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Impact of information feedback on residential electricity demand in China

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ABSTRACT

This paper examines the relationship between information feedback and residential electricity consumption, based on a household survey dataset collected in 2012 that covered 26 provinces in China. The results show that information feedback is strongly associated with residential electricity consumption. Electricity consumption is statistically lower in households who obtain consumption information through interactions with meter readers, receive ex ante feedback (use a prepaid metering system), and receive explicit feedback by directly paying meter readers. However, increased frequency of information feedback and installation of smart meters had no significant correlation with household electricity usage. The sensitivity analysis confirmed the robustness of the results. We suggest that policy-makers attach great importance to the demand side management of residential electricity consumption and improve the information feedback capacity of smart meters.

1. Introduction

The electricity consumption in Chinese residential sector experienced tremendous increaseover the past couple of decades. In 1990, residential electricity consumption in China was only 48.1 TWh, but by 2012 it increased to 621.9 TWh, an annual growth rate of about 12.3%. Moreover, the share of residential sector in total electricity demand increased from 7.7% in 1990 to 12.5% in 2012.[1] It is expected that this increasing trend will continue with further social and economic development, because electricity demand and GDP growth exhibit a significant positive causal nexus (Shiu and Lam, 2004; Yuan et al., 2007). Thus, residential electricity conservation is extremely important for energy saving and carbon abatement in China.

Traditional electricity policies focus on price-based interventions, such as multi-part tariffs and peak-load pricing. However, most previous studies have found that electricity consumption usually exhibits low income and price elasticities (Reiss and White, 2005; Shin, 1985; Zhou and Teng, 2013). Thus, price-based interventions are not very useful for electricity conservation. More recently, policies have placed a focus on information-based interventions. A large number of experiments have revealed that residential electricity consumption may not actually lack price elasticity, but only appear to due to lack of full information on energy price and quantity. Providing additional information on electricity consumption to households may help them better control their consumption (Darby, 2006; Faruqui et al., 2010; Fischer, 2008), although research has found that providing simple information had little to no effect on energy use behavior (Abrahamse et al., 2005).

Electricity consumption has specific features. The first is consumers make a real-time decisioins but pay for it intermittently (usually monthly when receive the bill). The separation of consumption and payment causes the problem of salience (Gilbert and Graff Zivin, 2014). The second feature is that the structure of electricity tariffs is usually complicated, and consumers probably do not fully understand the tariff structure or know how to optimize their consumption (Bushnell and Mansur, 2005; Ito, 2014). The consumer may have no idea about when, how or by which device electricity is used. Moreover, electricity consumption usually accounts for only a small share of household budgets, reducing motivation to invest too much effort into getting information about price and quantity.

Feedback has been considered a very specific type of information, and many studies categorize it as its own separate "tool". Unlike procedural information or information about a general problem, feedback gives people information on their own behavior (Abrahamse et al., 2005). The Chinese government is already aware of the importance of information feedback for residential electricity savings. A number of policies and programs (such as in-house display of meters and development of smart grids and meters) have been implemented to improve information feedback, though these measures are often not designed with consumers in mind (Sintov and Schultz, 2015). Moreover, there

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[1] Data source: China Statistical Yearbook.

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are quite a few studies that compare the relative effectiveness of various types of feedback in encouraging energy conservation. For example, it is evident that health and environmental messages outperform monetary cost-savings information, or at least have an equal direct effect on energy saving with additional behavioral spillover effects (Schwartz et al., 2015; Asensio and Delmas, 2015; Steinhorst et al., 2015). Social normative information can also be a powerful feedback tool for inducing household to save energy (Nolan et al., 2008; Mizobuchi and Takeuchi, 2013). However, in China's case, the effectiveness of various types of feedback has received little attention. For example, literature has suggested that prepaid systems can boost electricity conservation in developed countries (Faruqui et al., 2010). However, the effectiveness of such a system in China has not been investigated.

This paper examines the relationship between various types of information feedback and residential electricity consumption, providing several contributions to the literature. First, we employed data from a newly-collected large household survey. The dataset covers not only the majority of Chinese provinces, but also includes both urban and rural households. Second, we empirically investigated the relationship between a series of information feedback types and residential electricity consumption. The findings regarding interactions with meter readers are particularly unique, revealing defects in China's present smart meters. We found that present information from sources other than meter readers failed to deliver adequate information to end-users. Moreover, great efforts, such as a competitive electricity sales market and the development of energy services, are needed to improve information feedback capacity.

The paper proceeds as follows: Section 2 briefly reviews previous studies and raises the hypothesis; Section 3 introduces the household survey and describes the data; the empirical strategy and methodology are presented in Section 4; the results are discussed in Section 5; the final section concludes.

2. Literature review and hypothesis

2.1. Literature review

Early studies on the effect of information feedback on energy conservation, which have primarily been carried out by psychologists, can be traced back to the 1970s and 1980s (Seligman and Darley, 1977; Winett et al., 1978; Winkler and Winett, 1982; Sexton et al., 1989). Since then, a large number of field experiments and studies have focused on quantifying the effectiveness of information on household electricity demand (Faruqui et al., 2010; Fischer, 2008). This literature can be classified into two main branches based on type of feedback, indirect or direct (Darby, 2006; Ehrhardt-Martinez et al., 2010).

Indirect information feedback refers to feedback that was processed in some manner before reaching the end-user and is provided after consumption, normally through a billing mechanism. Indirect feedback can be appliance-specific, historial or socially comparative. Hartman (1988) estimated the impact of the residential household conservation programs run by Portland General Electric Company from July 1978 to December 1979. Results revealed that the conservation reasonably attributable to the programs is less than originally thought when correcting for self-selection bias. The programs accounted for roughly 50% of overall household electricity savings and 45–60% of savings for higher-income, better-educated, younger home oweners.

Waldman and Ozog (1996) argued that incentive-induced energy savings (including audits, rebates and loans) in the U.S. are overstated. Their results showed that 71% of total conservation was associated with incentive programs, and that the remaining 29% would have happened regardless. Henryson et al. (2000) reviewed Swedish energy saving programs based on information feedback, finding it difficult to establish effect prior to an information campaign, and revealing that such factors as metering, electricity bills and discounting have had positive effects on energy savings.[2]

Schultz et al. (2007) investigated the energy saving effect of social norms. They found that a descriptive normative information of neighborhood usage could bring greater energy conservation, or lead to boomerang effect. It depends on whether households were presently consuming at relatively lower or higher rate. Nolan et al. (2008) compared the effect of normative social influences and information highlighting other reasons to conserve. They found that the effect of normative messages produced the greatest change in behavior and is underdetected.[3]

Mizobuchi and Takeuchi (2013) conducted a field experiment from October to November 2011 in Japan, and found that comparative feedback is helpful to energy saving. In the study, 236 households were divided into three groups randomly, a control group and two treatment groups, who received monetary rewards for their own electricity savings with or without comparative feedback of their neighbor's electricity savings, respectively. Results found that people are inclined to save more energy if information on their neighbors savings is provided, implying that the behaviour of others may influence one's own electricity saving behaviour.

Gleerup et al. (2010) evaluated the impact of information feedback by sending text messages and emails to consumers about their level of household electricity consumption. Results showed that emails and text that delivering instant message about a household's exceptional consumption periods led to average 3% reductions in total annual electricity consumption. Allcott (2011) evaluated a series of energy conservation programs that sent Home Energy Report letters to residential electricity customers. The letters not only compared electricity consumptions of consumers and their neighbors, but also provided energy conservation tips. The results found that, on average, the program reduced about 2% of energy consumption, an effect equivalent to an electricity price increase of 11–20%.[4]

Direct information feedback is a kind of immediate feedback through a meter or associated display monitor that is provided in (nearly) real-time, including in-home display (IHD) and smart devices with a feedback function, etc. For example, Ueno et al. (2006) found that installation of an on-line information interactive system of energy consumption led to a 9% decrease in electricity usage. Gans et al. (2013) found that if consumers are allowed to track real-time electricity usage, electricity consumption in Northern Ireland would decline 11–17%. However, Hargreaves et al. (2013) showed that smart metering did not necessarily encourage residents to cut down their consumption in the UK. In Nilsson et al. (2017)'s pilot study in Sweden, no evidence was found that real-time spot price visualization could reduce overall household electricity consumption.[5]

Moreover, a considerable amount of literature has been published on the influence factors of residential electricity demand. For example, Terza (1986) examined the role of household income, size, dwelling type, appliance stock, electric heating and whole-house air conditioning on electricity demand. Alberini and Filippini (2011) offered an empirical regression model that included electricity price, gas price, household size, income per capita, and climatic condition as independent variables. The demographic characteristics of households (age, gender, occupation, education level) are usually included (Cao et al., 2016; Shi et al., 2012; Zhou and Teng, 2013). In addition, the theory assumes that the rational consumers will make decision based on

[2] The effect of incentives project is also investigated in household waste & recycling. Please see Timlett and Williams (2008), who designed a reward for family based on its performance.

[3] The effect of social norms is also investigated in household recycling. Please see Bertoldo and Castro (2016), Miliute-Plepiene et al. (2016) and Thomas and Sharp (2013).

[4] The effect of social media is also investigated in household waste & recycling. Please see Timlett and Williams (2008) and Young et al. (2017).

[5] The effect of information feedback is also investigated in household water usage. Please see Fan et al. (2013) and Liu et al. (2015).

marginal prices, but in practice they may be more resposive to the average price because the existence of information barriers and incomprehensible price-setting (Ito, 2014).

To date, research on consumer energy behavior in China has received increasingly attention in the literature. However, these kind of research has been limited on the regional level and a relatively small surveyed sample. Ouyang and Hokao (2009) surveyed 124 households in Hangzhou City, China, and suggested that improving occupants' behavior should prioritized over technological measures to save more electricity. They also suggested that energy-saving education is a useful way to raise awareness. By interviewing about 600 housheolds in Liaoning province of China, Feng et al. (2010) identified the barriers to improve residential energy efficiency. Sun and Feng (2011) conducted a survey of 1376 residents in Dalian City, China, and found that changes in attitudes towards energy through education, publicity, and economic incentives were motivators for residents to conserve. Zhou and Teng (2013) found a price- and income-inelastic for residential electricity demand by using household survey data in Sichuan Province of China from the year 2007–2009. Zhang et al. (2016) tested the effectiveness of real-time IHDs on energy consumption in residential sector by a pilot experiment on 131 respondents in Shanghai City of China. The monthly averages in electricity usage per household with and without an IHD were 91 kWh and 100.1 kWh, respectively, indicating that the IHDs led to around a 9.1% reduction in monthly electricity consumption. However, their study only covered urban residents in Shanghai. As far as we know, few studies have examined the linkage between information feedback and residential electricity conservation on a national level in China. Our work tries to fill this gap.

2.2. Hypotheses

In light of the previous literature, we propose the following hypotheses to be empirically examined:

H1. the more information accessed, the less electricity consumed

As explained by Wilhite and Ling (1995), information feedback is put into effect through the following transmission mechanism. First, increased information feedback promotes energy conservation awareness or knowledge; this information then enables people to change their energy-use behavior, promoting and reinforcing self-efficacy (Oltra et al., 2013); finally, these changes in behavior lead to a decrease in consumption. Thus, we hypothesize that users who obtained feedback about their electricity information would be more likely to change their consumption behavior, leading to lower electricity usage. In contrary, households that do not access any information feedback may lack necessary knowledge and have less incentive to change their behaviors, resulting in higher consumption of electricity.

H2. ex ante information feedback is associated with less electricity compared to ex post feedback

Under the prepayment system, the consumer charges money to an account before using power. The user is usually warned when the points reach a certain level, and once the credit points are used up, the power supply stops until a new payment is made. In comparison, the bill payment system allows the user to consume electricity before payment. The electricity company normally sets up a payment period (which could be monthly or less frequently) and signs a contract with the user. Even if the consumer does not pay immediately, the power service will not be stopped, but additional overdue fines will incur. The prepayment system feeds back ex ante information to the user, while the bill payment system provides ex post feedback. Households that receive ex ante feedback face a more certain and tighter constraints than those that receive ex post feedback. Similar to Faruqui et al. (2010), we hypothesize that households with ex ante feedback consume less electricity.

H3. explicit information feedback is associated with lower electricity demand relative to implicit feedback

We re-categorized the payment method into two groups. Householder who authorize the bank to automatically deduct from their associated accounts may be unconscious of the payment record in terms of quantity and price. Thus, we define this kind of information as implicit and passively delivered to customers. The other category is defined as explicit information feedback, because the payment is implemented in an active/interactive way, i.e., the householder must know the consumption quantity and cost expenditure when paying a bill (or charging an account) through a grid counter, bank or internet transfer or meter reader. We hypothesize that implicit information feedback (i.e., automatic bank deduction) is associated with higher electricity consumption.

H4. more frequent feedback is associated with less electricity demand

Numerous studies have concluded that the feedback frequency affects energy savings (Fischer, 2008; Wood and Newborough, 2003). In these studies, feedback frequency was divided into three categories: continuous/in-time feedback, daily feedback and weekly (or monthly) feedback. As Fischer (2008) suggested, high-frequency feedback strengthens the link between consumer behaviors and their effects, increasing consumer consciousness and knowledge about the outcome of their actions. Accordingly, we hypothesized that high-frequency information feedback is associated with lower electricity demand.

H5. smart meter user is associated with lower electricity consumption

Smart meter may help users to better understand and monitor their electricity usage through either feedback or other customer interactions.[6] Latest studies have examined how and to what extent the smart information feedback system affect electricity demand. For example, Carroll et al. (2014) and Zhang et al. (2016) found supportive evidence that the smart meter program significantly reduces electricity demand. However, some empirical studies found opposite results. However, Hargreaves et al. (2013) argued that the smart energy monitoring devices in the UK increase householders' knowledge, but do not necessarily decrease their electricity consumption. It also motive us to examine the Chinese case. Here, we hypothesize that the smart meter offers feedback to Chinese household and associated with lower electricity demand.

The information source of feedback and format throughout hypotheses H1–H5 are summarized in Table 2.

3. Introduction of survey and data

3.1. Introduction of survey

Our household survey data was collected from the *2012 China Residential Energy Consumption Survey* (CRECS-2012). The CRECS-2012 was conducted by the Department of Energy Economics at Renmin University of China, based on the U.S. Residential Energy Consumption Survey (RECS). The questionnaire has six modules: household and dwelling characteristics, ownership and usage of kitchen and home appliances, space heating, space cooling, transportation, and energy expenditure. The sampling distribution among provinces was based on the household population distribution reported in the 2010 6th National Population Census. A total of 1640 households in 26 provinces were initially selected to take the face-to-face survey and eventually 1542 participated (response rate is 94%). Finally, there remained 1450

[6] The smart meter itself does not lead to any changes in use. The rational behind the relationship between smart meter and electricity consumption is the feedback function or other interactions channels it provided. In turn, smart meter enabled feedback has been shown to be associated with lower consumption. We thank one reviewer to clarify this point.

Table 1
Comparison of CRECS-2012 with NBS.

Index	Unit	CRECS-2012			NBS		
		Total	#Urban	#Rural	Total	#Urban	#Rural
Number of observations	–	1450	1167	283	–	–	–
Male percentage	%	48.5	48.2	49.5	51.3[a]	50.6	51.5
Average household size	persons	2.7	2.6	2.9	3.0[a]	2.9	3.9
Dwelling area	m^2	103.7	96.2	134.9	–	94.1[b]	143.9
Ownership of refrigerator per 100 households	–	89	91	77	–	98.5[b]	67.3
Ownership of washing machine per 100 households	–	91	94	76	–	98[b]	67.2
Ownership of air conditioner per 100 households	–	113	127	51	–	126.8[b]	25.4

Note: [a]Derived from China Population and Employment Statistical Yearbook (2012); [b]Derived from China Statistical Yearbook (2013).

Table 2
Feedback source and format under each hypothesis.

Hypothesis	Feedback source	Feedback format
H1	meter-reader, bank billing statement, prepaid record, other channels	used quantity, monetary cost, price
H2	prepaid record, bill, other channels	used quantity, monetary cost, price
H3	bank billing statement, meter-reader, grid counter, bank or internet transfer record	used quantity, monetary cost, price
H4	meter-reader, bank billing statement, prepaid record, other channels	used quantity, monetary cost, price
H5	smart meter, other channels	used quantity, monetary cost, price

verified observations for analysis after validity and consistency checks.[7]

Our survey results show a high degree of consistency with China's National Bureau of Statistics (NBS) official data. Table 1 show that the CRECS 2012 similar to the official report in terms of gender percentage, household size, dwelling area, and ownership of durable goods for urban residences. However, the ownership of durable goods for the rural household in CRECS-2012 was higher than NBS's figure, possibly resulting from the small rural observations in CRECS-2012.

We estimated electricity consumption data using a bottom-up device-based accounting approach. The details are presented in the Appendix.

3.2. Types of information feedback

The survey data reflects household information from 2012 and offers cross-sectional data for analysis. Because our variable of interest is *Feedback*, the 136 of 1450 surveyed households that did not respond to one of the corresponding five questions related on *Feedback* variables were excluded. Finally, we were left with 1314 sample of respondents for whom complete all questions for further analysis.

First, we looked at the different ways that consumers receive electricity information. In the questionnaire, respondents answered whether and how access to their electricity usage information. Of our 1314 responding households, around 22% did not know any information about their electricity usage, and the remaining accessed their electricity information through four channels: "billing statement" (42%); "informed by meter readers" (19%); "prepayment record" (11%); and other methods (6%).

The two payment systems in use included pre-paid, in which the power supply will stop if the pre-paid credits run out, and bill pay after usage. There are around 34% of respondents using a pre-paid metering system and the remaining billed after usage.

Another relevant question is "how do you pay?". Over half of users indicated that they pay their bills at the counter of the electricity company (54%). 260 users, around 20% of respondents, paid through an automatic deduction from their bank account, about 15% of respondents transferred fees manually through their bank or the internet, and the remaining 11% paid the meter reader.

There were 1314 responses on information feedback frequency. Respondents indicated whether they paid (or pre-paid) their fees each month, every 2–5 months, or every six months, with results around 64%, 21% and 15%, respectively.

Finally, respondents were asked whether they use a smart-meter. Around 40% of households have installed a smart-meter while the remaining have not.

4. Estimation strategy

To empirically check these hypotheses, we used a regression approach. Following previous studies (Alberini et al., 2011; Alberini and Filippini, 2011; Fan and Hyndman, 2011; Shi et al., 2012; Zhou and Teng, 2013), the classical electricity demand model is specified in log–log function form[8] as below:

$$\ln\ KWH_i = \alpha + \beta \times feedback_i + \gamma \times X_i + \varepsilon_i \tag{1}$$

where the dependent variable $\boldsymbol{KWH_i}$ is the estimated electricity

[7] The sample selection process was as follows. In the first stage, we recruited around 120 interviewers from undergraduate and graduate students in Renmin University in December 2012. The sampling size of each province depended on the household population distribution reported in the 2010 6th National Population Census. This procedure yielded a geographic distribution of 38.3%, 43.2% and 18.5% for the east, central and west of China, respectively. The official population distribution in the east, central and west of China was 40.6%, 31.7% and 27.7%, respectively. In the second stage, a half-day training lecture was prepared for all interviewers to assure an understanding of the underlying meaning of each question and teach the necessary knowledge and skills. The survey was implemented in the third stage, in February to March 2013. The interviewers were required to collect detailed face-to-face information for each electric appliance by checking their nameplate (e.g., power capacity) and asking the householder their usage patterns for each device (e.g., usage frequency and duration). On average, an interview took 60–90 min. To avoid data bias and ensure quality, interviewers randomly choose the families in their social networks. However, the invited households must have met four criteria: (1) live in present home for more than six months in 2012; (2) use energy only for consumption and services rather than production; (3) only one candidate household for each community; (4) can provide electricity bill records in 2012. Each invited household got a prepaid card of mobile phone worth 50 RMB as remuneration upon finishing the survey. The interviewers were paid 50 RMB for each verified questionnaire. The fourth stage was to check the validity and consistency of the data. For each interviewer, 10% of questionnaires were randomly selected to conduct phone verification. If the respondent was not reachable or unavailable for three calls, the remaining households were selected to ensure that 10% of surveyed households for each interviewer were revisited via telephone contact. On the telephone, we asked them five questions from the original questionnaire that were easy to verify and remember. If two or more responses did not match with the record, the household was excluded and we selected another two households from the same interviewer for revisiting. In a case where two revisits from one interviewer were questionable, we excluded all surveyed households from the same interviewer. Finally, we got 1450 valid observations from 1542 recovered questionnaires. For more details on this survey, please refer to Zheng et al. (2014).

[8] The log–log function form is widely used in econometric analysis. The practical advantage is that the log transformation generates the linearity in parameters. Moreover, estimated coefficients of independent variables in log form can be explained as elasticity, making a straightforward interpretation of regression coefficients.

Table 3
Descriptive statistics of variables.

Category	Variable		obs	Unit	Mean	S.D.	Min.	Max.
Dependent Variable	*Estimated KWh*	*KWH*	1314	kWh	1773	1394	26.28	16540
Exogenous Variables (X)	*Electricity price*	*price*	1314	Yuan/kWh	0.532	0.0529	0.320	0.700
	Household income	*income*	1309	10,000 Yuan	9.612	15.76	0.500	350
	Household size	*size*	1310	person	2.644	1.049	1	8
	Householder's schooling years	*eduyear*	1215	year	11.28	3.943	0	22
	Dwelling area	*area*	1300	m^2	104.4	48.73	21	250
	Heating days	*HD*	1314	day/year	26.80	39.70	1	195
	Cooling days	*CD*	1314	day/year	30.92	33.44	1	150
	Urban or Rural	*citytown*	1311	–	0.798	0.402	0	1
Feedback Variables	*Information access*	*H1_infor*	1314	–	1.617	1.135	0	4
	Billing type	*H2_bill_type*	1314	–	1.664	0.472	1	2
	Payment type	*H3_pay_way*	1314	–	2.183	0.882	1	4
	Payment frequency	*H4_freq*	1314	–	1.518	0.749	1	3
	Smart meter	*H5_smart*	1314	–	0.404	0.491	0	1

consumption in KWh for the *i*-th household. The logrithmic form is ($\ln \boldsymbol{KWH_i}$). $\boldsymbol{X_i}$ is the explanatory variables which relate to residential electricity consumption, as listed below.

Electricity Price (denoted as ***price***): Electricity price is a key factor which affects electricity demand. The residential electricity prices in China are still under provincial-level regulation. In other words, each province has a uniform residential electricity price and it is hard to observe marginal prices. Following Filippini and Pachauri (2004), we used the average electricity price as a proxy variable, which is the price per kWh and is defined as the annual electricity expenditure over the annual electricity consumption, in logarithmic form (***lnprice***).

Household Income (denoted as ***income***): Household income is a household's annual gross income in Yuan. The questionnaire provided 18 income interval options, ranging from 10,000 to 5,000,000 Yuan. We used the mean value of each interval for estimation. The logarithmic form is employed (***lnincome***).

Household Size (denoted as ***size***)*:* Size measures the number of permanent residents in a household. The logarithmic form is (***lnsize***).

Dwelling area (denoted as ***area):*** Area expresses the dwelling's floor area in m^2. A larger space is normally associated with more lights and appliances. The logarithmic form is used (***lnarea***).

Householder's schooling year (denoted as ***eduyear):*** Measured by the years of householder spent in school. We take the logarithmic form for this variable (***lneduyear***). It is expected that higher education is associated with stronger environmental concerns (Franzen and Meyer, 2010).

Urbanization (denoted as ***citytown***): we use a dummy variable to differentiate urban and rural households. It equals to 1 for an urban household. Otherwise it equals to 0 for a rural household.

Heating days (***HD***) and ***Cooling days*** (***CD***) were used to reflect the actual electricity usage behavior affected by outdoor temperature. Heating days (*HD*) measures the number of days when the household used an electrical device for space heating, and cooling days (*CD*) for space cooling. Both variables were collected from the household self-report, and the logarithmic form was used (***lnHD*** and ***lnCD***).

Feedback was represented by five candidate variables according to our hypotheses. (1) Whether and how the household access the electricity information (***H1_infor***), equal to 0 if the household doesn't know any information and 1, 2, 3 or 4 if the information source is a meter reader, billing statement, prepayment record, or other, respectively. (2) The billing type (***H2_bill_type***) equals 1 if the household prepays the electricity fee and 2 for billing statement users. (3) The payment approaches (***H3_pay_way***) equal 1 for households that pay the bill (or charge) through authorized automatic deduction from a bank account, 2 at the electricity company counter, 3 through a bank or internet transfers or 4 directly to the meter readers. (4) The payment frequency (***H4_freq***) were assigned values 1, 2 or 3 for payment every month, 2–5 months or 6 or more months, respectively. (5) The use of smart meters (***H5_smart***) equals 1 if used and 0 if not.

Table 3 presents descriptive statistics of all variables.

5. Results and discussion

The regression results are listed in Table 4.[9] We firstly regressed residential electricity consumption on classical driving forces and presented the results in column (1). Considering the possible heterogeneity, an Ordinary Least Squares (OLS) estimation with Huber-White sandwich standard errors was applied.

5.1. Basic model

Column (1) presents the results of basic regression model. The price elasticity was −0.79 and significant at the 0.1% level ($p < 0.001$). When the *Feedback* variables were considered, the price elasticity ranged from −0.82 to −0.67. This finding is consistent with our expectation and most of the literature. For example, Filippini and Pachauri (2004) estimated price elasticity in India during 1993–1994, with results ranging from −0.42 to −0.29; Zhou and Teng (2013) obtained the price elasticity of urban residential electricity demand from −0.50 to −0.35 by using household survey data in Sichuan Province of China. The coefficient of household income was also significant at the 0.1% level ($p < 0.001$). Our estimation gives an income elasticity of 0.1, similar to Yoo et al. (2007) of 0.06–0.11 for Seoul residents in 2005 and Zhou and Teng (2013) of 0.14–0.33 for Sichuan urban residents from 2007 to 2009.

As we expected, other explanatory variables positively and significantly contributed to residential electricity consumption, i.e., the more permanent family members and the larger the area (Filippini and Pachauri, 2004; Yoo et al., 2007). The coefficient of householders' years of schooling was 0.168, significant at the 0.1% level ($p < 0.001$); this indicates that the education effect is dominant. The positive coefficient of the urban dummy variable was significant at the 5% level ($p < 0.05$), indicating that urban households generally use more electricity than rural households. Regarding climatic impacts, the remarkable positive signs for heating and cooling days across all columns showed that outdoor temperature plays a key role in electricity use. Ceteris paribus, extreme climatic conditions demand longer operation of home appliances, thus more electricity consumption.

In general, the basic model in column (1) shows results consistent with previous studies. Analyses found negative price elasticity and positive income elasticity for our surveyed data, and that urbanization

[9] We have checked the problem of multi-collinearity for all the regressions by Variance Inflation Factor (VIF). A rule of thumb is that a VIF value greater than 10 may indicate the presence of multicollinearity. The results show that all the VIF values are ranged from 1.28–1.5, indicating that multi-collinearity is not a severe problem.

Table 4
Regression results.

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
	Basic	H1	H2	H3	H4	H5	Mixed
lnPrice	−0.798***	−0.673***	−0.815***	−0.735***	−0.830***	−0.787***	−0.681***
	(−4.41)	(−3.46)	(−4.28)	(−3.93)	(−4.22)	(−4.23)	(−3.34)
lnIncome	0.0989***	0.0990***	0.0985***	0.0931***	0.0947***	0.0963***	0.0984***
	(4.06)	(3.89)	(3.87)	(3.66)	(3.68)	(3.79)	(3.82)
x_lnsize	0.161***	0.184***	0.176***	0.195***	0.183***	0.180***	0.189***
	(3.39)	(3.77)	(3.62)	(3.98)	(3.77)	(3.67)	(3.87)
x_lneduyear	0.168***	0.152**	0.170***	0.168***	0.164**	0.170***	0.153**
	(3.52)	(2.92)	(3.30)	(3.32)	(3.16)	(3.32)	(2.98)
x_lnarea	0.118**	0.111*	0.104*	0.101*	0.105*	0.112*	0.119**
	(2.73)	(2.42)	(2.27)	(2.21)	(2.29)	(2.44)	(2.63)
x_lnHD	0.0386***	0.0407***	0.0364***	0.0387***	0.0364***	0.0378***	0.0414***
	(3.71)	(3.74)	(3.33)	(3.56)	(3.33)	(3.46)	(3.76)
x_lnCD	0.0857***	0.0836***	0.0847***	0.0863***	0.0864***	0.0869***	0.0850***
	(8.21)	(7.81)	(7.89)	(8.06)	(7.95)	(8.15)	(7.80)
x_citytown	0.152**	0.182**	0.161**	0.168**	0.160**	0.161**	0.172**
	(2.65)	(3.04)	(2.72)	(2.83)	(2.67)	(2.71)	(2.88)
***H1_infor*: Information source (baseline: no information feedback)**							
1 m-reader		−0.147*					−0.163**
		(−2.55)					(−2.61)
2 bank billing statement		0.0204					−0.0190
		(0.40)					(−0.34)
3 prepaid record		−0.0536					−0.00704
		(−0.82)					(−0.11)
4 others		0.0848					0.0957
		(1.02)					(1.16)
***H2_bill_type*: Billtype (baseline: prepay system, or ex-ante feedback)**							
2 bill (ex-post feedback)			0.0825*				0.122**
			(2.24)				(2.69)
***H3_pay_way*: Payment mode (baseline: bank automatic debit, or implicit information feedback)**							
2 grid counter				−0.0370			−0.0291
				(−0.76)			(−0.60)
3 bank or internet transfer				−0.0769			−0.0462
				(−1.21)			(−0.71)
4 m reader				−0.205**			−0.194**
				(−3.21)			(−2.87)
***H4_freq*: information feedback frequency (baseline: monthly pay)**							
2 quarterly					0.00518		0.0375
					(0.11)		(0.77)
3 more than half a year					−0.0434		−0.0156
					(−0.81)		(−0.27)
***H5_smart*: smart meter (baseline: no smart meter)**							
2 smart						−0.0426	−0.0701
						(−1.17)	(−1.88)
Constant	5.120***	5.246***	5.099***	5.259***	5.156***	5.146***	5.204***
	(19.91)	(18.39)	(18.69)	(19.33)	(19.02)	(19.06)	(18.18)
Observations	1252	1185	1185	1185	1185	1185	1185
R-squared	0.184	0.189	0.182	0.186	0.179	0.180	0.201
AIC	2343.7	2223.4	2226.9	2224.8	2232.8	2230.2	2218.9
BIC	2389.9	2289.4	2277.7	2285.8	2288.6	2281.0	2320.5
Mean VIF	1.31	1.41	1.28	1.41	1.32	1.29	1.50
Log likelihood	−1162.8	−1098.7	−1103.4	−1100.4	−1105.4	−1105.1	−1089.5

Note: $t-$values in parentheses.

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

increases residential electricity demand. Moreover, electricity demand was positively correlated with family size, dwelling area, years of schooling and duration of operation of home appliances.

5.2. Hypotheses test

On the basis of the basic model in column (1), we examined our hypotheses by gradually adding relevant *Feedback* categorical variables in columns (2)–(6). Finally, we included all variables in column (7).

First, we added the variable *H1_infor* to examine hypothesis H1. The households that responded "they do not know any electricity information" were set as the reference group. From column (2), we found that information feedback through bank billing statements, prepayment records and other sources were not significant. The effect of "feedback from meter readers" was negative and significant at the 5% level, indicating that households who get information feedback from meter readers consume less electricity. Our results provided partial supportive evidence for H1 that feedback can be effective for residential energy conservation (Abrahamse et al., 2005).

Second, we looked at hypothesis H2 by adding the variable of billing types (***H2_bill_type***). The households that obtained ex ante information feedback, or used a prepaid system, were treated as a benchmark. In column (3), the coefficient for the group that gets ex post feedback was significantly positive at the 5% level, indicating that, ceteris paribus, households that pay the bill after consumption consume more electricity than households that prepay. This result confirms our hypothesis and is consistent with Faruqui et al. (2010), who suggested that prepaid users are associated with lower electricity consumption.

Third, we examined whether various payment types (***H3_pay_way***) mattered for hypothesis H3. In column (4), the reference group was "paying through automatic bank deductions". The coefficients of the "paying at the grid company counter" and "paying through bank/internet transfer" groups were -0.037 ($p = 0.448$) and -0.0769 ($p = 0.225$), respectively, indicating that their electricity consumption did not significantly differ from the benchmark group. However, the coefficient of the "paying through meter readers" group was -0.205 with $p = 0.001$, indicating a significant association with less electricity consumption.

Fourth, we checked hypothesis H4 by adding the variable of payment frequency (***H4_freq***). From column (5) we found that, compared with the base group that pays every month, the alternative groups were not significantly different, indicating that the information feedback frequency does not matter. This result is different from previous studies, which claim that quick feedback improves the link between action and effect (Dobson and Griffin, 1992; Fischer, 2008; McCalley and Midden, 2002). In those studies, the effect of consumption information feedback became less effective in a long term (Van Dam et al., 2010; Hargreaves et al., 2013). A possible reason is that those studies typically examined real-time or continuous feedback, which is much shorter and faster than our baseline monthly cycle.

Finally, we find that the smart meter variable (***H5_smart***), as described in hypothesis H5, was not as important as expected. Our results, as listed in column (6), showed that households who installed a smart meter consumed the same kWh as their non-smart meter counterparts. This finding was consistent with some previous empirical studies. For example, Hargreaves et al. (2013) used UK trial data to argue that smart meters do not necessarily lead to lower electricity consumption; their effect depends on some preconditions. Nilsson et al. (2017) also concluded that there was no evidence that real-time spot price visualization could reduce overall household electricity consumption. For our case, hypothesis H5 about the smart meter was not supported.

In column (7), we pooled all information feedback variables together for examination. The estimation results were similar to the discussions above, with better explanation power in terms of different statistical criteria (R^2, AIC and BIC). We found positive evidence for H1, H2 and H3. That is, information feedback through meter readers, ex ante information feedback (i.e., the prepaid system) and explicit information feedback through interactions with meter readers are effective ways to promote electricity conservation.

5.3. Robustness test

We offer a series of quantile regressions for robustness checks. Compared with the OLS, quantile regressions have the power to examine the relationships between variables outside of data means and offer detailed information to show how some percentiles of variables may be more correlated with others (Koenker and Hallock, 2001). The mixed model (column 7 in Table 4) was duplicated with various quantile settings. The regression results are listed in Table 5. The OLS results in column (1) were treated as the reference group. Quantile Regression results (QR hereafter) for 10th, 25th, 50th, 75th, and 90th are presented in columns (2)–(6).

Similar to the results given by OLS, the QR results found that residential electricity demand had low price elasticity, ranging from -0.878 to -0.455. Particularly, the 10th and 75th quantile of electricity consumption was not sensitive to price. The income elasticity was around 0.100 and significant across all columns. The OLS regression seemed to overestimate income elasticity at the 10th quantile. For other variables, family size, heating days and cooling days were significant factors in influencing electricity consumption for various quantile groups. However, the householder's education level, dwelling area, and location were not significant for some percentiles.

Now, let us look at information feedback. Our findings suggest that household feedback from meter readers is associated with lower electricity consumption, except at the 10th percentile. Most households who receive ex post feedback, i.e., if they pay the bill after consumption, used more electricity. Moreover, households that directly paid the electricity fee to the meter reader tended to use less electricity. However, the OLS regression of these two effects is not significant at the 10th and 25th quantile groups. Consistently, in the QR results, the frequency of feedback information had no influence on electricity demand for all columns. The effect of the smart meter was also not significant.

5.4. The role of the meter reader

The results regarding meter readers were quite fascinating, and may contradict the general anticipation. Understanding how meter readers work may help explain our findings. In most rural and some urban areas, prior to the application of remote smart meters, the grid companies employed many meter readers to periodically collect residential electricity consumption data. Each meter reader is responsible for several communities, with the duty of copying the meter numbers in a worksheet. In most cases, the power subscribers are listed by rows and months by columns, or each subscriber is recorded in an individual card. After calculating the number differences within a cycle, the meter reader then either informs the customer with a hand-write receipt or later mails a printed bill through the grid company. The receipt/bill usually includes the electricity consumption quantity and expense. In most villages, consumers can directly pay the meter readers because they know each other. In other cases, they can pay the bill at the counter of the electricity company, through the bank system or in other ways.

This system, on one hand, is inefficient compared with modern remote automatic meter readings. On the other hand, it creates face-to-face interactions between the electricity agency and the power subscriber, which cannot be substituted by technology. One reason meter readers worked well in our case was that this kind of feedback may provide customers with more in-depth information. For example, the meter readers are required to copy the meter number accompanied with the customer, if available. During this interaction, the meter reader's worksheet is visible to their clients. The conversation not only delivers consumption records for the last billing round, but may also relate users' historical records and/or neighbors' information. The more consumption information end-users obtained, the higher electricity efficiency would be expected in the home (Wilhite and Ling, 1995). Moreover, this kind of information comparison would promote energy conservation awareness by competition (Fischer, 2008; Mizobuchi and Takeuchi, 2013).

Another possible reason is the information feedback from meter-readers is more understandable and friendly. In some villages/communities, the meter reader is also the electrician responsible for routine facilities maintenance. Customers can obtain targeted advice and conservation tips, enhancing their perceived information and self-learning capacity, and leading to more effective energy savings (Allcott, 2011).

The application of smart meters are expected to assist clients reduce their electricity demand. However, it is not supported in our case. A possible explanation is lack of resident access to electricity consumption information. For example, there were 566 smart meter users in our sample, which accounts for 41% of total households. Among households with a smart meter, only 28 installed indoor smart meters, with the remaining centrally located either in apartment stairs or community distribution stations. Second, though the smart meters have multi-functions, the information feedback is absent in China. In Beijing, for

Table 5
Robustness test.

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	OLS	QR 10th	QR 25th	QR 50th	QR 75th	QR 90th
lnPrice	−0.681***	−0.565	−0.829***	−0.622**	−0.455	−0.878*
	(−3.34)	(−1.64)	(−3.36)	(−2.87)	(−1.93)	(−2.47)
lnIncome	0.0984***	0.160***	0.0986**	0.0986***	0.105***	0.0951*
	(3.82)	(3.71)	(3.21)	(3.65)	(3.57)	(2.16)
x_lnsize	0.189***	0.161	0.200**	0.186***	0.161**	0.213*
	(3.87)	(1.84)	(3.20)	(3.38)	(2.69)	(2.37)
x_lneduyear	0.153**	0.143	0.156*	0.110	0.146*	0.0579
	(2.98)	(1.54)	(2.34)	(1.89)	(2.30)	(0.61)
x_lnarea	0.119**	0.0567	0.0518	0.0547	0.139*	0.146
	(2.63)	(0.72)	(0.91)	(1.10)	(2.57)	(1.79)
x_lnHD	0.0414***	0.0408*	0.0450***	0.0401***	0.0397**	0.0740***
	(3.76)	(2.23)	(3.43)	(3.49)	(3.17)	(3.93)
x_lnCD	0.0850***	0.114***	0.0903***	0.0757***	0.0762***	0.0657***
	(7.80)	(6.02)	(6.69)	(6.39)	(5.91)	(3.39)
x_citytown	0.172**	−0.0185	0.120	0.195**	0.155*	0.376***
	(2.88)	(−0.18)	(1.62)	(3.00)	(2.19)	(3.55)
***H1_infor*: Information source (baseline: no information feedback)**						
1 m reader	−0.163**	−0.0852	−0.218**	−0.164*	−0.243**	−0.277*
	(−2.61)	(−0.76)	(−2.73)	(−2.33)	(−3.18)	(−2.41)
2 bank billing statement	−0.0190	−0.0675	−0.0431	0.0170	−0.0195	−0.0915
	(−0.34)	(−0.72)	(−0.64)	(0.29)	(−0.30)	(−0.95)
3 prepaid record	−0.00704	−0.0696	−0.0912	0.0136	−0.0570	−0.0740
	(−0.11)	(−0.58)	(−1.06)	(0.18)	(−0.69)	(−0.60)
4 others	0.0957	0.106	0.0574	0.101	0.102	0.225
	(1.16)	(0.74)	(0.56)	(1.11)	(1.04)	(1.52)
***H2_bill_type*: Billtype (baseline: prepay system, or ex-ante feedback)**						
2 bill (ex-post feedback)	0.122**	−0.0406	0.0178	0.182***	0.230***	0.281***
	(2.69)	(−0.50)	(0.30)	(3.54)	(4.12)	(3.35)
***H3_pay_way*: Payment mode (baseline: bank automatic debit, or implicit information feedback)**						
2 grid counter	−0.0291	0.000864	0.0288	−0.0345	0.0163	−0.162
	(−0.60)	(0.01)	(0.48)	(−0.65)	(0.28)	(−1.87)
3 bank or internet transfer	−0.0462	−0.143	−0.0457	0.00653	0.0560	−0.189
	(−0.71)	(−1.24)	(−0.56)	(0.09)	(0.71)	(−1.60)
4 m-reader	−0.194**	−0.0877	−0.0404	−0.210**	−0.181*	−0.405**
	(−2.87)	(−0.71)	(−0.46)	(−2.71)	(−2.15)	(−3.19)
***H4_freq*: information feedback frequency (baseline: monthly pay)**						
2 quarterly	0.0375	0.0323	0.0350	0.0519	0.0208	0.00486
	(0.77)	(0.37)	(0.55)	(0.94)	(0.35)	(0.05)
3 more than half a year	−0.0156	0.0389	−0.0459	−0.0334	0.00747	0.0577
	(−0.27)	(0.37)	(−0.60)	(−0.50)	(0.10)	(0.53)
***H5_smart*: smart meter (baseline: no smart meter)**						
2 smart	−0.0701	−0.117	−0.0768	−0.0691	−0.0771	−0.0888
	(−1.88)	(−1.76)	(−1.61)	(−1.65)	(−1.69)	(−1.29)
Constant	5.204***	4.944***	5.095***	5.607***	5.605***	5.759***
	(18.18)	(9.82)	(14.15)	(17.73)	(16.29)	(11.14)
Observations	1185	1185	1185	1185	1185	1185
R-squared	0.201					
Pseudo R-squared		0.125	0.110	0.109	0.129	0.137
AIC	2142.3					
BIC	2243.7					
Log likelihood	−1051.1					

Note: t − values in parentheses.

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

example, smart meter screens only display the cumulative electricity consumption in kWh and remaining account balance in RMB; accessing historical monthly consumption records through smart meters is disabled.[10] In addition, some of residents do not fully understand how to check the information via smart meters or realize the meaning of the numbers on the screen. Therefore, the meters cannot increase their consciousness of electricity conservation or change their consumption behavior. In other words, the smart meter does not perform well in terms of information feedback and there may be no substitute for face-to-face interactions with meter readers.

6. Conclusions and policy implications

To identify and examine the correlation between information feedback and residential electricity consumption, the present paper applied a log–log electricity demand function on 2012 micro-level Chinese household survey data. We found that price and income elasticity were significantly negative and positive, respectively. Urban

[10] According to an inquiry with the customer service hotline of Beijing Grid company, the clients can call the hotline 95598, login the grid's website, or visit grid counter to access their historical record.

households consume more electricity than rural, and residential electricity demand is positively associated with family size, dwelling area, householders' years of schooling, and heating and cooling days. We empirically checked five hypotheses regarding information feedback, revealing a significantly negative correlation between households who obtain electricity consumption information through meter readers or directly pay meter readers and electricity demand, with coefficients of -0.163 ($p = 0.009$) and -0.194 ($p = 0.004$), respectively. Households that used bill systems, compared with households using prepaid metering systems, were significantly positively associated with electricity demand, with a coefficient of 0.122 ($p = 0.007$). However, there is no supportive evidence for feedback frequency or smart meter in our case.

Our study suggests that residential electricity demand is partly determined by household characteristics and consumer behavior. Moreover, access to information feedback, or interactions with meter readers and prepaid systems, is highly correlated with residential electricity consumption. Findings do not suggest that old-fashioned meter reader systems are efficient in promoting residential energy conservation. They revealed that demand management is seriously absent in more modern systems for energy payment; either appropriate measures targeting the household sector are lacking or the energy saving programs that do exist, such as smart meters, are not effective. In other words, information from sources other than meter readers is not adequate or does not transform into knowledge or action.

A McKinsey report on "Evolution of the Smart Grid in China" revealed a tremendous need for smart grid technology to boost clean development in China (McKinsey and Company, 2010). China now is leading the world in smart grid investment, with more installed smart meters than the rest of the world combined (Yang, 2015). By the end of 2013, China had installed over 250 million smart meters, covering about 70% of households. The State Grid Corporation of China (SGCC) expects to achieve 100% smart meter coverage in 2017. Electricity utilities are greatly incentivized to replace old mechanic meters with new smart meters to improve the efficiency of power tariff collection. However, the utility companies are not incentivized to provide sufficient information feedback to their customers, since their revenue heavily depends on the electricity sold. For example, electricity sold accounted for 99.5% of SGCC's total business revenue in 2015 (SGCC, 2015).

Policy-makers concerned about social welfare should take multiple targets into consideration while simultaneously making infrastructure investment decisions. Considering the vast research demonstrating great potential for developed countries to save electricity through information feedback, China's policy-makers also should attach great importance to demand side management of residential electricity consumption and improve information feedback capacity. For example, the introduction of new electricity sales companies would increase competition and improve customer service quality. The development of energy service consulting companies could help users optimize their consumption and lower their expenditures. In addition, the development of new technologies such as mobile APPs and short message services (SMS) could deliver messages directly to clients and improve information feedback.

It is worth noting that, our sample size was relatively small, and rural households may be under-represented given the huge population and vast geographic disparity of China. Second, our analysis was not based on a purely randomized experiment. Strictly speaking, what we have investigated is not "causal effect" but "correlation". For further analysis, randomized experiments are required. Moreover, the present study reveals that the meter reader is more effective than the smart meter, but solid evidence is absent to uncover the mechanisms behind this. A larger survey covering more sample and more in-depth analyses, such as the control of potential self-report and recall biases during the interview are needed in the future. Given CRECS's special features on disaggregated energy consumption data per energy source and per activity, this unique database provides scholars opportunities to explore various topics in the future and make some additional contributions to the literature.

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Appendix A. Estimation of electricity consumption data

We use the bottom-up device-based accounting approach to estimate the electricity consumption, which was systematically developed by Wu and Wei (2017). The estimation strategy is as follows. Fuels are divided into seven categories: coal, firewood, LPG, natural gas, electricity, district heating and solar power. We also identify five energy end-use demand: cooking, home appliances, space heating, space cooling and water heating. We first estimate the daily energy consumption for each device (appliance) based on its output power (or consumption rate for stoves), energy efficiency grade, demanding frequency, usage durationand other parameters. Then, the annual household energy consumption is aggregated from the daily device-based energy usage and the living days in year 2012. This strategy has been applied in recent surveys and research (Niu et al., 2012; Zheng et al., 2014).

Our survey covered most electric appliances, including refrigerators, televisions, washing machines, personal computers, light bulbs, air-conditioners, electric fans and water heaters. The questionnaire and response options for home appliance in our survey is listed in Appendix A, Table A1. "Type" includes all of electricity appliance in the household (e.g. refrigerator, washing machine, air-condition, television et al) and cooking appliance (e.g. rich cooker, microwave oven et al.). "Number" records the ownership of home/cooking appliance. The options are designed to collect the information on appliance's output power, energy efficiency grade, usage duration and usage frequency.

Appendix A

For electricity use, our estimation process is given as follow. Suppose there are J home appliances for i-th household. The survey collects the following detailed information for each home appliance: output power ($Power_i^j$), energy efficiency grade (EE_i^j), usage duration every time ($Dura_i^j$) and usage frequency every day ($Freq_i^j$).

The annual electricity consumption for j-th appliance is further adjusted based on the resident's stay duration at home in 2012 ($Stay_i$).

$$KWH_i^j = Power_i^j \times EE_i^j \times Dura_i^j \times Freq_i^j \times Stay_i \tag{1}$$

The annual electricity use for i-th household in 2012 is given as:

Table A1
Questionnaire for home appliance.

Type		Number	Output Power	Energy Efficiency Grade	Usage Duration Every Time	Usage Frequency
			(1) ≤300 W (2) (300, 500] W (3) (500, 700] W (4) (700, 1000] W (5) (1000, 1500] W (6) > 1500 W	(1) None (2) Level 1 (3) Level 2 (4) Level 3 (5) Level 4 (6) Level 5	(1) ≤15 min (2) (15, 30] min (3) (30, 45] min (4) (45, 60] min (5) (60, 90] min (5) (90, 120] min (6) > 120 min	(1) ≥3 times/day (2) 2 times/day (3) 1 times/day (4) 4–6 times/week (5) 1–3 times/week (6) < 1 time/week (7) Never
Home Appliance	Refrigerator	1				
		2				
		…				
	Washing machine	1				
		2				
		…				
	Air-conditioner	1				
		2				
		…				
	others					
Cooking Appliance	Rich-cooker	1				
		2				
		…				
	Microwave oven	1				
		2				
		…				
	others	…				

$$KWH_i = \sum_{j=1}^{J} KWH_i^j \tag{2}$$

The device-based approach has three major advantages. First, it allows us to aggregate the household energy consumption by different fuel types or specific demand. Second, this approach can accommodate the energy that cannot be measured by meters (like biomass). Third, it collects the physical characteristics of durable goods and consumption behavior. The respondents have less incentive to hide the living preference and behaviour information (i.e., daily cooking frequency and duration) deliberately. More technical details on the bottom-up device-based accounting approach can refer to Wu and Wei (2017).

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