Exploring the direct rebound effect of residential electricity consumption: An empirical study in China

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HIGHLIGHTS

- The direct rebound effect (RE) of China’s residential electricity consumption is 72%.
- The direct RE is about 68% (55%) in the low (high) income regime.
- The direct RE is about 75% (90%) in the low (high) cooling degree days regime.
- The direct RE is about 68% (86%) in the light (heavy) rainfall regime.
- The rise (fall) of GDP per capita (cooling degree days, rainfall) may reduce the RE.

ABSTRACT

Due to the energy rebound effect, the electricity conservation brought about by improving the electricity efficiency of China’s households may be not as much as expected. Therefore, this paper employs the panel threshold model to investigate the direct rebound effect of China’s residential electricity consumption under different kinds of regimes and its main influencing factors during 2000–2013. The results show that, first, the direct rebound effect (RE) of China’s residential electricity consumption is about 72% on average. Second, the direct RE is about 68% (55%) in the low (high) income regime, and the increase in GDP per capita may help to reduce the direct RE. Third, the direct RE is around 75% (90%) in the low (high) cooling degree days regime, and the decrease in cooling degree days may reduce the direct RE. Fourth, the direct RE is around 68% (86%) in the light (heavy) rainfall regime, and the decrease of rainfall may help to reduce the direct RE. Finally, GDP per capita and population have significant positive impact on residential electricity consumption; while the impact of cooling degree days and rainfall appears relatively weaker.

1. Introduction

Nowadays, China has become the largest energy consumer and carbon emitter [1]. In 2015, China’s primary energy consumption reached 3.01 billion tons of oil equivalent, accounting for 22.9% of the global total; meanwhile China contributed to 27.3% of the world’s total carbon emissions [2]. As a responsible nation, China has paid more and more attention to global energy problems and climate change, and set a series of national targets for energy conservation and carbon emissions reduction [3,4]. For example, the Chinese Government targeted reduction of energy consumption per unit GDP to be 20%, 16%, and 15% through the 11th (2006–2010), 12th (2011–2015), and 13th (2016–2020) Five-Year Plan periods, respectively [5]. In reality, the energy intensity was reduced by 19% during the 11th (2006–2010) Five-Year Plan period, and the target of energy intensity reduction during the 12th (2011–2015) Five-Year Plan period was achieved. Additionally, China proposed that its carbon emissions would reach a peak in around 2030, and targeted the reduction of carbon dioxide emissions per unit of GDP in 2030 to be 60–65% compared with that in 2005. Over the past ten years, energy saving and consumption reduction is the main way to constrain energy consumption, and
the most effective way to conserve energy is, as always, to improve energy efficiency [6].

The Chinese Government has taken a series of measures to conserve energy and reduce carbon emissions in dominant sectors, such as industry and transport [5], and the residential sector is also one worth targeting. According to the statistics, energy consumption in China’s residential sector ranks behind only industrial energy consumption, accounting for 11% of the total energy consumed in China. Fig. 1 shows China’s residential energy consumption and its structure in 2002–2014. As seen, residential energy consumption almost increases annually. Besides, coal and electricity are the main energy sources supporting Chinese households, and the share of electricity use shows an increasing trend, ranging from 14.4% in 2002 to 18.68% in 2014. From this trend, we can conclude that residential electricity consumption plays a more important role in residential energy consumption. Meanwhile, electricity supply in China depends mainly on coal, whereas China is in the stage of optimising the structure of energy consumption in an effort to reduce the share of coal consumption. The residential sector is the key sector of electricity consumption, thus electricity efficiency improvements in households will contribute to optimising China’s energy consumption structure and reaching the energy constraint targets to some degree. The Chinese Government has instigated electricity efficiency improvement plans. For example, the Energy Development Strategy Action Plan (2014–2020) mentions that the upgrade project of coal-fired units for energy conservation and carbon emission reduction should be performed, and coal consumption for generating electricity should be reduced to 300 grammes of equivalent coal per kilowatt hour within five years. Additionally, during the 12th Five-Year Plan period (2011–2015), the demand side management has been strengthened, and price mechanisms have been commonly used to guide electricity efficiency improvements, for the sake of energy conservation and carbon emissions reduction. Theoretically, improving electricity utilisation efficiency has important positive influence on reducing electricity consumption, the share of coal consumption, and greenhouse gas emissions, but why did the residential electricity consumption increase rather than decrease with the improvement of electricity utilisation efficiency in the past decade?

Except for the impact of economic growth, there are two aspects at play here. On the one hand, there may be an energy rebound effect. The effectiveness of improving electricity efficiency for energy conservation is not as great as expected, whereas there will be some rebound energy consumption [7]. Residential electricity consumption arises mainly from household appliances, such as air conditioners for controlling the temperature, refrigerators, rice cookers, washing machines, and home lighting for daily life, and computers and TVs for work or entertainment. When electricity utilisation efficiency improves, the power consumed doing the same work (lighting, heating, cooling, etc.) decreases. Therefore, the cost for equal energy services may decrease, which in turn leads to a change in behaviour, and residents increase the demand for buying or using the household appliances, thus electricity consumption increases. On the other hand, electricity utilisation improves with technologic progress, which promotes economic growth to some degree. This will raise the buying power of residents, and they may increase their demand for using or buying household appliances, which results in increased electricity consumption. Obviously, residential electricity consumption may vary in different external environments. For example, the electricity consumption in regions with lower buying power is often less than that in those with higher buying power. There are also differences in residential electricity consumption in cold north-eastern China, Yunnan with a permanent spring-like climate, and central China with four distinct seasons. Meanwhile, the rebound effect of residential electricity consumption may also be different in various external environments. Therefore, it is imperative to estimate the rebound effect of residential electricity consumption to avoid over-estimating the effectiveness of energy efficiency policy. Also, it is of practical significance to estimate the heterogeneous rebound effect of residential electricity consumption for improving the effectiveness of energy efficiency policy in different external environments.

The contribution in this paper can be mainly summarised by three features: first, this paper investigates how the key factors (including residential electricity price, GDP per capita, population, cooling degree days and rainfall) have influenced China’s residential electricity consumption, and the linear and non-linear relationships between the influencing factors and residential electricity consumption, and searches for the ways to restrain residential electricity consumption. Second, given the impact of the rebound effect on the effectiveness of residential electricity conservation and emissions reduction measures, this paper not only estimates the direct rebound effect of China’s residential electricity consumption during 2000–2013 according to the price elasticity in linear relationship through the panel model, but also considers the direct rebound effect in non-linear relationship through the panel threshold model, and evaluates the energy conservation results of improving electricity utilisation efficiency in households. Finally, using GDP per capita, population, cooling degree days, and rainfall as threshold variables, this paper develops four panel threshold models and finds three kinds of regimes to estimate the different direct rebound effects of residential electricity consumption in different regimes, so as to find out the ways of reducing rebound effect and obtain targeted policy implications.

The remainder of this paper is organised as follows: Section 2 reviews related literature, Section 3 proposes models to investigate the main factors influencing residential electricity consumption and measure the direct rebound effect of residential electricity consumption as well as data definitions. Section 4 presents the results and detailed discussions, and Section 5 concludes the paper and proposes some policy implications.

2. Literature review

This paper reviews the literature mainly from the perspective of the factors influencing residential electricity consumption, the origin and mechanism of the energy rebound effect and the energy rebound effect of households as follows.

First of all, in terms of the factors influencing residential electricity consumption, existing research concentrates mainly on two aspects, i.e., economic factors and climatic factors [8]. There is a great amount of literature exploring electricity consumption characteristics in various countries. For example, Holtedahl and Joutz [9] use the level of urbanisation as a reasonable proxy for electricity-consuming equipment and examine the residential demand for electricity in Taiwan as a function of household disposable income, population growth, electricity price, cooling degree days, and urbanisation. The short- and long-term effects are separated through the use of an error correction model, and the empirical results indicate that the short-run income and price effects are small, and less than the long-run effects, besides, cooling degree day effects have a positive impact on short-run consumption. Craig and Feng [10] examine the relationship between residential electricity consumption, short-term climatic variability, long-term climatic trends, short-term reduction in electricity from energy efficiency programs, and long-term trends in energy efficiency programs in the United States. The results show that increasing cooling degree days significantly related to increased electricity use. Du


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et al. [11] investigate the feedbacks of household electricity consumption to the new pricing policy implemented in China in 2012 based on the micro household-level data from China’s Residential Energy Consumption Survey, and find that factors such as energy price, household income, and demographic attributes have significant impact on residential electricity consumption. Ang et al. [12] find that the residential electricity consumption is sensitive to small changes in climatic variables, particularly temperature, which is closely linked to the growing diffusion of electrical appliances for environmental control, and the future growth in electricity demand will arise from the growing need for air-conditioning. Ahmed et al. [13] show that the electricity demands in summer and spring in New South Wales of Australia would increase due to climate change, and an increase in temperature alone may lead to 1.36%, 2.72%, and 6.14% rise in per capita demand during the summer season and 2.09%, 4.5%, and 11.3% rise in per capita demand during the spring season in the 2030s, 2050s, and 2100s, respectively. Ziramba [14] examines the residential demand for electricity in South Africa as a function of real gross domestic product per capita, and the price of electricity during the period 1978–2005 by using a linear double-logarithmic relationship. The empirical results imply that income is the main determinant of electricity demand, while electricity price is insignificant in the long-term. Narayan and Smyth [15] estimate the long- and short-term elasticities of residential demand for electricity in Australia using a bounds testing approach to co-integration within an autoregressive distributive lag framework, and find that income and own price are the most important determinants of residential electricity demand, while temperature is significant some of the time and gas prices are insignificant.

Moreover, some researchers investigate other factors affecting residential electricity consumption, except for economic and climatic factors. For example, Sa’ad [16] estimates the electricity demand function for the residential sector in South Korea with the aim of examining the effects of improved energy efficiency, structural factors, and household lifestyles on electricity consumption, and finds that the long-term income elasticity is 1.33 and the long-term price elasticity is −0.27. The result suggests that, to encourage energy efficiency in the residential sector, the government should complement market-based pricing policies with non-market policies such as minimum energy efficiency standards and public enlightenment. Besides, Agarwal et al. [17] use a unique dataset of electricity consumption levels by public housing residents in Singapore from 2009 to 2011 and a difference-in-difference approach to test the effects of negative environmental externalities (i.e. noise pollution) due to construction activities within a half of one kilometre radius and how households react to such externalities by increasing the use of air-conditioners to mitigate noise from the construction work. They find that electricity consumption in those households living close to construction sites increases by 6% compared to that of households unaffected by noise from construction sites. It is thus clear that residential electricity consumption in various countries is often affected by purchasing ability, electricity prices, or substitute energy prices, and climate. China has been an emerging economy, so the changes in the economy will lead to changes in residential electricity consumption (more or less). Moreover, China has vast expanses of land with complicated topographies and different types of climate, therefore the characteristics of residential electricity consumption in different regions are different.

Second, energy rebound effect originates from the Jevons paradox [18] first posed in The Coal Question in 1865. He argued that technological progress improves the efficiency of energy utilisation, but energy consumption would increase therewith. Specifically, when technological progress causes an increase in efficiency by 1%, a reduction in energy consumption in obtaining the same products is often less than 1%. On the one hand, energy efficiency improves because of widely advanced technology, but at the same time, advanced technology generates rapid economic growth and then energy consumption demand increases substantially [19]. On the other hand, an increase of energy efficiency usually leads to a decline in the real cost of useful energy, which may lead to consumers’ behavioural responses changing and eventually causes an increase in energy consumption [20]. As for the mechanism underpinning the energy rebound effect, it can be classified as the direct effect, indirect effect, and economy-wide effect [21,22]. The direct energy rebound effect refers to the efficiency improvement of one certain energy service leading to the increased demand for the energy because of the decreased cost of the energy service [23]. The indirect energy rebound effect is related to the decreased cost of one certain energy service leading to the increased demand for other energy services [24]. For example,
the money saved by efficiency improvements in air conditioning is spent on taking holidays thus more energy is consumed by tourism. The economy-wide energy rebound effect consists of the direct and indirect energy rebound effects [25]. Different sizes of energy rebound effect have different implications: specifically, energy rebound effects between zero and one are partial energy rebound effects [26], which implies that real energy consumption is more than expected and less than the original, and a part of the energy conservation caused by energy efficiency improvement is offset by the extra energy consumption. A negative rebound effect called super conservation effect denotes that real energy savings are more than the expected from energy efficiency improvement [5]. Rebound effect whose size is more than one, i.e., backfire effect, means that energy efficiency improvement does not lead to any energy conservation, but increases energy consumption [27]. The energy rebound effect has been extensively explored with its existence being confirmed [28], but its magnitude remains the core of the controversy.

Third, because household energy consumption accounts for a large share of energy consumption, in the literature, the energy rebound effect in households, such as household heating, household cooling, and electricity use, is manifest. Concerning the rebound effect for household heating, Nesbakken [29] estimates that the short-term direct rebound effect varies from 15% to 55% for Norway’s household heating by using a multi-equation model and cross-sectional data from 1990. Guertin et al. [30] estimate that the long-term direct rebound effect ranges from 29% to 47% for Canada’s household heating sector by using a single equation model and cross-sectional data from 1993. As for rebound effect for household cooling, Dubin et al. [31] measure the rebound effect as ranging from 1% to 26% for US household cooling by using a discrete-continuous function and cross-sectional data from 1981. Hausman [32] combines the individual behavioural model with a discrete choice model using 46 cross-sectional datasets from 1978, and estimates that the short- and long-term rebound effects for US household cooling are 4% and 26.5%, respectively. In terms of the rebound effect of residential electricity consumption, Hsu & Gerner [33] estimate that the rebound effect for US residential electricity consumption is 35% using 253 cross-sectional data and a double logarithmic equation. Lin & Liu [34] adopt a linear approximation of the almost ideal demand system model to estimate the rebound effect of urban residential electricity consumption from 1996 to 2010, and the results show that the rebound effect is approximately 165.22%. Chitnis and Sorrell [35] estimate the combined direct and indirect rebound effects from various types of energy efficiency improvement by UK households, and the results show that the total rebound effects are 41% for measures that improve the efficiency of domestic gas use, 48% for electricity use and 78% for vehicle fuel use. Jin [36] estimates that the long- and short-term rebound effects of residential electricity use in South Korea in 2002 are 30% and 38%, respectively, by using price elasticity in the non-linear relationship between energy efficiency and energy consumption.

Besides, Wang et al. [37] estimate that the long-term rebound effect of Chinese urban residential electricity consumption is 74%, while the short-term rebound effect is 72%, using a co-integration equation, a panel error correction model and the panel data from 30 provinces from 1996 to 2010. Additionally, Wang et al. [38] estimate that the long-term direct and indirect rebound effects of residential electricity use in Beijing are 46–56%, and the short-term direct rebound effect is between 24% and 37% by a seven-sector environmental energy-input–output analysis. However, these studies often estimate the rebound effect, and lack discussing of the rebound effect changes in residential electricity consumption with different externalities.

To sum up, previous research about the factors influencing residential electricity demand or consumption mainly employs econometric approaches, and investigates the linear relationship between residential electricity consumption and its influencing factors, as well as the rebound effect in the linear relationship. Considering these, this work mainly compensates for the deficiency of the linear framework. First, excepting investigating the linear relationship between China’s residential electricity consumption and its main influencing factors as in previous studies, this work also explores the non-linear relationship among them using the panel threshold model. Second, excepting the estimation of the direct rebound effect of residential electricity consumption in the linear relationship between China’s residential electricity consumption and its main influencing factors by econometric approaches as in previous studies, this work also chooses a few threshold variables, and measures the direct rebound effect of residential electricity consumption and its changes under different regimes of the threshold variables.

3. Methods and data definitions

3.1. Methods

3.1.1. Definition of direct rebound effect

Provided that $S$ represents an energy service such as lighting, space-heating, or space-cooling, $E$ denotes the energy demand or energy input that is required to provide $S$ such as electricity consumption. Consequently, energy efficiency is defined as the ratio of useful energy output to energy input $e = \frac{S}{E}$ such as the amount of useful work (e.g., heating and lighting) from per unit electricity consumption. $P_e$ denotes the price of energy input, such as the cost per unit electricity, and $P_S$ denotes the price of energy services, such as the cost per unit lighting or heating, and the cost of an energy service can be expressed as $P_S = P_SE$ [5].

The main causes of the energy rebound effect are that: (1) an improvement in energy efficiency usually leads to a decline in the real cost of energy services, which may evoke consumer behavioural responses and eventually cause an increase in energy consumption and (2) energy efficiency improves with technological progress, while technoligica progress often leads to economic growth and income increase of people. Thus, more energy is consumed. As a result, actual energy consumption may be greater than expected, and some expected energy savings are offset. The offset energy consumption is the rebound part and the ratio of the rebound part to expected energy savings is the direct rebound effect.

A common approach to estimating direct rebound effect is through econometric analysis of secondary data sources that include information on the demand for energy, the relevant energy service or energy efficiency of the service [7]. The direct rebound effect can be estimated from one of two energy-efficiency elasticities: $\eta_d(E)$, i.e., the elasticity of energy demand (E) with respect to energy efficiency ($e$); $\eta_d(S)$, i.e., the elasticity of energy service ($S$) with respect to energy efficiency ($e$). Generally, $\eta_d(S)$ is taken as a direct measure of rebound effect [23]. Because $S = e \times E$, Eq. (1) can be easily obtained:

$$\eta_d(E) = \eta_d(S) - 1$$

(1)

When the energy service demand keeps unchanged following an energy efficiency improvement (i.e., $\eta_d(S) = 0$), the actual energy savings will only equal the expected savings from engineering calculations. That is, an $x\%$ improvement in energy efficiency will lead to $x\%$ reduction in energy consumption ($\eta_d(E) = -1$). $1 > \eta_d(S) > 0$ implies a partial rebound effect, and $0 > \eta_d(E) > -1$. In the circumstance, part of expected energy savings is taken back due to the
increased demand for energy service. $\eta_r(S) > 1$ and $\eta_c(E) > 0$ imply backfire effect. In this circumstance, energy efficiency improvement will lead to more energy consumption resulted from the increased demand for energy service. If one of the elasticities can be estimated, the direct rebound effect is obtained.

In many cases, data on energy efficiency is either unavailable or inaccurate. In this circumstance, the rebound effect can be measured from one of three price elasticities: $\eta_r(S)$, i.e., the elasticity of demand for energy service (S) with respect to energy cost of energy service ($P_e$); $\eta_c(S)$, i.e., the elasticity of demand for energy service (S) with respect to energy price ($P_e$); $\eta_c(E)$, i.e., the elasticity of demand for energy (E) with respect to energy price ($P_e$). The negative of either $\eta_r(S)$, $\eta_c(S)$ or $\eta_c(E)$ can be taken as an approximation to $\eta_r(S)$, and hence they can be used to measure the direct rebound effect under certain assumptions [7].

Assume that: (1) energy price is exogenous, i.e., $P_e$ does not depend on $e$, and any changes in energy efficiency derive from outside the model and (2) consumers respond in the same way to a decrease in energy price as they do to an improvement in energy efficiency and vice versa. That is, raising energy efficiency ($e$) when energy price ($P_e$) is constant should have the same effect on the energy cost of useful work ($P_e$) as falling energy price when energy efficiency is constant [23,39]. Then we choose $-\eta_r(E)$, i.e., the negative elasticity of energy demand with respect to energy price to estimate the direct rebound effect based on the data availability. Thus Eq. (2) is used to estimate the size of direct rebound effect for China's residential electricity consumption:

$$RE = -\eta_r(E) = -\frac{\partial \ln(E)}{\partial \ln(P_e)}$$

### 3.1.2. Estimation of the model for direct energy rebound

Residential electricity consumption ($E$) is affected by factors involving: socio-economic status, household characteristics, natural environment, and so on. We choose the main factors influencing residential electricity consumption: electricity price, income, population, temperature and rainfall [13,40,41]. In general, increasing the price of electricity will lead to a decrease in electricity consumption. Income is closely linked to residential electricity consumption. In developing countries, the increase of GDP per capita often makes people increase their demand for electricity services, for example, using washing machines and air-conditioners. In this way, residential electricity consumption increases. Residential electricity consumption is also affected by population. Generally, with other conditions unchanged, more people use more electricity. Additionally, temperature and rainfall have some influence on residential electricity consumption [8], and some research has proved the non-linear relationship between temperature and residential electricity consumption [42]. Different geographical features and natural conditions in different regions allow the different temperature characteristics, and the residential electricity consumption in regions with large annual temperature ranges is likely to be more than that in regions with spring-like weather all year round. The degree-day method is one of the well-known, and simple methods used in the heating, ventilating, and air-conditioning industry to estimate heating and cooling energy requirements [43]. The daily degree day is the difference between the mean daily temperature and a base temperature. The degree days include heating degree days and cooling degree days. Because northern China often uses centralised heating while southern China does not, and the centralised heating systems mainly use coal or oil as fuel, but do not use electricity directly, which is different from the cooling ways in China (mainly air conditioner), or heating ways in southern China (mainly air conditioner). Heating degree days may not explain residential electricity consumption for space heating in northern China. Hence, we use cooling degree days to reflect the influence of temperature on residential electricity consumption. Rainfall is also a key climatic factor. Rainy weather is often accompanied by a drop in temperature. It is colder when raining in winter, which makes people increase room temperatures and electricity consumption is eventually increased. It is cooler when raining in summer, which makes people decrease their use of air conditioner. Therefore, we also use rainfall as a climatic factor to reflect the influence of climate on residential electricity consumption.

After choosing the main factors influencing residential electricity consumption, we first build the linear panel model to investigate the direct rebound effect of China's residential electricity consumption in a linear relationship. Considering that estimated coefficients of double logarithmic equation can be treated as the elasticities of dependent variables with respect to the independent variables [44], we adopt the double logarithmic function to measure the direct rebound effect of China’s residential electricity consumption, as shown in Eq. (3):

$$\ln(E_{it}) = \beta_0 + \beta_1 \ln(P_{ei}) + \beta_2 \ln(P_GDP_{iti}) + \beta_3 \ln(P_{Pop_{iti}}) + \beta_4 \ln(\text{CDD}_{it}) + \beta_5 \ln(\text{RAIN}_{iti}) + \mu_{it}$$

where $E_{it}$ represents residential electricity consumption in province $i$ in year $t$ (unit: 100 million kilowatt hour), $P_{ei}$ stands for residential electricity price in province $i$ in year $t$ (unit: Yuan/kilowatt hour), $P_GDP_{iti}$ denotes GDP per capita in province $i$ in year $t$ (unit: Yuan), $P_{Pop_{iti}}$ represents population at the end of the year $t$ in province $i$ (unit: 10,000 persons), $\text{CDD}_{it}$ means cooling degree day in province $i$ in year $t$ (unit: centigrade), and $\text{RAIN}_{iti}$ represents rainfall (unit: millimetres) in province $i$ in year $t$. $\beta_0$ is a constant term, and $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, and $\beta_5$ are coefficients to be estimated, and they denote the elasticities, meaning the percentage change in residential electricity consumption following a percentage change in one independent variable. One Positive (negative) coefficient (e.g., $\beta_2$) means the increase by 100% in this independent (e.g., population) will lead to the increase (decrease) by $\beta_2\times 100\%$ in residential electricity consumption. $\mu_{it}$ is the random error. In this way, $-\beta_1$ denotes the size of the direct rebound effect of China’s residential electricity consumption according to Eq. (2).

To examine the non-linear relationship between residential electricity consumption and its main influencing factors, we develop the panel threshold models, and set different threshold variables to estimate the direct rebound effect of China’s residential electricity consumption under different regimes. The single threshold model and double threshold model can be expressed by Eqs. (4) and (5), respectively [35].

$$\ln(E_{it}) = \alpha_0 + \alpha_1 \ln(P_{ei}) * I(q_{it} \leq \gamma) + \alpha_2 \ln(P_{ei}) * I(q_{it} > \gamma) + \alpha_3 \ln(P_GDP_{iti}) + \alpha_4 \ln(P_{Pop_{iti}}) + \alpha_5 \ln(\text{CDD}_{it}) + \alpha_6 \ln(\text{RAIN}_{iti}) + u_{it}$$  \hspace{1cm} (4)

$$\ln(E_{it}) = \delta_0 + \delta_1 \ln(P_{ei}) * I(q_{it} \leq \gamma_1) + \delta_2 \ln(P_{ei}) * I(\gamma_1 < q_{it} < \gamma_2) + \delta_3 \ln(P_{ei}) * I(\gamma_2 \leq q_{it}) + \delta_4 \ln(P_GDP_{iti}) + \delta_5 \ln(P_{Pop_{iti}}) + \delta_6 \ln(\text{CDD}_{it}) + \delta_7 \ln(\text{RAIN}_{iti}) + u_{it}$$  \hspace{1cm} (5)

In Eqs. (4) and (5), $q_{it}$ represents a threshold variable, and we here take $\ln(P_GDP_{iti})$, $\ln(P_{Pop_{iti}})$, $\ln(\text{CDD}_{iti})$, and $\ln(\text{RAIN}_{iti})$ as the threshold variable, respectively; $I(\bullet)$ is the indicator function. In Eq. (4), $\gamma$ is the threshold of the single threshold model. $\alpha_1$ is the price elasticity of residential electricity consumption when $q_{it}$ is

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6 The empirical results do not involve multiple thresholds, we, therefore, just take single and double threshold models as examples.
not more than the threshold \( q_a \leq \gamma \), and \( z_2 \) is the price elasticity of residential electricity consumption when \( q_a > \gamma \). \( x_2 \sim x_6 \) have the same meaning to corresponding coefficients in Eq. (3). In Eq. (5), \( \gamma_1 \) and \( \gamma_2 \) are the thresholds in the double threshold model, and \( \delta_1 \) is the price elasticity of residential electricity consumption when \( q_a \) is more than the threshold \( q_a > \gamma_1 \), and \( \delta_2 \) is the price elasticity when \( q_a \) is between the two thresholds \( (\gamma_1 < q_a < \gamma_2) \), and \( \delta_1 \) is the price elasticity when \( q_a \) is not less than the larger threshold \( (q_a \geq \gamma_2) \), while \( \delta_1 \sim \delta_7 \) have the same meaning to corresponding coefficients in Eq. (3).

Meanwhile, the annual cooling degree days can be calculated by monthly temperature represented by all capital cities among provinces as Eq. (6) [45]:

\[
CDD = \sum_{j=1}^{12} CDD_j
\]

\[
CDD_j = \begin{cases} 
\ll(T_j - T_b)M_j, & \text{if } T_j > T_b \\
0, & \text{else}
\end{cases}
\]

where \( j = 1, \ldots, 12 \) denotes the month number; \( T_j \) is the mean temperature of month \( j \); \( T_b \) is the base temperature; and \( M_j \) is the number of days in month \( j \). The base temperature calculating cooling degree days is generally chosen in the range 18–28 °C [43,46], which is based on the adaptive comfort/neutral temperature predicted in earlier study [47], and here we choose 18.3 °C as the base temperature referring to [45].

Before the estimation of panel threshold models, it is necessary to test whether, or not, the threshold effect is statistically significant. Testing for the null hypothesis of no threshold effect (\( H_0^1 : z_1 = z_2 \)) is done through the use of Eq. (7):

\[
F_1 = (S_0 - S_1(\hat{\gamma}))/\hat{\sigma}^2
\]

where \( S_0 \) is the sum of the squared residual of the linear model, \( S_1 \) is the sum of the squared residual of the single threshold model, \( \hat{\gamma} \) is the OLS estimate of \( \gamma \), and \( \hat{\sigma}^2 \) is the variance estimate of the error term of the single threshold model. If the null hypothesis of no threshold is rejected, it is necessary to test whether, or not, there is a single threshold effect. Testing for the null hypothesis of the single threshold effect (\( H_0^2 : \delta_1 = \delta_2 \) or \( \delta_2 = \delta_3 \)) is through the LR statistic in Eq. (8):

\[
LR_1 = S_1(\gamma) - S_1(\hat{\gamma})/\hat{\sigma}^2
\]

Using the bootstrap approach suggested by Hansen [48], we can find the asymptotic distribution, so \( p \)-values constructed from the bootstrap are asymptotically valid. If the null hypothesis of the single threshold effect is rejected, the LR statistic for testing double threshold effects should be adapted, and detailed steps can be found [48].

### 3.2. Data definitions

Based on data availability, we collect the panel data from 29 provinces of China except Tibet, Ningxia, Taiwan, Hong Kong, and Macao for 2000–2013, including residential electricity consumption, residential electricity price, GDP per capita, population at the end of the year, cooling degree days, and rainfall. It should be mentioned that China has implemented three-tier-tariffs for household electricity in 2012, and in every province, >80% of residential electricity demand is covered in the first-tier-price.\(^7\) Hence, we use the first-tier-price as the residential electricity price in 2013. In addition, we use the cooling degree days and rainfall in the 29 capital cities to represent the values for their respective provinces. Besides, the data of residential electricity consumption come from the China Energy Statistical Yearbook 2001–2013 [49] and the Provincial Statistical Yearbook 2014; the residential electricity price data are provided by the Provincial Development and Reform Commission; data for GDP per capita, population at the end of the year, mean monthly temperature, and rainfall are from the China Statistical Yearbook 2001–2014 [50]. GDP per capita and residential electricity price data are all at the 2005 constant RMB price. Descriptive statistics of all variables are shown in Table 1.

### 4. Empirical results and discussion

#### 4.1. Linear regression results

To avoid the biases resulting from spurious regression problems, it is essential to conduct a stationarity test on each variable before constructing the panel data model. The panel unit root test is widely used to examine the stationarity of each variable [51], and the results are shown in Table 2. As is shown, all variables in levels have unit roots for the reason that all results of LLC, ADF, and PP tests cannot reject the null hypothesis at the 10% significance level. Furthermore, we test the stationarity of the first order difference of each variable, and the results of LLC, ADF, and PP tests indicate that the first order differences of all variables are stationary with no unit root at the 1% significance level. Therefore, we can say that all the variables are integrated at order one.

We develop the linear panel regression to estimate the coefficients according to Eq. (3). First, it is necessary to discern the specific regression forms of the models. Specifically, we make a choice between a mixed model and an individual fixed effect model via the F-test. The result of the F-test is 43.3532, which suggests the null hypothesis of using mixed model is rejected at the 1% significance level. So we adopt the individual fixed effect variable intercept model to estimate the coefficients of Eq. (3), and the regression results are shown in Table 3. It can be found that the model fits well, and all coefficients are significant at the 5% significance level. From Table 3, it was found that: in the linear relationship, there is a direct rebound effect in China’s residential electricity consumption, and the average size of the direct rebound effect for China’s residential electricity consumption is 71.53% during 2000–2013. It indicates that, in the linear relationship between residential electricity consumption and its influencing factors, when electricity utilisation efficiency improves, there are 71.53% of the expected electricity savings being offset by the extra electricity consumption due to efficiency improvements and the cheaper electricity service cost, and only 28.47% of the expected electricity savings can be attained. The result is approximate to the direct rebound effect of China’s residential electricity consumption estimated by Wang et al. [37], who use a panel error correction model and find the short-term and long-term direct rebound effects of China’s residential electricity consumption to be 72% and 74%, respectively. Besides, the result is approximately larger than the direct rebound effect in some developed countries. For example, Chitnis and Sorrell [35] estimate that the rebound effect of UK household electricity consumption is 48% using the almost ideal demand system model and input–output approach. This difference is consistent with the conclusion of Chakravarty et al. [52]. It is likely that the energy rebound effect in developing countries appears more significant [39], and the unmet energy demand in developing countries may, more or less, lead to a larger rebound effect.

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\(^7\) [http://www.nsr.gov.cn/mtdj/dfnt/201207/t20120719_492559.html](http://www.nsr.gov.cn/mtdj/dfnt/201207/t20120719_492559.html)

It was found that the models with GDP per capita, cooling degree days, and rainfall as the threshold variable has no threshold effect at the 10% significance level. Moreover, we use 300 bootstrap replications to test whether, or not, the model has threshold effects and estimates the direct rebound effect of China's residential electricity consumption for different regimes of the threshold variables. The results of the tests for threshold effect of the models are shown in Table 4, from which it was found that the models with GDP per capita, cooling degree days, and rainfall as threshold variables have only one threshold effect at the 10% significance level; however, the model with population as its threshold variable has no threshold effect at the 10% significance level.

According to Eqs. (7) and (8), we can attain the threshold estimates and their confidence intervals of corresponding models, as shown in Table 5. Taking the threshold estimates of GDP per capita, cooling degree days, and rainfall as the dividing line, there are two different regimes, respectively. For example, there are high income regime (ln(PGDP) > 10.1151, PGDP > 24713.38) and low income regime (ln(PGDP) < 10.1151, PGDP ≤ 24713.38) in the model with GDP per capita as the threshold variable, and there are high cooling degree days regime (ln(CDD) > 7.2749, CDD > 1443.61) and low cooling degree days regime (ln(CDD) ≤ 7.2749, CDD ≤ 1443.61) in the model with cooling degree days as the threshold variable. Also, there are heavy rainfall regime (ln(RAIN) > 7.4851, RAIN > 1781.30) and light rainfall regime (ln(RAIN) ≤ 7.4851, RAIN ≤ 1781.30) in the model with rainfall as the threshold variable.

Then, we can get the regression results of the models which use GDP per capita, cooling degree days, and rainfall as the threshold variables, respectively, and the results are shown in Table 6. All coefficients of the models are significant at the 10% significance level.

Furthermore, according to the divided regimes, we can find the provinces in the corresponding regimes during 2000–2013 (see Table 7). Based on the results in Tables 3–7, we can distil the results to the following arguments.

First, the increase of GDP per capita may promote the decline of direct rebound effect of China's residential electricity consumption. During 2000–2013, in the provinces where GDP per capita is lower than 24713.38 Yuan (most provinces, accounting for 73.40%), i.e., under the low income regime, the direct rebound effect of residential electricity consumption is 67.86%. Electricity utilisation efficiency improvement reduces electricity consumption, which in turn decreases the cost of electricity services, and promotes residents to increase their electricity consumption: 67.86% of the expected electricity savings are achieved. In the provinces where GDP per capita is higher than 24713.38 Yuan (such as Beijing, Shanghai, Guangdong, Tianjin, Jiangsu, and Zhejiang), i.e., under the high income regime, the direct rebound effect of residential electricity consumption is 54.74%, which is less than the direct rebound effect under the low income regime. This indicates that in regions with higher income, the direct rebound effect of residential electricity consumption appears smaller, and the increase in income contributes to diminishing the direct rebound effect of residential electricity consumption. Thus, electricity utilisation efficiency improvement in regions with higher income should be attached more significance for the better effectiveness of electricity savings resulted from electricity utilisation efficiency improvement. Orea et al. [53] write the rebound effect as a function of income, energy price, and average household size when estimating the rebound effect of U.S. residential energy consumption. Their empirical results show that income exerts a negative influence on the rebound effect, which is consistent with our findings. The main reason for this result is that, in high income regions, it is easy for residents to meet their demand for electricity without money limitation, and they are insensitive to the decrease of energy service cost. Thus there will not be a huge increase in electricity consumption as seen in low income regions, and the rebound electricity use decreases with increased income. Another candidate reason may be that some regions with lower income experienced higher growth rates of income than those with higher income in

### Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Std. Dev.</th>
<th>Kurtosis</th>
<th>F-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>128.5246</td>
<td>98.2300</td>
<td>711.3700</td>
<td>4.7910</td>
<td>111.5385</td>
<td>7.9602</td>
<td>1564.27 (0.0000)</td>
</tr>
<tr>
<td>$P_1$</td>
<td>0.4704</td>
<td>0.4573</td>
<td>0.7365</td>
<td>0.2637</td>
<td>0.0913</td>
<td>2.6522</td>
<td>203.1540 (0.0000)</td>
</tr>
<tr>
<td>PGDP</td>
<td>20359.5800</td>
<td>16323.4000</td>
<td>69655.2400</td>
<td>3229.0620</td>
<td>13765.9000</td>
<td>4.3800</td>
<td>155.9880 (0.0000)</td>
</tr>
<tr>
<td>POP</td>
<td>4469.8230</td>
<td>3829.5000</td>
<td>10644.0000</td>
<td>517.0000</td>
<td>2572.5290</td>
<td>2.4289</td>
<td>109.0660 (0.0000)</td>
</tr>
<tr>
<td>CDD</td>
<td>901.0121</td>
<td>803.4000</td>
<td>2678.9000</td>
<td>171.8000</td>
<td>496.4093</td>
<td>3.5357</td>
<td>70.4231 (0.0000)</td>
</tr>
<tr>
<td>RAIN</td>
<td>961.2505</td>
<td>971.8500</td>
<td>2583.5000</td>
<td>0.0000</td>
<td>526.0786</td>
<td>4.5964</td>
<td>203.1540 (0.0000)</td>
</tr>
</tbody>
</table>

*** Denotes the significance at the 1% level.

### Table 2
Results of panel unit root test.

<table>
<thead>
<tr>
<th>Variable</th>
<th>LLC test statistic</th>
<th>ADF - Fisher statistic</th>
<th>PP - Fisher statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(E)</td>
<td>-2.0005</td>
<td>33.0685</td>
<td>52.1485</td>
</tr>
<tr>
<td>Δ ln(E)</td>
<td>-13.9147***</td>
<td>203.1540***</td>
<td>237.1020***</td>
</tr>
<tr>
<td>ln(P1)</td>
<td>-0.5609</td>
<td>17.9632</td>
<td>237.1020***</td>
</tr>
<tr>
<td>Δ ln(P1)</td>
<td>-8.0347***</td>
<td>49.9855***</td>
<td>51.2094***</td>
</tr>
<tr>
<td>ln(PGDP)</td>
<td>-4.2905***</td>
<td>70.4231</td>
<td>63.2635</td>
</tr>
<tr>
<td>Δ ln(PGDP)</td>
<td>-5.9740***</td>
<td>109.0660***</td>
<td>118.1126***</td>
</tr>
<tr>
<td>ln(POP)</td>
<td>12.7781</td>
<td>9.8667</td>
<td>11.0917</td>
</tr>
<tr>
<td>Δ ln(POP)</td>
<td>-4.3209***</td>
<td>155.9880***</td>
<td>164.4190***</td>
</tr>
<tr>
<td>ln(CDD)</td>
<td>0.3792</td>
<td>28.1314</td>
<td>35.4475</td>
</tr>
<tr>
<td>Δ ln(CDD)</td>
<td>-21.9508***</td>
<td>413.3720***</td>
<td>433.107***</td>
</tr>
<tr>
<td>ln(RAIN)</td>
<td>0.9235</td>
<td>22.7766</td>
<td>25.1278</td>
</tr>
<tr>
<td>Δ ln(RAIN)</td>
<td>-29.2459***</td>
<td>506.0813***</td>
<td>567.743***</td>
</tr>
</tbody>
</table>

*** Denotes the significance at the 1% level.

### Table 3
Estimation of linear panel model. a

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-9.5843 (0.0000)</td>
<td>0.7725</td>
</tr>
<tr>
<td>ln(P1)</td>
<td>-0.7153 (0.0325)</td>
<td>0.1077</td>
</tr>
<tr>
<td>ln(PGDP)</td>
<td>0.8104 (0.0000)</td>
<td>0.0346 (0.0456)</td>
</tr>
<tr>
<td>ln(POP)</td>
<td>0.9235</td>
<td>0.0153</td>
</tr>
<tr>
<td>ln(CDD)</td>
<td>1.5642 (0.0000)</td>
<td>0.0153</td>
</tr>
<tr>
<td>ln(RAIN)</td>
<td>1.5462 (0.0000)</td>
<td>0.0153</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>F-statistic</td>
<td>1564.27 (0.0000)</td>
<td>1564.27 (0.0000)</td>
</tr>
</tbody>
</table>

Direct rebound effect 71.53%

a The p-value of corresponding statistics are reported in parentheses.

4.2. Results of panel threshold model

According to Eqs. (4) and (5), we employ GDP per capita, population at the end of the year, cooling degree days, and rainfall as the threshold variable of the panel threshold model, respectively. Moreover, we use 300 bootstrap replications to test whether, or not, the model has threshold effects and estimates the direct rebound effect of China's residential electricity consumption for different regimes of the threshold variables. The results of the tests for threshold effect of the models are shown in Table 4, from which it was found that the models with GDP per capita, cooling degree days, and rainfall as threshold variables have only one threshold effect at the 10% significance level; however, the model with population as its threshold variable has no threshold effect at the 10% significance level.

According to Eqs. (7) and (8), we can attain the threshold estimates and their confidence intervals of corresponding models, as shown in Table 5. Taking the threshold estimates of GDP per capita, cooling degree days, and rainfall as the dividing line, there are two different regimes, respectively. For example, there are high income regime (ln(PGDP) > 10.1151, PGDP > 24713.38) and low income regime (ln(PGDP) ≤ 10.1151, PGDP ≤ 24713.38) in the model with
recent years, because of which people in lower income regions can afford some new household appliances that people in higher income regions already have, and substantially increase electricity use. It should be noted that as time goes by, the number of low income provinces decreases while the number of high income provinces increases, as shown in Table 7. This suggests that the direct rebound effect of China’s residential electricity consumption has a declining trend over time because of the smaller direct rebound effect in regions with higher income. Thus, electricity utilisation efficiency improvement may be more effective for energy conservation in China over time.

Second, the decrease in cooling degree days helps to decline the direct rebound effect of residential electricity consumption. During 2000–2013, in the provinces where cooling degree days are less than 1443.61 centigrade (most provinces, accounting for 83.99%), i.e., under the low cooling degree days regime, the direct rebound effect of residential electricity consumption is 74.52%. In regions with little use of cooling appliances, 74.52% of the expected energy savings by electricity utilisation efficiency are offset by the extra electricity consumption due to cheaper electricity service costs. In provinces where cooling degree days exceed 1443.61 centigrade (such as Fujian, Guangdong, Guangxi, Hainan, Chongqing, and Sichuan), i.e., under the high cooling degree days regime, the direct rebound effect of residential electricity consumption is 89.23%. In regions with high frequency use of cooling appliances, only about 10% of the expected energy savings by electricity utilisation efficiency can be achieved and about 90% are offset, which is larger than the direct rebound effect under the low cooling degree days regime. This comparison indicates that the effectiveness for energy conservation from residential electricity utilisation efficiency improvement proves better in regions with lower cooling degree days. Temperature has a more and more important influence on electricity consumption [54], and in the high cooling degree days regions, there is unsatisfied demand for electricity. The frequency of using the household cooling appliances is higher in regions with unsatisfied demand for electricity [55]. Therefore, when the electricity utilisation efficiency improves, and the cost of electricity service decreases, the electricity demand accounted for by use of household cooling appliances is further unrestrained, which in turn promotes electricity consumption and offsets most of the expected electricity savings.

Third, the decrease in rainfall contributes to diminishing the direct rebound effect of residential electricity consumption. During 2000–2013, in the provinces where rainfall is less than 1781.3 mm (most provinces, accounting for 95.32%), i.e., under the light rainfall regime, the direct rebound effect of residential electricity consumption is 89.23%. In regions with little rainfall, 68.30% of the expected energy savings realised by electricity utilisation efficiency are offset by the extra electricity consumption due to cheaper electricity service costs. In provinces where rainfall is greater than 1781.3 mm (such as Hainan and Guangdong), i.e., under the heavy rainfall regime, the direct rebound effect of residential electricity consumption is 74.52%.

### Table 4
Tests for threshold effect.\(^a\)

<table>
<thead>
<tr>
<th>Threshold variable</th>
<th>Null hypothesis: no threshold effect</th>
<th>Null hypothesis: single threshold effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LR test</td>
<td>LR test</td>
</tr>
<tr>
<td>ln(PCDP)</td>
<td>30.90 (0.0667)</td>
<td>14.21 (0.3200)</td>
</tr>
<tr>
<td>ln(PPOP)</td>
<td>27.46 (0.5300)</td>
<td>–</td>
</tr>
<tr>
<td>ln(CDD)</td>
<td>21.33 (0.0667)</td>
<td>7.21 (0.7133)</td>
</tr>
<tr>
<td>ln(RAIN)</td>
<td>14.93 (0.0867)</td>
<td>10.55 (0.2167)</td>
</tr>
</tbody>
</table>

\(^a\) The p-value of corresponding statistics are reported in parentheses.

### Table 5
Threshold estimates.

<table>
<thead>
<tr>
<th>Threshold variable</th>
<th>Threshold value ((\gamma))</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(PCDP)</td>
<td>10.1151</td>
<td>(10.1070, 10.1166)</td>
</tr>
<tr>
<td>ln(PPOP)</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ln(CDD)</td>
<td>7.2749</td>
<td>(7.2688, 7.2795)</td>
</tr>
<tr>
<td>ln(RAIN)</td>
<td>7.4851</td>
<td>(7.3729, 7.4949)</td>
</tr>
</tbody>
</table>

### Table 6
Threshold effect results.\(^a\)

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>–11.8205</td>
<td>–9.3403</td>
<td>–9.6429</td>
</tr>
<tr>
<td>ln(PCDP)</td>
<td>0.8596</td>
<td>0.7773</td>
<td>0.8056</td>
</tr>
<tr>
<td>ln(PPOP)</td>
<td>0.9415</td>
<td>0.7429</td>
<td>0.7671</td>
</tr>
<tr>
<td>ln(CDD)</td>
<td>0.0302</td>
<td>0.0180</td>
<td>0.0264</td>
</tr>
<tr>
<td>ln(RAIN)</td>
<td>–0.0683</td>
<td>–0.0789</td>
<td>–0.1043</td>
</tr>
<tr>
<td>ln((P + l(\ln(\text{PCDP})&lt;10.1151)))</td>
<td>–0.6786</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ln((P + l(\ln(\text{PCDP)}&gt;10.1151)))</td>
<td>–0.5474</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ln((P + l(\ln(\text{CDD})&lt;7.2749)))</td>
<td>–</td>
<td>–0.7452</td>
<td>–</td>
</tr>
<tr>
<td>ln((P + l(\ln(\text{CDD)}&gt;7.2749)))</td>
<td>–</td>
<td>–0.8923</td>
<td>–</td>
</tr>
<tr>
<td>ln((P + l(\ln(\text{RAIN})&lt;7.4851)))</td>
<td>–</td>
<td>–</td>
<td>–0.6830</td>
</tr>
<tr>
<td>ln((P + l(\ln(\text{RAIN})&gt;7.4851)))</td>
<td>–</td>
<td>–</td>
<td>–0.8631</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>1009.17 (0.0000)</td>
<td>1031.72 (0.0000)</td>
<td>1011.03 (0.0000)</td>
</tr>
</tbody>
</table>

\(^a\) The p-value are reported in parentheses; Models A, B and C refer to the models whose threshold variable are ln(PCDP), ln(CDD) and ln(RAIN), respectively.
consumption is 86.31%, and only 13.69% of the expected energy savings realised by electricity utilisation efficiency improvements can be obtained, while most of the expected electricity savings are offset. Additionally, the direct rebound effect of residential electricity consumption in regions with light rainfall proves smaller than that in regions with heavy rainfall. Thus, when electricity utilisation efficiency improves, regions with lighter rainfall tend to have more effective performance for energy savings compared with those with heavier rainfall. This is closely related to geographic position. Regions with heavy rainfall are often tropical, or sub-tropical, and have greater need for cooling. Besides, these regions often have big demands for lighting and drying, and they are, therefore, regions with huge electricity demand. The residents in these places are often sensitive to the cost of electricity. When electricity utilisation improves and the cost of electricity service decreases, electricity demand among residents is promoted, and more electricity is consumed, leading to relatively big rebound electricity consumption.

Finally, GDP per capita and population contribute greatly to promoting residential electricity consumption, while cooling degree days contribute slightly to its promotion. On the contrary, rainfall is helpful in restraining residential electricity consumption, but the effect extent appears small. From Tables 3 and 6, we can find that the coefficients of GDP per capita and population are positive and close to one, which indicates that GDP per capita and population have significant positive impact on China’s residential electricity consumption. In fact, income is the key factor promoting residential electricity consumption in developing countries. Residents who have stronger buying power are more likely to impose more demands for household appliances and energy services, and then electricity consumption may increase. Meanwhile, more population often increase the total demands for electricity, thus population has a positive influence on residential electricity consumption. Moreover, the coefficient of cooling degree days is positive but small, which denotes that cooling degree days contribute slightly to electricity consumption promotion. Cooling degree days refer to the cumulative differences when the mean temperature is higher than the base temperature in a year, often as a factor reflecting energy consumption for cooling requirements. The more cooling degree days in a year indicates more times of relatively high temperature, and residents have higher use of air-conditioners to keep comfortable, thus electricity consumption increases. In fact, the empirical results of Wang et al. [38] also show that cooling degree days have a positive influence on residential electricity consumption. Besides, the coefficient of rainfall is negative and small, which denotes that rainfall has small negative impact on China’s residential electricity consumption. Rainfall helps to restrain residential electricity consumption, which may be related to the drop in temperature when it is rainy, and the decreased demand for household cooling appliances.

5. Conclusions and policy implications

By investigating the linear and non-linear relationships of China’s residential electricity consumption and its main influencing factors, we estimate the direct rebound effect of residential electricity consumption in a linear relationship by use of a panel model. Also, we estimate the direct rebound effect in different regimes using GDP per capital, population, cooling degree days, and rainfall as threshold variables, respectively, in the non-linear relationship by the panel threshold model. The following conclusions were drawn:

First, in the linear relationship, the direct rebound effect of China’s residential electricity consumption during 2000–2013 is 71.53% on average.

Second, the increase of GDP per capita helps to reduce the direct rebound effect of China’s residential electricity consumption. The direct rebound effect of China’s residential electricity consumption is 67.86% in the low income regime, while it is 54.74% in the high income regime.

Third, the decrease in cooling degree days contributes to reducing the direct rebound effect of China’s residential electricity consumption. The direct rebound effect of China’s residential electricity consumption is 74.52% in the low cooling degree regime, while it is 89.23% in the high cooling degree day regime.

Fourth, the decrease of rainfall may be helpful to reduce the direct rebound effect of China’s residential electricity consumption. The direct rebound effect of China’s residential electricity consumption is 68.30% in the light rainfall regime, while it is 86.31% in the heavy rainfall regime.

Finally, both in linear and non-linear relationships, GDP per capita and population have great positive impact on residential electricity consumption; and cooling degree days have small positive impact on residential electricity consumption; while rainfall has small negative influence on residential electricity consumption.

The conclusions above have rich policy implications. First and foremost, when making energy efficiency policies, the government is supposed to consider not only energy conservation caused by energy efficiency improvements, but also the rebound effect to avoid overestimating energy savings achieved by implementing energy efficiency policies in China’s residential sector. Second, when preserving increases in GDP per capita, electricity efficiency policy implementation can be inclined to regions with higher incomes, such as Beijing and Shanghai, where the direct rebound effect is smaller and electricity utilisation efficiency improvement tend to be more effective for energy conservation. Third, electricity utilisation efficiency improvement is supposed to be widely implemented, and prioritised, in regions with low cooling degree days, such as all regions except Fujian, Guangdong, Guangxi, Hainan, Chongqing, and Sichuan. Finally, electricity utilisation efficiency improvement can be reinforced in the regions with light rainfall, such as all regions except Guangdong and Hainan.

As for the future work, there is still much to be done. For instance, on the one hand, some further research can be done to estimate the indirect rebound effect of residential electricity consumption, and investigate how it changes. On the other hand, more research can be concentrated on the direct, or indirect, rebound effect of residential energy consumption, not only for electricity, but for natural gas and coal.

Acknowledgments

We gratefully acknowledge the financial support from the National Natural Science Foundation of China (Nos. 71273028 and 71322103), the National Special Support Program for High-Level Personnel from the central government of China, Cheung Kong Scholars Program of the Ministry of Education of China and the Hunan Youth Talent Plan. We also would like to thank Prof. Jinyue Yan, Prof. Bin Chen, the conference participants at CUE 2016 in Jinan, China, and three reviewers for their constructive comments.

References


