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Abstract:

China's residential electricity demand has grown rapidly over the last three decades and given the expected continued growth, demand side management (DSM) can play an important role in reducing electricity demand. By using micro-level data collected from 1450 households in 27 provinces in the first-ever China Residential Energy Consumption Survey in 2012, this study uses empirical analysis to estimate the effects of three DSM measures: tiered household electricity pricing, China Energy Label program, and information feedback mechanisms. We find these measures have contributed to moderating residential electricity demand growth but additional policy reform and tools are needed to increase their effectiveness and impact. Residential electricity demand is found to be price- and income- inelastic and tiered pricing alone may not be as effective in electricity conservation. The statistically significant relationship between China Energy Label efficient refrigerators - but not televisions - and lowered residential electricity consumption reflect mixed program effectiveness. Lastly, of the information feedback currently available through electricity bills, payment frequency and meters, only meter reader is estimated to be statistically significant. Important policy implications and recommendations for changing each of these three DSM measures to expand their impact on reducing residential electricity consumption are identified.

Keywords:

Residential electricity demand management; Tiered pricing; China Energy Label; Information feedback

1. Introduction

In line with rapid economic growth, rising household incomes, and the acceleration of urbanization, residential electricity consumption in China has increased tremendously over the past four decades. China's residential electricity consumption has increased from only 48 billion kWh in 1990 to 718 billion kWh in 2014 (NBS, 2015), but its 2014 share of 12.7% in total electricity consumption is much lower than other developed countries[1]. Residential electricity consumption is expected to continue growing with further economic growth because electricity consumption and GDP growth exhibit a positive long-run causal relationship (Shiu and Lam, 2004; Yuan et al., 2007). In Hu et al. (2013)'s outlook of economic development and elecricity demand in China, total residential electricity demand could reach 2129 TWh in 2030 under a baseline scenario. By 2050, residential electricity demand could reach 4161 TWh – nearly the equivalent of China's 2012 total national electricity consumption.

Rapidly growing residential electricity demand poses a challenge for China as it strives to meet its national short- and long-term energy and CO_2 emissions intensity reduction targets and goals. According to the *Energy Development Strategy Action Plan (2014-2020)* (State Council, 2014), China plans to cap its annual energy use to 5.0 billion tonnes of coal equivalent (Btce[2]) and cap its annual coal use to 4.2 billion tonnes of coal in 2020, respectively. Additionally, China will lower its national CO_2 intensity by 60% to 65% from the 2005 level by 2030 (NDRC, 2015). Electricity demand growth could make it difficult for China to meet its CO_2 emissions targets, given that coal currently accounts for 76% of electricity generated (NBS, 2015). While China has adopted various supply-side policies to reduce CO_2 emissions from the power sector, including non-fossil targets and the recently announced green

[1] Residential electricity consumption was 35.9% of total electricity consumption in the United States (U.S.) (EIA, 2015) and average of 29.6% in 28 European Union (EU) countries (Eurostat, 2015).
[2] Million tonnes of coal equivalent (Mtce) is the standard unit for energy in China. 1 Mtce = 29.27 million GJ.

dispatch directive, demand-side policies are nevertheless a crucial component to moderating electricity demand growth.

As a supplement to supply-side policies, power sector Demand Side Management (DSM) policies and measures is receiving greater attention for its potential in controlling electricity demand. Price policy, among these tools, has a particularly important role to play in promoting energy conservation and energy efficiency. The implementation of tiered pricing for household electricity use (TPHE) started on July 1, 2012 (NDRC, 2011). Two other important DSM tools are energy information labeling for residential appliances and information feedback mechanisms. Both of these tools aim to overcome key information barriers to energy efficiency and conservation by increasing consumers' understanding and knowledge of cost-saving energy efficiency opportunities and behaviors. These information tools have been adopted in numerous countries around the world, including the U.S., Canada, EU members, Japan, Korean, and Australia and credited with effectively reducing electricity demand and CO_2 emissions (APERC, 2012; Bekker et al., 2010; Carroll et al., 2014; Ellis, 2007; Fischer, 2008; Khanna et al., 2013; McNeil et al., 2008; Mizobuchi and Takeuchi, 2013; Schultz et al., 2007; UNDESA, 2007; Wiel and McMahon, 2003; Zhou et al., 2011b). For China, however, both types of information DSM tools are relatively new and their actual effectiveness on slowing residential electricity demand have not been proven.

This study uses the dataset from the first-ever China Residential Energy Consumption Survey (CRECS) conducted in 2012 (Zheng et al., 2014) to conduct an empirical evaluation of the estimated impact of DSM policies and programs on Chinese residential electricity demand. We contribute to the existing literature in two main aspects. First, compared to regional electricity consumption studies (Feng et al., 2010; Shi et al., 2012; Zhou and Teng, 2013), we use a robust set of nationwide micro-level household level data collected from 1450 households across 27 provinces to provide empirical analysis of the quantity, expenditure, billing, and even consumption structure of household electricity demand, and the socio-economic, demographic and geographical characteristics that impact energy usage patterns.

Second, using this unique data set and rigorous econometric analysis, we are able to evaluate the actual effectiveness of three kinds of DSM measures, specifically TPHE, China Energy Label program, and electricity consumption information feedback, rather that only one unique policy as has been done in other recent studies (Du et al., 2015; Khanna et al., 2013; Lin and Jiang, 2012; Sun, 2015; Sun and Lin, 2013; Zeng et al., 2014). The empirical findings of this study provide important policy implications for policymakers, and can inform the design and improvement of policies and measures to further energy market reform.

The rest of the paper is organized as follows. Section 2 reviews literature on tiered pricing system, the China Energy Label program and information feedback. Section 3 introduces the empirical methods, China's national and surveyed data, and the residential electricity demand model. Section 4 presents the empirical results and policy discussion for the three DSM measures, followed by Section 5 on overall conclusions and policy implications.

2. Literature Review

2.1 TPHE

The application of increasing block tariffs (IBTs) is widespread in the water and electricity sectors as a solution to address social equity, cost recovery, energy efficiency, and environmental concerns (Bar-Shira et al., 2005; Borenstein, 2008, 2010, 2012; Fankhauser and Tepic, 2006; Filipovic and Tanic, 2009; Lin and Liu, 2013; Sun, 2015; Sun and Lin, 2013). Many regions began implementing IBTs around the world after national or regional energy crises, including the global Oil Crisis in 1973. In the U.S., for example, the state of California adopted increasing block electricity tariffs with two-tiered block residential rate structures in the 1980s and then changed to a five-tier increasing block electricity price after the California electricity crisis in the early 2000s (Borenstein, 2008). Japan, Korea and Malaysia also implemented IBTs in the residential sector with three-tier and six-tier tariff rate structures, respectively (Huang et al., 2012; Li and Yu, 2010). Four- and six-tier increasing block electricity tariffs are also in use in the Hong Kong area by two power companies (Zhuang, 2014), while Taiwan has had six-tier IBT since 2007 (Hung and Huang, 2015). China began implementing its TPHE on July 1, 2012 with household electricity prices set in three tiers based on the volume of electricity consumption by provincial governments (Du et al., 2015).

The effects of IBTs on energy and CO_2 emissions reduction are usually evaluated through consumers' responsiveness to energy demand given the price change. In general, residents in higher tiers of electricity consumption would be more responsive to price change under the IBTs and incentivized to reduce their consumption while the lower-tier residents benefit from price subsidies and can consume more. The combined impact is expected reduction in total electricity consumption and energy-related CO_2 emissions (Bar-Shira et al., 2005; Dalhuisen et al., 2003; Davoudpour and Ahadi, 2006; Du et al., 2015; Sun, 2015; Sun and Lin, 2013). Sun (2015) demonstrated that the current TPHE scheme in China effectively incentivizes consumers to reduce electricity consumption and reduced the distortion of cross-subsidies in electricity tariffs in China by a linear probability model. However, Ito (2010) found that electricity reductions in the higher tier was less than the electricity increase in the lower tier in California during its transition from uniform pricing to the current nonlinear rate schedule, resulting in a slight net increase in aggregate electricity consumption.

Instead of considering the aggregated impact of TPHE, this study reexamines the positive effects of TPHE by separating the urban residential sample into three blocks and used statistical tests rather than regression to avoid the bidirectional causality relationship between electricity consumption and tiered pricing.

2.2 China Energy Label

On March 1, 2005, China established the China Energy Label, a national mandatory energy information label, for refrigerators and room air conditioners. This categorical label ranks a specific product between the Grades of 1-5 (or 1-3 for some products) based on its efficiency compared to other similar product models, with Grade 1 designating the most efficient products and Grade 5 (or Grade 3 for some products) designating least efficient products that only meet the minimum energy efficiency standard. The China Energy Label program now covers 33 products, including most major household appliances, such as television sets, refrigerators, monitors, washing machines, and water heaters.

By providing consumers with more information to identify and compare the energy efficiency of similar product models in their purchase decision-making, the China Energy Label is intended to accelerate market adoption of more efficient products and transform the market towards higher energy efficiency products (Khanna et al., 2013). From 2009 to 2012, the national government also introduced subsidies to promote the purchase of designated energy efficient products with a qualifying China Energy Label efficiency grade. These subsidies have had a significant impact on increasing the purchase of more efficient products such as room air conditioners, with the market share of efficient (i.e. Grade 1 and 2) products rising from 5% in 2008 to 80% in May 2010 (Zhan et al., 2011). Besides promoting efficiency improvements in residential electricity use, the China Energy Label program is also expected to improve consumer welfare, national economic efficiency, and contribute towards national progress in achieving other economic (e.g. competiveness and market transformation), environmental and climate change goals (e.g. emission reduction), even in the long-term (APERC, 2012; Ellis, 2007; Khanna et al., 2013; McNeil et al., 2008; UNDESA, 2007; Wiel and McMahon, 2003; Zhou et al., 2011b).

Previous studies have evaluated the potential energy and CO_2 emissions impacts of the China Energy Label program, but assumed full implementation and 100% effectiveness in the absence of empirical data (Zhou et al. 2011). Other studies have shown that there are real implementation challenges to the China Energy Label program based on results from pilot testing and surveys, including uneven local enforcement of labeling requirements and energy performance validation (Khanna et al. 2013) and mixed consumer awareness and understanding despite the prevalent national subsidy program for efficient appliances (Zeng et al., 2014). This study uses the 2012 CRECS dataset to address the previous data constraints that have limited empirical analyses of the effectiveness of the China Energy Label program as a DSM measure.

2.3 Information Feedback

Information feedback (including detailed electricity bills, payment frequency, or meter type) is considered to be another important tool for DSM. Information feedback can be instrumental in reducing household electricity consumption through several channels, including potentially affecting habitual behavior, such as turning off lights or unplugging appliances (Bekker et al., 2010; Jacucci et al., 2009), and influencing appliance purchasing decision-making in terms of replacing energy-intensive appliances with more efficient ones (Fischer, 2008). Information feedback can also to be regarded as a reminder. Gans et al. (2013) found that the replacement of prepayment meters with advanced meters that allow the consumer to track usage in real time in Northern Ireland is associated with 11-17% decline in electricity consumption. Carroll et al. (2014) found that participation in a smart metering program in Ireland with time-of-use tariff significantly reduces electricity demand. In contrast, Hargreaves et al. (2013) found that the smart energy monitor device in the United Kingdom increased residents' knowledge, but did not necessarily motivate householders to reduce their electricity consumption. Studies have also found adding in comparative information component with social norm to be more effective (Fischer, 2008; Mizobuchi and Takeuchi, 2013; Schultz et al., 2007). Darby (2006) suggested that sometimes people need help in interpreting their feedback and in deciding what courses of action to take. Schleich et al. (2013) analyzed the effects of providing feedback on electricity consumption in a field trial involving more than 1500 households in Austria. Their results indicated that information feedback on electricity conservation is statistically significant only for households in the 30th to the 70th percentile of electricity consumption.

Few studies have focused on residential electricity savings in China using household survey data, and none have focused specifically on information feedback. Feng et al. (2010) investigated the barriers to energy efficiency in the residential sector based on a survey questionnaire covering more than 600 households in Liaoning province China. This study will fill a major research gap of using micro-level household data to estimate the effectiveness of three key residential electricity demand management measures.

3. Methods

3.1. Residential Electricity Demand Data

The CRECS survey was administrated by the Department of Energy Economics at Renmin University of China during February 2013. The questionnaire covered six main areas: household demographics, dwelling characteristics, household appliances, space heating and cooling, patterns of private transportation, and electricity billing, metering, and pricing options. We collected detailed energy-related information, such as appliance type, frequency and duration of device use, different types of energy costs, and electricity bill information. After validity and consistency checks, 1450 total observations in 27 provinces remained (Fig.1). More background and details of the CRECS can be found in Zheng et al. (2014).

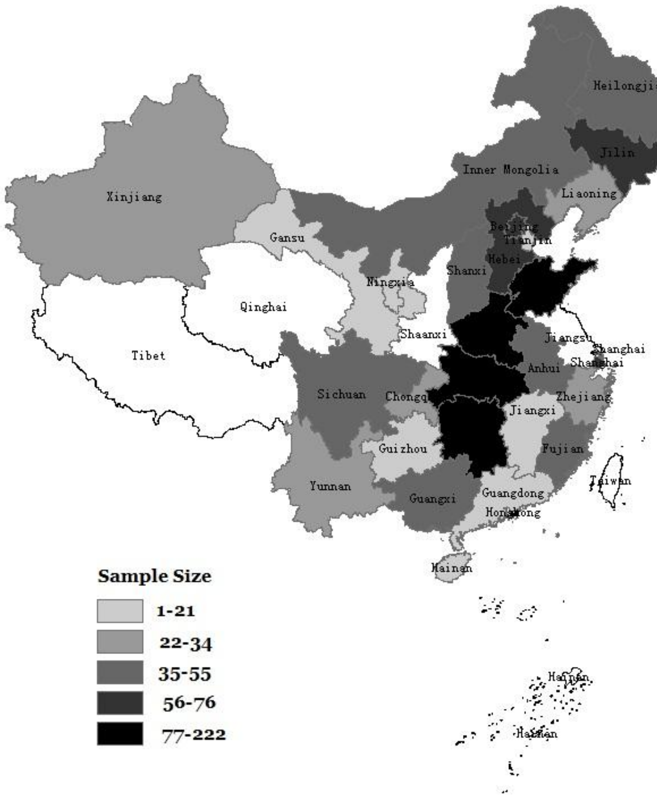


Fig.1 Regional distribution of surveyed households.

The survey results found that electricity accounts for 15% of the total energy supply and are used for diverse purposes, such as powering household appliances (including lighting), cooking, cooling, and water heating. The composition of household electricity consumption by end-use is presented in Fig.2. Electricity is primarily used for household appliances, which accounts for 46.6% of total electricity end use, followed by cooking (23.3%), space cooling (12.8%) and water heating (12.3%). Only 5.0% of total electricity consumption is used for space heating.

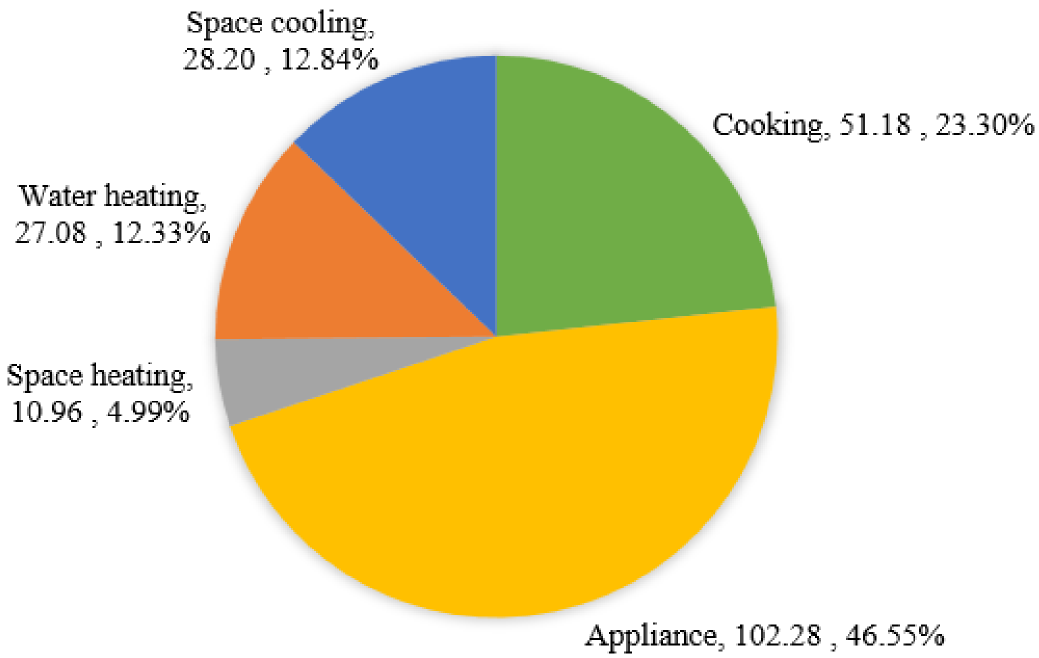


Fig.2 Composition of nationwide household electricity consumption

Household appliances are the most important electricity end-use and urbanization and income growth would both lead to greater household appliance ownership (Auffhammer and Wolfram, 2014; O'Neill et al., 2012; Wolfram et al., 2012; Zhou et al., 2011a). Fig.3 shows the ownership of some durable household appliances per 100 urban households by level of income in 2012: as expected, the higher the income level, the higher the ownership rate. This is especially true for air conditioners: ownership increases from 52.5 sets per 100 households for the lowest income households to 223.6 sets per 100 households for the highest income households.

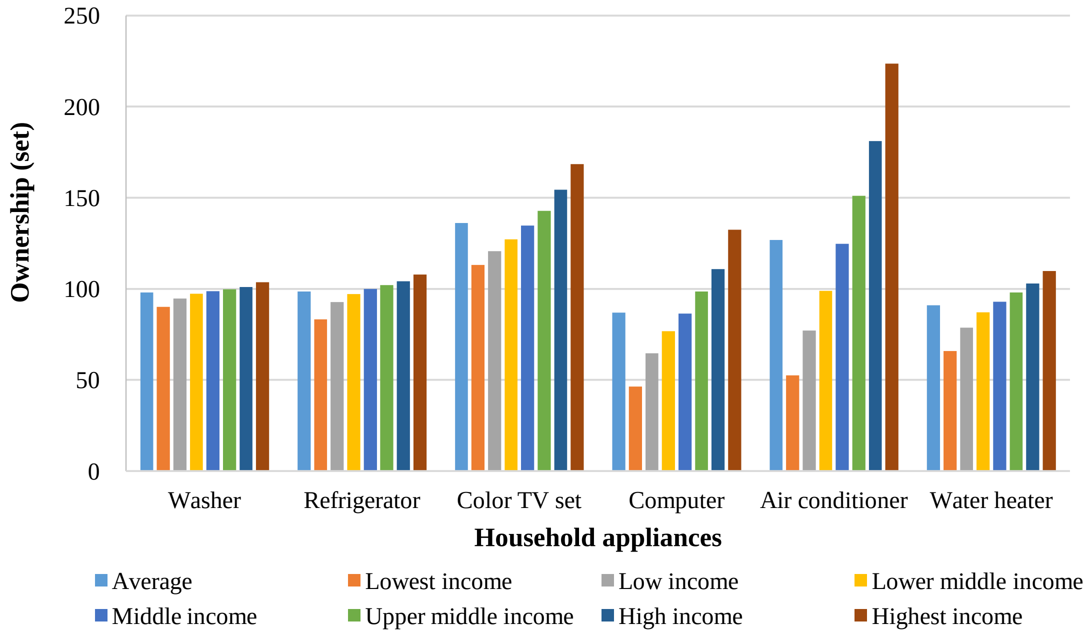
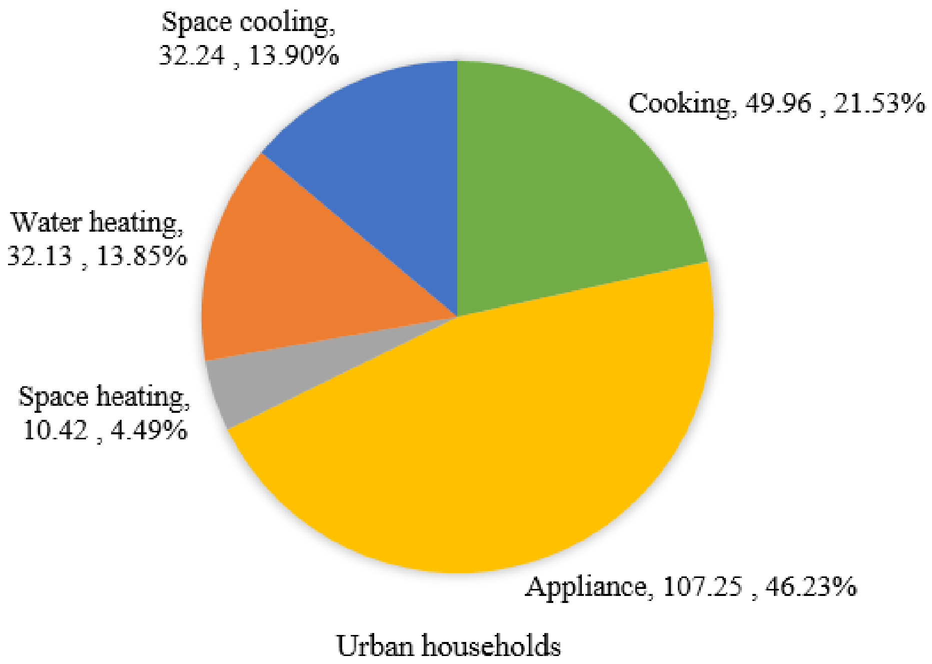


Fig.3 Ownership of durable household appliances per 100 urban households by income level (2012)

Source: *China Statistical Yearbook, 2014*

The survey results show a notable gap in residential electricity consumption between urban and rural areas. The electricity consumption of urban households is about 1.4 times that of rural households in 2012, with absolute value of 1888 kWh/household/year and 1375 kWh/household/year, respectively. The composition of urban versus rural household electricity consumption from the survey results is presented in Fig.4. Household appliances still consume most of the electricity used by both urban and rural households, with shares of 46.2% and 48.7%, respectively. This is followed by cooking, which has a higher share of 33.2% of total electricity consumption in rural households. Electricity used in water heating, space heating and space cooling are very different across urban and rural households. Electricity used for water heating and space cooling in urban households are more than twice that of rural households, which tend to rely more on LPG and solar. Since district heating is not accessible in most rural regions, electricity used for space heating in rural households is 7.9% of total electricity consumed, which is much higher than in urban regions.



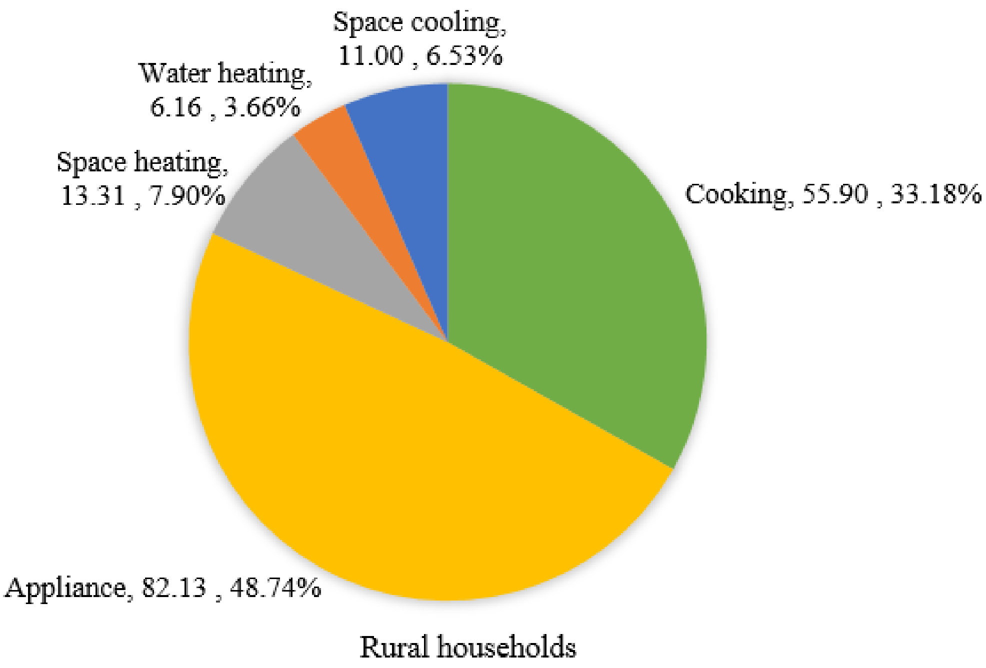


Fig.4 Composition of household electricity consumption in urban and rural area

The ownership rates of household appliances are also very different between urban and rural households. Fig.5 shows the nationally reported ownership of some durable household appliances per 100 urban households from 1990-2012. Urban ownership of color televisions and air conditioner increased rapidly from 1990-2012, reaching ownership rates of 136.1% and 126.8%, respectively. In urban areas, washing machines and refrigerators have reached market saturation, with ownership rates rising from 78.4% and 42.3%, respectively, in 1990 to relatively stable levels of 98.0% and 98.5%, respectively, in 2012. The urban ownership rates of computers and water heaters are still relatively low, and growth in ownership has slowed in the last few years.

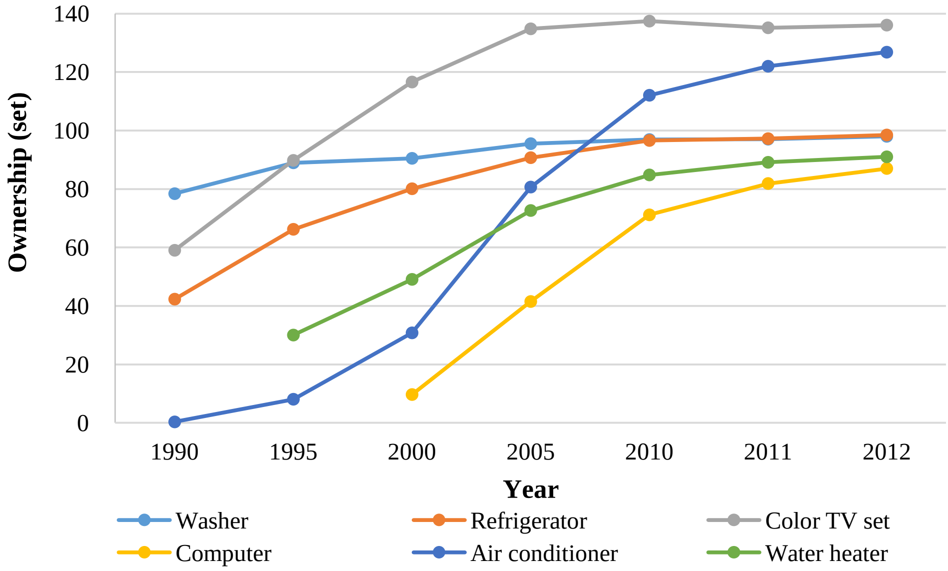


Fig.5 Ownership of durable household appliances per 100 urban households

Source: *China Statistical Yearbook, 2014*

Compared with urban households, rural ownership rates of household appliances are much lower, representing a time lag in appliance ownership growth. Fig.6 shows the ownership of some durable household appliances per 100 rural households from 1990-2012. The ownership rates of washing machine and refrigerator increased from 9.1% and 1.2% in 1990 to 67.2% and 67.3% in 2012, respectively, but remain below saturation. Similarly, rural ownership rates of computer and air conditioner were only 0.5% and 1.3% in 2000, and rural ownership rates were still only about 1/5 of the urban ownership rates for these two products in 2012. The one exception is the ownership of color televisions, which have grown dramatically from 4.7% in 1990 to 116.9% in 2012.

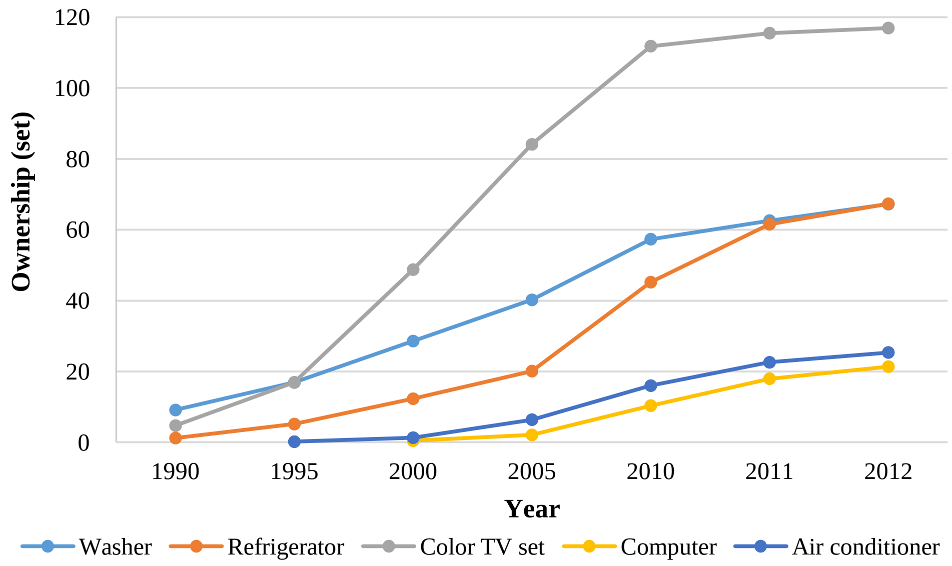


Fig.6 Ownership of durable household appliances per 100 rural households

Source: *China Statistical Yearbook, 2014*

Residential electricity consumption in China grew at an average growth rate of 11.9% during 1990-2014 (NBS, 2015). Three patterns of Chinese residential electricity demand can be observed from national statistics and CRECS survey data: (i) Household appliances are the most important end-use purpose, in both urban and rural households. (ii) Household appliances ownership will increase as household income grows, which will increase electricity consumption. (iii) There is a big gap in electricity consumption between urban and rural households, suggesting that urbanization will continue to sustain residential electricity demand growth.

3.2 Electricity Demand Model

This study uses the classical electricity demand specification in log-log function form that is given as follows (Alberini and Filippini, 2011; Filippini and Pachauri, 2004; Terza, 1986):

$$\ln(Ele_i) = \alpha + \beta_1 \ln(income_i) + \beta_2 \ln(price\_ele_i) + \beta_3 \ln(price\_gas_i) + \gamma X_i + \varepsilon_i$$

where dependent variable ***ln(Ele$_i$)*** is the electricity consumption of the *i*-th household measured in kWh. It is estimated according to the reported home appliance, capacity power, usage frequency, energy efficiency label and other technology characteristics. The detailed estimation procedure can be found in Zheng et al. (2014). The mean value is 1795 kWh/household/year, with the median value of 1477 kWh/household/year.

The first category of independent variables are household's disposable income (***ln(income$_i$)***), electricity price (***ln(price_ele$_i$)***) and gas price (***ln(price_gas$_i$)***), which are all in logarithmic form. The coefficients indicate income elasticity, own price electicity and cross price elasticity of residential electricity demand, repectively. From the survey results, the household's annual disposable income ranges from 5,000 Yuan to 3,500,000 Yuan, with a mean value of 98,891 Yuan and median value of 65,000 Yuan. The income elasticity is expected to be positive, indicating an increase in disposable income would lead to an increase in electricity demand.

The price of electricity is a key component of electricity consumption behavior. In the utility-maximizing framework, the theory assumes consumer responses to marginal electricity price but in reality, people tend to respond to average price differently for various reasons, such as incomprehensible price-setting and information barriers (Ito, 2010; Ito, 2014). Limited by data availability, we cannot obtain the actual marginal electricity price at a micro-level. We choose a reported average price as a proxy variable. The quantity of and expenditure on household electricity consumption is obtained from the survey results directly. As in Filippini and Pachauri (2004), the average electricity price is determined from the sample data as unit values, or in other words, monetary expenditures divided by physical quantities of consumption. A potential endogeneity problem created by bidirectional relation between demand and price can be mitigated by the absence of perfect market mechanisms and low awareness of nonlinear price structure in China. Without the TPHE, the electricity price is state-administered and residential electricity consumption is subsidized by industrial consumption which leads to a lower residential electricity price (Lin and Jiang, 2012). After the implementation of TPHE, only 448 households (31%) know the actually implemented TPHE in our surveyed sample. In addition, the schemes of TPHE are designed by provincial governments (Du et al., 2015). The presence of many different pricing levels and schemes at different regions in China also help weaken the endogeneity problem (Shin, 1985).

The average electricity price ranges from 0.32 yuan/kWh to 0.80 yuan/kWh, with the mean value of 0.53 yuan/kWh and the median value of 0.55 yuan/kWh. The price elasticity is expected to be negative for normal good such as electricity, indicating that an increase in price would lead to a decrease in electricity demand.

Since electricity is not the only energy source for a household, electricity demand can also be influenced by the price of other alternative fuels. Besides electricity, natural gas is another alternative fuel source, accounting for 17.8% of total energy consumption in our sample. There are 767 households (52.9% of total sample) that use both electricity and natural gas. Therefore, the price of natural gas is included in the estimation of the demand function and also included in the model in order to test the hypothesis of whether natural gas is complementary to or substitutes for electricity. The natural gas price is obtained from the *China Urban Life and Price Yearbook* (NBS, 2012) for large cities and matched to surveyed households by cities. Natural gas price ranges from 1.37 yuan/m^3 to 5.93 yuan/m^3, with the mean value of 2.52 yuan/m^3 and the median value of 2.35 yuan/m^3. If there is a complementary relationship between natural gas and electricity, the cross price elasticity is negative. If a substitutive relationship is detected, the cross price elasticity is positive. Generally, natural gas is substitutive for electricity in cooking and space heating,[3] implying that when the natural gas price increases, end-users tend to consume more substitutive energy, such as electricity.

The second category of independent variables are demographic and geographical characteristics of households. The following variables are taken into account.

Family size (ln(fm_size)). This is measured by the number of family members. Most of surveyed households have two or three persons in the family, which accounts for 77.3% of total households. The average size of a family is 2.6 persons. Other things being equal, a larger family size tends to use more electricity.

Dwelling area (ln(dw_area)). This is measured by the actual used area of dwelling. In the sample surveyed, 56.2% of respondents have a house (or an

[3] The substitutive relationship between electricity and natural gas is not always possible. For example, for households that heavily depend on electricity or households that rely on centralized district heating in Northern China, there is no incentive to switch energy fuels. Evidence in China can be found in Shi et al. (2012).

apartment) with an area greater than 100 m^2 with mean and median values of 104.6 m^2 and 105 m^2 respectively. As the dwelling size increases, residential electricity consumption is also expected to increase.

Education level (ln(edu_year)). This includes the years of education of the head of the household. In all, half of the respondents have finished 12 years' education while 15.8% of the household members have a level of education equal to or greater than 16 years. The mean value and median value schooling years are 11.3 years, with 22 years being the longest years of education. Education has two distinct effects on electricity demand. On one hand, households with highly-educated members tend to consume less electricity because they have greater awareness of energy conservation and environmental concerns. On the other hand, highly educated households are generally associated with higher income groups, which could result in an increase in electricity use. Therefore, the efficiency effect of education is ambiguous.

Weather condition (HDD and CDD). These two variables are measured in heating degree days (*HDD*) and cooling degree days (*CDD*). Usually, these two measures are defined as follows (Blázquez et al., 2013; Labandeira et al., 2012).

$$HDD = \sum_{t=1}^{nd} \max(0; T^* - T_t)$$

$$CDD = \sum_{t=1}^{nd} \max(0; T_t - T^*)$$

where *nd* is the number of days of a particular year, T^* is the threshold temperature of cold or heat, and T_t the observed temperature on day *t*. *HDD* and *CDD* represent the number of days on which the temperature is respectively below and above the predetermined thresholds of cooling and heating, and by how many degrees. The threshold is a "temperature-barrier" over or under which the heating or cooling appliances will be switched on. In this study, the heating and cooling threshold temperature are identified as 16℃ and 28℃.[4] The daily average temperature data is

[4] Definition of heating and cooling threshold temperature: refer to *Indoor Air Quality Standard* (IAQS, GB/T 18883-2014), the standard temperature with space heating in winter is 16℃-24℃. The standard temperature with air conditioner cooling in summer is 22℃-28℃. We identified the heating and cooling threshold temperature as the lowest temperature in winter 16℃ and the highest temperature in summer 28℃. The daily average outdoor temperature is a proxy variable to indoor standard temperature.

obtained from the National Oceanic and Atmospheric Administration using meteorological stations around China, and matched to the household level using the shortest distance between a meteorological station to a given household's location, measured by longitude and latitude. The average heating degree days and cooling degree days are 177.6 days and 36.1 days, respectively.

Urbanization (Urban). This is measured by a dummy variable based on a given household's location.[5] This dummy variable is equal to 1 for urban households and 0 for rural residents. A positive relationship is expected between urbanization and consumption as previously discussed. In our sample, 80.3% households are located in urban areas.

The descriptive statistics characteristics of variables are summarized in Table 1.

Table 1 The descriptive statistics characteristics of variables

Variable	Unit	Obs.	Mean	S.D.	Min.	Max.
Ele	kWh/household/year	1402	1794.52	1385.22	26.28	16539.96
Price_ele	Yuan/kWh	1402	0.53	0.06	0.32	0.80
Price_gas	Yuan/m^3	1402	2.52	0.96	1.37	5.93
Income	10,000 yuan	1402	9.89	15.88	0.50	350.00
Fm_size	Person/household	1402	2.66	1.07	1.00	8.00
Dw_area	m^2	1402	104.62	48.71	21.00	250.00
Edu_year	Year	1402	11.35	3.79	0.00	22.00
HDD	Day/year	1402	177.64	46.46	30.00	366.00
CDD	Day/year	1402	36.15	30.65	0.00	144.00
Urban	Dummy	1398	0.80	0.40	0.00	1.00

Note: the annual average ratio of the U.S. Dollar to the Chinese currency unit Yuan in 2012 is 6.3125.

We used a combination of statistical analysis and econometric analysis to estimate the impacts of the three DSM measures. To evaluate TPHE's effectiveness in electricity saving, we use kernel density distribution, non-parametric and parametric tests to examine whether the difference of consumption between affected and non-affected group is statistically significant. Regression method based on the basic electricity demand model was not used to evaluate TPHE for two main reasons. First, if we put the tiered price, rather than the average price, into the model, there is only a

[5] Definition of urban and rural: refer to National Bureau of Statistics of the P.R. China (NBS), 2006, *Interim Provisions on the Division of Urban and Rural in the Statistics*, the city (prefecture-level and county-level), county and township are defined as urban area. The country and village are defined as rural area.

small sample size of 448 observations which will affect the effectiveness and robustness of the regression. Second, the endogeneity of the marginal price and the rate structures (e.g. tiered price) is determined by and also affects consumer's demand at the same time (Billings, 1982; Hung and Huang, 2015; Zheng et al., 2012). Though various econometrics methods can solve the endogeneity problem, estimation from a small sample is not robust. In order to avoid the causality relationship between electricity demand and tiered pricing running in both directions, we separate the whole sample into three groups based on the highest standard of electricity demand among various provinces in China. Then we classified households by surveyed dummy variable of *know about the actually implemented TPHE or not*, and examined whether the tiered pricing policy is helpful for electricity conservation in each block. For the other two DSM measures, specifically the China Energy Label program and information feedback mechanisms, we put a series of proxy variables into the basic residential electricity demand model and used regression method to estimate the effects of these two measures.

4. Results and Discussion

The empirical findings for three power DSM measures are discussed based on our survey results and statistical and econometric analysis, including tiered pricing system for household electricity, China Energy Label program, and information feedback.

4.1 TPHE

In China, local governments were authorized to set up electricity-price tiers according to local conditions such as local income levels and climate conditions. Our sample average per capita residential electricity consumption in 2012 was 674.6 kWh, which is higher than the officially statistically reported national average of 460.4 kWh (NBS, 2015). This is likely due to the fact that about 80% of surveyed households are located in urban area, so a higher average value is obtained. Therefore, we used a rate structure of TPHE according to Beijing for our analysis, where electricity demand level is the highest amongst all regions for every block. In our surveyed sample, there are 948 urban households (85.3%), 110 urban households (9.9%) and 53 urban households (4.8%) in the first, second and third electricity consumption blocks, respectively. The specific details of Beijing's TPHE tier structure and our survey sample results are shown in Table 2.

Table 2 Information about TPHE (2012)

Tier	Electricity consumption level (kWh/household/year)	Observation (household)	Percentage (%)
Block 1	≤ 2800	948	85.33
Block 2	(2800, 4800]	110	9.90
Block 3	> 4800	53	4.77

We classify households into two groups using the surveyed dummy variable of *know about the actually implemented TPHE or not*. It equals to 1 if household answered *Yes*. Otherwise, it is 0 if the answer was *No*. The results of two-sample *t*-test and kernel densities distributions in each block are presented in Table 3 and Fig.7. We first use the traditional *t* test to examine whether there is a significant difference in electricity consumption between the affected (*Tiered*) and non-affected (*Others*) groups. Our null hypothesis assumes that the two groups have the same mean, which fits both unpaired and paired data. This test produces a *t* value of 5.3221, which suggests that the null hypothesis can be rejected at the 0.1% significance level in the Block 1. But the differences in Block 2 and Block 3 are not significant, and Fig.7 show that these two groups are not all normally distributed. The two groups' distributions in Block 1 are normally distributed, with the mean values of 1571.20 kWh/household/year and 1346.82 kWh/household/year in *Tiered* and *Others* groups, respectively. The distributions in Block 2 and Block 3 are not normally distributed. Compared with *Other* group, the distributions of *Tiered* group in both blocks are flatter, less concentrated and with higher mean values.

Furthermore, we conduct two nonparametric tests, the Kolmogorov–Smirnov test and Wilcoxon-Mann-Whitney test, to find out whether the two groups are drawn from the same population distribution. Compared with the *t*-test, Kolmogorov–Smirnov test and Wilcoxon-Mann-Whitney test do not rely on the mean's location only; it can be used for non-normal data, and is not sensitive to scaling. It is widely used for two-sample comparisons due to its robustness. The null hypothesis in this case is that there is no difference in the distributions. The Kolmogorov-Smirnov test and Wilcoxon-Mann-Whitney test report that the two samples are not drawn from the same distribution in Block 1 but there is no difference in the distributions between the tiered and non-tiered groups in Block 2 and Block 3.[6] These results suggest that the TPHE does not have a statistically significant relationship with lowered residential electricity consumption. [7]

Table 3 Two-sample T-test in electricity consumption for TPHE's effects

Block 1				
Group	Observations	Mean (kWh/household/year)	S.E.	S.D.
Tiered	356	1571.20	33.39	630.01
Others	592	1346.82	25.80	627.76
Difference		**224.38*** (5.3221)**	**42.16**	
Block 2				
Group	Observations	Mean (kWh/household/year)	S.E.	S.D.
Tiered	56	3636.98	70.98	531.16
Others	54	3497.68	68.10	500.47
Difference		**139.30 (1.4146)**	**98.48**	
Block 3				
Group	Observations	Mean (kWh/household/year)	S.E.	S.D.
Tiered	36	6883.24	387.57	2325.42
Others	17	6115.86	415.11	1711.52
Difference		**767.38 (1.2119)**	**633.22**	

Note: *t*-values are in parentheses.

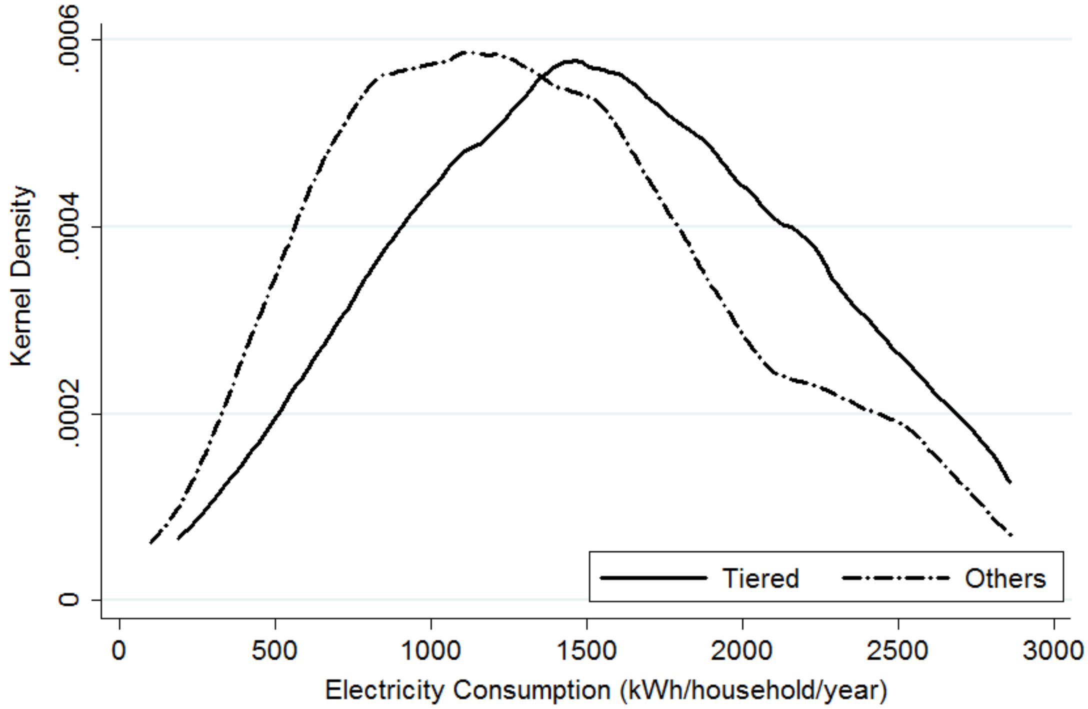
*** 0.1% significance level, ** 1% significance level, * 5% significance level.

Tiered (treatment group): know about the actually implemented TPHE.

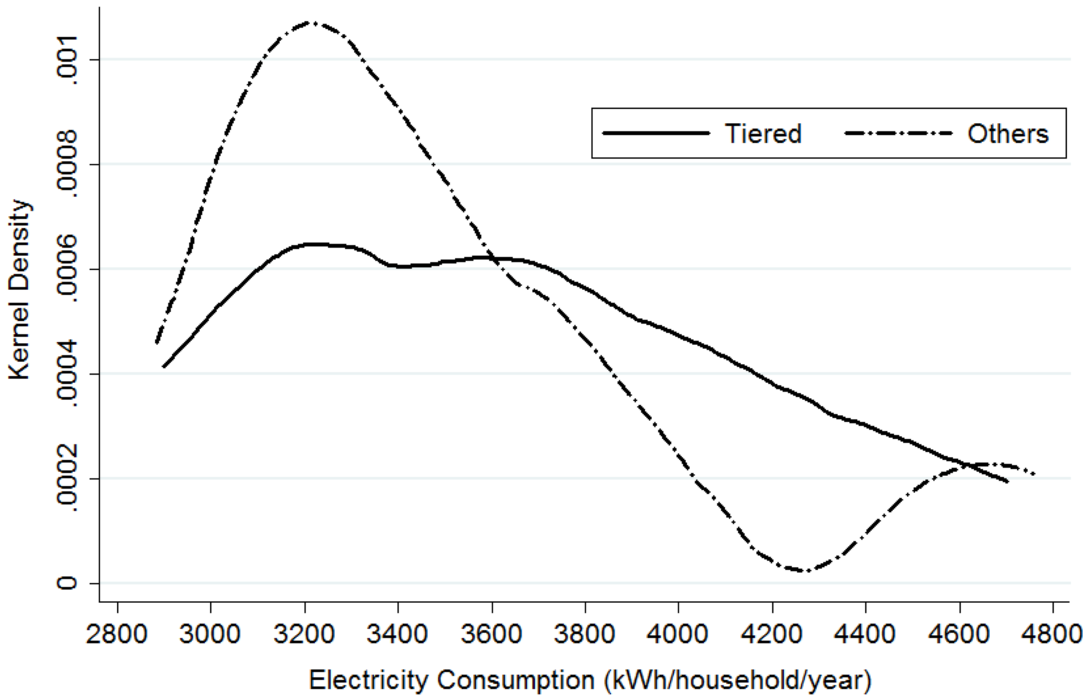
[6] Block 1: Kolmogorov-Smirnov test reports a distance value of 0.1807 and zero p-value.
Wilcoxon-Mann-Whitney test reports a variance value of 16666970 and zero p-value.
Block 2: Kolmogorov-Smirnov test reports a distance value of 0.2262 and 0.120 p-value.
Wilcoxon-Mann-Whitney test reports a variance value of 27972 and 0.1350 p-value.
Block 3: Kolmogorov-Smirnov test reports a distance value of 0.3301 and 0.161 p-value.
Wilcoxon-Mann-Whitney test reports a variance value of 2754 and 0.1585 p-value.

[7] As a robust test, the average effects of TPHE is positive and statistically significant. Detailed regression result is in the Appendix, Table A1.

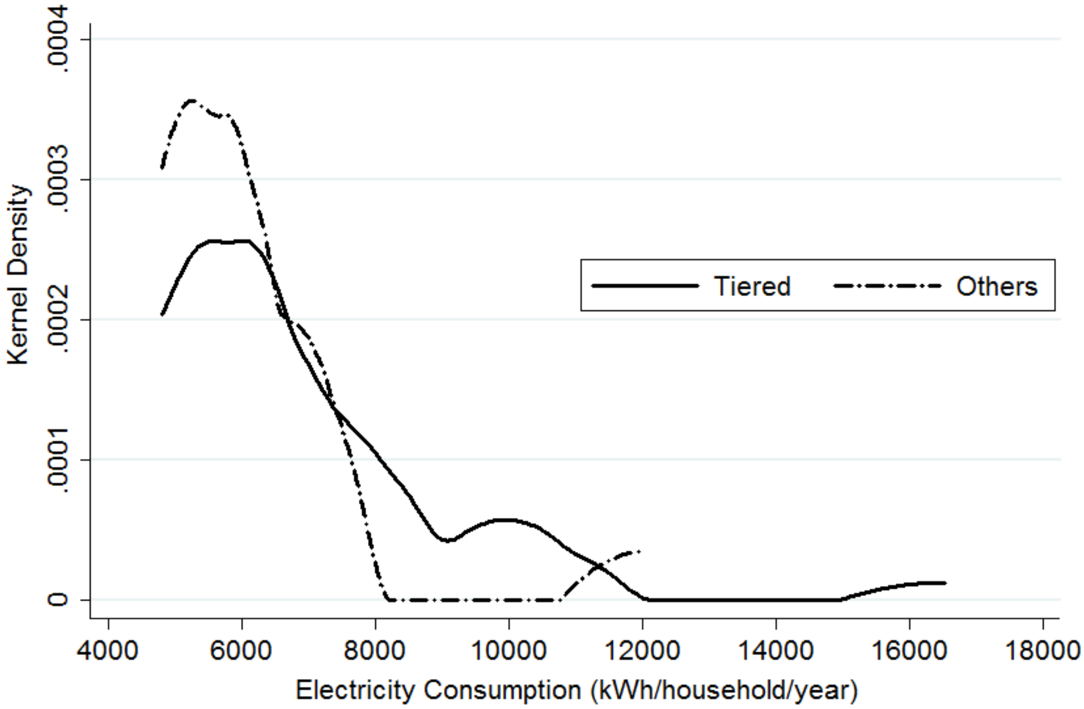
Others (control group): do not know about the actually implemented TPHE.
Difference: the difference of mean value between *Tiered* group and *Others* group.



Block 1



Block 2



Block 3

Fig.7 Kernel density residential electricity consumption by two groups

Note:

Tiered (treatment group): know about the implemented TPHE.

Others (control group): do not know about the implemented TPHE.

These results are somewhat surprising given that Sun and Lin (2013) and Sun (2015) found effective incentives for electricity conservation and reduced distortion of cross-subsidies in electricity tariffs under the current TPHE scheme and suggest that additional research is needed to tease out the differences in findings. We believe there may be three possible explanations for the different findings: (i) We confirmed that the own price elasticity of electricity demand decreases with the electricity consumption growth.[8] This implies that end users are less sensitive to price change if they consume more and supports previous findings that the increase in electricity consumption by lower tier households offsets reductions by households in higher tiers under TPHE (Ito, 2010). (ii) There is no effective sharing of price information with consumers. The availability of information in a comprehensive form is found to be

[8] Detailed results of quantile regressions of residential electricity consumption is in the Appendix, Table A2.

very important for consumers' abilities to respond to price signals (Faruqui and George, 2006; Reiss and White, 2005). (iii) Our survey began in the winter 2012, only six months after the implementation of the TPHE when many consumers were still unaware of the new tier structure which caused the lag of policy's effects. This is evidenced by the low awareness rate of only 31% among our surveyed residents. This mandatory electricity tariff was not well publicized because the power utilities lacked incentives to notify residents of the new tier structure. In China, utilities were actually disincentivized from informing consumers of the tiered pricing and promoting efficiency and conservation to reduce electricity consumption because their revenue (profit) is directly linked to total electricity sales. This problem can be mitigated by decoupling mechanisms that separate utilities' profits from their electricity sales and instead base utilities' rate of return on their ability to meet pre-set revenue targets. Decoupling can prevent energy efficiency activities from lowering utilities' profits and prevent electricity sales from directly increasing profits. Under this condition, decoupling will make the utility indifferent between increasing electricity sales and promoting energy efficiency that reduces electricity sales (Kihm, 2009). For households that know about the new price policy, another mechanism that delays the effects of TPHE on electricity consumption is that households' current and future consumption behavior is based on the past information they obtained. The households usually receive electricity bills at the end of the month or quarter and then pay for the past electricity consumption. In other words, the households would base their future electricity usage on their past electricity consuming and payment experiences. An expected result is that households tend to respond to lagged price with a larger price elasticity than contemporaneous price. In particular, they are detected to be more sensitive to the lagged average price rather than lagged marginal price (Ito, 2014). Therefore, the incentives for consumers to reduce electricity consumption under TPHEs may not be reflected at the time our survey data was collected.

4.2 China Energy Label

The regression estimation of our basic residential electricity demand model and two models with the policies' proxy variables are presented in Table 4. The basic model (Model I) shows that residential electricity demand is found to be income and price-inelastic. The income elasticity of electricity demand is estimated to be 0.15, and the own price elasticity is -0.51. Both are statistically significant at the 1% level. Since income and price-elasticity are well below unity, this indicates that households have low responsiveness to electricity price changes or income growth. A substitutive relationship between electricity and natural gas is identified, with the coefficient value of 0.15. As expected, demographic and geographical characteristics of households are found to affect electricity demand and large residential electricity consumption gap between urban and rural area is observed. The estimation is consistent with our expectation and other regression results in Model II and Model III within different variables, and also Appendix with quantile regression method. This result is also consistent with studies which estimated the elasticity of residential electricity demand in China (He et al., 2011; Shi et al., 2012; Sun and Ouyang, 2016; Zhou and Teng, 2013). The price elasticity of residents is estimated to range from -2.477 to -0.300, and the income or expenditure elasticity is estimated to range from 0.058 to 0.626.

Table 4　Regression results for China Energy Label and Information Feedback

Electricity Consumption	**Basic**	**China Energy Label**	**Information Feedback**
	Model I	**Model II**	**Model III**
Ln(income)	0.15***	0.13***	0.14***
	(0.0227)	(0.0236)	(0.0241)
Ln(price_ele)	-0.51***	-0.64***	-0.42**
	(0.169)	(0.150)	(0.184)
Ln(price_gas)	0.15**	0.32***	0.17***
	(0.0639)	(0.0687)	(0.0654)
Ln(fm_size)	0.18***	0.13***	0.19***
	(0.0447)	(0.0462)	(0.0458)
Ln(dw_area)	0.13***	0.14***	0.13***
	(0.0431)	(0.0428)	(0.0455)
Ln(edu_year)	0.24***	0.17***	0.23***

	(0.0485)	(0.0476)	(0.0530)
HDD	-0.00037	0.0000036	-0.00048
	(0.000722)	(0.000770)	(0.000718)
CDD	0.0022**	0.0036***	0.0018*
	(0.00102)	(0.00108)	(0.00105)
Urban	0.16***	0.16***	0.16***
	(0.0540)	(0.0551)	(0.0563)
Refrigerator, baseline: no labelling			
Grade 1		-0.21***	
		(0.0410)	
Grade 2		-0.28***	
		(0.0593)	
Grade 3		-0.27***	
		(0.0721)	
Grade 4		-0.32***	
		(0.106)	
Grade 5		-0.016	
		(0.172)	
TV, baseline: no labelling			
Grade 1		0.031	
		(0.0543)	
Grade 2		0.13	
		(0.0766)	
Grade 3		0.0078	
		(0.0702)	
Information source (*Infor*), baseline: do not know electricity information			
Payment bills			-0.0099
			(0.0460)
Meter reader			-0.17***
			(0.0563)
Other sources			0.023
			(0.0798)
Frequency to pay (*Freq*), baseline: pay 6 or more months			
Quarterly			0.051
			(0.0565)
Monthly			0.058
			(0.0573)
Smart meter usage (*Smart*), baseline: mechanical meter			
IC meter			0.019
			(0.0583)
Smart meter			-0.019
			(0.0399)
Constant	5.09***	5.11***	5.17***

	(0.326)	(0.328)	(0.347)
Observations	1386	1170	1308
R-squared	0.145	0.178	0.148

Note: robust standard errors are in parentheses.
*** 1% significance level, ** 5% significance level, * 10% significance level.

Model II reveals the effects of China Energy Label program on reducing residential electricity consumption. The proxy variables for evaluating the effectiveness of the China Energy Label program are the labeled efficiency grade of two common appliances of refrigerators and televisions (*Refrig*, *TV*) that households purchased. These categorical variables are set to zero if appliances have no label or a resident is not familiar with the label. The non-zero values of 1-5 correspond to the China Energy Label's energy efficiency grade from 1 (High) to 5 (Low) for refrigerators and 1-3 for televisions. If households own more than one refrigerator or television set, we choose the one that is used more frequently and regarded that as the main device that survey respondents listed first. In surveyed households, 36.6% of refrigerators have no label, and 37.7%, 14.7% and 8.2% of refrigerators are labelled Grade 1, Grade 2 and Grade 3, respectively. For televisions, more than 75% of television sets had no appliance label, and only 12.4% of televisions are rated Grade 1. The large share of televisions without a label is likely due to the relatively recent introduction of the China Energy Label for televisions in 2010. Intuitively, the purchase and use of energy-efficient appliances by a given household would result in lower residential electricity consumption assuming no changes in usage patterns or behavior (i.e. zero rebound effect).

Compared with the base group of refrigerators and television sets without the label, the coefficients of Grade 1-4 labelling in refrigerators are estimated to be negative and statistically significant at 1% level. However, the coefficients of efficiency grade labelling in televisions are insignificant. This finding implies that refrigerators with Grade 1-4 label would lead to significant electricity savings for households as expected. However, the Energy Label in television sets had no significant impact on total residential electricity consumption. Similar results have been reported by Krishnamurthy and Kriström (2015), who used a dummy variable for presence of at least one top-rated energy efficient appliance that was found to be insignificant in 11 selected OECD-countries in 2011. The estimated coefficients of other variables in Model II remain stable.

The difference in observed impact of the China Energy Label on refrigerator and television electricity use may be attributed to differences in purchase and operation that affect total electricity use of the two products as well as the cost-effectiveness of more efficient products. First, television purchase decisions are impacted by many other factors other than energy efficiency while energy efficiency alone is a key determinant in refrigerator purchasing decisions. This can be seen by looking at China's largest online electric product retailer, JD.com, where energy efficiency information is clearly shown for the best-selling refrigerators but not available for televisions, even in the detailed specification descriptions. Instead, performance and functionality parameters such as picture display quality and contrast, availability of network connections and media storage devices are emphasized as key factors used by consumers in making their television purchasing decisions. This is consistent with Zeng et al. (2014)'s finding that the price of flat-panel televisions were influenced more by the screen size than energy efficiency tier, and that the differences between efficient and non-efficient televisions were not obvious for the same screen size. Second, the electricity consumption of a refrigerator is much larger than that of a television on a per unit basis. Refrigerators consumes a relatively stable[9] amount of electricity daily for 365 operating days a year and its electricity consumption is not impacted by usage patterns, whereas televisions consume electricity primarily when it is used in active mode for only 3-5 hours[10] per day with 0.5 W or less consumed during standby mode. For example, Letschert et al. (2012) found that the average baseline refrigerator in the Chinese market consumed 550 kWh per unit per year, versus only 47 kWh consumed per television unit. The significantly larger per unit

[9] Li et al. (2016) found that the average daily consumption of televisions on the Chinese market was 0.61 kWh in 2013.

[10] The RECS survey found that televisions are watched on average only 3.5 hours on weekdays and 4.6 hours on weekend days.

electricity consumption of refrigerators compared to televisions suggest that consumers may be more motivated to purchase an efficient refrigerator versus an efficient television. In particular, it may be more cost-effective for consumers to purchase a highly efficient refrigerator than a highly efficient television, as a highly efficient refrigerator will likely save more electricity on an annual basis than a highly efficient television. This is especially true given the rapid advancement in LCD and LED backlighting technologies for televisions, which has reduced the marginal electricity saving of more efficient television.

4.3 Information Feedback

Model III examines the effects of information feedback mechanisms on residential electricity saving. We use three relevant variables to determine information feedback hypotheses. We hypothesize that the more information consumers can access, the less electricity they consume (*Infor*). In particular, comparing the consumption of another household to that of their own can engender social pressure for residents to understand why consumption levels differ; this can in turn result in energy conservation (Iyer et al., 2006; Kempton and Layne, 1994; Mizobuchi and Takeuchi, 2013; Schultz et al., 2007). We also hypothesize the more frequent the information feedback, the greater the likelihood of energy conservation resulting in less electricity demand (*Freq*). A number of studies conclude that feedback frequency is a key factor in energy savings (Fischer, 2008; Jessoe and Rapson, 2014; Wood and Newborough, 2003). Finally, recent studies have identifed the energy saving effect of smart information feedback devices on electricity demand (*Smart*) (Carroll et al., 2014; Gans et al., 2013). However, some studies found a negative effect of smart information feedback devices. For example, Hargreaves et al. (2013) suggested that the smart energy monitor device in the UK increased householders' knowledge but it did not necessarily motivate householders to reduce their electricity consumption. Since there is very limited research in this area in China, we are also interested in the Chinese case.

The values of each of these variables ranging from 0 to 3 are assigned to represent different sources of information feedback. Detailed information about these variables and the distribution of household observations for different types of information feedback is presented in Table 5.

Table 5 Variables and distribution of information feedback

Information feedback	Variable	Observation (household)	Percentage (%)
Whether and how the electricity information can be accessed (*Infor*)	0 information inaccessible	298	21.45
	1 meter reader	261	18.79
	2 billing statement	739	53.20
	3 other sources	91	6.55
The frequency of paying electricity bills (*Freq*)	1 six or more months	206	15.47
	2 quarterly	275	20.65
	3 monthly	851	63.89
The use of smart meter (*Smart*)	1 mechanical meter	627	45.01
	2 integrated circuit card meter	197	14.14
	3 smart meter	569	40.85

First, we examine whether access to information would change consumption behavior and lead to lower electricity consumption. The households with the response that "*we do not have any information about electricity consumption*" are treated as the base group. We find that information feedback does matter, depending on the information source. Information feedback from prepayment bills and other sources have no significant impact on electricity consumption, but the coefficient for "*feedback from meter readers*" is -0.17 at the 1% significance level. This shows that households that obtain electricity information from meter readers use less electricity. A meter reader can be important in terms of affecting a resident's electricity-saving behavior as the meter reader knows the entire electricity usage information of every household in the community and, more importantly, some residents will spend some time discussing their bills with the meter reader, their family, friends and neighbors, and even their own historical consumption .[11]

[11] The potential bias created by distribution of "*meter readers*" can be mitigated by two ways. First, we controlled the effects of urbanization by introducing "*Urban*" variable in regressions. Second, there are 18.79% (261 households) of total survey households get electricity bills and consumption information from meter readers. This ratio is 18.18% in the urban households and 21.53% in the rural.

Second, we examine whether more frequent feedback would result in lowered electricity demand by comparing it with the base group of residents that pay their electricity bills least frequently at once every six or more months. We found that the alternative groups that paid their electricity more frequently (every three months or every month) did not have statistically significantly lower electricity consumption. This indicates that the frequency of information feedback did not impact electricity demand in our sample. One possible reason for this is that monthly feedback is still too long of a time lag for residents to take aggressive action to reduce their electricity consumption compared with real-time or continuous feedback. Previous studies have found that information feedback's effectiveness on reducing energy consumption decreases over a longer period of time (Hargreaves et al., 2013; Van Dam et al., 2010).

Finally, our result shows that households with a smart meter consume the same amount of electricity as their counterparts who do not use a smart meter. This could be because a majority of residents do not really understand their smart meters so the smart meters alone did not help increase their motivation to conserve electricity or change their behavior, a finding consistent with Hargreaves et al. (2013).

Compared with basic result in Model I, the estimated coefficients of other variables in Model III remain stable. Our results reveal that information feedback matters. The households that obtain electricity consumption information through interacting with meter readers have lower electricity demand. However, we do not find supportive evidence for information feedback frequency or for the smart meter program.

5. Conclusions and Policy Implications

This paper evaluates three residential Power DSM measures using micro-level data collected from 1450 households in 27 provinces in the CRECS conducted in 2012. First, we found residential electricity consumption to be price- and income-inelastic with the coefficient values of -0.51 and 0.15, respectively. This result implies that price change and income growth would result in a much less than proportional change in electricity consumption. The relatively low price elasticity of residential electricity demand, combined with residential electricity demand drivers of continued urbanization and rising household incomes, suggest that electricity price reforms such as tiered pricing for household electricity may not be very effective in moderating electricity growth in China. Further statistical analysis of the CRECs data found that residents in the first tier who knew about the new tiered pricing policy actually consumed more electricity. Because TPHE is a relatively new policy and there is significant variation in the setting of tier price and electricity consumption limits between regions, more nuanced analysis of regional TPHE schemes are needed to fully assess the policy's effectiveness in reducing electricity consumption. The low awareness rate of the TPHE scheme amongst surveyed residents also suggest that more public education, awareness and outreach efforts are needed to inform the public of the new pricing policy and the specific local TPHE scheme. This could include greater publicity of the TPHE scheme by including the specific rate structure on residential utility bills and sending alerts to residents when they reach a new tier of electricity consumption. Over the longer term, power sector reform including decoupling can help better motivate utilities to play a more active role in informing consumers about opportunities to reduce electricity and alerting consumers when they approach higher tiers of electricity consumption. The decoupled power sector in California provides one example of effective TPHE schemes that have been complemented by active utility participation in informing and promoting energy efficiency and conservation amongst consumers, resulting in flat per capita electricity consumption since the mid-1970s.

Second, the China Energy Label program has been recognized as an important program for achieving residential electricity savings, as well as in providing other economic and environmental benefits. Its effectiveness and impacts are partially reflected in our results. Specifically, we found that refrigerators with China Energy Label Grade 1-4 label corresponded to statistically significant lower electricity consumption for households. However, efficient televisions with the China Energy

Label did not appear to have significant impact on reducing residential electricity consumption in our analysis. A key factor was that the China Energy Label was not used by consumers as a key criteria for purchasing televisions and energy efficiency information for televisions was missing from many online retailer websites. This suggest that certification and labeling compliance for the China Energy Label program could be improved, particularly for online retailers, as the label should be visible and easily accessible for all 33 products covered by the program including televisions. Moreover, this finding also highlights that the effectiveness and impact of energy labeling on reducing residential electricity consumption may differ by products as a result of different product characteristics, such as product pricing, functionalities and usage. For products such as televisions where technological change has been rapid and the market efficiency has improved quickly, more frequent revisions of the China Energy Label may be needed to help consumers identify and differentiate between efficiency levels.

Third, although information feedback (including detailed electricity bills, pay frequency, or meter type) has been considered an important tool for demand-side management, our analysis found that its role in the Chinese residential sector is currently limited. Information feedback from sources other than meter reader were not able to deliver sufficient information or transform information into knowledge or action to impact residents' electricity consumption. This implies that more mechanisms or tools to better communicate electricity usage information to Chinese residents are needed, such as usage alerts, websites to track usage and compare usage to other similar households, and mobile applications. The lack of a statistically significant relationship between the frequency of electricity billing and residential electricity consumption further suggest that more frequent information feedback beyond the current billing periods are needed. The current electricity billing timeframes of monthly, quarterly or bi-annually are not frequent enough to impact consumer usage patterns and change behavior, and access to daily or even real-time information about usage is needed to help reduce electricity consumption. Lastly, the insignificant impact of smart meters on residential electricity consumption identified from this study suggest that more research is needed to evaluate if smart meters can really influence Chinese residents' electricity usage and if so, greater education and awareness are needed to increase consumer understanding and usage of smart meters.

In sum, each of the three DSM measures evaluated in this study had some statistically significant impact on reducing household electricity consumption but their impact could be significantly expanded through additional policy changes.

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Appendix

Table A1 Regression of the average effects of TPHE

We added an indicator variable *TPHE* (know about the actually implemented TPHE = 1; don't know about the actually implemented TPHE = 0) into the electricity demand model with urban households. The coefficient of indicator *TPHE* is 0.22, positive and statistically significant at the 1% level. It suggests that on average level, the households who know about TPHE consume more electricity. The estimated coefficients of other variables remain stable. The regression result is presented below.

Electricity consumption	**The average effects of TPHE**
Ln(income)	0.13***
	(0.0254)
Ln(price_ele)	-0.54***
	(0.173)
Ln(price_gas)	0.05
	(0.0776)
Ln(fm_size)	0.13***
	(0.0514)
Ln(dw_area)	0.13***
	(0.0488)
Ln(edu_year)	0.31***
	(0.0560)
HDD	0.00024
	(0.000714)
CDD	0.0036***
	(0.00117)
TPHE	0.22***
	(0.0396)
Constant	4.96***
	(0.346)
Observations	1106
R-squared	0.164

Note: robust standard errors are in parentheses.

*** 1% significance level, ** 5% significance level, * 10% significance level.

Table A2 Quantile regressions of residential electricity consumption

Electricity consumption	**Quantity of residential electricity consumption**		
	Model II (Q10)	**Model III (Q50)**	**Model IV (Q90)**
Ln(income)	0.20***	0.14***	0.18***
	(0.0394)	(0.0245)	(0.0366)
Ln(price_ele)	-1.01***	-0.48**	-0.50*
	(0.302)	(0.188)	(0.281)
Ln(price_gas)	0.098	0.13*	0.12
	(0.114)	(0.0709)	(0.106)
Ln(fm_size)	0.14*	0.17***	0.085
	(0.0812)	(0.0506)	(0.0755)
Ln(dw_area)	0.16**	0.099**	0.15**
	(0.0754)	(0.0470)	(0.0702)
Ln(edu_year)	0.15	0.16***	0.28***
	(0.0890)	(0.0554)	(0.0828)
HDD	-0.00028	-0.00040	-0.00069
	(0.00116)	(0.000720)	(0.00108)
CDD	0.0010	0.0024**	0.0031*
	(0.00176)	(0.00109)	(0.00163)
Urban	0.11	0.17***	0.063
	(0.0925)	(0.0576)	(0.0861)
Constant	4.13***	5.50***	5.79***
	(0.568)	(0.354)	(0.529)
Observations	1386	1386	1386
Pseudo R-squared	0.076	0.078	0.099

Note: robust standard errors are in parentheses.

*** 1% significance level, ** 5% significance level, * 10% significance level.