

Article

# Decomposition Analysis of Aggregate Energy Consumption in China: An Exploration Using a New Generalized PDA Method

Dequn Zhou <sup>1,2</sup>, Xiao Liu <sup>1,2,\*</sup>, Peng Zhou <sup>1,2</sup> and Qunwei Wang <sup>1,2</sup>

<sup>1</sup> College of Economics and Management, Nanjing University of Aeronautics and Astronautics, 29 Jiangjun Avenue, Nanjing 211106, China; dequnzhou@163.com (D.Z.); pzhou88@163.com (P.Z.); wqw0305@163.com (Q.W.)

<sup>2</sup> Research Centre for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, 29 Jiangjun Avenue, Nanjing 211106, China

\* Correspondence: liuxiao@nuaa.edu.cn or liuxiaonuaa@163.com; Tel.: +86-25-84896161

Academic Editors: Jeffrey Logan and Doug Arent

Received: 22 March 2017; Accepted: 22 April 2017; Published: 26 April 2017

**Abstract:** As the largest energy consumer, China is facing greater pressure to guarantee energy supply and energy security. Investigating the driving factors of energy consumption is very important. Decomposition analysis is an analytical tool for decomposing an aggregate indicator into its contributing factors. This paper introduces index decomposition analysis (IDA) into production decomposition analysis (PDA) and provides a new decomposition framework for analyzing energy consumption. Two application studies are presented to illustrate the use of our proposed approach. The first deals with the decomposition of aggregate energy consumption from 1991 to 2012; the second application studies seven sectors of China from 2001 to 2012. The empirical studies result in four meaningful findings: (1) the rapid economic growth has already resulted in severe energy supply crises; (2) China's energy sector consumption structure has changed significantly; (3) potential economic effect is the largest driving factor for energy consumption growth; (4) potential energy intensity effect and technical change of economic output effect were the two primary driving factors in reducing energy consumption.

**Keywords:** energy consumption; decomposition analysis; IDA; PDA; China

## 1. Introduction

China's economy has grown rapidly in the past three decades, which has resulted in severe environmental pollution and an acute shortage of energy supply. Its energy consumption rose from 1037.8 Mtce (million tons of coal equivalent) in 1991 to 3617.3 Mtce in 2012, representing an annual average growth rate of 6.1%. According to the Statistical Review of World Energy 2012, China has replaced the US as the largest energy consumer, contributing to 20.3% of global energy consumption. In order to impel the sustained economic growth and the construction of a resource conserving and environment friendly society, China's 12th five-year plan, launched in 2011, stipulated that all government divisions must reduce energy consumption and primary pollution. Understanding the driving factors behind energy consumption changes will provide insights about consumption patterns and can inform targeted energy saving policies. Therefore, there is a great practical significance to investigate the driving forces dominating China's energy consumption levels.

At present, decomposing the growth of energy consumption into possible affecting factors is an available approach. Decomposition analysis is conducted by using an identical equation to decompose the changes in energy consumption into several pre-defined factors [1]. So far, structural decomposition analysis (SDA) and index decomposition analysis (IDA) have been successfully used to quantify impact factors in many previous studies [2–4].

Generally, the popular IDA methods can be divided into two groups: the Laspeyres index and the Divisia index. The Laspeyres index measures the percentage change in some aspect of a group of items over time, using weights based on values in some base year. However, the Divisia index is a weighted sum of logarithmic growth rates, where the weights are the components' shares in total value, given in the form of a line integral [5]. Xu and Ang [6] provided a complete literature review of the evolution of the IDA approach, and its applications to the carbon emissions field.

Compared to IDA, the SDA approach is based on the input-output model to analyze the direct or indirect effects. Conclusions based on SDA are more complete, but the approach requires more data. Particularly, IDA adopts both additive and multiplicative forms, while SDA mainly uses the additive form [7]. Recently, there were some methodological improvements in multiplicative SDA. For example, Su and Ang [8] introduced the attribution analysis into the multiplicative SDA to give the contributions of the individual components at the finer level. Additionally, in the context of multiplicative SDA of intensity indicators, Wang et al. [9] investigated three specific methodological issues.

Due to the flexibility of adoption, ease of use, as well as a relatively low data requirement, IDA is a more widely accepted decomposition tool for policy making at the national level [4,10]. A representative example of the Laspeyres index is the research by Hirst et al. [11], where the method was firstly applied to study the change of energy demand due to production structure changes. Based on the principle of "jointly created and equally distributed factors", Sun [12] proposed to equally split the residual terms, which arise by interactions among factors in the decomposition. Thereafter, the refined Laspeyres index approach was used to study energy consumption in China during 2000–2010. This decomposition approach is also utilized by Andreoni and Galmarini [13] to investigate the main factors influencing the CO<sub>2</sub> emissions of European transport activities for the period 2001–2008.

Among the varieties of different IDA methods, a summary of the various methods including their advantages and disadvantages were provided by Ang [10]. After introducing the IDA application and methodology, Ang [10] advocated the logarithmic mean Divisia index (LMDI) for general use. Because of its theoretical foundation, adaptability, and result interpretation, logarithmic mean Divisia index (LMDI) method was the preferred IDA method [14,15].

A great many studies have focused on decomposing China energy consumption and energy-related CO<sub>2</sub> emissions, and identified the impact factors quantitatively by using LMDI method. Zha et al. [16] used the LMDI method to decompose the residential CO<sub>2</sub> emissions in urban and rural China. The generalized LMDI technique was used by Wang et al. [17] to analyze the respective contributions of changes of energy consumption in China from 1991 to 2011. Zhang et al. [18] used the LMDI method to study the difference of residential energy consumption between urban and rural Jiangsu areas.

Recently, a decomposition technique using distance function estimated through data envelopment analysis has been presented in several studies. This decomposition technique is called the production theoretical decomposition analysis (PDA) [19–21]. Zhou and Ang [21] presented two applications on decomposing the CO<sub>2</sub> emission for world regions and OECD countries. By comparing PDA with the well-known IDA and SDA techniques, they pointed out the highlights of PDA in CO<sub>2</sub> emission decomposition. Li [22] assessed productive efficiency through output distance function for desirable output sub vector while holding bad output and inputs constant, which avoided symmetric scaling on good and bad outputs. The proposed approach was used to investigate the sources of CO<sub>2</sub> emission changes in China from 1991 to 2006. Zhang et al. [23] proposed an alternative PDA decomposition model and applied it to empirically analyze 20 developed countries. Kim and Kim [24] concentrated on the production technology to analyze worldwide CO<sub>2</sub> emissions. They provided more detailed information about the influence of both production technical efficiency and technological change on CO<sub>2</sub> emissions, and they showed that the relative degree of each country's energy efficiency paradox phenomenon can be identified empirically. Wang et al. [25] investigated the challenge of the infeasibility of (data envelopment analysis) DEA liner programming by modifying the PDA approach and applying it to analyze the driving factors of carbon dioxide emissions in China, using data from 2005 to 2010.

The studies above demonstrate the successful use of the PDA method for decomposition analyses in the field of energy and environmental systems. However, opportunities for improvements remain.

First, existing PDA methods are based on the framework of multiplicative decomposition. As such, the decomposition results can only express the influence degree of each driving factor, its specific impact value cannot be acquired. Second, it was found that previous PDA literature has mainly focused on the decomposition analysis of carbon emissions rather than energy consumption, nevertheless energy-related carbon emissions accounted for the majority of the total. Therefore, it is not conducive to accurately identify the profound causes that lead to the changes of energy consumption and carbon emissions.

Considering the above two points, the main contribution of this paper lies in two aspects. First, this study introduced PDA theory into the IDA method and developed an additive decomposition framework with which we can explore the driving factors on the change of energy consumption from absolute and relative amount dimensions. Second, with the newly built decomposition model, two application studies on decomposing the China energy consumption for time-series and seven sectors are presented. In addition to the economic development effect and structure change effect, this study emphasizes the impact of production technology effects (technological change and technical efficiency change) on energy consumption.

## 2. Methodology

The energy consumption in year  $t$  ( $E^t$ ) can be expressed as Equation (1)

$$E^t = \sum_{i,j} E_{ij}^t = \sum_{ij} \frac{E_{ij}^t}{E_i^t} \times \frac{E_i^t}{E^t} \times \frac{E^t}{Y^t} \times Y^t \quad (1)$$

where  $t$  is the time in years;  $E^t$  is the energy consumption in time  $t$ ; the subscript  $i$  represents industrial sector; the subscript  $j$  represents fuel type;  $E_i^t$  denotes energy consumption of the  $i$ th sector in time  $t$ ;  $E_{ij}^t$  denotes energy consumption of the  $i$ th sector based on  $j$  fuel type in time  $t$ ;  $E_{ij}^t/E_i^t$  is the share of the  $j$ th energy form to  $i$  sector total energy consumption in year  $t$ ;  $E_i^t/E^t$  is the share of the  $i$ th sector energy consumption to the total in time  $t$ ;  $Y^t$  denotes the Gross Domestic Production (GDP) in year  $t$ ;  $E^t/Y^t$  is the total energy intensity in year  $t$ .

### 2.1. Production Technology

For each time period, the production technology can be described as the following set [20–22]:

$$S = \{(E, K, L, Y) : (E, K, L) \text{ can produce } Y\}$$

where  $E, K, L$  are, respectively, energy consumption, fixed asset investment, and the amount of labor input. The variable  $S$  is often assumed to be a closed and bounded set, which implies that a finite amount of inputs can only produce a finite amount of output [26]. Assume that there are  $m = 1, 2, \dots, M$  entities and for entity  $m$  the observed data are  $E_m, K_m, L_m, Y_m$ , then the piecewise linear polluting technology  $S$  can be formulated as follows [20,25]:

$$S = \{(E, K, L, Y) : \begin{aligned} & \sum_{i=1}^M z_i E_i \leq E \\ & \sum_{i=1}^M z_i K_i \leq K \\ & \sum_{i=1}^M z_i L_i \leq L \\ & \sum_{i=1}^M z_i Y_i \geq Y \\ & z_i \geq 0, i = 1, 2, \dots, M \end{aligned} \} \quad (2)$$

In the literature,  $S$  is also referred to as the environmental DEA technology exhibiting constant returns to scale (CRS), since it is formulated in the DEA framework.

We begin by defining the following two Shephard distance function for input (energy consumption) and output (GDP):

$$D_e(E, K, L, Y) = \sup\{\lambda : (E/\lambda, K, L, Y) \in S\}$$

$$D_y(E, K, L, Y) = \inf\{\eta : (E, K, L, Y/\eta) \in S\}$$

$D_e(E, K, L, Y)$  can be interpreted as the maximum proportional contraction of energy input given outputs and technology;  $D_y(E, K, L, Y)$  measures the maximum feasible expansion of observed output given inputs and technology [23].

The distance functions can be estimated by using the production technology in time period  $s, t \in \{0, T\}$ . According to the definitions of these distance functions and the DEA technology, we can drive them by solving the following DEA type models (all the distance functions in DEA approach were calculated by Lingo 9.0) [27]:

$$\begin{aligned}
 [D_E^s(E_i^t, K_i^t, L_i^t, Y_i^t)]^{-1} &= \min \theta \\
 \text{s.t. } \sum_{i=1}^M z_i E_i^s &\leq \theta E_i^t \\
 \sum_{i=1}^M z_i K_i^s &\leq K_i^t \\
 \sum_{i=1}^M z_i L_i^s &\leq L_i^t \\
 \sum_{i=1}^M z_i Y_i^s &\geq Y_i^t \\
 z_i &\geq 0, i = 1, \dots, M
 \end{aligned} \tag{3}$$

$$\begin{aligned}
 [D_Y^s(E_i^t, K_i^t, L_i^t, Y_i^t)]^{-1} &= \max \eta \\
 \text{s.t. } \sum_{i=1}^M z_i E_i^s &\leq E_i^t \\
 \sum_{i=1}^M z_i K_i^s &\leq K_i^t \\
 \sum_{i=1}^M z_i L_i^s &\leq L_i^t \\
 \sum_{i=1}^M z_i Y_i^s &\geq \eta Y_i^t \\
 z_i &\geq 0, i = 1, \dots, M
 \end{aligned} \tag{4}$$

where  $s, t \in \{0, T\}$ .

### 2.2. Decomposition Approach

Now suppose that the aggregate energy consumption of a certain entity, i.e., entity  $m$ , varies from  $E^0$  in the period 0 to  $E^t$  in time period  $t$ , which can be, respectively, expressed in the following multiplicative form:

$$\begin{aligned}
 E^0 &= \sum_{i,j} \frac{E_{ij}^0}{E_i^0} \times \frac{E_i^0}{E^0} \times \frac{E^0}{Y^0} \times \frac{E^0}{[D_E^0(E^0, K^0, L^0, Y^0) \cdot D_E^t(E^0, K^0, L^0, Y^0)]^{\frac{1}{2}}} \\
 &\times \left[ Y^0 \times [D_Y^0(E^0, K^0, L^0, Y^0) \cdot D_Y^t(E^0, K^0, L^0, Y^0)]^{\frac{1}{2}} \right] \\
 &\times D_E^0(E^0, K^0, L^0, Y^0) \times \frac{1}{D_Y^0(E^0, K^0, L^0, Y^0)} \\
 &\times \left[ \frac{D_E^t(E^0, K^0, L^0, Y^0)}{D_E^0(E^0, K^0, L^0, Y^0)} \right]^{\frac{1}{2}} \times \left[ \frac{D_Y^0(E^0, K^0, L^0, Y^0)}{D_Y^t(E^0, K^0, L^0, Y^0)} \right]^{\frac{1}{2}}
 \end{aligned} \tag{5}$$

$$\begin{aligned}
 E^t &= \sum_{i,j} \frac{E_{ij}^t}{E_i^t} \times \frac{E_i^t}{E^t} \times \frac{E^t / [D_E^0(E^t, K^t, L^t, Y^t) \cdot D_E^t(E^t, K^t, L^t, Y^t)]^{\frac{1}{2}}}{Y^t} \\
 &\times \left[ Y^t \times [D_Y^0(E^t, K^t, L^t, Y^t) \cdot D_Y^t(E^t, K^t, L^t, Y^t)]^{\frac{1}{2}} \right] \\
 &\times D_E^t(E^t, K^t, L^t, Y^t) \times \frac{1}{D_Y^t(E^t, K^t, L^t, Y^t)} \\
 &\times \left[ \frac{D_E^0(E^t, K^t, L^t, Y^t)}{D_E^t(E^t, K^t, L^t, Y^t)} \right]^{\frac{1}{2}} \times \left[ \frac{D_Y^t(E^t, K^t, L^t, Y^t)}{D_Y^0(E^t, K^t, L^t, Y^t)} \right]^{\frac{1}{2}}
 \end{aligned} \tag{6}$$

On the right-hand side of Equations (5) and (6), the first and second components, respectively, account for the consumption structure of energy form (CSEF) and the industrial structure factor change (IS). Following Zhou and Ang [20], the third component could be interpreted as the potential energy intensity (PEI), since the energy consumption is deflated by its energy usage technical efficiency. Inefficiency in energy consumption will result in the observed energy intensity being larger compared to the case where there is no inefficiency. An increase in energy usage technical efficiency from period 0 to period  $t$  will lead to a larger energy intensity change and therefore more of the change in energy consumption being assigned to the change in energy intensity. We interpret the fourth component as the potential economic effect (PY), since GDP is deflated by its output efficiency. Inefficiency in GDP output will result in the observed GDP being larger compared to the case where there is no inefficiency. An improvement in GDP output efficiency from period 0 to period  $t$  will lead to a smaller GDP change and therefore less of the change in energy consumption being assigned to the change in GDP. The fifth and sixth components, respectively, reflect the energy usage efficiency (EUE) and GDP output efficiency (YOE). The seventh and eighth components, which are essentially two Malmquist index numbers, respectively measure the technical change of energy saving (TCES) and the technical change of economic output (TCYO).

### 2.3. Joint Decomposition Approach

According to the LMDI method given by Ang [10], the change of energy consumption between a base year 0 and a target year  $t$ , denoted by  $\Delta E_{tot}^t$ , can be decomposed into the following determinant factors:

$$\begin{aligned}
 \Delta E_{tot}^t &= E^t - E^0 \\
 &= \Delta E_{csef} + \Delta E_{is} + \Delta E_{pei} + \Delta E_{py} + \Delta E_{eue} + \Delta E_{yoe} + \Delta E_{tces} + \Delta E_{tcyo}
 \end{aligned} \tag{7}$$

Each effect in the right-hand side of Equation (4) can be computed as follows:

$$\Delta E_{csef} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln\left(\frac{CSEF^t}{CSEF^0}\right), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{8}$$

$$\Delta E_{is} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln\left(\frac{IS^t}{IS^0}\right), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{9}$$

$$\Delta E_{pei} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln\left(\frac{PEI^t}{PEI^0}\right), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{10}$$

$$\Delta E_{py} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln\left(\frac{PY^t}{PY^0}\right), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{11}$$

$$\Delta E_{eue} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln\left(\frac{EUE^t}{EUE^0}\right), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{12}$$

$$\Delta E_{yoe} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln(\frac{YOE^t}{YOE^0}), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{13}$$

$$\Delta E_{tces} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln(\frac{TCES^t}{TCES^0}), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{14}$$

$$\Delta E_{tcyo} = \begin{cases} 0, & \text{if } E_{ij}^0 \times E_{ij}^t = 0; \\ \sum_{ij} L(E_{ij}^t, E_{ij}^0) \ln(\frac{TCYO^t}{TCYO^0}), & \text{if } E_{ij}^0 \times E_{ij}^t \neq 0; \end{cases} \tag{15}$$

Here,

$$E_{ij}^t = \frac{E_{ij}^t}{E_i^t} \times \frac{E_i^t}{E^t} \times \frac{E^t}{E^t} \times \frac{E^t}{[D_E^0(E^t, K^t, L^t, Y^t) \cdot D_E^t(E^t, K^t, L^t, Y^t)]^{\frac{1}{2}}} \\ \times \left[ Y^t \times [D_Y^0(E^t, K^t, L^t, Y^t) \cdot D_Y^t(E^t, K^t, L^t, Y^t)]^{\frac{1}{2}} \right] \\ \times D_E^t(E^t, K^t, L^t, Y^t) \times \frac{1}{D_Y^t(E^t, K^t, L^t, Y^t)} \\ \times \left[ \frac{D_E^0(E^t, K^t, L^t, Y^t)}{D_E^t(E^t, K^t, L^t, Y^t)} \right]^{\frac{1}{2}} \times \left[ \frac{D_Y^t(E^t, K^t, L^t, Y^t)}{D_Y^0(E^t, K^t, L^t, Y^t)} \right]^{\frac{1}{2}}$$

and

$$L(E_{ij}^t, E_{ij}^0) = (E_{ij}^t - E_{ij}^0) / (\ln E_{ij}^t - \ln E_{ij}^0)$$

### 3. Date Description

In this paper, two application studies are presented to illustrate the use of our proposed approach. The first deals with the decomposition of aggregate energy consumption from 1991 to 2012 and implements DEA in two 11-year sub-periods (i.e., two 11-year pairs 1991–2001 and 2002–2012) (Firstly, at the end of 2001, China joined the World Trade Organization (WTO), which helped China to integrate into the globalization of trade and economy. As engines of economic growth and social development, there are enormous differences of energy consumption between periods before and after 2001. Secondly, DEA is more successful when there are more decision-making units (DMUs) (in this case, each year) than the products, and when the DMU number is at least two times larger than the sum of the number of inputs and outputs. As such, each sub-period should contain at least 8 years. Considering these two points, this study only divides the whole period into two 11-year sub-periods). In the second application, we applied our model to seven sectors of China from 2001 to 2012.

The energy consumption, labor input, and the fixed asset investment are treated as inputs. The GDP is treated as output. All the energy consumption data are converted into standard coal consumption in 10<sup>6</sup> tons of coal equivalent (Mtce) in calorific value calculation. The labor input data are calculated by the average number of employed persons at the beginning and end of the year, and its unit is 10,000 persons. Fixed asset investment data are total investment in fixed assets in the whole country measured in billion yuan in constant 1991 price terms. GDP data are in billion yuan in constant 1991 price terms. The data has been collected from various issues from the China Energy Statistical Yearbook (CESY, 1991–1996, 1997–1999, 2000–2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013) [28] and China Statistical Yearbook (CSY 2013) [29].

China economy is divided into three aggregated industries (primary, secondary, and tertiary industry). The primary industry includes agriculture and its related activities: farming, forestry, husbandry, and fishing. The secondary industry includes mining, manufacturing, water supply, electricity generation and supply, steam, the hot-water and gas sectors, and construction. The tertiary industry sector is the rest. In the second application, China’s industry sector was categorized into seven parts (i.e., 1: farming, forestry, animal husbandry, fishery, and water conservancy; 2: industry; 3: construction; 4: transport, storage, postal and telecommunications services; 5: wholesale, retail trade, and catering services; 6: residential consumption; 7: other).

In order to simplify the problem, this study follows the idea of Wang et al. [17], where energy types used in China are aggregated into four groups: coal product, oil product, natural gas, and other fuel type. The coal product is composed of coal, cleaned coal, other washed coal, briquettes, coke, coke oven gas, other gas, and other coking products. Crude oil, gasoline, kerosene, diesel oil, fuel oil, LPG, refinery gas, and other petroleum products are summed into oil products. Other fuel type includes electricity, heat, and the remaining energy types. The energy for non-energy use is excluded from the related energy type. In the first application, the aggregated energy consumption is divided into three industries, and we further classify the four different types of energy consumption in each industry, while, in the second application, the aggregated energy consumption is divided into seven sectors, and we further classify the four different types of energy consumption in each sector.

## 4. Results and Discussions

### 4.1. China's Energy Situation

Since 1991, China's economy has grown rapidly, which has resulted in severe environmental pollution and an acute shortage of energy supply. According to the Statistical Review of World Energy 2013, China has replaced the US as the largest energy consumer, contributing to 21.3% of global energy consumption (CESY, 1991–2013). It is obvious that ensuring an adequate and reliable energy supply in China has become increasingly important. Whereas, as is seen from Figure 1, China's indigenous energy production has grown slowly (climbing from 1048 Mtce in 1991 to 3318 Mtce in 2012), meanwhile in the same period its energy consumption has increased more rapidly (soaring from 1038 Mtce to 3617 Mtce), yielding an average annual growth rate of 6.1%. Correspondingly, China has become a net energy importer since 1992 when its energy consumption had already surpassed its energy production.

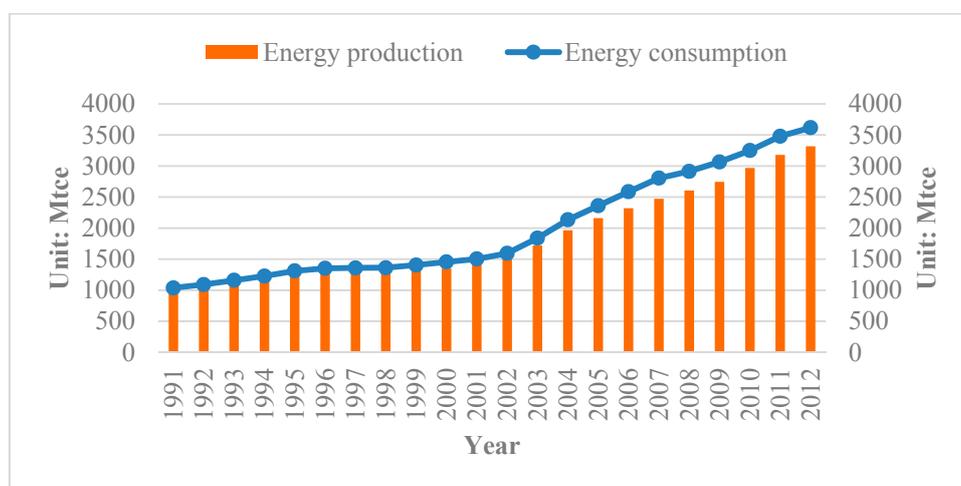
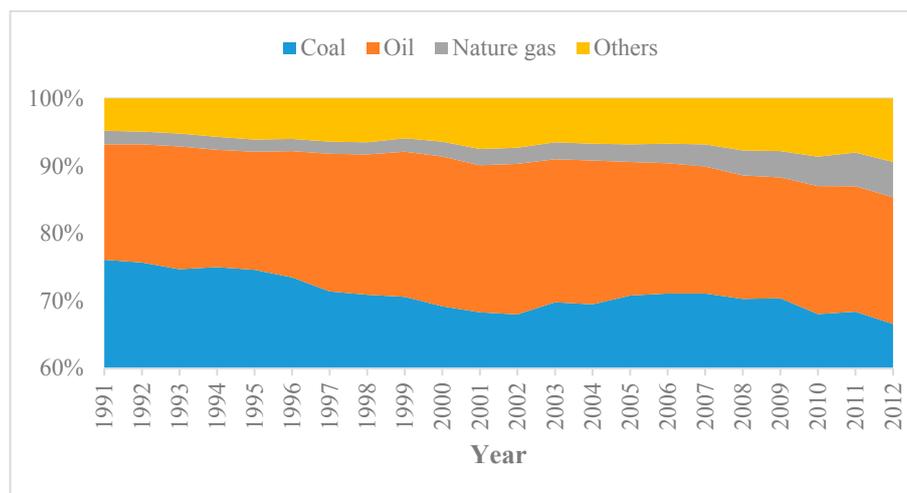


Figure 1. China's energy production and consumption, 1991–2012.

In China's fuel mix, as is clearly shown in Figure 2, coal has always played a major role. Even though the share of coal decreased from 76.1% in 1991 to 66.6% in 2012, coal still accounted for over 66% of the total energy demand. We can see that coal is being replaced by natural gas and primary electricity (hydro-nuclear and wind electricity), and the share of oil, natural gas, and primary electricity increased from 17.1% to 18.8%, 2.0% to 5.2%, and 4.8% to 9.4%, respectively.



**Figure 2.** The share of fuel type of energy consumption, 1991–2012.

Although oil has not traditionally taken up a significant proportion of total energy use, oil consumption has grown rapidly from 177.5 Mtce to 679.7 Mtce from 1991 to 2012. As a result, due to the lack of oil resources, China became a net oil importer in 1993. Statistics data shows that oil is the main energy import in China, with import dependency increasing rapidly from 7.5% in 1993 to 60.6% in 2012.

## 4.2. Empirical Analysis

### 4.2.1. Temporal Decomposition Analysis

After employing the use of Equation (7) in Section 2, findings obtained from the decomposition are shown in Table 1. The decomposition model was applied to analyze the intrinsic driving factors of energy consumption from 1991 to 2012, which was divided into two sub-periods with 11-year intervals. The 11 years of each sub-period were regarded as DMUs. The components of the decomposition analysis, i.e.,  $\Delta E_{csef}$  (consumption structure of energy form),  $\Delta E_{is}$  (industrial structure),  $\Delta E_{pei}$  (potential energy intensity),  $\Delta E_{py}$  (potential economic),  $\Delta E_{eue}$  (energy usage efficiency),  $\Delta E_{yoe}$  (economic output efficiency),  $\Delta E_{tces}$  (technical change of energy saving),  $\Delta E_{tcyo}$  (technical change of economic output), are calculated based on Equations (8)–(15), respectively.

**Table 1.** Complete decomposition of china energy consumption change (1991–2012).

Factor	Value (Mtce)	Ratio
$\Delta E_{csef}$	74.32	4.27%
$\Delta E_{is}$	3.30	0.19%
$\Delta E_{pei}$	−989.01	−56.87%
$\Delta E_{py}$	3436.40	197.61%
$\Delta E_{eue}$	−311.93	−17.94%
$\Delta E_{yoe}$	124.51	7.16%
$\Delta E_{tces}$	−37.99	−2.19%
$\Delta E_{tcyo}$	−560.58	−32.24%

Our decomposition results showed that, in addition to certain years, the positive driving factors from 1991 to 2012 included *CSEF*, *IS*, *PY*, and *YOE*. The contribution growth rate of *IS* was less than 1%. The negative driving factors included *PEI*, *EUE*, *TCES*, and *TCYO*, which had contribution growth rates of −56.87, −17.94, −2.19, and −32.24%, respectively.

As seen from Table 1, the economic output efficiency (*YOE*) effect was a major positive driving factor, as it had an accumulated effect of 124.51 Mtce and accounted for 7.16% of the total energy consumption in absolute value. It is an indication that the economic output efficiency has notably improved during the study period. Meanwhile, the potential economic (*PY*) effect played the most dominant role in increasing energy consumption. This result is consistent with the research by Lin and Du [30]. The accumulated *PY* effect was a growth of 3436.4 Mtce, which accounted for 197.61% of the total energy consumption in absolute value. In fact, *PY* is a hypothetical variable, which means that the economic output was adjusted by the output efficiency. The change in economic output efficiency leads to GDP change and therefore changes in energy consumption being assigned to the change in GDP. China's GDP has grown rapidly with an average annual growth rate of 10.61% during 1991–2012, and the GDP reached 171,573 billion yuan (1991 price) at the end of 2012. Clearly seen from Figure 3, the energy and GDP growth rate exhibited a similar trend. This indicates that, from 1991 to 2012, the rapid economic development has been the most important reason behind the increasing energy consumption. As a developing country, inevitably, China's continuous and quick economic growth will still play a critical role in increasing energy consumption. Thus, under the strategy of sustainable development, striking a balance between economic growth and energy consumption has become particularly important.

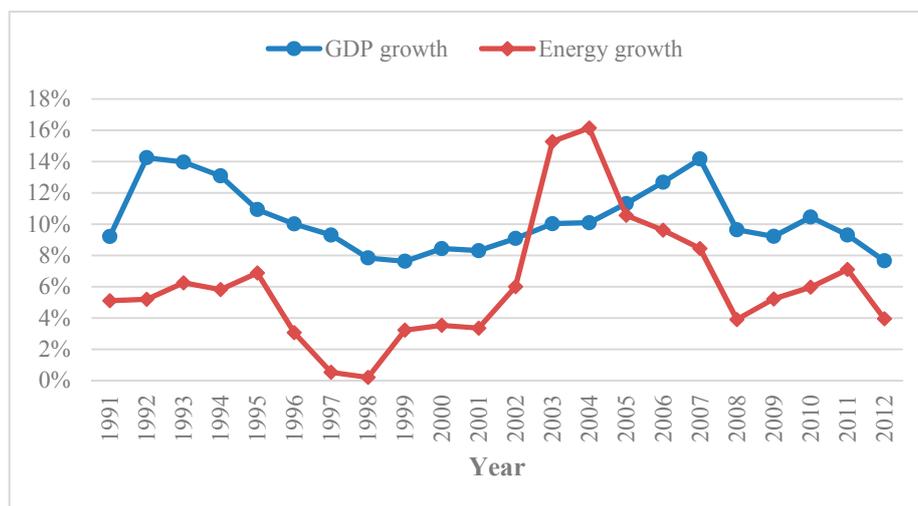


Figure 3. China's energy consumption and GDP growth rate, 1991–2012.

Table 1 also showed that *CSEF* and *IS* both played positive roles in increasing energy consumption, with accumulated effects of 74.32 and 3.29 Mtce, respectively. Compared with the *PY* and *YE* effects, however, the contribution growth rate of *CSEF* and *IS* were relatively minor, representing 4.27% and 0.19%, respectively.

As we know, the average net calorific value decreased in the order gasoline > kerosene > diesel > natural gas > coke > coal. Therefore, if other factors remain unchanged, a decrease in the proportional consumption of coal and increase in the proportion of petroleum and natural gas would reduce energy consumption, vice versa. As is shown in Figure 2, the change of the percentage of fuel types was very little. Furthermore, as seen from Figure 4, the secondary industry accounted for about 70% of the total energy consumption. Over the period 1991–2012, however, the shares of oil and natural gas in the total secondary industry energy demand stayed at around 14% and 4%, respectively. The minor changes in the percentages of secondary industry and fuel types may explain why the effects of *CSEF* and *IS* are small.

Because China's fuel structure was dominated by coal and coke, and the natural sources endowment was difficult to modify in the short-term. To this end, in the long-run, changing the

fuel mix and improving the tertiary industry proportion will still have great potential in achieving the target of energy conservation.

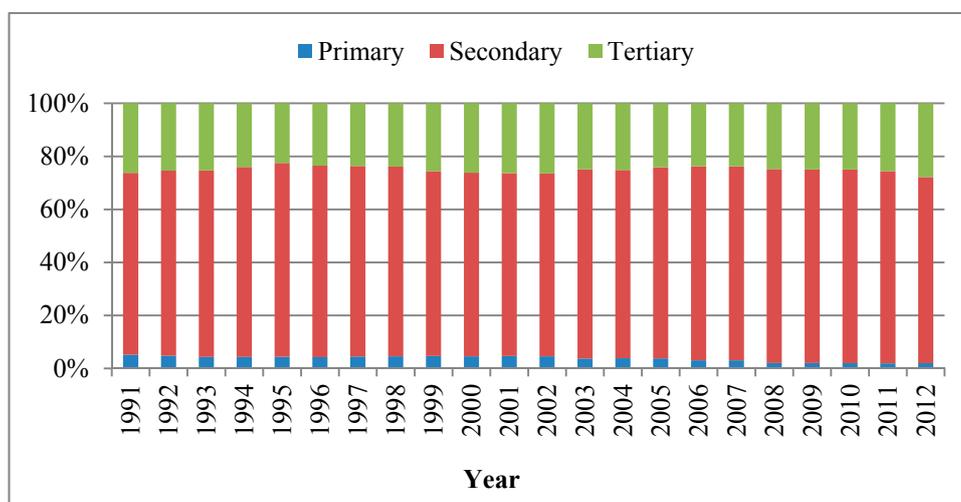


Figure 4. Industrial share of energy consumption in China, 1991–2012.

As a whole, among the components which led to the decrease in energy consumption, potential energy intensity (*PEI*) was the most important factor. This result is consistent with the research by Wang et al. [25]. As we know, energy intensity is a measure of the input-output characteristics of an energy system in units of GDP per energy consumption and reflects the overall efficiency of energy and economic activity. Unlike energy intensity, however, *PEI* is a hypothetical variable, which refers to the energy intensity based on efficient energy usage. In other words, potential energy intensity is a kind of adjusted energy intensity [20]. From Table 1, the accumulated *PEI* factor was a decrease of 989.01 Mtce, which accounted for 56.87% of the total energy consumption in absolute value. This is an indication that the economic growth was derived from less energy intensive industries. Improvements in energy infrastructure, energy demand change, and the implementation of best practices in energy usage technologies may be the main reasons.

In addition to *PEI*, *TCYO*, *EUE*, and *TCES* effects were three other critical factors for reducing energy consumption (Table 1). As factors of production technical effects, the technical change of economic output, energy usage efficiency, and technical change of energy saving effects are all based on a comparison, through the DEA framework, of the DMUs on the best-practice production frontier [24]. As such, these factors depend largely on the production technology. Since the early 1990s, the Chinese government had already begun formulating and implementing about 30 energy conservation laws, which concerned the economic, technological, and legislative aspects of energy conservation. Furthermore, the energy efficiency label system was established in 2003. From 2005 to 2011, following the proposal in the “11th five-year” plan (2005–2010) to decrease the energy intensity by 20%, the high energy intensity of China’s production sectors decreased. Correspondingly, these effects all contributed to positive effects in reducing energy consumption. Especially, *PEI* became the largest driving factor for energy conservation over time. It is noteworthy that *TCES* played the least important role, which was in a way different from what was expected. Nevertheless, it is an indication that energy saving technologies may still need further improvement. For example, technologies could be modified to improve combustion efficiency, energy reuse, and so on. Furthermore, energy saving and economic output technology regulations should also be formulated and implemented for industries as soon as possible. Tough enforcement of these laws should then be emphasized to ensure that technical progress constantly improves to meet the goals of the legislation.

#### 4.2.2. Sectoral Decomposition Analysis

In our second application study, the change of aggregate energy consumption for seven sectors from 2001 to 2012 were decomposed by the proposed approach, where  $i$  denotes the  $i$ th sector. Results are shown in Table 2. The components and the calculation methods of the decomposition analysis were similar to the first application study. Viewed from the decomposition results, only  $PEI$ ,  $YOE$ , and  $TCYO$  contributed to the reduction in energy consumption for the seven sectors as a whole. Meanwhile, the effect of  $CSEF$ ,  $PY$ ,  $EUE$ , and  $TCES$  played positive roles in increasing energy consumption.

**Table 2.** Complete decomposition of energy consumption changes for seven sectors, 2001–2012 (Unit: Mtce).

Sector	$\Delta E_{csef}$	$\Delta E_{is}$	$\Delta E_{pei}$	$\Delta E_{py}$	$\Delta E_{eue}$	$\Delta E_{yoe}$	$\Delta E_{tces}$	$\Delta E_{tcyo}$
1	0.01	−0.40	−25.17	72.40	0.97	−0.01	18.08	−22.35
2	2.97	19.72	−598.06	1720.63	23.04	−0.13	429.61	−531.06
3	0.22	1.37	−17.13	49.27	0.66	−0.01	12.30	−15.21
4	4.81	35.74	−92.08	264.92	3.54	−0.02	66.14	−81.76
5	0.97	−0.63	−18.26	52.52	0.70	−0.01	13.11	−16.21
6	3.85	−11.30	−97.86	281.55	3.77	−0.02	70.30	−86.89
7	1.71	−2.20	−37.06	106.63	1.43	−0.01	26.62	−32.91

Note: The sectors are as follows. 1: farming, forestry, animal husbandry, fishery, and water conservancy; 2: industry; 3: construction; 4: transport, storage, postal and telecommunications services; 5: wholesale, retail trade and catering services; 6: residential consumption; 7: other.

The effects of  $PY$  and  $PEI$  respectively played dominant roles in increasing and decreasing energy consumption over the study period among all the sectors. Specifically, in the residential sector, the urban area contributes most of the economic output. As such, the urban area should be mainly responsible for the increasing residential energy consumption; this result is consistent with Zhang et al. [18]. In the long term, Fan et al. [31] also indicated that the urbanization process will continuously contribute to drive residential energy consumption. Followed by the effect of  $PEI$ ,  $TCYO$  was the second most critical factor in reducing energy consumption (Table 2). These findings were consistent with the results in the first application. Interestingly, the results showed that the effects of  $EUE$  and  $TCES$  both had positive rather than negative effects on the increase of energy consumption in all the sectors. This situation was particularly notable in the industrial sector (sector 2), with the effects of  $EUE$  and  $TCES$  accounting for increases of 23.04 Mtce and 429.61 Mtce, respectively.

Additionally, unlike the other seven components, the effect of  $IS$  helped in inhibiting energy consumption in four sectors, meanwhile, increasing the energy consumption in the sector of industry, construction, and transport, storage, postal and telecommunications services. For a long time, at the mention of large energy consumption, people would naturally think of the secondary enterprises. However, the energy consumption related problems stemming from of transport, storage, postal and telecommunications services have become increasingly serious. In fact, along with the expansion of the traffic network, storage scale, and the boost of postal business, the distribution of China's energy consumption has changed significantly. During the study period, the energy consumption of the fourth sector increased from 92.13 Mtce to 293.43 Mtce, and the share increased from 8.3% to 11.5%. The above analysis may explain why the effect of  $IS$  lead the sector of transport, storage, and post to increase the most among all the seven sectors.

## 5. Conclusions

The decomposition of energy changes in energy consumption has been dealt with in a number of studies. This paper presented a PDA-based IDA approach, expanding the production theory approach. The key goal of this new approach was to develop an additive decomposition framework, allowing for the calculation of each driving factor's impact value. It allowed the decomposition results to more intuitively describe the affecting factors. With the newly built decomposition model, two

application studies on decomposing the China energy consumption for time-series and seven sectors were presented. The main conclusions and recommendations drawn from the present study may be summarized as follows.

First, the rapid economic growth in China has already resulted in severe energy supply crises. Since 1992, China's energy consumption has surpassed its energy consumption. Especially from the perspective of oil imports, the net oil import dependency rapidly increased from 7.5% to 60.6% during the period 1993–2012. Even despite the high level of oil imports and the dangerous external dependency, China's fuel mix was still dominated by coal, and it accounted for over 66% of the energy consumed from 1991 to 2012.

Second, *PEI* and *TCYO* were the two primary driving factors in reducing energy consumption in the two studies. This is an indication that, from a national standpoint, economic growth was derived from less energy intensity industries. The improvement in energy infrastructure, energy demand change, and the implementation of best practice in energy usage technologies may be the main reasons. In recent years, China's economic output technology reform and innovation have greatly limited the increase of energy consumption. Possible future strategies should be formulated and implemented to contribute to improving the technology. These strategies should include developing and promoting innovative technologies throughout the processes of energy exploration, exploitation, transformation, and use.

Third, *PY* was the largest driving factor for energy consumption growth. Its contribution value and rate were much higher than those of the other factors. As a developing country, China's continuous and quick economic growth will still play the dominant role in increasing energy consumption, especially in the secondary industry. Adjusting the industrial structure and balancing adequate energy supply and economic development in China have become increasingly important.

**Acknowledgments:** This work was supported by Funding of Jiangsu Innovation Program for Graduate Education. The authors are grateful for the financial support from the Fundamental Research Funds for the Central Universities (No. KYZZ16-0146), the National Natural Science Foundation of China (Nos. 71203151, 71573186, 71573121), the "333 programme" research project in Jiangsu province (No. BRA2015332), and Jiangsu Qing Lan project.

**Author Contributions:** All authors contributed equally to this work. All authors wrote, reviewed and commended on the manuscript. All authors have read and approved the final manuscript.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Ang, B.W.; Zhang, F.Q. A survey of index decomposition analysis in energy and environmental analysis. *Energy* **2000**, *25*, 1149–1176. [[CrossRef](#)]
2. Rose, A.; Casler, S. Input-output structure structural decomposition analysis: A critical appraisal. *Econ. Syst. Res.* **1996**, *8*, 33–62. [[CrossRef](#)]
3. Wang, C.; Chen, J.; Zou, J. Decomposition of energy-related CO<sub>2</sub> emission in China: 1957–2000. *Energy* **2005**, *32*, 1326–1333. [[CrossRef](#)]
4. Zhang, H.; Qi, Y. A structure decomposition analysis of China's production-source CO<sub>2</sub> emissions: 1992–2002. *Environ. Resour. Econ.* **2011**, *49*, 65–77. [[CrossRef](#)]
5. Ang, B.W.; Liu, N. Handling zero values in the logarithmic mean Divisia index decomposition approach. *Energy Policy* **2007**, *35*, 238–246. [[CrossRef](#)]
6. Xu, X.; Ang, B.W. Index decomposition analysis applied to CO<sub>2</sub> emission studies. *Ecol. Econ.* **2013**, *93*, 313–329. [[CrossRef](#)]
7. Su, B.; Ang, B.W. Structural decomposition analysis applied to energy and emissions: Some methodological developments. *Energy Econ.* **2012**, *34*, 177–188. [[CrossRef](#)]
8. Su, B.; Ang, B.W. Attribution of changes in the generalized Fisher index with application to embodied emission studies. *Energy* **2014**, *69*, 778–786. [[CrossRef](#)]
9. Wang, H.; Ang, B.W.; Su, B. Multiplicative structural decomposition analysis of energy and emission intensities: Some methodological issues. *Energy* **2017**, *123*, 47–63. [[CrossRef](#)]
10. Ang, B.W. Decomposition analysis for policy making in energy: Which is the preferred method? *Energy Policy* **2004**, *32*, 1131–1139. [[CrossRef](#)]

11. Hirst, E.; Marlay, R.; Greene, D. Recent changes in US energy consumption: What happened and why. *Annu. Rev. Energy* **1983**, *8*, 193–245. [[CrossRef](#)]
12. Sun, J.W. Changes in energy consumption and energy intensity: A complete decomposition model. *Energy Econ.* **1998**, *20*, 85–100. [[CrossRef](#)]
13. Andreoni, V.; Galmarini, S. European CO<sub>2</sub> emission trends: A decomposition analysis for water and aviation transport sectors. *Energy* **2012**, *45*, 595–602. [[CrossRef](#)]
14. Zhang, M.; Mu, H.L.; Ning, Y.D. Accounting for energy-related CO<sub>2</sub> emission in China, 1991–2006. *Energy Policy* **2009**, *37*, 767–773. [[CrossRef](#)]
15. Kim, S.Y. LMDI decomposition analysis of energy consumption in the Korean manufacturing sector. *Sustainability* **2017**, *2*, 202. [[CrossRef](#)]
16. Zha, D.L.; Zhou, D.Q.; Zhou, P. Driving forces of residential CO<sub>2</sub> emissions in urban and rural China: An index decomposition analysis. *Energy Policy* **2010**, *38*, 3377–3383.
17. Wang, W.W.; Liu, X.; Zhang, M.; Song, X.F. Using a new generalized LMDI (logarithmic mean Divisia index) method to analyze China's energy consumption. *Energy* **2014**, *67*, 617–622. [[CrossRef](#)]
18. Zhang, M.; Song, Y.; Li, P.; Li, H.N. Study on affecting factors of residential energy consumption in urban and rural Jiangsu. *Renew. Sustain. Energy Rev.* **2016**, *53*, 330–337. [[CrossRef](#)]
19. Pasurka, J.A. Decomposing electric power plant emissions within a joint production framework. *Energy Econ.* **2006**, *28*, 26–43. [[CrossRef](#)]
20. Wang, C. Decomposing energy productivity change: A distance function approach. *Energy* **2007**, *32*, 1326–1333. [[CrossRef](#)]
21. Zhou, P.; Ang, B.W. Decomposition of aggregate CO<sub>2</sub> emissions: A production-theoretical approach. *Energy Econ.* **2008**, *30*, 1054–1067. [[CrossRef](#)]
22. Li, M. Decomposing the change of CO<sub>2</sub> emissions in China: A distance function approach. *Ecol. Econ.* **2010**, *70*, 77–85. [[CrossRef](#)]
23. Zhang, X.P.; Tan, Y.K.; Tan, L.Q.; Yuan, J.H. Decomposition of aggregate CO<sub>2</sub> emissions within a joint production framework. *Energy Econ.* **2012**, *34*, 1088–1097. [[CrossRef](#)]
24. Kim, K.; Kim, Y. International comparison of industrial CO<sub>2</sub> emission trends and energy efficiency paradox utilizing production-based decomposition. *Energy Econ.* **2012**, *34*, 1724–1741. [[CrossRef](#)]
25. Wang, Q.W.; Chiu, Y.H.; Chiu, C.R. Driving factors behind carbon dioxide emissions in china: A modified production-theoretical decomposition analysis. *Energy Econ.* **2015**, *51*, 252–260. [[CrossRef](#)]
26. Färe, R.; Primont, D. *Multi-Output Production and Duality: Theory and Applications*; Kluwer Academic Publishers: Boston, MA, USA, 1995.
27. Färe, R.; Grosskopf, S.; Norris, M. Productivity growth, technical progress and efficiency change in industrialized countries. *Am. Econ. Rev.* **1994**, *84*, 66–83.
28. National Bureau of Statistics of China. *China Energy Statistical Yearbook*; National Bureau of Statistics of China: Beijing, China, 2013.
29. National Bureau of Statistics of China. *China Statistical Yearbook*; National Bureau of Statistics of China: Beijing, China, 2013.
30. Lin, B.Q.; Du, K.R. Decomposing energy intensity change: A combination of index decomposition analysis and production-theoretical decomposition analysis. *Appl. Energy* **2014**, *129*, 158–165. [[CrossRef](#)]
31. Fan, J.L.; Zhang, Y.J.; Wang, B. The impact of urbanization on residential energy consumption in China: An aggregated and disaggregated analysis. *Renew. Sustain. Energy Rev.* **2017**, *75*, 220–233. [[CrossRef](#)]

