T denote the total output and time trends; and A the technological progress from diversified sources of trade channels, which are set to be biased. Relying on the convenience[1] of unconditional constraints on the substitution relationship, we employ the following second-order approximation of the cost function (1):

$$\begin{aligned}\ln C &= \alpha_0 + \sum_i \alpha_i \ln P_i + \frac{1}{2}\sum_{i,j}\alpha_{ij}\ln P_i \\ &\times \ln P_j + \alpha_T T + \frac{1}{2}\alpha_{TT}\times T^2 \\ &+ \sum_i \alpha_{it}\ln P_i \\ &\times T + \alpha_Y \ln Y + \sum_i \alpha_{YP}\ln Y \\ &\times \ln P_i + \frac{1}{2}\alpha_{YY}\ln^2 Y + \alpha_A \ln A \\ &+ \sum_i \alpha_{AP}\ln A \\ &\times \ln P_i + \frac{1}{2}\alpha_{AA}\ln^2 A + \alpha_{YA}\ln Y \\ &\times \ln A + \alpha_{TA} T \times \ln A,\end{aligned} \tag{2}$$

$\forall i,j \in \{E,K,L\}$. From the Shephard Lemma, the factor demand and share equations follow from the partial derivatives with respect to the corresponding factor prices:

$$x_i = \frac{\partial TC}{\partial P_i}, \quad S_i^* = \frac{P_i x_i}{TC} = \frac{P_i}{TC}\frac{\partial TC}{\partial P_i} = \frac{\partial \ln TC}{\partial \ln P_i}, \tag{3}$$

where x_i represents the demand for the ith-type factor, and S_i^* the conditional expectation of the cost share of factor, which can be further expressed as

$$\begin{aligned} S_i^* &= \frac{\partial \ln TC}{\partial \ln P_i} = \alpha_i + \beta_i t + \sum_j \gamma_{ij} \ln P_j \\ &+ \delta_i \ln Y + \sum \gamma_A \ln A, \quad \forall i,j \in \{E,K,L\}. \end{aligned} \tag{4}$$

The observable cost of factor share is given by

$$S_i = E(S_i|\Omega) + v_i = S_i^* + v_i, \quad \forall i,j \in \{E,K,L\}. \tag{5}$$

The following restrictions must be met:

(i) $\sum_i \alpha_i = 1, \ \sum_i \delta_i = \sum_i \beta_i = \sum \gamma_A = 0$ *(adding-up)*

(ii) $\sum_i \gamma_{ij} = \sum_j \gamma_{ji} = 0$ *(price homogeneity).*

(iii) $\gamma_{ij} = \gamma_{ji}$ *(symmetry)*

More specifically, *adding-up* is based on the sum of factor inputs being equal to 1. Consistently with the requirements of production theory, the cost function should satisfy *price homogeneity*. And, finally, *symmetry* follows from the Young Theorem, that is,

$$\frac{\partial^2 \ln TC}{\partial \ln P_i \partial \ln P_j} = \frac{1}{2}\gamma_{ij} = \frac{\partial^2 \ln TC}{\partial \ln P_j \partial \ln P_i} = \frac{1}{2}\gamma_{ji}. \tag{6}$$

Due to the constant sum of factor share being equal to 1, the use of the Seemingly Unrelated Regression (SUR) approach would result in singularity. Therefore, it is typically necessary to remove one equation from the system for estimation. Here, we remove the labor factor share equation, so that the estimated equations are non-singular and can be estimated linearly via (7), and the labor force coefficient can be calculated via the above constraints (i)–(iii):

$$\begin{aligned} S_i^{Factor} &= \alpha_i + \beta_i t + \sum_j \gamma_{ij} \ln \frac{P_j}{P_L} \\ &+ \delta_i \ln Y + \sum \gamma_A \ln A + v_i, \quad \forall i,j \in \{E,K\}. \end{aligned} \tag{7}$$

The energy types share equation set is also constructed according to the above steps:

$$\begin{aligned} S_i^* &= \varphi_0 + \sum_i \varphi_{ij} \ln P_i \\ &+ \varphi_{it} t + \omega_i, \quad \forall i,j \in \{NG, CO, GA, EL, DI\}, \end{aligned} \tag{8}$$

where NG, CO, GA, EL, DI represent five energy types: natural gas, coal, gasoline, electricity, and diesel. Similar to the factor share equations, to avoid singularity, the natural gas share equation is removed, and then the non-singular energy types share equations are further expressed as

$$\begin{aligned} S_i^{Fuel} &= \varphi_0 + \sum_j \varphi_{ij} \ln \frac{P_j}{P_{NG}} + \varphi_{it} t \\ &+ \omega_i, \quad \forall i,j \in \{CO, GA, EL, DI\}. \end{aligned} \tag{9}$$

2.2 | The Dynamic Feature Model

The dynamic model extends over the static to better capture the reality of factor price changes. Here, the effect of "substitution" is not immediate, but rather a lagging response to changes in factor inputs. This allows for a more realistic representation of how manufacturers and industries adjust their factor inputs in response to price changes. To incorporate this lagged adjustment, the dynamic model introduces an error correction (see Lin and Wesseh 2013), which allows for a more accurate representation of how factor inputs are optimally adjusted over time.

Denoting the share of the optimal level factor or energy type i at time t as S_{it}^* and the actual share level as S_{it}, the one-period lagging adjustment can be expressed as

$$S_{it} - S_{it-1} = (1 - \lambda_i)(S_{it}^* - S_{it-1}) + v_{it}, \tag{10}$$

where S_{it}^* is obtained from the conditional expectation of (10). We have that $(1 - \lambda_i)$ is the adjustment coefficient of determining the actual share to the optimal level share. Substituting (10) in (7) and (9), the dynamic adjustment translog factor and the cost function of energy types are obtained:

$$\begin{aligned} S_{it}^{Factor} &= \alpha_i^* + \beta_i^* t + \sum_j \gamma_{ij}^* \ln P_j \\ &+ \delta_i^* \ln Y + \lambda_i S_{it-1}^{Factor} + \sum \gamma_A \ln A + v_i, \end{aligned} \tag{11}$$

$\forall i,j \in \{E,K,L\}$, and

$$\begin{aligned} S_{it}^{Fuel} &= \varphi_0^* + \sum_i \varphi_{ij}^* \ln P_i + \varphi_{it}^* t \\ &+ \lambda_i S_{it-1}^{Fuel} + \omega_{it}, \quad \forall i,j \in \{CO, GA, EL, DI\}, \end{aligned} \tag{12}$$

where

$$\begin{aligned} \alpha_i^* &= (1-\lambda_i)\alpha_i, \ \beta_i^* = (1-\lambda_i)\beta_i, \ \gamma_{ij}^* = (1-\lambda_i)\gamma_{ij}, \ \delta_i^* = (1-\lambda_i)\delta_i, \\ \varphi_0^* &= (1-\lambda_i)\varphi_0, \ \varphi_{ij}^* = (1-\lambda_i)\varphi_{ij}, \ \varphi_{it}^* = (1-\lambda_i)\varphi_{it}. \end{aligned}$$

From (11) and (12), the dynamic adjustment model encompasses the static situation as a special case. If it is assumed that the share change caused by price change is "instant", then $\lambda_i = 0$.

2.3 | Substitution, Biased Technological Progress, and Decomposition of Energy Efficiency

The own-price and cross-price elasticities can be calculated by estimating the parameters of the factor share equations. The own-price elasticity can also be calculated from the cost share equation and the corresponding price coefficient, which reflects the change in the quantity of the factor input caused by the price change of the factor itself:

$$\eta_{ii} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i}. \tag{13}$$

In contrast, the cross-price elasticity measures the absolute change in the input factor i caused by the price change of factor j, while the input and output of other factors remain unchanged. It can be expressed as

$$\eta_{ij} = \frac{\beta_{ij} + S_i S_j}{S_i}. \tag{14}$$

In more details, own-price elasticity reflects the extent to which changes in the price of a commodity or factor affect its quantity demanded. A high own-price elasticity implies that even a small price change can lead to a substantial change in demand. For investors, this suggests that reducing costs, and, therefore, prices, can significantly stimulate market demand, increasing product sales and revenues. Cross-price elasticity measures the impact of a change in the price of one commodity on the quantity demanded for another. If the cross-price elasticity between two energy sources, such as natural gas and diesel, is positive and large, it indicates that they are substitutes, that is, when the price of diesel rises, the demand for natural gas increases. Investors may then consider increasing investment in natural gas production, transportation, and related infrastructure to accommodate the shift in demand resulting from diesel price fluctuations. Conversely, if the cross-price elasticity is negative, it means the two commodities are complements, such as electric vehicles and charging stations. Investors may allocate capital to both sectors simultaneously to support their coordinated development and meet integrated market demand.

The Morishima Elasticity of Substitution (MES) is incorporated into our research as an economic measure of the substitution between factors of production. Unlike the Hicksian Elasticity of Substitution, MES provides a more comprehensive depiction of substitution or complementarity among multiple input factors, which is particularly important for production investment decisions involving multi-factor inputs. At the macro level, it helps investors anticipate long-term structural adjustments in industries driven by changes in factor prices. For example, in the context of the energy transition, analyzing Morishima elasticities between energy and other production factors across industries enables investors to identify which sectors are more likely to experience growth or face challenges due to energy price shifts and factor substitution relationships. MES is expressed as the change of the ratio of the factor input X_i to X_j with respect to changes of the price P_i of factor i:

$$MES_{ij} = \frac{\partial \ln \frac{X_i}{X_j}}{\partial \ln P_i}. \tag{15}$$

$MES_{ij} > 0$ implies existing Morishima substitution between the two factors. An increase in the price of factor i reduces the relative input of i to j; if $MES_{ij} < 0$, the relationship between the two factors is Morishima-complementary. MES can also be expressed in terms of the own-price and cross-price elasticities:

$$MES_{ij} = -(\eta_{ii} - \eta_{ji}). \tag{16}$$

If the marginal productivity of factor i grows more than that factor j under the influence of technological progress, we conclude that this technological progress is biased towards factor i. It can also be interpreted as a smaller reduction in the input factor i compared with factor j for a given output level. The biased technological progress also depends on the substitution relationship between factors. When two factors are substitutes, the impact of technological progress on factor i is greater than factor j, resulting in a reduction of the ratio of factors i and j, that is, the overall effect of technological progress is biased towards factor i. If the overall relationship is complementary, then when the impact of technological progress on factor i increases, it reduces the input ratio of factor j to i (j-biased). The technological progress bias is determined by calculating

$$\frac{\partial \ln \frac{X_j}{X_i}}{\partial \ln A} = \frac{\partial \ln X_j}{\partial \ln A} - \frac{\partial \ln X_i}{\partial \ln A} = \frac{\beta_{Aj}}{S_j} - \frac{\beta_{Ai}}{S_i}, \tag{17}$$

where β_{Aj} represents the impact of a specific channel of the technological progress A on factor j. This can be estimated from the factor share equations. The other parameters are interpreted as above. As explained earlier, if the factors have substitution relationships and the result (17) is greater than 0, the technological progress is i-biased; otherwise, it is j-biased.

There are multiple close connections between biased technological progress and forecasting. In the context of predicting changes in energy efficiency, understanding the direction and nature of technological bias is particularly important. Quantitative analysis of biased technological progress enables the construction of more accurate predictive models, offering relatively reliable projections of future energy efficiency levels. Regarding manufacturing development, biased technological progress influences the evolution of energy utilization patterns in different sub-sectors. Recognizing this bias allows for better forecasting of energy efficiency shifts and provides a foundation for industrial structure adjustment and sustainable development planning.

Finally, in accordance with the Welsch method for energy efficiency decomposition, we have that

$$\begin{aligned} \hat{e} = \frac{E}{Q} = \frac{P_Q}{P_E} S_E \quad &= \frac{P_Q}{P_E}(\hat{\alpha}_E^* + \hat{\gamma}_E^* \ln P_E \\ &+ \hat{\gamma}_L^* \ln P_L + \hat{\gamma}_K^* \ln P_K + \hat{\delta}_E^* \ln P_Q \\ &+ \hat{\gamma}_{EX} \ln EX + \hat{\gamma}_{IM} \ln IM \\ &+ \hat{\gamma}_{STAV} \ln STAV + \hat{\beta}_E t) = \sum\nolimits_{i=0}^{8} \hat{e}_i, \end{aligned} \tag{18}$$

where $\hat{\alpha}_E^*$ is the estimated intercept in the energy factor equation system and $\hat{\gamma}_{\cdot}^*$ the estimated coefficients of the factor prices and the technological progress of trade channels. The energy efficiency is decomposed into nine parts: $\hat{e}_0^*$ represents the budget; $\hat{e}_2^*$, $\hat{e}_3^*$ the factors caused by price changes substitution; $\hat{e}_4^*$ the output; $\hat{e}_5^*$, $\hat{e}_6^*$, $\hat{e}_7^*$ the technological progress of trade channels; and $\hat{e}_8^*$ the technological progress not included in trade. Then, the dynamic decomposition of energy efficiency can be expressed as

$$\frac{\Delta \hat{e}}{\hat{e}} = \sum_{i=0}^{8} \frac{\Delta \hat{e}_i}{\hat{e}_i} \frac{\hat{e}_i}{\hat{e}}, \tag{19}$$

where $\Delta \hat{e}_i$ is the first difference of $\hat{e}_i$, that is, the change of energy efficiency relative to the base year.

3 | Empirical Results

In this study, we cover balance panel data from 2000 to 2017 for 26 sub-sectors (large categories) of China's manufacturing. Some sub-sectors have been adjusted for consistency within the period, in accordance with Wei et al. (2020). Manufacturing economic data mainly come from the "China Industrial Economic Statistics Yearbook" edited by the Industry Department of the National Bureau of Statistics, and industrial energy data from the "China Energy Statistics Yearbook" edited by the Energy Statistics Department of the National Bureau of Statistics. Commodity trade data are from the "China Trade and External Economic Statistics Yearbook" edited by the Trade and Foreign Economic Statistics Department of the National Bureau of Statistics. A descriptive statistical analysis of the key variables has been conducted, which we present in Table 1. More details on data collection and processing steps are documented in Appendix B.

Moving to more details of our empirical analysis, Table 2 presents the parameter estimates for the energy share equations (9) and (12). The Breusch–Pagan test supports the applicability of the SUR method for system estimation, as intra-class correlation is rejected in both model types at the 1% significance level. Most of the coefficients are statistically significant. The dynamic model, which has smaller coefficients and a higher goodness of fit R^2, demonstrates stronger explanatory power. Additionally, the significant (at the 5% level) dynamic adjustment coefficient λ_i indicates that incorporating lag period provides a more comprehensive explanation of energy share compared with limiting to the contemporaneous period.

From Table 3, the estimated own-price coefficients are all positive, implying positive effects of own-price changes on the cost share of each type of energy. The electricity shows the highest elasticity coefficient (0.1348). This suggests significant impact of electricity costs and price changes on overall energy expenditure, highlighting its dominant role in manufacturing energy consumption. Despite coal being a major domestic energy source, accounting for 59% of the total consumption in 2018, factoring in price and primary consumption reveals that electricity cost shares constitute the largest percentage in manufacturing (69. 18%). This is followed by raw coal (15. 73%) and natural gas (3. 22%).

The energy type elasticity coefficients, obtained by merging the dynamic model with the average energy share value (2000–2016), reveal negative own-price elasticity for all types of energy, implying a reduction in energy input as prices increase. Diesel exhibits the highest own-price elasticity (-0.3629), followed by raw coal (-0.3272) and electricity (-0.1134). The fact of estimated negative own-price elasticity of energy sources is consistent with the conclusion of Yang et al. (2014) on the own-price elasticity of energy in China. In the power share equation group, the one-period lagged value λ_{EL} is estimated at 0.4573 (see Table 2). This is the smallest value compared with the estimates for the other energy equation types. This is justified by high fixed investments on manufacturing power facilities and the standardization of "electricity change" equipment, leading to elevated replacement costs; hence, the companies' conservative power reform strategies and electricity demand insensitivity to price changes.

Li and Lin (2016) analyzed the price elasticity of own-energy for three energy types in six productive sectors, including agriculture; mining; manufacturing; electricity, heat, gas, and water production and supply; construction; and transportation and storage. Despite some differences in research subjects and calculation methods regarding the costs of different energies, as well as the focus on just electricity, coal, and crude oil, the findings still support the primary conclusion that electricity's own-price elasticity is the weakest compared with coal and crude oil. This implies that the correlation between electricity prices and demand fluctuations is not significant in manufacturing, where electricity plays a relatively stable, dominant role in energy consumption costs. At the same time, the overall price elasticity coefficients for each energy type are relatively low, particularly for clean energies, such as electricity

TABLE 1 | Descriptive statistical analysis of key variables.

	Coal	Gasoline	Diesel	Electricity	Natural gas	Capital	Labor	Energy
Mean	5506.23	13.08	31.34	984.93	47.33	1.06	31091.85	7802.21
Maximum	47774	42.72	294.03	6003.3	959.04	1.6	155392	69342
Minimum	3	0.52	1.31	9.79	0.17	0.86	5556.7	52
Standard Deviation	11579.32	11.05	51.75	1466.65	140.19	0.23	21513.24	14924.49
Variance	134080740	122.12	2677.98	2151059.09	19653.78	0.05	462819402.5	222740318.1

Notes. Coal, gasoline, and diesel consumption in 10,000 tons, electricity consumption in billion kWh, natural gas in billion cubic meters, capital (loan interest rate), labor (yuan), and energy in 10,000 tons of standard coal.

TABLE 2 | Regression analysis of energy type share equations. Results of equations (9) and (12) under "Static SUR model" and "Dynamic SUR model" columns, respectively.

	Static SUR model		Dynamic SUR model	
	Estimated coefficients	**Standard errors**	**Estimated coefficients**	**Standard errors**
Case of diesel				
φ_{DI-DI}	0.1728***	0.0113	0.0414**	0.0217
φ_{DI-EL}	-0.1217***	0.0064	-0.1312**	0.0641
φ_{DI-CO}	-0.3031***	0.0021	-0.2819*	0.1658
φ_{DI-GA}	0.0045	0.0038	0.0141**	0.0072
$\varphi_{DI,t}$	0.0251**	0.0117	0.0082	0.0078
φ_{DI}	1.3723***	0.1892	1.0043***	0.2109
λ_{DI}	—	—	0.6817***	0.0282
R^2	0.9027		0.9253	
Case of electricity				
φ_{EL-EL}	0.2188***	0.0283	0.1348*	0.0792
φ_{EL-DI}	-0.1217***	0.0064	-0.1312**	0.0625
φ_{EL-CO}	-0.3021***	0.0232	0.0002	0.0001
φ_{EL-GA}	0.0935**	0.0411	0.2217***	0.0341
$\varphi_{EL,t}$	-0.0116***	0.0002	0.0012	0.0112
φ_{EL}	0.9812*	0.5971	0.0064	0.0061
λ_{EL}	—	—	0.4573*	0.2755
R^2	0.8371		0.8712	
Case of gasoline				
φ_{GA-GA}	0.1137***	0.0012	0.0357*	0.0216
φ_{GA-EL}	0.0935**	0.0521	0.2217***	0.0341
φ_{GA-CO}	0.0041	0.0028	0.0183	0.0101
φ_{GA-DI}	0.0045	0.0038	0.0141**	0.0069
$\varphi_{GA,t}$	0.1372***	0.0031	0.0315*	0.0165
φ_{GA}	0.3643***	0.0211	0.1491*	0.0877
λ_{GA}	—	—	0.6721***	0.1483
R^2	0.9016		0.9233	
Case of raw coal				
φ_{CO-CO}	0.0861***	0.0058	0.0811***	0.0031
φ_{CO-EL}	-0.3021***	0.0072	0.0002	0.0005
φ_{CO-GA}	0.0042	0.0038	0.0183*	0.0109
φ_{CO-DI}	-0.3031***	0.0021	-0.2819*	0.1698
$\varphi_{CO,t}$	0.0794*	0.0467	0.0382	0.0293
φ_{CO}	-0.7268***	0.0172	-0.6347***	0.119
λ_{CO}	—	—	0.4793**	0.2731

(Continues)

TABLE 2 | (Continued)

	Static SUR model		Dynamic SUR model	
	Estimated coefficients	Standard errors	Estimated coefficients	Standard errors
R^2	0.8215		0.8732	
Breusch–Pagan test	17.3818***		132.4627***	

Notes. Breusch–Pagan test is based on $\chi^2(1)$, Pr = 0.0000. ***, **, * correspond to significance of estimated parameters at 1%, 5%, 10% level, respectively.

TABLE 3 | Price elasticities of energy types. Results of equation (13) in the last column.

Ratio of energy sources	Value	Estimated coefficients SUR share equations	Estimated values elasticity coefficients	Own-price elasticity	Elasticity coefficients
S_{DI}	0.0734	φ_{DI-DI}	0.0414	η_{DI-DI}	-0.3629
S_{EL}	0.6918	φ_{EL-EL}	0.1348	η_{EL-EL}	-0.1134
S_{CO}	0.1573	φ_{CO-CO}	0.0811	η_{CO-CO}	-0.3272
S_{GA}	0.0452	φ_{GA-GA}	0.0357	η_{GA-GA}	-0.1651
S_{NA}	0.0322	φ_{NG-NG}	0.0246	η_{NG-NG}	-0.2043

and natural gas, which are at the lower end compared with other energy sources. This underscores that achieving the restructuring of the energy consumption structure, which entails increased demand for specific energy types, requires considering the price adjustment mechanism alongside the deployment of additional policy instruments. Diesel exhibits the highest own-price elasticity. Widely used across multiple sectors, such as manufacturing, its diverse applications mean that when diesel prices change, producers can more readily substitute it with alternative energy sources, such as natural gas or electricity. With the advancement and wider adoption of clean energy technologies, new energy-powered solutions are gradually maturing. For example, electrification is increasingly applied to manufacturing equipment. In particular, for some small- and medium-sized machinery with less extreme power demands, electric drive can serve as an effective substitute for diesel.

In Table 4, we explore the substitution relationships between factors following the own-price elasticity of energy types via (7) and (11). The labor share equation is not included in the overall estimation, but its coefficient can be calculated from the constraints. The Breusch–Pagan test and the statistical significance of λ_C at the 1% level suggest existence of error correction between factor share equations and lag of input changes. The elasticity coefficients of lagging capital (0.3671) and energy (0.4651) are generally smaller than the lag term coefficients of the energy types share equations in Table 2, indicating that the share of energy types is less adjustable than the share of the factor. Energy equipment in industrial production has a long-life cycle, and the demand for energy types is stable (Li and Lin 2016). Capital investment is more "sensitive" than energy investment, which is reflected in the estimated lag term coefficient 0.3671 of the capital factor share equation. All commodity exports negatively impact capital and energy shares at the 5% significance level. Productive service trade shows different influences on capital share and energy share, suggesting that productive service trade saves more capital than energy costs in the sample period. The non-zero hypothesis of the commodity import coefficient in the capital share equation cannot be rejected, but is significant in the energy share equation, suggesting that commodity imports significantly increase the energy share. The effect of trade channels on relative productivity between factors is further explored through the measurement of biased technological progress.

In this paper, we use a dynamic SUR model to study the substitution relationship between factors and technological progress bias. From Table 5, the own-price elasticity is found to be negative, with labor having the highest absolute value (0.7069), followed by energy (0.6715) and capital (0.1853). This suggests that labor demand is highly responsive to price changes. The cross-price elasticity between energy and labor is the highest. This reflects the trend of increasing automation in manufacturing, replacing manpower, leading to a relative increase in energy consumption. Our findings are in line with previous research (Li and Lin 2016), highlighting the impact of cost structures on factor substitution and the influence of trade channels on relative productivity. Compared with cross-price elasticity, Morishima elasticity offers a more comprehensive account of the interrelationships among multiple input factors. In multi-input production settings, it can precisely measure how a change in the price of one factor affects the substitution or complementarity relationships among several others. Our results indicate a substitution relationship among the three factors. Specifically, energy and capital are Morishima substitutes, consistent with the findings of Fan et al. (2010) regarding factor substitution in 20 sectors. Among them, the substitution elasticity between energy and labor is the highest; a conclusion aligned with the

TABLE 4 | Regression analysis of factor share equations. Results of equations (7) and (11) under "Static SUR model" and "Dynamic SUR model" columns, respectively.

	Static SUR model		Dynamic SUR model	
	Estimated coefficients	Standard errors	Estimated coefficients	Standard errors
Capital share equation				
γ_{C-L}	0.1572***	0.0103	0.0184***	0.0055
γ_{E-L}	-0.0668***	0.0097	-0.0088**	0.0034
δ_C	-0.0194***	0.0052	-0.0002	0.0021
β_C	0.0049***	0.0012	0.0034***	0.0005
λ_C	—	—	0.3671***	0.0156
α_C	0.6839***	0.0413	0.0329*	0.0197
γ_{STAV_C}	-0.0483***	0.0093	-0.0442**	0.0182
γ_{EX_C}	-0.0225***	0.0045	-0.0035**	0.0017
γ_{IM_C}	-0.0008	0.0037	-0.0002	0.0014
R^2	0.8911***		0.9085***	
Energy share equation				
γ_{C-L}	-0.0668***	0.0097	-0.0088**	0.0034
γ_{E-L}	-0.0197	0.0181	0.0035	0.0038
δ_E	0.0468***	0.0093	0.0017	0.0021
β_E	-0.0113***	0.0019	-0.0026***	0.0004
λ_E	—	—	0.4651**	0.1379
α_E	0.2056***	0.0738	-0.0026***	0.0004
γ_{STAV_E}	0.0729***	0.0169	0.0535**	0.0273
γ_{EX_E}	-0.0496***	0.0082	-0.0468**	0.0183
γ_{IM_E}	0.0390***	0.0069	0.0297*	0.0153
R^2	0.9571***		0.9668***	
Breusch–Pagan test	282.524***		171.819***	

results of Wang and Qi (2021) on substitution elasticities among four input factors across 36 industrial sectors in China. This research also finds that the two-way Morishima substitution elasticities between energy and labor are the highest, supporting the reliability of the conclusions. This implies a significant shift towards labor being replaced by automation in the sample period: as labor costs increased, the adoption of automated equipment in manufacturing resulted in a relative rise in energy consumption compared with labor input.

The cross-price elasticity between energy and capital factors is 0.1383 and 0.1675, respectively, indicating a limited substitution relationship and suggesting incomplete factor substitution between energy and capital in manufacturing, akin to China's heavy industry (Liu et al. 2018). In manufacturing, this substitution typically manifests through capital investment in energy-efficient equipment, which reduces energy input for a given output level. However, increased capital input can also lead to higher energy consumption due to production scale expansion, thus undermining the substitution whose nature depends on whether the capital input is energy-saving or energy-consuming.

The relationship of substitution, rather than complementarity, can be confirmed, serving as the basis for judging the bias of technological progress. Table 6 shows the bias of trade channels calculated from the estimated factor cost equations and the average factor share. A 1% increase in technological progress in productive services trade causes the relative share of labor and energy to increase by 0.1978%, resulting in a decreased share of energy relative to labor and trade in productive services more inclined to save energy. Also, commodity imports show an energy bias. In judging the bias between capital and energy, only commodity exports show a bias towards capital saving, and the rest is energy-biased. Only commodity imports are shown to be labor-biased between labor and capital. The bias of technological progress is primarily driven by two micro-level factors. The

TABLE 5 | Factor substitution elasticities. Results of equations (13), (14) and (16).

Own-price	Elasticity coefficients	Cross-price	Elasticity coefficients	Morishima elasticity	Elasticity coefficients
η_{L-L}	-0.7069	η_{L-C}	0.0183	MES_{L-C}	0.7247
		η_{L-E}	0.6634	MES_{L-E}	1.2401
η_{C-C}	-0.1853	η_{C-L}	0.0178	MES_{C-L}	0.2036
		η_{C-E}	0.1675	MES_{C-E}	0.3236
η_{E-E}	-0.6715	η_{E-L}	0.5332	MES_{E-L}	1.3349
		η_{E-C}	0.1383	MES_{E-C}	0.839

TABLE 6 | Bias of technological progress from trade channels.

Technological progress channels	Labor-Energy	Bias	Labor-Capital	Bias	Capital-Energy	Bias
Productive service imports	0.1978	Energy	0.1163	Capital	0.3141	Energy
Commodity exports	-0.2854	Labor	0.1434	Capital	-0.1419	Capital
Commodity imports	0.1747	Energy	-0.0769	Labor	0.0978	Energy

first is the price, that is, the technological progress has a more significant impact on factors with relatively high prices, increasing their marginal productivity. The second is the market size, where technological progress tends to enhance the marginal productivity of factors with larger input quantities (and thus lower costs). Conserving these less expensive production factors helps expand their market share. As market-oriented energy reforms progress, domestic energy prices shift from government regulation to market-driven supply and demand, becoming increasingly aligned with international energy price fluctuations.

In the 18-year period covered by our data, the overall energy price has increased by 76.54%, while the capital prices by 57.12% and the labor prices by 43.26%. Therefore, in comparison with the other two factors, most trade channels demonstrate a conservation of the energy factor, with the role of the price being more pronounced. Additionally, since China's formal entry into the World Trade Organization (WTO) in 2001, its labor-intensive manufacturing has experienced rapid growth, driven by an abundant labor force and low labor costs. As a result, in this period, price factors have played a dominant role in the comparison of labor and capital. Most technological progress achieved through trade channels has been capital-saving in nature. Based on the estimation of the factor share equations, the decomposition results of the energy efficiency changes are obtained from (18) and (19). Table 7 presents the impact of budget, output, factor substitution, and technological progress on energy efficiency in each three-year period, as well as the overall period. Figure 2 presents the trend characteristics of the decomposed energy efficiency results for the manufacturing industry and two types of sub-sectors, namely high-tech and high energy-consuming.

In the overall period, the energy efficiency of manufacturing increased by 36.28%, with the highest contributions coming from the budget and technological spillovers, which were 21.11% and 17.48%, respectively. This is consistent with the conclusions of Ma et al. (2009) and Wei et al. (2019). Notably, output played an important role in reducing energy efficiency by 12.84%. Looking at the changes over different periods, the output had a positive effect on energy efficiency in the first three periods, possibly due to insufficient marketization of energy prices in the early stages, leading to the growth of energy consumption demand being lower than that of the manufacturing added value. However, the drawbacks of this growth model (the extensive growth model in the early stages of China's accession to the WTO) gradually emerged, leading to effect reversal.

Factor substitution improved energy efficiency by 7.29% over the entire period, while capital generally exhibited a positive effect of 12.45%. Although labor had a negative effect on energy efficiency during the overall period, examining the labor changes across the different three-year periods revealed that its impact gradually weakened.

Technological spillover contributed positively to energy efficiency overall, particularly in the three time periods after 2009. In addition to trade channels, the total technology spillover includes the general technological progress characterized by a time trend. Looking at the impact of technological spillover from three trade channels, the overall effect of commodity imports is negative at 1.87%, the uplifting effect of service trade is significant at 5.8%, and the commodity exports come afterwards at 3.44%. The import of productive service trade directly accelerates technological progress by compensating for domestic inefficiency and limited related services through the acquisition of advanced foreign services. This boosts the productivity of the service segment in the short term and, in turn, drives the overall technological progress.

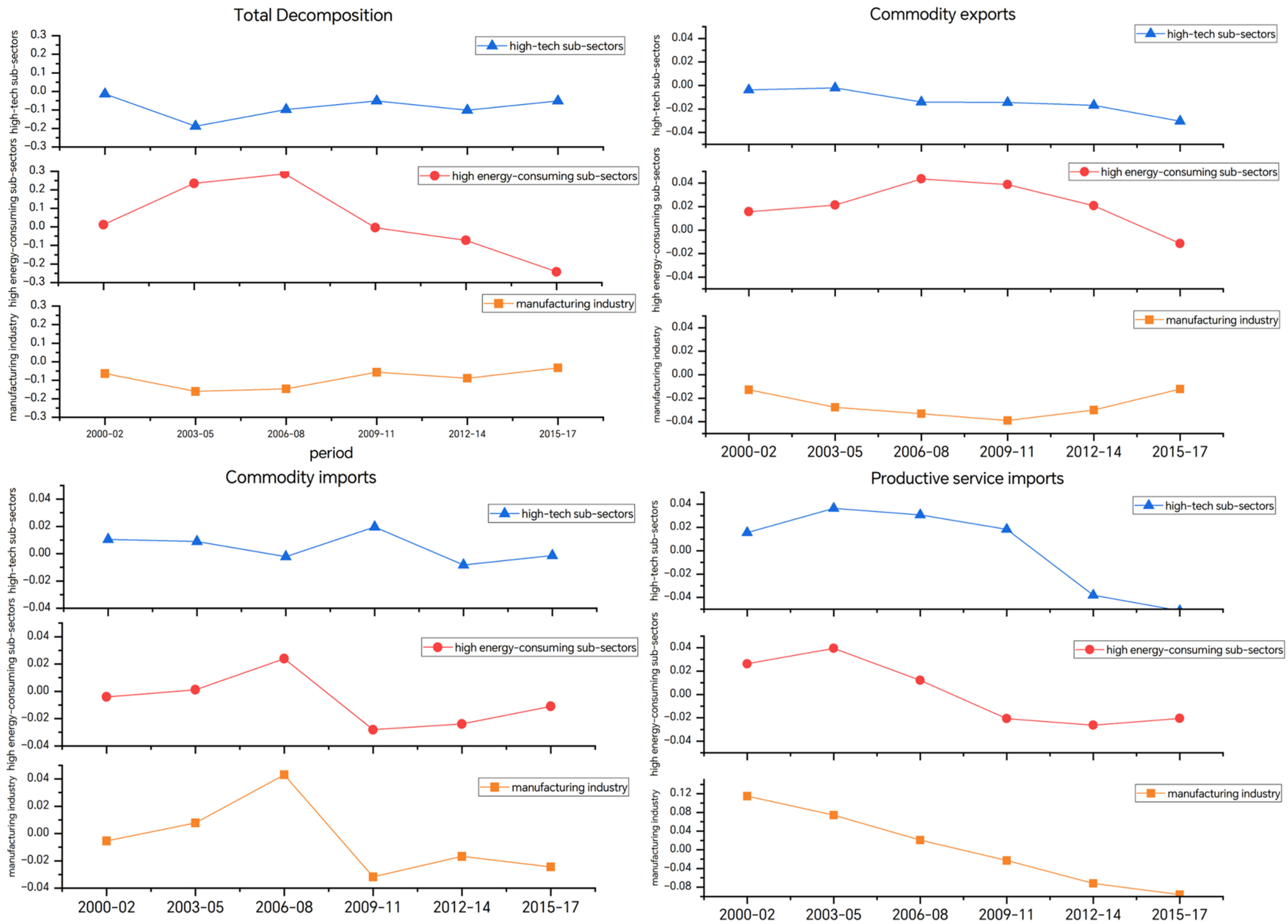

FIGURE 2 | Trends of decomposed energy efficiency for manufacturing and high-tech and high energy-consuming sub-sectors.

TABLE 7 | Decomposition of energy efficiency changes in manufacturing industry. Results of equations (18) and (19).

	2000–02	2003–05	2006–08	2009–11	2012–14	2015–17	2000–17
$\hat{e}/e$	-0.064	-0.1598	-0.146	-0.0565	-0.089	-0.0326	-0.3628
Budget	-0.1363	-0.1216	-0.0542	-0.0379	-0.0068	-0.0041	-0.2111
Outputs	-0.0143	-0.0812	-0.062	0.1091	0.0735	0.1155	0.1284
Total factor substitution	0.0476	0.0087	-0.0306	-0.0013	-0.0066	-0.0534	-0.0729
Labor	0.0555	0.0417	0.0377	0.0312	0.0232	-0.0186	0.1056
Capital	-0.005	-0.0248	-0.056	-0.0233	-0.0149	-0.0116	-0.1245
Energy	-0.0029	-0.0081	-0.0123	-0.0092	-0.0149	-0.0232	-0.0539
Total technological progress	0.0389	0.0342	0.0009	-0.1263	-0.1491	-0.0907	-0.1748
Service trade	0.1148	0.0744	0.021	-0.0228	-0.072	-0.0958	-0.058
Commodity exports	-0.0128	-0.0277	-0.0331	-0.0389	-0.03	-0.0121	-0.0344
Commodity imports	-0.0054	0.0078	0.0431	-0.0317	-0.0167	-0.0244	-0.0187
Time trends	-0.0577	-0.0203	-0.0301	-0.023	-0.0104	0.0216	-0.0637

Productive service trade, as an intermediate input integrated in the production process, tends to have relatively condensed effects in terms of technological progression. In contrast, technological progress in commodity export trade relies on the "learning-by-exporting" effect, which involves improving processes to meet the environmental and energy efficiency standards of importing countries, thereby driving energy efficiency improvement. On the other hand, commodity import trade allows the importing country to integrate high-quality products, adopt reverse engineering to transform local technologies, while also indirectly acquiring production management experience embedded within the products, leading to enhanced energy efficiency.

Taking into account the heterogeneity of the factor composition, this study further decomposes energy efficiency changes in specific sub-sectors. Five high energy-consuming sectors and five high-tech sectors (see Appendix A) in manufacturing are selected for an in-depth analysis. Table 8 shows that energy efficiency in high energy-consuming sectors increased by 12.83% between 2000 and 2017, with the budget and technological spillovers playing a major role. Energy efficiency increased from 2002 to 2008, but improved by 7.24% from 2012 to 2014, and by 24.22% from 2015 to 2017. The budget played a significant role, contributing an improvement in energy efficiency of 6.31% from 2012 to 2014 and 8.58% from 2015 to 2017, while technological spillovers only contributed 4.91% and 5.09%. Therefore, the role of trade channels was relatively limited in this period, with commodity exports showing a reverse effect on energy efficiency overall. However, this reverse effect gradually weakened in the more recent years and, from 2015 to 2017, it showed a positive effect of 1.14%.

The lack of significant effect of technology spillover of trade channel in high energy-consumption sectors can be attributed to several factors. First, the input structure of high energy-consumption sectors greatly differs from general sectors due to their resource-driven nature, resulting in a high proportion

TABLE 8 | Decomposition of energy efficiency changes in high energy-consuming sub-sectors. Results of equations (18) and (19).

	2000–02	2003–05	2006–08	2009–11	2012–14	2015–17	2000–17
$\hat{e}/e$	0.0122	0.2347	0.2866	-0.0045	-0.0724	-0.2422	-0.1283
Budget	-0.0239	0.0221	0.0497	0.0323	-0.0631	-0.0858	-0.134
Outputs	-0.0093	0.0328	0.0362	-0.0298	0.0691	-0.0235	0.0612
Total factor substitution	0.0122	0.1201	0.1312	0.0205	-0.0293	-0.082	0.0109
Labor	0.0431	0.0484	0.0683	0.0336	0.0374	-0.0015	0.0618
Capital	-0.0009	0.0033	-0.0352	-0.0073	-0.0308	-0.0004	-0.0637
Energy	-0.03	0.0684	0.098	-0.0057	-0.0359	-0.0801	0.0128
Total technological progress	0.0332	0.0597	0.0695	-0.0275	-0.0491	-0.0509	-0.0664
Service trade	0.0263	0.0395	0.0121	-0.0207	-0.0263	-0.0205	-0.0386
Commodity exports	0.0157	0.0213	0.0436	0.0388	0.0208	-0.0114	0.0395
Commodity imports	-0.0041	0.0012	0.0239	-0.0281	-0.0239	-0.011	-0.0452
Time trends	-0.0047	-0.0023	-0.0101	-0.0175	-0.0197	-0.008	-0.0221

TABLE 9 | Decomposition of energy efficiency changes in high-tech sub-sectors. Results of equations (18) and (19).

	2000–02	2003–05	2006–08	2009–11	2012–14	2015–17	2000–17
$\hat{e}/e$	-0.0131	-0.1873	-0.0981	-0.0511	-0.1016	-0.0509	-0.3378
Budget	-0.0186	-0.0959	-0.0541	-0.0615	-0.013	-0.0139	-0.2124
Outputs	-0.0008	0.0057	0.0064	0.0099	0.0237	0.0321	0.0421
Total factor substitution	0.0224	0.0602	0.0629	-0.0291	-0.0572	-0.0503	0.0682
Labor	0.0012	0.0024	0.0043	0.0022	0.0015	-0.0036	0.0137
Capital	0.0153	0.0226	0.0471	-0.0285	-0.0468	-0.028	0.0312
Energy	0.0058	0.0351	0.0115	-0.0028	-0.0119	-0.0186	0.0233
Total technological progress	0.0224	0.0433	0.0146	0.0235	-0.0632	-0.0832	-0.1936
Service trade	0.0156	0.0363	0.0308	0.0183	-0.038	-0.0514	-0.0436
Commodity exports	-0.0037	-0.002	-0.014	-0.0145	-0.0169	-0.0303	-0.0616
Commodity imports	0.0105	0.009	-0.0022	0.0196	-0.0083	-0.0014	0.0053
Time trends	-0.0543	-0.018	-0.0293	-0.0276	-0.0407	-0.0138	-0.0937

of energy factors. This restricts the substitution of energy with other factors (see Table 8), suggesting that factor substitution did not play a positive role in the overall period. Second, sectors such as metal smelting and processing, coking and coke, and chemical industries are highly sensitive to energy-saving policies. The drawbacks of previous growth models (in the early stages of China's accession to the WTO) had deeply accumulated prior to the implementation of new environmental policies. Third, the energy embodied in goods increases with the growth of trade, especially export trade. Since 2001, China has become a net exporter of embodied energy (Xia 2016), and the export of high energy-consumption commodities in China has grown rapidly in the following decade (Tang et al. 2022). Taking the steel sector as an example, steel exports in 2006 increased by 109.1% compared with the previous year. In 2007, the net export of crude steel was 54.882 million tons, which had a significant impact on the energy efficiency of the sector (Chen et al. 2011). This may partially explain the negative impact of commodity exports prior to 2014.

Finally, from Table 9, the energy efficiency in the high-tech sectors has decreased by 33.78%, while the technology spillover has demonstrated a significant increment of 19.36%, with commodity exports and service trade contributing 6.16% and 4.36%, respectively. Although the factor substitution has caused a 6.82% decrease in energy efficiency, it has been positive overall in the recent three periods, with the most obvious effect of capital contributing 2.85%, 4.68%, and 2.8%, respectively. Previous research indicated a nonlinear relationship between China's energy intensity and capital stock growth, with a turning point of 15.1% annual growth rate in capital stock in the inverted U-shape curve (Wu 2012). The annual growth rate of capital investment by high-tech sector enterprises above the designated size was 28.42% from 2012 to 2017, surpassing the overall annual growth rate of manufacturing (20.51%). This could explain the positive effect demonstrated by capital.

4 | Conclusions and Policy Implications

In this paper, we construct a manufacturing energy efficiency model, incorporating factor substitution and technological progress bias theories. We use a dual translog cost function model to analyze energy consumption and substitution in manufacturing sub-sectors, considering five energy types and three trade channels. Studies have shown that services import reduces the share of capital while increasing the share of energy, and commodity exports promote the reduction of both capital and energy shares. A clear Morishima substitution exists between factors, with the highest elasticity between energy and labor. Service and commodity imports are energy-biased in the combinations of energy with labor and capital, whereas commodity exports are labor- and capital-biased. Technological progress and trade have driven energy efficiency improvements, but factor substitution has become increasingly prominent over the past few years.

China's energy price market reform is still underway, with a significant gap relative to the level of marketization in major developed countries. Refining the energy pricing mechanism is crucial to aligning end-user prices more directly with market demand. By leveraging the regulatory role of market-based pricing mechanisms, the manufacturing sector can improve energy efficiency, thus creating a comparative advantage in industrial production, domestic logistics, and international transportation costs. This, in turn, can promote the export trade of the manufacturing sector.

In recent years, manufacturing has made notable progress in energy conservation and consumption reduction, with the proportion of clean energy consumption continuously increasing. However, the overall substitution elasticity remains relatively low. Relevant authorities could further increase the proportion of clean energy in manufacturing by implementing periodic regulatory policies or administrative measures, reflecting the negative externalities of traditional energy consumption in energy prices. This would encourage the use of clean energy, particularly natural gas, wind power, and hydropower, to improve the factor substitution elasticity for traditional fossil fuels.

By formulating scientific fiscal policies that adjust the relative prices of input factors, the substitution effect of energy could be leveraged. This could involve increasing taxes on traditional energy consumption or establishing special funds for investing in clean production technologies, thereby maximizing the role of capital in energy substitution. The high energy-consuming sectors should take full advantage of rewards and subsidies to optimize labor and improve efficiency. High-tech manufacturing businesses should be encouraged to introduce new key technologies into the trade field, through cooperation, investment, patent authorization and licensing, to further expand energy efficiency improvements from the technological spillover of commodity exports.

The analysis of technological progress through trade channels can be viewed from multiple dimensions in relation to practical scenarios. Trade activities involving the flow of commodities and services only capture the technological knowledge embedded in tangible products and services. However, this analysis can be extended to include R&D driven by trade activities, foreign direct investment (FDI), and technological progress through commercial activities, such as mergers and acquisitions or patent licensing. Furthermore, examining shifts in trade structures could provide deeper insights into the impact of technological progress on the efficiency of manufacturing.

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Endnotes

[1] That is, the non-neutral technological progress and non-fixed returns to scale.

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Appendix A

Manufacturing and Service Trade Sub-sectors

Appendix B

Data Processing

We begin this section by providing a unified explanation of the sources, units, and roles of the key variables involved in the study, as summarized in Table B1.

B.1 | The Energy Factor

The study on energy prices by Apergis (2023) provides a detailed forecasting methodology; however, in this instance, we adhere to the use of official statistical data for straightforward processing. Integrated industry energy price statistics are not released by official agencies. Here, using 2010 as the base year, the producer price index (PPI) and consumer price index (CPI) are used to obtain the energy prices from 2000 to 2009 and from 2011 to 2017. The index itself contains price fluctuation factors that reflect the changing trend of prices to a certain extent.

The method for calculating comparable prices of energy types uses standard coal (kg) as an anchor: (1) the physical quantity of an energy on one kilogram of standard coal is obtained using the conversion coefficient of standard coal in Table B3, which is then unified. As shown in Table B2, gasoline, for instance, converted into standard coal yields the largest quantity, followed by diesel; (2) given the calculated unit price of the energy type in physical quantity, this is converted into the unit price based on standard coal, thus obtaining a uniformly comparable price. For the same period, the unit cost of electricity is the highest and the cost of raw coal the lowest, as shown in Table B4.

The above comparable quantities and prices of energy types provide an empirical basis for analyzing the substitution of energy types. However, to analyze the substitution relationship between factors, the key variable of integrated energy price is also required, following a previous study by Wei et al. (2019).

B.2 | Other Factors

B.2.1 | Capital

The capital input is represented by capital stock data, calculated using the perpetual inventory method, as follows:

$$K_{it} = K_{it-1}\left(1 - \delta_{it}\right) + I_{it}, \tag{B1}$$

where K_{it} denotes the capital stock of sub-sector i in year t; K_{it-1} the value of capital stock in the previous year; and δ_{it} the asset depreciation rate. Here, we account for the heterogeneity of sub-sectoral capital distribution and adopt the dynamic fixed capital depreciation rate by Wei et al. (2020). I_{it} represents the corresponding new asset investment in sub-sector i in year t. For capital prices, we use the "real interest rate estimation method", expressed as follows:

$$P_{kt} = r_t + \delta_t - \pi_t. \tag{B2}$$

The loan interest rate, r_t, is based on the three- to five-year interest rate of the People's Bank of China, as reported in the "China Finance Yearbook". δ_t is the depreciation rate set at 10%; and, π_t, the GDP deflator, is used to represent the actual inflation rate.

B.2.2 | The Labor Factor

The labor factor input is measured by the average annual number of employees by industry. The labor factor price is represented by the average salary of urban employees, with the nominal wage deflated using the CPI.

B.2.3 | The Energy Type and Energy Factor Share Composition

Using the method for energy types described above, the standard consumption and prices of the five energy types, adjusted to comparable quantities and prices, can be obtained, and the share is expressed as follows:

$$S_{it} = \frac{i \times P_{it}}{CO_t \times P_{CO_t} + GA_t \times P_{GA_t} + DI_t \times P_{DI_t} + NG_t \times P_{NG_t} + EL_t \times P_{EL_t}}, \tag{B3}$$

$\forall i \in \{CO, GA, DI, NG, EL\}$. Similarly, the share of the three input factors of energy, capital, and labor is also expressed as

$$S_{it} = \frac{i \times P_{it}}{E_t \times P_{E_t} + K_t \times P_{K_t} + L_t \times P_{L_t}}, \quad \forall i \in \{E, K, L\}. \tag{B4}$$

B.2.4 | Technological Progress in Trade Channels

Technological progress in trade channels is measured based on productive service trade and commodity trade. Specifically, productive service import is used to represent the overall level of service trade involved in manufacturing production. This calculation is based on the input-output relationship of service and manufacturing, taking into account the amount of service trade. The commodity trade is expressed as the proportion of sub-sectoral import and export trade relative to sub-sectoral added value, as follows:

$$EX_{it} = \frac{\text{exportvalue}_{it}}{\text{addedvalue}_{it}}, \quad IM_{it} = \frac{\text{importvalue}_{it}}{\text{addedvalue}_{it}}. \tag{B5}$$

The core explanatory variable of this study is the amount of productive services imported from the service industry used by manufacturing. Accurately measuring this variable is central to our analysis. To this end, we adopt the method of Chen and Liu (2014) to measure the import of productive service trade. Specifically, the calculation is as follows:

$$STAV_{jt} = \sum_i \frac{X_{ji}}{Y_j} \times \frac{M_{it}}{P_{it} + M_{it} - E_{it}}, \tag{B6}$$

where X_{ji} indicates that sub-sector j in manufacturing receives service product input from sub-sector i in service industry, $Y_j$indicates the total intermediate product input received by sub-sector j in manufacturing, and M_{it}, P_{it}, and, E_{it} are, respectively, the total import, output, and export of sub-sector i in service industry. M_{it}, E_{it} are obtained from the UN Comtrade, while P_{it} is represented by the industrial added value reported in the "China Statistical Yearbook" . X_{ji} and Y_j are measured after matching the service trade and service product data, respectively, used by manufacturing.

The Input-Output Society of the National Bureau of Statistics of China compiles input-output tables containing 135 sectors every five years. Four tables have been released for the years 2002, 2007, 2012, and 2017. The sample data range for this study spans from 2000 to 2017. Since each table only reflects the input-output relationship of various sectors in the current year, the remaining years are typically replaced by existing ones. Here, we adopt a strategy of "forward" replacing. For instance, the missing data for the years 2000 and 2001 are supplemented using the 2002 table, and a similar approach is applied for subsequent years. The specific calculation is as follows: the quantity of intermediate goods provided by the service sub-sector i used by sub-sector j of manufacturing in a blank year is derived from the published table. The ratio of this value to the total output of the sub-sector i is then calculated. The missing X_{ji} is determined by multiplying the output of i by this ratio. Similarly, for the variable Y_j, the ratio of total intermediate goods in each sub-sector of manufacturing to the total output of that sub-sector is calculated using the base year. This ratio is then used to multiply the

TABLE A1 | Merged manufacturing sub-sectors.

Serial number	After the merger manufacturing sub-sectors	2002 input-output table	2007, 2012, 2017 input-output table
1	Agricultural and sideline	Grain milling industry	Grain milling industry
	food processing industry	Feed processing industry	Feed processing industry
		Vegetable oil processing industry	Vegetable oil processing industry
		Sugar industry	Sugar Industry
		Slaughter and meat processing industry	Slaughter and meat processing industry
		Aquatic products processing industry	Aquatic Products Processing Industry
2	Food manufacturing	Other food processing and food manufacturing	Other food processing industry
			Convenience food manufacturing
			Liquid milk and dairy products manufacturing
			Condiments and fermented products manufacturing
			Other food manufacturing
3	Liquor, beverage and tea product manufacturing	Alcohol and beverage wine manufacturing	Alcohol and liquor manufacturing
		Other beverage manufacturing	Soft drink and refined tea processing industry
4	Tobacco manufacturing	Tobacco products industry	Tobacco products industry
5	Textile manufacturing	Cotton, chemical fiber textile and printing and dyeing fine processing industry	Cotton, chemical fiber textile and printing and dyeing fine processing industry
		Wool spinning and dyeing and finishing industry	Wool spinning and dyeing and finishing industry
		Linen spinning, silk spinning and finishing industry	Linen spinning, silk spinning and finishing industry
		Textile manufacturing	Textile manufacturing
		Knitwear, knitted products and their products manufacturing	Knitwear, knitted products and their products manufacturing
6	Textile, clothing, shoes and hat manufacturing	Textile, clothing, shoes and hat manufacturing	Textile, clothing, shoes and hat manufacturing
7	Leather, fur, feather (velvet) and their products	Leather, fur, feather (down) and their products industry	Leather, fur, feather (down) and their products industry
8	Wood processing and wood, bamboo, rattan, palm and straw products	Wood processing and wood, bamboo, rattan, palm and grass products industry	Wood processing and wood, bamboo, rattan, palm and grass products industry
9	Furniture products	Furniture manufacturing	Furniture manufacturing
10	Paper and paper products	Paper and paper products industry	Paper and paper products industry

(Continues)

TABLE A1 | (Continued)

Serial number	After the merger manufacturing sub-sectors	2002 input-output table	2007, 2012, 2017 input-output table
11	Printing and recording media reproduction	Printing industry and recording media reproduction industry	Printing industry and recording media reproduction industry
12	Cultural, educational and sporting goods manufacturing	Stationery manufacturing	Cultural, educational and sporting goods manufacturing
		Toys, sports and entertainment products manufacturing	
13	Petroleum processing, coking and nuclear fuel processing (high-energy consuming)	Petroleum and nuclear fuel processing industry	Petroleum and nuclear fuel processing industry
		Coking industry	Coking industry
14	Chemical raw materials and chemical products (high energy-consuming)	Basic chemical raw material manufacturing	Basic chemical raw material manufacturing
		Fertilizer manufacturing	Fertilizer manufacturing
		Pesticide manufacturing	Pesticide manufacturing
		Paint, pigment, ink and similar product manufacturing	Coatings, inks, pigments and similar products manufacturing
		Synthetic material manufacturing	Synthetic material manufacturing
		Specialty chemical product manufacturing	Specialty chemical product manufacturing
		Daily chemical product manufacturing	Daily chemical product manufacturing
15	Pharmaceutical manufacturing (high-tech)	Pharmaceutical manufacturing	Pharmaceutical manufacturing
16	Chemical fiber manufacturing	Chemical fiber manufacturing	Chemical fiber manufacturing
17	Rubber products plastic products	Rubber products industry	Rubber products industry
		Plastic products industry	Plastic products industry
18	Non-metallic products (high energy-consuming)	Cement, lime and gypsum manufacturing	Cement, lime and gypsum manufacturing
		Glass and glass products manufacturing	Cement and gypsum product manufacturing
		Cement, lime and gypsum manufacturing	Brick, stone and other building materials manufacturing
		Refractory product manufacturing	Glass and glass products manufacturing
		Other non-metallic mineral products manufacturing	Ceramic products manufacturing
			Refractory product manufacturing
			Graphite and other non-metallic mineral products manufacturing

(Continues)

TABLE A1 | (Continued)

Serial number	After the merger manufacturing sub-sectors	2002 input-output table	2007, 2012, 2017 input-output table
19	Ferrous metal smelting and rolling processing (high energy-consuming)	Ironmaking industry	Ironmaking industry
		Steelmaking industry	Steelmaking industry
		Steel rolling processing industry	Steel rolling processing industry
		Ferroalloy smelting industry	Ferroalloy smelting industry
20	Non-ferrous metal smelting and rolling processing (high energy-consuming)	Non-ferrous metal smelting industry	Non-ferrous metal smelting and alloy manufacturing
		Non-ferrous metal rolling processing industry	Non-ferrous metal rolling processing industry
21	Made from metal	Metal products industry	Metal products industry
22	General equipment manufacturing	Boiler and prime mover manufacturing	Boiler and prime mover manufacturing
		Metal processing machinery manufacturing	Metal processing machinery manufacturing
		Other general equipment manufacturing	Lifting and transportation equipment manufacturing
			Manufacturing of pumps, valves, compressors and similar machinery
			Other general equipment manufacturing
23	Special equipment manufacturing	Special machinery manufacturing for agriculture, forestry, animal husbandry and fishery	Mining, metallurgy and construction special equipment manufacturing industry
		Other special equipment manufacturing	Chemical, wood, and non-metal processing equipment manufacturing industry
			Special machinery manufacturing for agriculture, forestry, animal husbandry and fishery
			Other special equipment manufacturing
24	Transportation equipment manufacturing (high-tech)	Railway transportation equipment manufacturing	Railway transportation equipment manufacturing
		Automotive manufacturing	Automotive manufacturing
		Auto parts and accessories manufacturing	Ship and floating device manufacturing industry
		Ship and floating device manufacturing industry	Other transportation equipment manufacturing
		Other transportation equipment manufacturing	
25	Electrical machinery and equipment manufacturing (high-tech)	Motor manufacturing	Motor manufacturing

(Continues)

TABLE A1 | (Continued)

Serial number	After the merger manufacturing sub-sectors	2002 input-output table	2007, 2012, 2017 input-output table
		Home appliance manufacturing	Transmission and distribution and control equipment manufacturing industry
		Other electrical machinery and equipment manufacturing	Wire, cable, optical cable and electrical equipment manufacturing
			Household electric and non-electric appliance manufacturing
			Other electrical machinery and equipment manufacturing
26	Communication equipment, computers and other electronic equipment (high-tech)	Communication equipment manufacturing	Communication equipment manufacturing
		Computer manufacturing industry	Radar and broadcasting equipment manufacturing
		Other electronic computer equipment manufacturing	Computer manufacturing
		Electronic components manufacturing	Electronic components manufacturing
		Home audio-visual equipment manufacturing	Home audio-visual equipment manufacturing
		Other communication and electronic equipment manufacturing	Other electronic equipment manufacturing
27	Instrumentation and culture, office machinery (high-tech)	Instrumentation manufacturing	Instrumentation manufacturing
		Cultural and office machinery manufacturing	Cultural and office machinery manufacturing
		Arts and crafts manufacturing	Crafts and other manufacturing
28	Other manufacturing	Other industries	Scrap waste
		Scrap	

TABLE A2 | Merged service trade sub-sectors.

Merged service	UN Comtrade	China Ministry of Commerce Service Trade Statistics	Input-output table
Transportation and communication services	Transportation (205)	Transportation and storage industry; postal industry	Railway passenger transportation industry
	Communications services (245)		Railway freight industry
			Road transport industry
			Urban public transportation industry
			Water transportation
			Air passenger transport
			Air cargo industry
			Pipeline transportation industry
			Warehousing industry
			Postal industry
Computer information service industry	Computer and information services (262)	Information transmission, computer service and software industry	Information transmission service industry
			Computer services and software industry
Financial insurance service industry	Insurance services (253)	Financial industry	Financial industry
	Financial services (260)		Insurance
Technology R&D service industry	Royalties and license fees (266)	Research and experimental development industry; comprehensive technical service industry	Scientific research career
			Professional technology and other technology services
			Geological prospecting industry
			Water conservancy industry
			Environmental resources and public facilities management industry
Education, culture, social service industry	Personal, cultural, and recreational services (287)	Education industry; culture, sports and entertainment industry; health, social security and social welfare industry	Education
			Health service

(Continues)

TABLE A2 | (Continued)

Merged service	UN Comtrade	China Ministry of Commerce Service Trade Statistics	Input-output table
			Social security and social welfare industry
			Culture, art, radio, film and television industry
			Sports career
			Entertainment industry
			Public administration and social organization
Business and other services	Other business services (268)	Leasing and business services; residents services and other services	Leasing industry
			Business service industry
			Resident services and other services

output of the blank years to obtain the total intermediate input of j in those years.

Since the input-output table published in 2002 contains 122 sectors, while the tables from 2007 onward include 135 sectors, slight differences exist. According to the "National Economic Industry Classification and Code", the two industry classifications were matched, and 28 manufacturing sub-sectors corresponding to the input-output table were sorted out, as shown in Table A1. Another key consideration is how to align the statistical calibre of service trade and productive import services. Based on the nature of the service industry and with reference to the matching method of Chen and Liu (2014), the 11 service trade statistical classifications in the UN Comtrade database and the 16 service industry statistical classifications in the "China Statistical Yearbook" were adjusted and merged. This study selects eight types of service trade provided by the UN Comtrade database and consolidates them into six categories. Subsequently, 11 sub-sectors from the Statistics Department of the Ministry of Commerce of China and 29 sectors from the input-output table are selected to match these eight types of service trade (Table A2). Notably, the code 245-3 in the UN Comtrade database, which reports the service trade import and export values of communication, has missing data for the period 2009 to 2017. To address this, the growth rate of China's Total EBOPS Services, as provided by the UN Comtrade data, is used for estimation. The annual average price of the RMB exchange rate, sourced from the "China Statistical Yearbook", is used to convert the US dollar price.

TABLE B1 | Summarized key variables.

Name	Source	Unit	Role
Energy (physical quantity)	Comprehensive conversion	10,000 tons of standard coal	Input variable
Energy (unit price)	Wei et al. (2019)	10,000 yuan	Price variable
Capital (stock)	Perpetual inventory method	100 million yuan	Input variable
Capital (price)	Wei et al. (2020)	Loan interest rate	Price variable
Labor (input)	China Statistical Yearbook	10,000 people	Input variable
Labor (price)	China Statistical Yearbook	10,000 yuan	Price variable
Commodity trade export	China Statistical Yearbook	Percentage (%)	Trade-related variable
Commodity trade import	China Statistical Yearbook	Percentage (%)	Trade-related variable
Productive service trade	Chen and Liu (2014)	Percentage (%)	Trade-related variable

TABLE B2 | Unit price in physical quantity for different energy types.

Type	Unit price of energy type in physical quantity					
	2007	2008	2009	2010	2011	2012
Raw coal (yuan/ton)	409.23	412.22	415.22	573.91	526.99	510.42
Gasoline (yuan/ton)	5996	6472.33	6416.72	8004.33	9277.86	9583.67
Diesel (yuan/ton)	5326	5814	5362.67	6324.64	8083.42	8296.67
Natural gas (yuan/ton)	2.47	2.61	2.74	2.88	3.11	3.19
Electricity (yuan/kWh)	0.66	0.69	0.71	0.75	0.76	0.94

TABLE B3 | Coefficients of conversion of standard coal for different energy types.

Type	Coefficients	Physical quantity
Raw coal	0.7143 kg standard coal/kg	1.3999 kg
Gasoline	1.4714 kg standard coal/kg	0.6796 kg
Diesel	1.4571 kg standard coalkg	0.6863 kg
Natural gas	1.1000 kg standard coal/m3	0.909m3
Electricity (equivalent)	0.1229 kg standard coal/kWh	8.1367kWh

TABLE B4 | Unit prices of energy types converted into standard coal.

Type	Unit price of energy type					
	2007	2008	2009	2010	2011	2012
Raw coal	0.57	0.58	0.58	0.8	0.74	0.71
Gasoline	4.07	4.4	4.36	5.44	6.31	6.51
Diesel	3.66	3.99	3.68	4.34	5.55	5.69
Natural gas	2.25	2.37	2.49	2.62	2.83	2.9
Electricity	5.37	5.59	5.79	6.09	6.15	7.62