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Direct Rebound Effect for Electricity Consumption of Urban Residents in China Based on the Spatial **Spillover Effect**

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Abstract: Based on methods of price decomposition and spatial econometrics, this paper improves the model for calculating the direct energy rebound effect employing the panel data of China's urban residents' electricity consumption for an empirical analysis. Results show that the global spatial correlation of urban residents' electricity consumption has a significant positive value. The direct rebound effect and its spillover effects are 37% and 13%, respectively. Due to the spatial spillover effects, the realization of energy-saving targets in the local region depends on the implementation effect of energy efficiency policies in the surrounding areas. However, the spatial spillover effect is low, and the direct rebound effect induced by the local region is still the dominant factor affecting the implementation of energy efficiency. The direct rebound effect for urban residents' electricity consumption eliminating the spatial spillover effect does not show a significant downward trend. The main reason is that the rapid urbanization process at the current stage has caused a rigid residents' electricity demand and large-scale marginal consumer groups, which offsets the inhibition effect of income growth on the direct rebound effect.

Keywords: energy efficiency; direct energy rebound effect; spatial spillover effect; price decomposition

1. Introduction

China has been the world's largest energy consumer since 2009, accounting for 23% of global energy consumption and 27% of global energy consumption growth in 2016 [1]. Meanwhile, China is currently the world's largest emitter of carbon dioxide and sulfur dioxide. The annual economic losses caused by air and water pollution account for 8–12% of GDP [2]. However, China's electricity production is still dominated by coal, and the carbon dioxide emitted by electricity and heat production is more than 50% of the total fuel emissions, which is contrary to the current economic transformation goals. Among all terminal electricity consumption, residential electricity consumption accounts for a relatively large proportion, and due to the energy substitution policy effect, electric energy substitution will further expand residents' electricity consumption. Therefore, it is necessary to control residents' electricity consumption. Although improving the electricity efficiency through technical means can inhibit the increase of household electricity consumption to a certain extent, improving energy efficiency will induce a direct rebound effect, and its negative effect on energy conservation and emission reduction cannot be ignored [3,4]. In view of the spatial agglomeration of electricity consumption in China, there are two problems that need to be studied in depth: Is there a spatial spillover effect of the direct rebound effect of residential electricity consumption? How to distinguish the direct rebound effect and its spatial spillover effect if there is a spatial spillover effect, so as to accurately and comprehensively examine the magnitude and trend of the direct rebound effect of residential electricity.



1.1. Types of the Energy Rebound Effect

The energy rebound effect can be divided into four categories [5]:

- The same consumer for the same goods or services;
- Different consumers for the same goods or services;
- The same consumer for different goods or services;
- Different consumers for different goods or services.

The first two categories correspond to the direct rebound effect; the latter two categories belong to the indirect rebound effect, and the macroeconomic rebound effect covers all of the types above [6]. In general, the estimation of direct rebound effect follows the "bottom-up" principle and examines the change of individual consumption patterns. However, the estimation of the macroeconomic rebound effect follows the "top-down" principle, which examines the change of total energy consumption without paying attention to the decomposition of the total energy consumption [7]. Some studies hold the view that if the direct and indirect rebound effects can be identified and calculated separately, and the macroeconomic effects are the sum of the two effects, but others have the opposite view that the macroeconomic rebound effect is different from the direct and indirect rebound effects [8–10]. The main economic mechanism of the macroeconomic rebound effect is composed of the economic growth effect [11] and the change effect [12]. The former refers to the technological progress in promoting economic growth, and in turn it results in increased energy consumption. The latter means that the technical progress can change consumer preferences and the industry, so energy consumption is also changed. In recent years, the study suggests that in addition to the secondary effects (indirect effect), the indirect effect also contains an implicit effect (a so called embedded effect). For example, although the consumer does not directly increase energy consumption with the increase of real income, they may increase their consumption of other goods or services. The process of production and transportation of these goods or services will consume energy, so the energy consumption increase is embedded in the non-energy goods and services [12,13].

In fact, the direct effect is the basis of the indirect effect and the macroeconomic rebound effect. The indirect effect is even considered to be a part of the direct effect in some studies [14,15]. For example, if the direct effect is 30%, the average direct and indirect rebound effect (DIRE) of the European Union's 27 countries is 73.6%. If the direct effect is 50%, the average DIRE is 81.16% [16], so restraining direct rebound effect is the foundation of restraining indirect and macroeconomic rebound effect.

1.2. Evidences of the Direct Rebound Effect

The existing empirical studies cover personal passenger transport [17–22], household heating [23,24] or other household services [25–30]. However, based on the data from different regions, or different energy services, the results are controversial. The direct rebound effect of developed countries is no more than 40%, meaning that improving energy efficiency will reduce energy consumption, and only a part of the expected savings is offset [31]. However, the direct rebound effect of developing countries is extremely serious, sometimes even exceeding 100% [27]. The income gap may be the main reason behind the difference between different regions [12]. Residents in developed countries have higher income and tend to demand saturation [32], so the energy consumption induced by the improvement of energy efficiency will decrease, and the magnitude of the direct rebound effect is smaller than that in developing countries. The energy demand in developing countries is far from saturated [6], so income growth may not inhibit the direct rebound effect in developing countries in the short term.

What's the magnitude of China's direct rebound effect? Taking residents' electricity consumption as an example, the direct rebound effect for urban residents' electricity consumption is less than 100% [18]. However, it may rise up to 165.22%, mainly due to "marginal consumer groups" [27]. If the heterogeneity of urban and rural direct rebound effect is ignored, the direct rebound effect for residents' electricity consumption would have a threshold effect based on per capita income [33]. With the steady growth of per capita income, the magnitude of direct rebound effect tends to decrease. To sum up,

the magnitude and the change of direct rebound effect for China's residents' electricity consumption are still controversial.

There are three reasons that cause the difference mentioned above. First, the electricity consumption of urban residents in China is much larger than that of rural residents, which leads to heterogeneity between urban and rural residents. Taking the two groups as a whole to avoid differences will result in inaccurate results. Second, the effect of power price on residents' electricity consumption between price increase periods and price decline periods is not completely reversible [34]. The calculation result of the direct rebound effect for residential electricity consumption without price decomposition will be different between the two periods. Third, the definition of direct rebound effect given by Berkout et al. [3] and Greening et al. [35] which implies the assumption that energy consumption among regions is independent, is the basis of the empirical studies above. However, Tobler's First Law of Geography shows that everything is related to everything else, but near things are more related to each other. China' economic development and energy consumption have obvious clustering properties in geospatial space. Therefore, the spatial spillover effect cannot be ignored when the direct rebound effect is explored. In essence, economic activities cause widespread connections between regions [36]. The aggregation of users may improve the energy efficiency of users' communities; for instance, shared-use of common resources [37] and demand side management participation though an aggregator [38]. Users or local governments that actively cooperate for a common goal of reducing energy consumption may be one of the reasons for spatial aggregation. The improvement of electricity efficiency in a local area will affect not only the residents' electricity consumption in the local region, but also the residents' electricity consumption in neighboring areas, so the direct rebound effect will spill over between regions. Ignoring the spatial dependence will confuse the direct rebound effect and its spatial spillover effect, leading to incorrect results.

In view of this, the main contributions of this paper are in the following aspects. First, based on the perspective of spatial spillover, the measurement model of direct rebound effect is improved, so that the direct rebound effect can be measured more accurately and comprehensively. Second, considering the asymmetric influence of price on demand and the heterogeneity of the direct rebound effect between urban and rural areas, the spatial panel data of urban residents are used for empirical test, and multiple price decomposition models are introduced to ensure the robustness of the results. Finally, the trend of the direct rebound effect on urban residents' electricity consumption is examined. The research results have important reference to the realization of energy savings and emission reduction targets.

2. The Improved Method of Calculating Direct Rebound Effect

Improving energy efficiency will decrease energy consumption with the same level of energy service. For instance, if the rate of electricity use and cooling area decrease, residents will use less electricity cooling the same area. However, improving efficiency means a decrease in real power price, which will incentivize residents to use more electricity in turn. Calculating the direct rebound effect is to calculate the gap between the expected savings and the actual savings. Direct rebound effect is then defined as: Direct rebound = (expected savings – actual savings)/expected savings. The traditional calculation method of the direct rebound effect controls no other variables, so some studies recommend that the price elasticity could be an ideal proxy indicator of direct rebound effect with other variables controlled [39]. The definition and identification of direct rebound effect can be found in Appendix A.

The calculation method above only analyzes the energy consumed by the same consumers (consumers in the local region) and does not consider other consumers (consumers in the adjacent region). It implies the assumption that energy consumption in different regions is independent. However, if there is a spatial "convergence effect" in energy consumption, whereby the increased energy efficiency in a local region will have an influence on the energy consumption not only in the local region, but also in the adjacent regions, leading to a "spatial feedback effect". For the same reason, the improvement of energy efficiency in the adjacent region also induces a direct rebound effect in the local region. This paper views this as the spatial spillover effect of the direct rebound effect. It is

impossible to distinguish whether the additional energy consumption in the local region is caused by the energy efficiency improvement in the local region or in the adjacent region without considering spatial spillover effect.

Based on spatial spillover effect, this paper improves the calculating model of direct rebound effect. The spatial lag of electricity consumption is introduced into the model, and the spatial lag model (SLM) controlling other variables is:

$$y_t = \lambda W y_t + X_t \beta + c + u_t \tag{1}$$

where both the explained variable and the explanatory variable are logarithmized. y_t is the urban residents' electricity consumption of n regions in year t. W is the space weight matrix, and Wy_t is the spatial lag of y_t . λ measures the effect of spatial lag Wy_t on y_t , reflecting spatial dependence. X_t is the explanatory variables matrix of n regions in year t. β is the coefficient of the explanatory variable. c is the individual effect of n regions. According to the individual effect, the model can be divided into fixed effect model and random effect model.

If the spatial correlation of urban residents' electricity consumption is not considered, Equation (1) is reduced to a standard static panel model.

Rewrite Equation (1) as a reduced form:

$$y_t = (I - \lambda W)^{-1} (X_t \beta + c + u_t)$$
⁽²⁾

$$E(y_t|X_t, W) = (I - \lambda W)^{-1} (X_t \beta)$$
(3)

Equation (3) shows that measuring the direct rebound effect should consider the spatial feedback effect. According to the research on direct and indirect effects in spatial econometric models by LeSage and Pace [40], the calculation of the direct rebound effect in the space lag fixed effect model is:

$$RE = -\frac{1}{nT} \sum_{t=1}^{T} \sum_{i=1}^{n} \frac{\partial E(\hat{y}_{it} | X_t, W)}{\partial \ln P_i}$$
(4)

where $\hat{y}_t = y_t - (I - \lambda W)^{-1}c$. The direct rebound effect calculated here is the average value of the direct rebound effect of *n* regions, so it can be called the average direct rebound effect (abbreviated as RE).

The calculation of the space spillover effect of direct rebound effect is defined as:

$$SRE = -\frac{1}{nT(n-1)} \sum_{t=1}^{T} \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} \frac{\partial E(\hat{y}_{it} | X_t, W)}{\partial \ln P_j}$$
(5)

Equation (5) also calculates the average spatial spillover effects of *n* regions, so it can be called the average spatial spillover effect (abbreviated as SRE).

The spatial lag model only considers the endogenous interaction effects, ignoring the spatial correlation of unobservable random impacts. In the case of multiple spatial interactions, a more appropriate method is to use the spatial autoregressive model with spatial autoregressive disturbances (SARAR) model. Since urban residents' electricity consumption may have both the interaction of endogenous interaction and error terms, the SARAR model is introduced to measure the direct rebound effect and its spatial spillover effect:

$$y_t = \lambda W y_t + X_t \beta + c + \varepsilon_t, \varepsilon_t = \rho W \varepsilon_t + \varphi_t \tag{6}$$

where ρ is the coefficient of spatial lag $W \varepsilon_t$. The calculation of the average direct rebound effect and the average spatial spillover effect of the SARAR model is consistent with the SLM model.

The process of using spatial econometric models is as follows: before establishing a spatial econometric model, it is necessary to test the spatial autocorrelation and heterogeneity in the data, using two types of spatial autocorrelation test: local autocorrelation and global autocorrelation. Then multiple models are set up. For nested models, a likelihood ratio (LR) test can be used to choose the best model. Due to endogeneity problems, the ordinary least squares (OLS) estimators are inconsistent. This paper uses the maximum likelihood estimator method (MLE) to get the consistent estimator. For panel data, individual effects need to be tested, so the Hausman test is used to select the appropriate model between the fixed effect and random effect models. And we use the method proposed by Lee and Yu [41] to estimate the panel spatial econometric model. Firstly, the individual effects are eliminated, then the maximum likelihood estimator method is performed.

3. Variables and Data Description

3.1. Variables Selection

Electricity consumption (*y*). The electricity consumption is an endogenous variable, which is measured by the electricity consumption of urban residents.

Power price (*P*). The power price is the core explanatory variable, which is measured by the average selling price of electricity used by residents. The power price has both rising and falling periods, and the impact of rising and falling price on the demand for electricity is not completely reversible. However, the direct rebound effect is mainly related to the falling price. So the power price is decomposed into three parts [4]:

$$P_{it} = P_{max,it} \times P_{rec,it} \times P_{cut,it} \tag{7}$$

where P_{it} , $P_{max,it}$, $P_{rec,it}$ and $P_{cut,it}$ represent the actual price, maximum price, cumulative rising price and cumulative falling price in province *i* in year *t*, respectively. The decomposed price is calculated as follows:

$$P_{max,it} = \max\{P_{i1}, P_{i2}, \cdots, P_{it}\}$$
 (8)

$$P_{rec,it} = \prod_{j=0}^{t} \max\left\{1, \frac{P_{max,ij-1}/P_{ij-1}}{P_{max,ij}/P_{ij}}\right\}$$
(9)

$$P_{cut,it} = \prod_{j=0}^{t} \min\left\{1, \frac{P_{max,ij-1}/P_{ij-1}}{P_{max,ij}/P_{ij}}\right\}$$
(10)

The power price is also decomposed into two parts [28]:

$$P_{inc,it} = P_{max,it} \times P_{rec,it} \tag{11}$$

$$P_{dec,it} = P_{max,it} \times P_{cut,it} \tag{12}$$

The two decomposition methods are both used for a robust test.

Degree day (*DD*). The degree day, referring to the deviation between the daily average temperature and the base temperature, is an environmental factor that should be controlled. It reflects the climate characteristics. Urban residents will use household appliances such as air conditioners more frequently with high degree days, so the electricity consumption is larger. Degree days are divided into heating degree days (HDD) and cooling degree days (CDD), and their calculation is as follows [28]:

$$HDD = \sum_{m=1}^{12} (1 - rd)(T_{b1} - T_m) \times M$$
(13)

$$CDD = \sum_{m=1}^{12} rd(T_m - T_{b2}) \times M$$
(14)

where *HDD* and *CDD* are the heating degree day value and the cooling degree day value. T_m is the monthly average temperature. T_{b1} and T_{b2} represent the base temperature of the heating degree day and the cooling degree day, respectively. rd is a dummy variable, and if the monthly average temperature is higher than the base temperature, it is 1. Then, DD = HDD + CDD.

Income (*I*). Income is an economic factor that should be controlled, which is measured by the per capita disposable income of urban residents. Income is an important factor affecting consumer spending. Since 2006, urban residents' income has been increasing with a high rate.

Population (*POP*). Population is measured by the number of permanent residents of urban residents. Obviously, the more people, the greater electricity consumption. In order to accurately measure the increase in electricity consumption induced by efficiency, it is necessary to control the population factor.

3.2. Data Sources

The data sample is from 2006 to 2016, and includes 29 provincial units. Data come from the China energy statistical yearbook (2007–2017), China electricity yearbook (2007–2017), China statistical yearbook (2007–2017), China national bureau of statistics website and the Wind database. The power price and the income are converted into constant prices based on 2006. Table 1 presents correlation coefficients between main variables as well as their means and standard deviations. We take logarithms of all variables to reduce heteroscedasticity.

Variable	Mean	St.d	(1)	(2)	(3)	(4)	(5)
(1) E	105.4	74.88	1.000				
(2) <i>P</i>	432.2	63.41	0.545	1.000			
(3) I	170.5	60.85	0.579	0.252	1.000		
(4) <i>POP</i>	232.3	142.5	0.895	0.577	0.330	1.000	
(5) DD	105.4	33.01	-0.393	-0.314	-0.165	-0.346	1.000

Table 1. Statistical description and correlation table.

Table 1 shows that the average of China's urban residents' electricity consumption and power price are 10.54 billion kilowatt hours and 0.432 yuan per kilowatt hours. It reflects that the cost of electricity consumption is very small, leading to rapid electricity demand growth. Thus, the magnitude of the direct rebound effect for urban residents' electricity consumption in China may be larger than in other countries whose power price is higher than in China. The standard deviation of all variables is small, meaning that all variables are distributed very evenly. The correlation coefficients show that there is no serious collinearity between variables.

4. Empirical Analysis

4.1. Analysis of Results of Static Panel Model

In order to compare with the calculation results of SARAR and SLM model, the static panel model is used. Table 2 shows the static panel model estimation results. Hausman test results reject the null hypothesis at the 1% level, meaning that the individual fixed effect model is superior to the individual random effect model. The fixed effect estimation results show that the direct rebound effect is 39.0%, which means that 39.0% of the electricity consumption of urban residents saved by improving electricity efficiency is offset by the direct rebound effect. Actually only 61.0% of the expected savings can be achieved. The fixed effect estimation results also show that population, income and degree day have significant effects on the electricity consumption of urban residents. Then, we use improved models to analyze the direct rebound effect and its spatial spillover effect.

Variable	Fixed Effect	Random Effect		
ler D	0.592 ***	0.601 **		
InP _{inc}	(0.007)	(0.005)		
ln D	-0.390 *	-0.455 **		
IIII ^o dec	(0.066)	(0.033)		
1 00	0.344 ***	0.025		
InDD	(0.002)	(0.740)		
	0.917 ***	0.911 ***		
InPOP	(0.000)	(0.000)		
1 7	0.711 ***	0.718 ***		
InI	(0.000)	(0.000)		
R^2	0.882	0.878		
TT	19.4	50 ***		
Hausman test	(0.004)			

Table 2. Estimation results of static panel model.

Note: The number in parentheses is the level of significance. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

4.2. Spatial Correlation Test

Before applying the spatial econometric model, it is necessary to analyze the local and global spatial correlation to test whether there is spatial dependence in the urban residents' electricity consumption between regions. First, the local correlation types are analyzed. Although the Moran scatter plot can infer spatial correlation to some extent, the Moran scatter plot cannot determine whether the local correlation type is statistically significant. So the local indicators of spatial association (LISA) map is used to analyze the local spatial autocorrelation. Figures 1 and 2 show the LISA maps of China's urban residents' electricity consumption in 2006 and 2016, respectively.



Figure 1. Spatial aggregation of urban residents' electricity consumption in 2006.



Figure 2. Spatial aggregation of urban residents' electricity consumption in 2016.

The LISA maps show that there are four types of spatial agglomeration in China's urban residents' electricity consumption, and there is little change in local correlation patterns over time. From the perspective of aggregation effect, various types of spatial aggregation reflect the spatial heterogeneity of urban residents' electricity consumption. In terms of time, although the provinces with low-low aggregation and low-high aggregation have a small increase, it does not show a significant leap (for example, high-high to low-low), indicating that the spatial aggregation in urban residents' electricity consumption is stable.

The local spatial aggregation in urban residents' electricity consumption indicates that the spatial dependence cannot be ignored when the direct rebound effect is examined. Table 3 lists the test results of Moran's *I* index of urban residents' electricity consumption, in order to judge the global correlation in urban residents' electricity consumption.

Year	Moran's I	Ζ	Р
2007	0.210	2.186	0.020
2009	0.235	2.366	0.013
2011	0.201	2.058	0.019
2013	0.252	2.471	0.010
2015	0.187	1.999	0.028

Table 3. Spatial autocorrelation test.

Table 3 shows that there is a significant spatial autocorrelation in urban residents' electricity consumption, and the spatial correlation is positive, indicating that the urban residents' electricity consumption mainly reflects convergence effect.

4.3. Analysis of Estimation Results of SARAR and SLM Models

Table 4 displays the estimation results of the SLM and the SARAR model and the robust test results. Hausman test results of the SLM and the SARAR model reject the null hypothesis at the 1% level, meaning that the individual fixed effect model is superior to the individual random effect model. The SARAR fixed effect model has a larger log likelihood value than the SLE fixed effect model. The statistic of the LR test for the SLM model and the SARAR model is 7.448, rejecting the null hypothesis at the 1% level, showing that the SARAR fixed effect model is better than the SLM fixed effect model.

Then the direct rebound effect for residents' electricity consumption and its spatial spillover effect are calculated based on SARAR model estimation results.

	S	LM	SARAR		
variable	Fixed Effect	Random Effect	Fixed Effect	Random Effect	Kobust lest
Wy	0.275 *** (0.000)	0.037 (0.156)	0.317 *** (0.000)	0.036 (0.233)	0.318 *** (0.000)
Wε	-	-	-0.363 *** (0.006)	0.017 (0.912)	-0.363 *** (0.006)
lnP _{inc}	0.464 ** (0.023)	0.583 *** (0.006)	0.525 *** (0.003)	0.578 *** (0.008)	-
lnP _{dec}	-0.355 * (0.074)	-0.422 ** (0.042)	-0.363 ** (0.034)	-0.422 ** (0.043)	-
lnP _{max}	-	-	-	-	0.158 (0.321)
lnP _{rec}	-	-	-	-	0.538 * (0.053)
lnP _{cut}	-	-	-	-	-0.361 ** (0.036)
lnDD	0.305 *** (0.003)	0.093 (0.331)	0.326 *** (0.000)	0.086 (0.468)	0.326 *** (0.000)
ln <i>POP</i>	0.691 *** (0.000)	0.888 *** (0.000)	0.661 *** (0.000)	0.888 *** (0.000)	0.661 *** (0.000)
lnI	0.541 *** (0.000)	0.692 *** (0.000)	0.508 *** (0.000)	0.693 *** (0.000)	0.508 *** (0.000)
Log likelihood	243.326	205.289	247.050	205.295	247.052
Hausman test	63.51 *** (0.000)		215.16 *** (0.000)		-

Table 4. Estimation results of SLM and SARAR model and robust test.

Note: The number in parentheses is the level of significance. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

All the variable coefficients in the SARAR fixed effect models are significant. However, the absolute value of all variable coefficients in the SARAR fixed effect model is lower than that in static panel fixed effect model, indicating that ignoring the spatial correlation will overestimate the influence of these variables on electricity consumption.

This is because residents' electricity consumption in the local region is affected not only by power price, population and per capita income in the local region, but also by the positive impact of the spatial lag of residents' electricity consumption. The static panel model classifies the positive impact of spatial lag on residents' electricity consumption into other explanatory variables. So, the contribution of these explanatory variables is exaggerated.

4.4. Analysis of RE and SRE

In the SARAR fixed effect model, due to the existence of spatial lag, the spatial feedback effect should be considered to measure the direct rebound effect. Combined with Equation (4), the average direct rebound effect is 37.00%, indicating that improving the electricity efficiency does induce a direct rebound effect. However, the direct rebound effect for urban residents' electricity consumption is much lower than 100%, and is lower than that of the static panel model. This means that the direct rebound effect value is reduced after considering the spatial correlation. Increasing the efficiency of electricity consumption will ultimately reduce the urban residents' electricity consumption. 37% of the expected savings are offset, and 63% of the expected targets can be achieved actually. So, improving the efficiency plays an important role in reducing the urban residents' electricity consumption. Table 4 also shows that in addition to the decline in power price, the growth of population, per capita income

and degree day value will also increase the urban residents' electricity consumption, especially when the inter-regional urban residents' electricity consumption has a mutual pulling effect. When the government measures the restraining effect of electricity efficiency on residents' electricity consumption, the factors above should be controlled. Otherwise, the direct rebound effect for residents' electricity consumption will be overestimated, and the inhibition effect of improving efficiency on electricity conservation will be underestimated.

The spatial spillover effect of direct rebound effect for urban residents' electricity consumption can be calculated and tested by using Equation (5). The test results confirm that the direct rebound effect for urban residents' electricity consumption has a significant spatial spillover effect at 1% level, and the spatial spillover effect is 13.30%. That is to say, per 1% decrease in power price due to the increased efficiency in adjacent areas will increase the urban residents' electricity consumption in the local region by 0.133%. Adding RE and SRE together, the total electricity consumption induced by the increased efficiency is 50.30%. The proportion of RE is 73.56%, and the proportion of SRE is 26.44%.

The calculating results above show that if the spatial dependence in urban residents' electricity consumption is not considered, the direct rebound effect and its spatial spillover effect will be confused. Due to the spatial spillover effect, the realization of energy-saving targets in local area depends on the implementation effect of energy efficiency in surrounding areas. Moreover, due to the low spatial spillover effect, direct rebound effect induced by efficiency improvement in the local region is still the main reason affecting the implementation effect of energy efficiency of energy efficiency policies in the local region.

4.5. Robust Test

In addition to the two-part decomposition method adopted above, some studies also adopt a three-part decomposition method. Then the three-part decomposition method is used for a robustness test, shown in the last column of Table 4. The results of the robustness test are consistent with the empirical results above, indicating that the direct rebound effect measurement value for urban residents' electricity consumption is not sensitive to the price decomposition methods.

4.6. Analysis of the Temporal Change of Direct Rebound Effect

In order to investigate the change of direct rebound effect for urban residents' electricity consumption, the coefficient of $\ln P_{dec,it}$ is allowed to change with time. The estimated results are shown in Table 5.

Variable	Coefficient	Variable	Coefficient
Wu	0.318 ***	$\ln P = 2009$	-0.336 *
vvy	(0.000)	nu dec_2009	(0.098)
TA7	-0.419 ***	$\ln P_{\star} = 2010$	-0.332
VV C	(0.002)	nur _{dec_} 2010	(0.105)
ln D	0.472 **	lmD 2011	-0.328
$\ln P_{inc}$	(0.033)	m_{dec}_{2011}	(0.109)
lnDD	0.330 ***	1 D 2012	-0.322
	(0.004)	m_{dec}_{2012}	(0.115)
ln <i>POP</i>	0.539 ***	1 0 0010	-0.315
	(0.001)	$\ln P_{dec} = 2013$	(0.123)
ln <i>I</i>	0.166	1 D 0014	-0.312
	(0.340)	m_{dec}_{2014}	(0.126)
1 0 0000	-0.356 *	L- D 2015	-0.310
$\ln P_{dec} = 2006$	(0.078)	m_{dec}^{2015} (0	(0.130)
$\ln P_{dec}$ _2007	-0.347 *	L-D 2016	-0.309
	(0.086)	m_{dec}_{2016}	(0.133)
1 D 2009	-0.343 *	T T I III I 070 700	
$\ln P_{dec}_{2008}$	(0.091)	Log Likelihood	250.522

Table 5. Estimation results of SARAR fixed-effect model with partial variable coefficients.

Note: The number in parentheses is the level of significance. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

According to Table 5, the calculating results of direct rebound effect for urban residents' electricity consumption in some years are shown in Table 6.

Table 6. Calculation results of direct rebound effect for urban residents' electricity consumption.

Year	2007	2009	2011	2013	2015
RE	35.4% *	34.2% *	33.4%	32.1%	31.6%
	(0.086)	(0.098)	(0.109)	(0.123)	(0.130)

Note: The number in parentheses is the level of significance. * indicates significance levels at 10%.

Table 6 shows that direct rebound effect for urban residents' electricity consumption declined from 2006 to 2009, but the decline is very small. The calculation results of direct rebound effect after 2009 are not significant, indicating that there is no obvious downward trend in direct rebound effect in the short term. The changes of RE, SRE and the total effect (abbreviated as TE) are displayed in Figure 3.



Figure 3. The changes of RE, SRE and TE from 2006 to 2015.

Figure 3 shows that the change characteristics of the three effects are similar, and the decrease range is small. In order to verify this conclusion, the significance of the power price and time interaction term are tested. The test results still cannot reject the null hypothesis at 10% significance level, meaning that the direct rebound effect is fixed over these years, so the direct rebound effect for urban residents' electricity consumption will not decrease currently.

According to Zhang et al. [33], consumers' energy demand tends to be saturated with income growth, and direct rebound effect will decline. However, the empirical test in this paper shows that direct rebound effect for urban residents' electricity consumption in China has not shown a significant downward trend although the urban residents' income has been increasing. The main reason is that China's urbanization rate increased by 1.31% annually from 2006 to 2016, indicating that China's urbanization is large and the process is relatively fast. It has caused the rigidity of electricity demand. In particular, the transfer of rural residents to urban areas will bring a large-scale marginal consumer group. Therefore, the rigidity of electricity demand and the large marginal consumer group will eventually offset the inhibition effect of income growth on the direct rebound effect.

5. Conclusions and Policy Implications

Based on price decomposition methods and spatial econometric models, the calculation method of the direct rebound effect is improved. The panel data of China's urban residents' electricity consumption are used for our empirical analysis. The conclusions are as follows:

First, spatial analysis indicates that there are four types of spatial aggregation in China's urban residents' electricity consumption, and the global spatial correlation has a significant positive value. Studies of the direct rebound effect for urban residents' electricity consumption should not ignore the spatial feedback effect and spatial spillover effect. The improved model can subdivide the calculation results into direct rebound effect and its spatial spillover effect, improving the accuracy and explanatory power of the results. In addition, due to the asymmetric influence of price on demand, the introduction of the price decomposition methods can avoid the upward bias of the calculation results to some extent.

Second, the direct rebound effect for urban residents' electricity consumption in China and its spatial spillover effect are 37.00% and 13.30%, respectively. This shows that although improving the electricity efficiency has induced a direct rebound effect, the direct rebound effect is not serious, and improving efficiency is still an important measure to curb the urban residents' electricity consumption. Moreover, compared with the spatial spillover effect of direct rebound effect, direct rebound effect induced by energy efficiency improvement in the local region is still the main factor affecting the implementation effect of energy efficiency policy in the same region.

Third, direct rebound effect for urban residents' electricity consumption without spatial spillover effects does not show a significant downward trend. The reason is that the rapid urbanization process at the current stage has caused rigid residents' electricity demand and large-scale marginal consumer groups, which offsets the inhibition effect of income growth on the direct rebound effect.

According to the analysis above, the main policy implications are as follows: first, the government must attach importance to the direct rebound effect, and establish a comprehensive, multi-sectoral monitoring system for direct rebound effect, so as to avoid failure of energy efficiency policy caused by serious direct rebound effect. Second, the direct rebound effect is mainly caused by the price effect. The government should promote the marketization of power prices through environmental regulations (such as resource taxes), and reduce the excessive consumption of electricity due to low cost. At the same time, in order to achieve the expected energy-saving goals of energy efficiency policies more effectively, local governments should focus on the synergy of policy formulation and implementation between the local region and adjacent areas.

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Appendix A

There are some equivalent definitions of direct rebound effect, which allows identification of the rebound effect

Firstly, we define the energy efficiency. Energy efficiency at the household level can be expressed as the ratio of energy services to energy inputs:

$$\varepsilon = S/E$$
 (A1)

where ε , *S*, and *E* denote the energy efficiency, energy services and energy inputs, respectively.

Definition A1.

Direct rebound = (expected savings – actual savings)/expected savings (A2)

- If the energy efficiency improvement does not lead to an increase in energy services, the actual savings are equal to the expected savings, so the direct rebound effect is equal to zero.
- However, energy efficiency improvement means that real energy service cost is reduced, and consumers will increase energy services. Therefore, the actual savings are less than the expected savings, and the direct rebound effect is greater than zero.
- If the increase of energy service caused by the decrease of real energy service cost is greater than the expected savings, the actual savings are less than zero, and the direct rebound effect is greater than 100%, which is called backfire effect.

Since it is difficult to distinguish between actual savings and expected savings, Definition A1 is rarely used for empirical research.

Definition A2.

$$DR = 1 + \eta_{\varepsilon}^{E} \tag{A3}$$

where DR represents direct rebound and η_{ε}^{E} represents the elasticity of energy demand with respect to efficiency. Definitions A1 and A2 are equivalent, and we explain in detail below.

Equation (A1) can be rewritten as:

$$S = \varepsilon E$$
 (A4)

Total differentiation of Equation (A4) after applying natural logarithms is:

$$\frac{\mathrm{d}S}{S} = \frac{\mathrm{d}E}{E} + \frac{\mathrm{d}\varepsilon}{\varepsilon} \tag{A5}$$

If energy efficiency improvement does not result in an increase in energy services, then dS = 0. Equation (A5) is simplified to:

$$\frac{\mathrm{d}E}{E} = -\frac{\mathrm{d}\varepsilon}{\varepsilon} \tag{A6}$$

then:

$$\eta_{\varepsilon}^{E} = \frac{\mathrm{d}E}{\mathrm{d}\varepsilon}\frac{\varepsilon}{E} = -1 \tag{A7}$$

- The above analysis shows that if energy efficiency improvement does not lead to an increase in energy services, the proportion of energy demand reduction is the same as the proportion of energy efficiency improvement. That is to say, η^E_ε = −1. So, the direct rebound effect is equal to zero.
- However, energy efficiency improvement means that real energy service cost is reduced, and consumers will increase energy services. Therefore, dS > 0 and η^E_ε > −1. So the direct rebound effect is greater than zero.
- If the increase of energy service caused by the decrease of real energy service cost is greater than the expected savings, η^E_ε > 0, and the direct rebound effect is greater than 100%, which is called backfire effect.

Energy efficiency at the household level is often unobservable, so Definition A2 is also rarely used for empirical research.

Definition A3.

$$DR = -\eta^E_{P_r} \tag{A8}$$

where $\eta_{P_F}^E$ represents the elasticity of energy demand with respect to energy price.

Equation (A8) is equivalent to Equation (A3), and the derivation process of Equation (A8) will be described in detail below.

According to Equation (A1), the relationship between energy service price (or energy service cost) and energy price (or energy cost) is:

$$P_S = P_E / \varepsilon \tag{A9}$$

where P_S represents energy service price and P_E represents energy price.

Combined with Equations (A1), and (A9), Equation (A3) can be rewritten as:

$$DR = 1 + \eta_{\varepsilon}^{E} = 1 + \frac{\partial \ln E}{\partial \ln \varepsilon} = 1 + \frac{\partial \ln(S/\varepsilon)}{\partial \ln \varepsilon} = 1 + \left(\frac{\partial \ln S}{\partial \ln \varepsilon} - 1\right) = \frac{\partial \ln S}{\partial \ln P_{S}} \frac{\partial \ln P_{S}}{\partial \ln \varepsilon} = \frac{\partial \ln S}{\partial \ln P_{S}} \frac{\partial \ln(P_{E}/\varepsilon)}{\partial \ln \varepsilon} = \frac{\partial \ln S}{\partial \ln P_{S}} \left(\frac{\partial \ln P_{E}}{\partial \ln \varepsilon} - 1\right)$$
(A10)

Because nominal energy prices are not affected by energy efficiency, therefore $\partial \ln P_E / \partial \ln \varepsilon = 0$. Equation (A10) is simplified to:

$$DR = -\frac{\partial \ln S}{\partial \ln P_S} = -\frac{\partial S}{\partial P_S} \frac{P_S}{S} = -\eta_{P_S}^S$$
(A11)

where $\eta_{P_S}^S$ represents the elasticity of energy service demand with respect to energy service price. Combined with Equations (A1), and (A9), $\eta_{P_S}^S$ can be rewritten as:

$$\eta_{P_{S}}^{S} = \frac{\partial \ln S}{\partial \ln P_{S}} = \frac{\partial \ln S}{\partial \ln P_{E}} \frac{\partial \ln P_{E}}{\partial \ln P_{S}} = \frac{\partial \ln(\varepsilon E)}{\partial \ln P_{E}} \frac{\partial \ln(\varepsilon P_{S})}{\partial \ln P_{S}} \\ = \left(\frac{\partial \ln \varepsilon}{\partial \ln P_{E}} + \frac{\partial \ln E}{\partial \ln P_{E}}\right) \left(\frac{\partial \ln \varepsilon}{\partial \ln P_{S}} + \frac{\partial \ln P_{S}}{\partial \ln P_{S}}\right)$$
(A12)

Assuming that energy efficiency is exogenous, then $\frac{\partial \ln \varepsilon}{\partial \ln P_E} = 0$ and $\frac{\partial \ln \varepsilon}{\partial \ln P_S} = 0$. Equation (A12) is simplified to:

$$\eta_{P_S}^S = \left(0 + \frac{\partial \ln E}{\partial \ln P_E}\right)(0+1) = \frac{\partial \ln E}{\partial \ln P_E} = \eta_{P_E}^E$$
(A13)

The electricity efficiency here mainly refers to energy efficiency ratio of household appliances, which is usually determined by the technical level of the manufacturer. Consumers can only improve the utilization efficiency of household appliances. In fact, some researches point out that higher efficiency may only be achieved by purchasing more expensive new equipment in China, so the electricity efficiency is exogenous.

Combined with Equations (A10), (A11) and (A13), Equation (A3) can be rewritten as:

$$DR = 1 + \eta_{\varepsilon}^{E} = -\eta_{P_{E}}^{E}$$
(A14)

Equation (A14) indicates that the price elasticity could be an ideal proxy indicator of direct rebound effect with other variables controlled.

Definition A3 allows identification of the rebound effect. Due to the ease of data acquisition, most empirical studies have adopted Definition A3.

The above analysis shows that the direct rebound effect is mainly related to the falling of real energy price induced by improvement in energy efficiency. However, the power price has both rising and falling periods in the real economy, and the impact of rising and falling price on the electricity demand is not completely reversible. Generally, price elasticity during price rise period is greater than during the price decline period. Direct use of Definition A3 will overestimate the direct rebound effect, and it is necessary to decompose the price, so the price decomposition method is not used to identify the rebound effect. However, it is introduced to improve the accuracy of measurement results.

References

- 1. Statistical Review of World Energy. 2017. Available online: https://www.bp.com/en/global/corporate/energy-economics.html (accessed on 28 April 2019).
- 2. Lin, M. The clean energy consumption, environment governance and the sustainable economic growth in China. *J. Quant. Tech. Econ.* **2017**, *12*, 4–22.
- 3. Berkhout, P.H.G.; Muskens, J.C.; Velthuijsen, J.W. Defining the rebound effect. *Energy Policy* **2000**, *28*, 425–432. [CrossRef]
- 4. Haas, R.; Biermayr, P. The rebound effect for space heating empirical evidence from Austria. *Energy Policy* **2000**, *28*, 403–410. [CrossRef]
- Madlener, R.; Alcott, B. Energy rebound and economic growth: A review of the main issues and research needs. *Energy* 2009, 34, 370–376. [CrossRef]
- 6. Van den Bergh, J.C. Energy conservation more effective with rebound policy. *Environ. Resour. Econ.* **2011**, *48*, 43–58. [CrossRef]
- 7. Llorca, M.; Jamasb, T. Energy efficiency and rebound effect in European road freight transport. *Transp. Res. Part A Policy Pract.* **2017**, *101*, 98–110. [CrossRef]
- 8. Wei, T. Impact of energy efficiency gains on output and energy use with Cobb–Douglas production function. *Energy Policy* **2007**, *35*, 2023–2030. [CrossRef]
- 9. Wei, T.; Liu, Y. Estimation of resource-specific technological change. *Technol. Forecast. Soc. Chang.* **2019**, *138*, 29–33. [CrossRef]
- 10. Wei, T.; Zhou, J.; Zhang, H. Rebound effect of energy intensity reduction on energy consumption. *Resour. Conserv. Recycl.* **2019**, *144*, 233–239. [CrossRef]
- 11. Saunders, H.D. Fuel conserving (and using) production functions. *Energy Econ.* **2008**, *30*, 2184–2235. [CrossRef]
- 12. Saunders, H. Is what we think of as "rebound" really just income effects in disguise? *Energy Policy* **2013**, *57*, 308–317. [CrossRef]
- 13. Brockway, P.; Saunders, H.; Heun, M.; Foxon, T.; Steinberger, J.; Barrett, J.; Sorrell, S. Energy rebound as a potential threat to a low-carbon future: Findings from a new exergy-based national-level rebound approach. *Energies* **2017**, *10*, 51. [CrossRef]
- 14. Freire-González, J. Methods to empirically estimate direct and indirect rebound effect of energy-saving technological changes in households. *Ecol. Model.* **2011**, *223*, 32–40. [CrossRef]
- 15. Freire-González, J. A new way to estimate the direct and indirect rebound effect and other rebound indicators. *Energy* **2017**, *128*, 394–402. [CrossRef]
- 16. Freire-González, J. Evidence of direct and indirect rebound effect in households in eu-27 countries. *Energy Policy* **2017**, *102*, 270–276. [CrossRef]
- 17. Graham, D.J.; Glaister, S. Road traffic demand electricity estimates: A review. *Transp. Rev.* **2004**, *24*, 261–274. [CrossRef]
- Wang, Z.; Lu, M. An empirical study of direct rebound effect for road freight transport in China. *Appl. Energy* 2014, 133, 274–281. [CrossRef]
- 19. Winebrake, J.J.; Green, E.H.; Comer, B.; Li, C.; Froman, S.; Shelby, M. Fuel price elasticities in the U.S. combination trucking sector. *Transp. Res. Part D* 2015, *38*, 166–177. [CrossRef]
- 20. Stapleton, L.; Sorrell, S.; Schwanen, T. Estimating direct rebound effects for personal automotive travel in Great Britain. *Energy Econ.* **2016**, *54*, 313–325. [CrossRef]
- 21. Moshiri, S.; Aliyev, K. Rebound effect of efficiency improvement in passenger cars on gasoline consumption in Canada. *Ecol. Econ.* 2017, *131*, 330–341. [CrossRef]
- 22. Sorrell, S.; Stapleton, L. Rebound effects in UK road freight transport. *Transp. Res. Part D Transp. Environ.* **2018**, *63*, 156–174. [CrossRef]
- 23. Nesbakken, R. Energy consumption for space heating: A discrete–continuous approach. *Scand. J. Econ.* **2001**, 103, 165–184. [CrossRef]
- 24. Schwarz, P.M.; Taylor, T.N. Cold hands, warm hearth: Climate, net takeback, and household comfort. *Energy J.* **1995**, *16*, 41–54. [CrossRef]
- 25. Jin, S.H. The effectiveness of energy efficiency improvement in a developing country: Rebound effect of residential electricity use in South Korea. *Energy Policy* **2007**, *35*, 5622–5629. [CrossRef]

- 26. Davis, L.W. Durable goods and residential demand for energy and water: Evidence from a field trial. *Rand J. Econ.* **2008**, *39*, 530–546. [CrossRef]
- 27. Lin, B.; Liu, X. Electricity tariff reform and rebound effect of residential electricity consumption in China. *Energy* **2013**, *59*, 240–247. [CrossRef]
- 28. Wang, Z.; Lu, M.; Wang, J.C. Direct rebound effect on urban residential electricity use: An empirical study in China. *Renew. Sustain. Energy Rev.* **2014**, *30*, 124–132. [CrossRef]
- 29. Lin, B.; Liu, H. A study on the energy rebound effect of China's residential building energy efficiency. *Energy Build.* **2015**, *86*, 608–618. [CrossRef]
- 30. Labidi, E.; Abdessalem, T. An econometric analysis of the household direct rebound effects for electricity consumption in Tunisia. *Energy Strategy Rev.* **2018**, *19*, 7–18. [CrossRef]
- 31. Sorrell, S.; Dimitropoulos, J.; Sommerville, M. Empirical estimates of the direct rebound effect: A review. *Energy Policy* **2009**, *37*, 1356–1371. [CrossRef]
- 32. Ouyang, J.; Long, E.; Hokao, K. Rebound effect in Chinese household energy efficiency and solution for mitigating it. *Energy* **2010**, *35*, 5269–5276. [CrossRef]
- 33. Zhang, Y.J.; Peng, H.R. Exploring the direct rebound effect of residential electricity consumption: An empirical study in China. *Appl. Energy* **2017**, *196*, 132–141. [CrossRef]
- 34. Hymel, K.M.; Small, K.A. The rebound effect for automobile travel: Asymmetric response to price changes and novel features of the 2000s. *Energy Econ.* **2015**, *49*, 93–103. [CrossRef]
- 35. Greening, L.A.; Greene, D.L.; Difiglio, C. Energy efficiency and consumption-the rebound effect-a survey. *Energy Policy* **2007**, *28*, 389–401. [CrossRef]
- 36. Liu, M.; Zhao, Y.Y. Measurement and empirical study of spatial spillover effects of Chinese manufacturing industry based on input factors. *J. Appl. Stat. Manag.* **2018**, *37*, 122–134.
- 37. Carli, R.; Dotoli, M. Cooperative distributed control for the energy scheduling of smart homes with shared energy storage and renewable energy source. *IFAC-PapersOnLine* **2017**, *50*, 8867–8872. [CrossRef]
- 38. Chapman, A.C.; Verbic, G.; Hill, D.J. Algorithmic and strategic aspects to integrating demand-side aggregation and energy management methods. *IEEE Trans. Smart Grid* **2016**, *7*, 1–13. [CrossRef]
- 39. Sorrell, S.; Dimitropoulos, J. The rebound effect: Microeconomic definitions, limitations and extensions. *Ecol. Econ.* **2008**, *65*, 636–649. [CrossRef]
- 40. Lesage, J.P.; Pace, R.K. Introduction to Spatial Econometrics; CRC Press: Boca Raton, FL, USA, 2009.
- 41. Lee, L.F.; Yu, J.H. Estimation of spatial autoregressive panel data models with fixed effects. *J. Econom.* **2010**, 154, 165–185. [CrossRef]



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