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Urban form and household electricity consumption: A multilevel study

Chaosu Li[a], Yan Song[b,c,*], Nikhil Kaza[a]

[a] Department of City and Regional Planning, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599, USA
[b] Department of City Planning, Shenzhen University, Shenzhen, 518060, China
[c] Program on Chinese Cities, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599, USA

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ABSTRACT

While urban form affects building energy consumption, the pathways, direction and magnitude of the effect are disputed in the literature. This paper uses a unique dataset to examine the effect of urban form on residential electricity consumption in Ningbo, China. Using survey and utility bill data of 534 households in 46 neighborhoods in the city, we model the electricity use of households using a multilevel regression model. We find that neighborhood street configuration and tree shade are important in controlling residential electricity consumption and, consequently, greenhouse gas emissions. Our results suggest that seasonality and dwelling type condition the effect of neighborhood densities on electricity consumption. Neighborhood density is associated with household electricity consumption in summer months, while there is no such association in winter months. As neighborhood density increases, households in slab and tower apartments in dense urban neighborhoods consume more electricity in summer months, which can be partly explained by exacerbated heat island effect. Interestingly, the neighborhood density is negatively associated with summer electricity consumption for single-family houses, suggesting that the effect of neighborhood density is different for different types of dwelling units.

1. Introduction

Urban form and land use patterns significantly influence a city's energy consumption and, consequently, its GHG emissions. It is widely believed that physical urban form affects urban transportation energy consumption [1–4], and there are numerous studies on the relationship between urban form and transportation energy use [1–6]. Energy use in buildings is one of the major sources of greenhouse gas (GHG) emissions from cities, and most of these emissions are from building operations [7–9]. However, there have been a relatively limited number of studies on the relationship between urban form and operational energy use in buildings. A comprehensive understanding of the relationship between urban form and energy use is key to formulating climate change mitigation policies at a city level. Therefore, it is important to evaluate how various elements of urban form affect building energy consumption [10–13]. The pathways, direction and magnitude of the effects of urban form on building energy consumption are disputed in current literature [14]. Furthermore, most of these studies are limited to cities in Europe and the Americas. Few studies to date have assessed the roles of physical development and urban form on residential energy consumption in the context of dense urban environment, such as fast-growing megacities in Asia, where urban form policies might play a more important role in promoting building energy efficiency.

In China, residential sector is the second largest energy-consuming sector after Industry and consumes about 13% of the total energy consumption [15].[1] Together with the unprecedented scope of urbanization in recent decades, residential energy consumption in China has increased enormously: the growth rate in residential electricity demand has reached an annual average of 11.9% [15]. Since this growth shows no signs of abatement, it is crucial to know how changes to physical development patterns and modifications to urban built environment can contribute to lowering residential energy consumption. However, existing studies

* Corresponding author.
E-mail addresses: chaosuli@live.unc.edu (C. Li), ys@email.unc.edu (Y. Song), nkaza@unc.edu (N. Kaza).

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[1] According to National Bureau of Statistics of China, energy consumption from the transportation sector is underestimated since it only includes commercial transportation, postal and warehousing industries. The energy consumption from non-commercial transportation (e.g., private cars and motorcycles) is not included [50].

on residential energy consumption in China have largely focused on occupants' socio-economic status and behavior, price deregulation, policy effectiveness, as well as technical measures to improve energy efficiency [16–19].

The purpose of this paper is to explore the effects of urban form on residential energy consumption, in the contexts of urban environments in China, so as to shed light on the role of urban form on residential energy efficiency. We first review current literature debate concerning urban form and building energy consumption and justify the research questions. We then present our research design, data collection and analysis methods, including the household survey, urban form measures, and model specification. We then present the results for the study area in Ningbo city and set these in the context of existing literature. We discuss directions for future research and conclude with policy implications.

2. Literature review and research questions

Urban density, a measure that is central to physical planning, was long considered an important driver for building energy consumption [14]. Early expositions of this relationship suggested that urban development patterns with higher physical density are associated with higher urban temperatures and heat island effect [20,21], which could in turn increase cooling loads in buildings [22]. In recent years, the relationship between urban form and energy consumption has enjoyed a resurgence of interest [11]. However, there has been disagreement among literature concerning pathways, direction and magnitude of the effects of urban form (especially urban density) on building energy consumption. Ewing and Rong [23] posit three possible pathways through which urban form impacts residential energy consumption: energy loss through electric transmission and distribution, increased energy demand associated with the urban heat island effect, and energy consumption variance through size and type of housing stocks. The complicated stepped analysis and the conclusions of this study are still under debate, as Randolph [24] argues that urban form is still an excessively blunt tool without sufficient empirical evidence and Ewing and Rong fails to consider the dynamic aspects of markets or consumer behavior in their study. More recently, Lee and Lee [13] examined the effects of urban form on households' carbon dioxide emissions in the 125 largest urban areas in the United States and found that doubling population-weighted density can reduce residential energy consumption by 35%; this supports the idea that smart growth polices and compact urban form are an important part of macro-efforts to mitigate greenhouse gas emissions. A notable limitation of this study is that the authors only evaluated macro urban form measures at the city-level, which leaves out micro-level urban dimensions such as neighborhoods.

Interestingly, Wilson [11] used a sample of single-family detached homes in Illinois (United States) to explore how density and other urban form indicators affect residential electricity consumption. The most notable finding from this study is the negative relationship between density (dwelling units per acre) at the subdivision level and summer household electricity consumption, which is consistent with a nuanced argument that low-density residential development with large lawn areas may contribute radiant heat energy that increases the surface heat island effect [25,26]. By using the national Residential Electricity Consumption Survey (RECS) data in the United States, Kaza [27] did not find any impact of self-reported neighborhood density on household energy use; this contradicts the argument that compact neighborhoods are more energy efficient with regard to electricity consumption [11]. In addition, by using a sample mostly composed of single-family houses from Sacramento, California (United States), at the land parcel level, Ko and Radke [10] did not find that physical density had a significant effect on summer residential cooling energy consumption, which again contradicts Wilson's results [11]. The authors found that other urban form features such as east–west street orientation, higher green space density, and larger vegetation on the east, south, and west sides of dwelling units have significant effects in reducing cooling energy use in summer months.

In addition to the above empirical studies, there are also no consensus in studies that use simulation methods: By using a digital elevation model of London, Steemers [28] found that increasing urban density leads to increased energy consumption in office buildings across the city. In contrast to Steemers' findings, Rode et al. [29] did not find any positive effect of increasing urban density on building heat-energy consumption. Instead, this study found that heat-energy efficiency of buildings can be achieved through high urban densities or taller buildings that allow lower densities at the neighborhood scale. Based on six typical neighborhood types in Shanghai, China, a recent study by Yang and Zhang [30] indicates that higher density leads to higher energy performance of buildings in the neighborhoods. Their simulation results can hardly be confirmed with the actual electricity bill data since quantifying more complicated interrelationships should consider local socioeconomic context. Interestingly, by using samples in Portland and Atlanta (United States), Quan et al. [31] found that building energy consumption decreased as the floor area ratio increased until it reached a certain point, beyond which the energy-urban density relationship reversed.

In summary, both empirical and simulation studies to date provide an unclear picture of how urban form, especially physical density at the neighborhood-level, affects energy consumption. One potential factor that leads to the differences between the simulation and empirical results is that, most simulation studies merely modeled the relationship between physical density and building energy consumption on an annual basis; the relationship might be totally different if it is modeled on a seasonal basis. Additionally, most existing empirical studies on urban density and residential energy consumption were conducted within the geographical contexts of the United States and Europe, and focus heavily on single-family houses in low-density urban environments. It is far from clear whether similar patterns will hold true in other geographical and cultural contexts such as dense residential neighborhoods in Asian megacities. Therefore, our study aims to provide more empirical evidence of how different urban forms, particularly density at the micro-scale, affect residential energy consumption in a geographical context with varying urban density and different types of dwelling units. We aim to provide more detailed empirical understanding of how urban form characteristics shape residential energy consumption for different seasons, and for different types of dwelling units located in different neighborhoods by answering the following questions:

1) Is there a relationship between urban form (especially neighborhood density) and residential energy consumption after controlling for differences in demographic, socioeconomic, behavioral, and property-related characteristics at the household level?
2) Are the effects of urban form on residential energy consumption consistent across seasons? How do these effects differ between the summer and the winter?
3) Does neighborhood density affect residential energy consumption differently for households located in different types of residential buildings?

3. Methods

3.1. Description of the survey

In order to probe the research questions of this study in detail, we conducted a household survey in Ningbo, a sub-provincial city located along the eastern coast of China. Ningbo is a typical city in the Yangtze River Delta Metropolitan Region, which is situated in China's "hot summer and cold winter" climate zone. The total population within the built-up area of Ningbo is 2.182 million, with a residential density in the city center of 10,399 people per square kilometer. We selected Ningbo mainly because its residential urban form is representative of development in other cities in Yangtze River Delta Metropolitan Region, which is the largest metropolitan area in China. Additionally, we have got pre-permission from the Ningbo Electric Power Bureau to access the residents' utility bills for this study. The typical types of residential buildings in Ningbo include slab apartment homes, tower apartment homes, and single-family houses, which is also consistent with other Chinese cities.

The household survey instrument used in this study (Appendix A) was developed based on previous studies [11,16,32], as well as the U.S. Residential Energy Consumption Survey; these surveys are designed to capture the important demographic, socioeconomic, behavioral, and property-related explanatory variables for household electricity consumption. In the survey, we required our participants to provide us the identification numbers for their electricity meters. Participants agreed to participate in our survey and let us access their utility bills from the Ningbo Electric Power Bureau and use this information for our study before our survey started. The survey is composed of four parts. The first part of the survey was completed by the surveyors and is composed of basic questions about participants, including addresses, floor levels,[2] dwelling types, and the electricity meter identification number of the households. The second part of the survey deals with building ages, the area of the dwelling units, and households' estimates of their monthly utility bills. Information about home heating equipment was also gathered in this section. The third part of the survey primarily comprised of questions about the demographic and socio-economic status of the participating households, including the ages of family members and household incomes. A survey of major household appliances[3] was also completed during this part of the survey and used to calculate the home appliance index in the regression model. The final section of the survey includes seven questions to learn about electricity conservation actions[4] used within the households as well as other micro-level urban form characteristics, such as whether their households have tree shade and whether their neighborhoods are adjacent to water bodies.

Initially, we conducted a priori sample size estimation to determine how many observations are needed for this study.[5] By setting a desired statistical power level of 0.95, we calculated the minimum sample sizes for different effect sizes of 0.05 (small), 0.15 (medium), and 0.35 (large). Our required sample size ranged from 105 to 634 observations. By referring to previous studies [11,16,32], we targeted 560 households as our desired sample size to ensure a relatively large sample.

Our sampling strategies are as follows: First, we selected six different "typical" communities (Fig. 1) across Ningbo in different locations (Table 1). We then used a random drawing to select 560 households within these communities based on addresses gathered from the Ningbo Planning Institute. The selected households are located in 46 residential neighborhoods[6] with various building types, densities, and urban form features. After the samples were selected, we hired a survey company to do households surveys. We paid the surveying company 120 RMB for each survey. To ensure survey quality, every surveyor was required to attend a half-day training lecture. During the training process, one of our questionnaire designers discussed each question with all surveyors. Each surveyor received intensive training on sampling strategy and interview skills.

A pilot survey of 20 households was conducted in June 2015 to reveal any possible misinterpretations of survey questions, ambiguity in response categories, or other issues. The survey instrument was slightly revised based on the responses from our pilot survey. The formal survey was conducted during July 2015. After that, monthly electricity data in the most recent year for each household was collected from the Ningbo Electric Power Bureau. After validity checks on both the electricity data and the survey results, 534 total observations in 46 different neighborhoods remained in our final sample.

3.2. Urban form measures

Urban form measures in this study are derived both at the housing unit- and neighborhood-levels. At the housing unit-level, the type of dwelling in which the household is located is deemed as an important micro-level urban form factor. Numerous previous studies indicate that dwelling type can have a major effect on household energy consumption, as single-family units tend to consume more energy than multi-family units [27,33,34]. In the context of Chinese cities, primary dwelling types include slab and tower apartments located in high-density neighborhoods. Thus, in this study, three binary variables were included to capture if a housing unit is in a single-family house, a slab apartment, or a tower apartment (Fig. 2). Similar to Wilson [11], our household survey includes a question which indicates if the surveyed housing unit has tree shade.

Neighborhood-level urban form measures were primarily calculated from GIS datasets provided by the Ningbo Planning Bureau. In this study, our metric for measuring neighborhood density is floor area ratio, which is calculated by dividing the total floor area of all the buildings within a residential neighborhood by the total area of the residential neighborhood.[7] A higher floor area ratio indicates a denser urban neighborhood. We chose floor area ratio as the indicator to measure urban density because local governments in China use it as a standard in urban planning codes to regulate residential development, making this metric policy-relevant. The second neighborhood-level urban form measure is street configuration, which has been identified as another important factor in influencing household energy consumption since the ideal east-west orientation of a street will result in more south-facing buildings in

[2] Since floor level (e.g., differences between first floor, intermediate floor, and top floor) could be a potential factor affecting the household's insulation and its exposure to external temperature [51], we included it in our survey and classified each household's floor level into four categories: first floor, middle floor (floor level 2–8), high floor (floor level >8), and top floor.

[3] Following Chen et al. (2013), the term "major household appliances" refers to electricity-intensive appliances in Chinese homes, including air-conditioners, fridges, washing machines, water heaters, computers, and televisions [16].

[4] We calculated the electricity conservation index for each housing unit based on the information that we derived from part 4 of our household survey (Appendix A). We coded questions 23–27 on a 0–2 ordinal scale and summed up all the coded values of these questions to get the electricity conservation index.

[5] We used the methods recommended by Faul et al. (2009) to conduct the power analysis for multiple regressions [52]. We set 20 as the number of predictors.

[6] Residential neighborhood in this study refers to "juzhuzutuan", which is the primary unit in residential areas in China. It is often maintained by a single property management company and composed of homogenous residential buildings.

[7] In this study, we initially envisioned utilizing three neighborhood density measures: floor area ratio, building coverage ratio, and housing units per square kilometer. These three measures are highly correlated (e.g. Pearson correlation coefficient > 0.7, $p < 0.05$). We decided to use floor area ratio as the neighborhood density measure for this study since it is most relevant to urban planning codes in China.

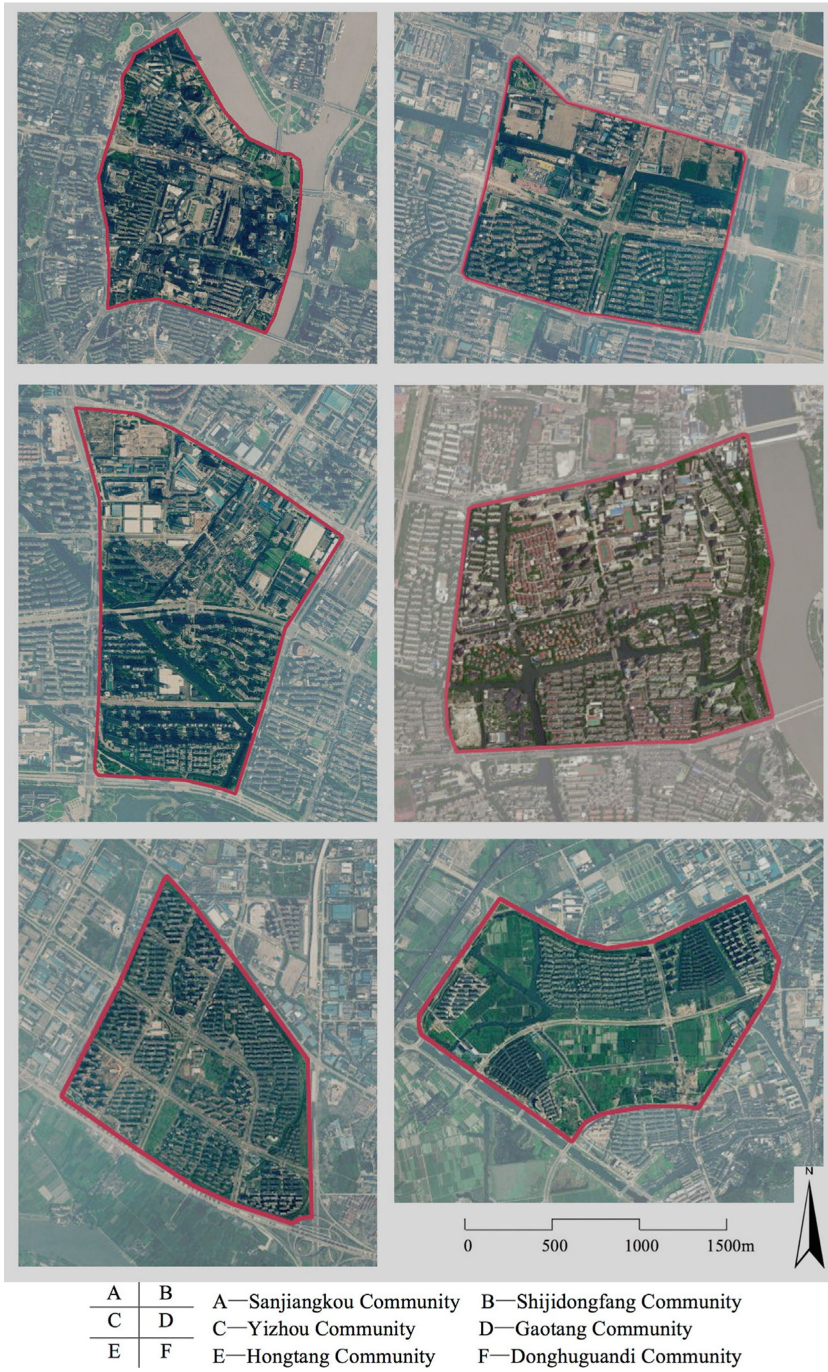

Fig. 1. Images of the six communities across Ningbo used in this study, accessed December 10, 2015. *Photograph: Baidu Map.*

Table 1
Key characteristics of the six communities.

Characteristics	Sanjiangkou	Shijidongfang	Yizhou	Gaotang	Hongtang	Donghuguandi
Distance to city center	Close	Medium	Distant	Medium	Distant	Distant
Distance to city sub-centers	Medium	Close	Medium	Distant	Distant	Distant
Relative housing density	High	Medium	Medium	High	High	Low
Housing type(s).	Slab apartment/Tower apartment	Slab apartment/Tower apartment	Slab apartment/Tower apartment	Slab apartment/Tower apartment/Single-family house	Slab apartment/Tower apartment	Slab apartment/Single-family house

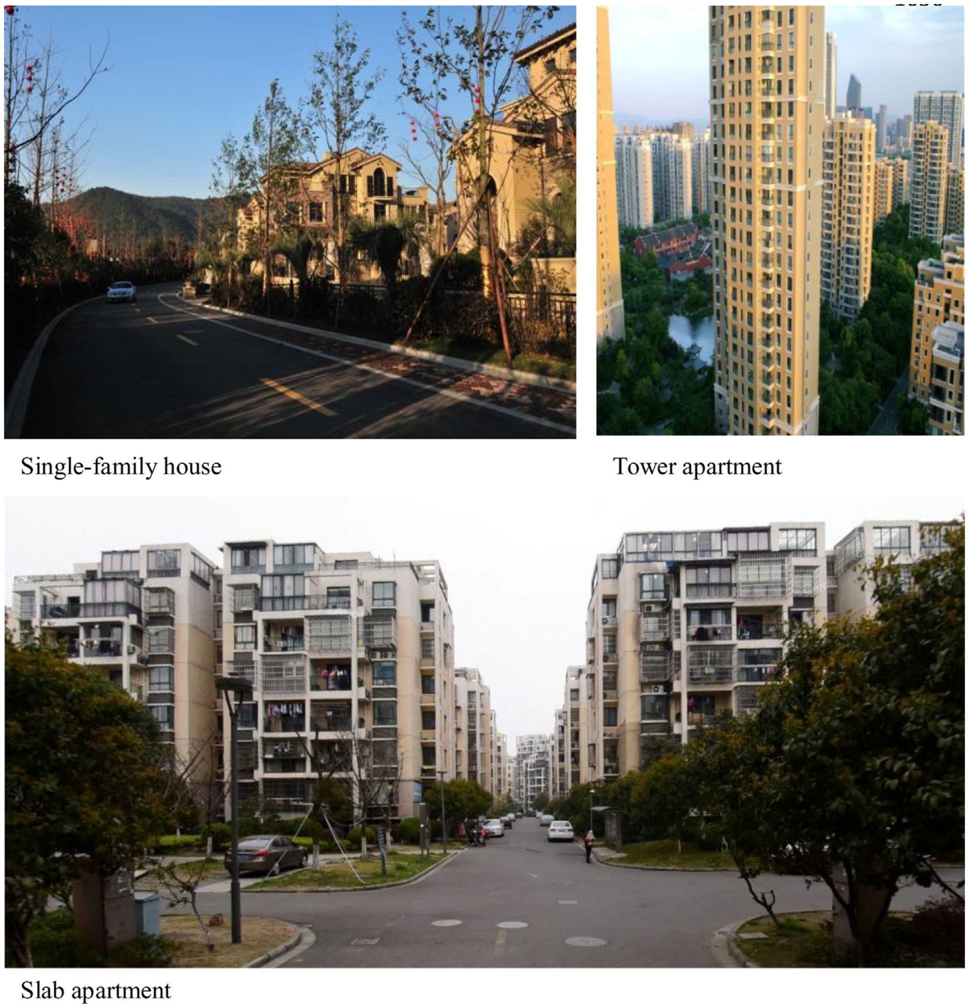

Fig. 2. Pictures of the different dwelling types included in this study.

a neighborhood [10,12,35–37]. To measure street configuration, we initially determined the major axis of streets using street network GIS data. We then calculated the orientation angle for each street in the major axis. If more than 80% of the streets in the major axis are within five degrees of the ideal east-west orientation, the street configuration variable for the neighborhood was coded as 1; otherwise, it was coded as 0. The last neighborhood urban form measure, also coded as a binary variable, indicates whether a neighborhood is adjacent to natural water bodies (e.g., rivers, lakes). This variable was primarily derived from the household survey and confirmed with Google Earth images.

3.3. Model specification

Multilevel regression was used in this study since it is designated to analyze hierarchically clustered data. It is also known as a hierarchical linear model or linear mixed model, which deals with the within-group dependency issues whilst estimating ecological effects [38–40]. Furthermore, the multilevel specification also models spatial autocorrelation by capturing spatial structure in the data [41].

The decision whether to use a hierarchical linear model is based on both statistical and theoretical criteria. The general statistical guideline for checking the need to use a hierarchical linear model is based on the calculation of intraclass correlation which, in this case, gives an estimate of the degree of variance in electricity consumption in the surveyed households that can be explained by neighborhood effects [38–40]. The model to estimate intraclass correlation is as follows:

Household level:

$$Y_{ij} = \beta_{0j} + \gamma_{ij}$$

$$\gamma_{ij} \sim N(0, \sigma^2)$$

Neighborhood level:

$$\beta_{0j} = \gamma_{00} + \eta_{0j}$$

$$\eta_{0j} \sim N(0, \tau_0{}^2)$$

Where Y_{ij} is the natural log of the electricity consumption in the ith household of the jth neighborhood, and γ_{ij} is the household-level residual. γ_{00} is the overall mean of household electricity consumption across neighborhoods, and η_{0j} is the neighborhood-level residual. Thus, $\tau_0{}^2$ is the measure of variation of household electricity consumption between neighborhoods, while σ^2 is the measure of variation of household electricity consumption within neighborhoods. Further, the intraclass correlation is calculated as the proportion of variation at the neighborhood level:

$$\rho = \tau_0{}^2/(\sigma^2 + \tau_0{}^2)$$

According to the results presented in Table 2, the intraclass correlations for annual, summer, and winter electricity consumption are 35.50%, 34.79%, and 31.57%, respectively; all of these

Table 2
Analysis of intraclass correlation.

Dependent variable	Neighborhoods (N = 46)			
	Between-group variation	Within-group variation	Intraclass correlation	Prob > F
Annual electricity usage (logged)	0.1412	0.2564	0.3550	0.0000
Summer electricity usage (logged)	0.1302	0.2441	0.3479	0.0000
Winter electricity usage (logged)	0.1710	0.3706	0.3157	0.0000

results are statistically significant. This indicates that a moderate proportion of variance in electricity usage can be attributed to differences between neighborhoods. Additionally, existing studies have already identified neighborhood urban form as having a significant impact on household energy consumption [10,11]. Therefore, utilizing a hierarchical linear regression is an appropriate method to estimate the effects of urban form on household electricity consumption. After other explanatory variables at both household and neighborhood levels are added, the model becomes:

Household level:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \beta_{2j}Z_{ij} + \gamma_{ij}$$

Neighborhood level:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \eta_{0j}$$

$$\beta_{1j} = \gamma_{10} + \eta_{1j}$$

$$\beta_{2j} = \gamma_{20} + \eta_{2j}$$

Where, Y_{ij} is the natural log of the electricity consumption in the ith household of the jth neighborhood. X_{ij} denotes household-level urban form variables, which includes binary variables for tower apartments and single-family houses, and whether the household has tree shade. Z_{ij} denotes household-level demographic, socioeconomic, property, and behavioral variables, including household size, average ages of adults, income per capita, homeownership, sizes of the apartments/houses, floor levels, ages of apartments/houses, an appliance index, and an electricity conservation index. W_j are neighborhood-level urban form indicators of the jth neighborhood, including floor area ratios, street configurations, and adjacencies to water bodies.

In the third stage, our analysis was expanded to include cross-level interactions. Since we hypothesize that neighborhood density would have different effects for households located in different types of dwelling units, $Den_j \times Typ_{ij}$ was added into the model to test the hypothesized interaction between neighborhood density and dwelling type. Here Den_j denotes the floor area ratio of the jth neighborhood, while Typ_{ij} includes two binary variables which indicate if the ith household of the jth neighborhood is located in a tower apartment or a single-family house. Thus, after the cross-level interaction term was added, the model becomes:

Household level:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \beta_{2j}Z_{ij} + \gamma_{ij}$$

Neighborhood level:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \gamma_{02}Den_j \times Typ_{ij} + \eta_{0j}$$

$$\beta_{1j} = \gamma_{10} + \eta_{1j}$$

$$\beta_{2j} = \gamma_{20} + \eta_{2j}$$

3.4. Descriptive statistics

Table 3 provides descriptive statistics for the measures used in the multilevel model. Annual electricity usage refers to annual household electricity usage from October 2014 to September 2015, in the unit of kWh. Summers and winters in Ningbo both last four months, with summer months including June, July, August, and September, and winter months including December, January, February, and March. Thus, we calculated the summer electricity usage by using the household electricity data from June 2015 to September 2015; accordingly, winter electricity consumption was derived from the electricity data from December 2014 to March 2015. Annual household electricity usage ranged from 466 kWh to 39,117 kWh, with 2,882.03 kWh as the mean and 2717.21 kWh as the standard deviation. Not surprisingly, the annual, summer, and winter usages are all right-skewed, so we transferred them to natural log form. According to the descriptive statistics, the dominant housing type is slab apartment, which accounts for 74% of our sample, followed by tower apartments (20%) and single-family houses (6%).

Since residential electricity in Ningbo is solely provided by the Ningbo Electric Power Bureau with a consistent pricing scheme across neighborhoods, we did not consider energy price as a factor that causes variations in household electricity consumption. Because electricity price is not included in our model, it is crucial to include household income in our residential energy consumption model [11,42]; this data is derived from the household survey.[8] Additionally, according to our survey results, 98.6% of households use air-conditioners and (or) electric heaters as their primary home heating equipment(s) during winter, thus electricity is the primary home heating fuel for the households we surveyed in Ningbo.[9]

4. Results

Multilevel regression results for annual, summer, and winter electricity consumption are presented in Table 4. In each case, base models (Annual Model 1, Summer Model 1, and Winter Model 1) only include household-level variables; Annual Model 2, Summer Model 2, and Winter Model 2 include both household-level variables and neighborhood urban form metrics as explanatory variables. Based on the chi-square values of the summer and winter electricity consumption models, the summer electricity consumption models generally have more explanatory power than the winter models. For the annual models, after the neighborhood urban form metrics were added, the chi-square value increases from 314.15 to 401.46, which is quite significant with 3 degrees of freedom. Similar patterns can be found in summer and winter models: the addition of neighborhood urban form metrics can cause

[8] The low-, medium-, and high-income categories were derived from 2015 municipal income data from the Ningbo Bureau of Statistics. The low-income category is defined as monthly per capita income less than 3000 RMB, while the high-income category is defined as monthly per capita income greater than 8000 RMB. Other incomes are included in the medium-income category.

[9] China's heating system is very different from other countries in the world. In the 1950s, the central government drew a line across the country, only allowing places located north of the line to utilize central heating systems with subsidies from the government. Ningbo is located below this line. Central heating systems are not provided in Ningbo, even though Ningbo experiences cold and dry winters. Households in Ningbo use air-conditioners or electric heaters during winter months. In recent years, some rich households also install and use radiant floor heating systems as heating equipment in winter.

Table 3
Descriptive statistics (N = 534).

Variables	Mean	SD	Min.	Max.	Source
Dependent variables					
Annual electricity usage	2882.03	2717.21	466	39117	Ningbo Electric Power Bureau
Summer electricity usage	1025.52	851.40	180	11371	Ningbo Electric Power Bureau
Winter electricity usage	1076.02	1221.72	130	16454	Ningbo Electric Power Bureau
Household level variables					
Size of the housing unit (square meters)	106.71	61.56	32	393	Household survey
Age of the housing unit (years)	13.18	7.37	2	37	Household survey
Household size	3.09	1.11	1	7	Household survey
Average age of adults (years)	46.04	11.39	19	87.5	Household survey
Monthly income per capita < 3000 RMB[a] (binary)	0.26	–	0 (395)	1 (139)	Household survey
Monthly income per capita 3000–8000 RMB (binary)	0.64	–	0 (193)	1 (341)	Household survey
Monthly income per capita > 8000 RMB (binary)	0.10	–	0 (480)	1 (54)	Household survey
Appliance index[b]	8.77	2.00	3	16	Household survey
Electricity conservation index[c]	8.02	1.50	0	10	Household survey
Homeownership (binary)	0.92	–	0 (41)	1 (493)	Household survey
Tree shade (binary)	0.19	–	0 (432)	1 (102)	Household survey
First floor (binary)	0.17	–	0 (443)	1 (91)	Household survey
Middle floor (binary, floor level 2–8)	0.56	–	0 (233)	1 (301)	Household survey
High floor (binary, floor level >8)	0.11	–	0 (476)	1 (58)	Household survey
Top floor (binary)	0.16	–	0 (451)	1 (83)	Household survey
Tower apartment (binary)	0.20	–	0 (429)	1 (105)	Household survey, GIS data
Slab apartment (binary)	0.74	–	0 (137)	1 (397)	Household survey, GIS data
Single-family house (binary)	0.06	–	0 (502)	1 (32)	Household survey, GIS data
Neighborhood level variables					
Floor area ratio	1.80	0.69	0.45	3.45	GIS data
Street configuration (binary)	0.76	–	0 (127)	1 (407)	GIS data
Adjacency to water bodies (binary)	0.55	–	0 (242)	1 (292)	Household survey, Google Earth

Notes:
[a] RMB is the basic unit of official currency in China.
[b] Appliance index is the count of the electricity intensive appliances in the housing unit[3].
[c] Electricity conservation index is a measure of common electricity conservation actions taken by the housing unit[4].

increases to chi-square values of 92.78 and 54.57 respectively, which are both significant with 3 degrees of freedom. Overall, the addition of neighborhood urban form metrics can significantly improve model fit for annual and seasonal electricity consumption models.

Annual Model 3, Summer Model 3, and Winter Model 3 are the extension models with the interaction terms of neighborhood density and dwelling type added. In Summer Model 3, after the interaction terms are added, the chi-square values increase from 419.83 to 436.30, which is significant with 2 degrees of freedom. However, the addition of the same interaction terms would not improve the overall model fit for either annual or winter models, since the increase of the chi-square values are not statistically significant at the 0.1 level.

The regression results reveal the effects of neighborhood urban form variables on residential electricity consumption. When other important covariates have been controlled for, floor area ratio, which measures the physical density of residential neighborhoods, does not appear to have a significant effect on annual electricity consumption ($p > 0.1$ in Annual Model 2). However, the positive effect becomes significant when we modeled the effect of floor area ratio on summer electricity consumption ($p < 0.01$). This is consistent with what might be expected in the context of an exacerbated heat island effect in the summer. Additionally, the regression results of Winter Model 2 show no statistically significant association between neighborhood density and winter electricity consumption, which is consistent with the results from an existing study by Wilson [11]. As was previously stated, we also hypothesized that neighborhood density has different effects on households located in different types of dwelling units. In Summer Model 3, we find evidence of a significant negative interaction between floor area ratio and the single-family house binary variable. Interestingly, when this interaction is accounted for, the effect of neighborhood density on summer electricity use becomes negative and significant, which indicates higher densities can somehow reduce electricity consumption for families in single-family houses; this statistically significant negative effect of neighborhood density on electricity consumption for single-family homes only exists in summer months.

Street configuration has a significant effect on annual, summer, and winter electricity usage, which is consistent with existing studies and theories indicating that east-west street orientation is more energy efficient since it results in more south-facing buildings with greater passive solar gains [10,12,35–37]. Additionally, based on our regression results, there exists no statistically significant relationship between a neighborhood's adjacency to rivers and electricity consumption in the households, as the adjacency variable is not significant in any of these models; this is consistent with Ko and Radke's results [10].

Among household-level urban form variables, tree shading appears to have a statistically significant impact on household electricity consumption. When controlled for other variables, homes with tree shading are associated with lower electricity consumption in summer months; this effect is also significant in winter month, most likely because trees located near housing units block winds during the winter, thus reducing indoor heating energy consumption. Dwelling type is a statistically significant predictor of household electricity consumption, as our regression results for annual, summer, and winter electricity consumption all indicate that homes located in single-family houses are likely to consume more electricity than homes located in slab apartments. Our results also indicate that, while other important covariates are controlled for, there are no statistically significant differences in electricity consumption between homes located in tower apartments and slab apartments.

In addition to urban form variables, the size of the apartments/houses, household sizes, average ages of adults, income levels, and the number of household electricity-intensive appli-

Table 4
Annual and seasonal multilevel regression results.

Variable	Annual Model 1	Annual Model 2	Annual Model 3	Summer Model 1	Summer Model 2	Summer Model3	Winter Model 1	Winter Model 2	Winter Model 3
Household level variables									
Ln(Size of the apartment/house)	0.3207***	0.3032***	0.3047***	0.3220***	0.3053***	0.3059***	0.3625***	0.3458***	0.3476***
	(0.0813)	(0.0810)	(0.0810)	(0.0782)	(0.0777)	(0.0719)	(0.1002)	(0.1013)	(0.1014)
Age of the apartment/house	−0.0003	−0.0002	−0.0008	0.0018	0. 0015	0. 0009	−0.0042	−0.0038	−0.0044
	(0.0042)	(0.0038)	(0.0039)	(0.0040)	(0.0036)	(0.0037)	(0.0051)	(0.0048)	(0.0049)
Household size	0.1062***	0.0980***	0.0970***	0.0992***	0.0909***	0.0891***	0.1175***	0.1087***	0.1079***
	(0.0191)	(0.0190)	(0.0191)	(0.0184)	(0.0183)	(0.0182)	(0.0237)	(0.0236)	(0.0236)
Average age of adults	−0.0049***	−0.0052***	−0.0054***	−0.0058***	−0.0061***	−0.0064***	−0.0049**	−0.0053**	−0.0054**
	(0.0019)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0023)	(0.0023)	(0.0023)
Income per capita <3000 RMB	−0.1826***	−0.1766***	−0.1826***	−0.1573***	−0.1440***	−0.1480***	−0.2109***	−0.2076***	−0.2090***
	(0.0552)	(0.0542)	(0.0552)	(0.0533)	(0.0521)	(0.0518)	(0.0683)	(0.0676)	(0.0675)
Income per capita >8000 RMB	0.1196	0.1406	0.1208	0.1201	0.1376	0.0964	0.1071	0.1337	0.1193
	(0.0798)	(0.0786)	(0.0807)	(0.0771)	(0.0757)	(0.0775)	(0.0989)	(0.0979)	(0.1007)
Appliance index	0.0387***	0.0496***	0.0496***	0.0417***	0.0521***	0.0524***	0.0362**	0.0468***	0.0467***
	(0.0141)	(0.0135)	(0.0135)	(0.0123)	(0.0130)	(0.0130)	(0.0166)	(0.0169)	(0.0169)
Electricity conservation index	−0.0273*	−0.0243*	−0.0241*	−0.0205	−0.0184	−0.0165	−0.0371**	−0.0332*	−0.0334*
	(0.0136)	(0.0138)	(0.0139)	(0.0136)	(0.0133)	(0.0134)	(0.0174)	(0.0172)	(0.0174)
Homeownership	−0.0482	−0.0920	−0.0883	−0.0553	−0.0938	−0.0912	−0.0224	−0.0681	−0.0642
	(0.0818)	(0.0802)	(0.0804)	(0.0789)	(0.0772)	(0.0770)	(0.1012)	(0.1000)	(0.1003)
Tree shade	−0.1719***	−0.1829***	−0.1796***	−0.1723***	−0.1837***	−0.1754***	−0.1785***	−0.1994**	−0.1976**
	(0.0687)	(0.0667)	(0.0677)	(0.0661)	(0.0638)	(0.0638)	(0.0847)	(0.0836)	(0.0837)
First floor	0.0997*	0.0924*	0.0938*	0.0140*	0.0079	0.0098	0.1817***	0.1736**	0.1748***
	(0.0543)	(0.0539)	(0.0538)	(0.0525)	(0.0519)	(0.0517)	(0.0673)	(0.0670)	(0.0670)
High floor (floor level >8)	−0.0278	−0.0323	−0.0268	−0.0112	−0.0151	−0.0127	−0.0520	−0.0539	−0.0475
	(0.0811)	(0.0797)	(0.0809)	(0.0783)	(0.0767)	(0.0775)	(0.1004)	(0.0994)	(0.1009)
Top floor	0.0400	0.0286	0.0304	0.0370	0.0264	0.0352	0.0430	0.0242	0.0243
	(0.0715)	(0.0718)	(0.0723)	(0.0690)	(0.0691)	(0.0695)	(0.0885)	(0.0894)	(0.0902)
Tower apartment	0.0018	0.00247	0.0817	−0.0429	−0.0314	−0.0249	−0.0525	0.0769	0.1470
	(0.0689)	(0.0645)	(0.0689)	(0.0662)	(0.0618)	(0.1646)	(0.0848)	(0.0808)	(0.2186)
Single-family house	0.6648***	0.6601**	1.3054**	0.6017***	0.6041***	1.8725***	0.7132***	0.7006***	1.1854
	(0.1544)	(0.1446)	(0.6161)	(0.1486)	(0.1383)	(0.5862)	(0.1902)	(0.1811)	(0.7718)
Neighborhood level variables									
Floor area ratio		0.0707	0.0806*		0.0914***	0.0999**		0.0358	0.0461
		(0.0461)	(0.0489)		(0.0436)	(0.0456)		(0.0583)	(0.0619)
Street configuration		−0.2519***	−0.2411***		−0.2445***	−0.2244***		−0.2591**	−0.2508**
		(0.0586)	(0.0590)		(0.0553)	(0.0548)		(0.0742)	(0.0750)
Adjacency to water bodies		−0.0307	−0.0307		−0.0219	−0.0172		−0.0624	−0.06373
		(0.0554)	(0.0556)		(0.0524)	(0.0519)		(0.0699)	(0.0750)
Cross-level interactions									
Floor area ratio × Tower apartment			−0.0332			−0.0052			−0.0404
			(0.0921)			(0.0873)			(0.1157)
Floor area ratio × Single-family house			−0.8224			−1.6275**			−0.6114
			(0.7731)			(0.7369)			(0.9675)
Intercept	6.1286***	6.2439***	6.2249***	5.0927***	5.1643***	5.1386***	4.949***	5.1463***	5.1290***
	(0.3803)	(0.3957)	(0.3955)	(0.3661)	(0.3796)	(0.3771)	(0.4690)	(0.4947)	(0.4949)
Wald Chi^2	314.15***	401.46***	405.56***	327.05***	419.83***	436.30***	247.49***	302.06***	303.76***
Log likelihood	−333.52	−324.93	−324.31	−314.94	−305.23	−302.81	−447.99	−442.17	−441.91
Degree of freedom	16	19	21	16	19	21	16	19	21
Groups	46	46	46	46	46	46	46	46	46

Notes: 1) Standard errors in parentheses.
2) *$p<0.10$, **$p<0.05$, ***$p<0.01$.

ances are also significant predictors of household electricity consumption, which is consistent with existing theory. Our results also suggest that the size of apartments/houses and household sizes are dominant factors influencing household electricity consumption, which is similar to existing findings in different geographic contexts [11,43]. In contrast, ages of apartments/houses and homeownership do not exhibit a significant association with annual, summer, or winter electricity consumption, as is indicated in our regression results. Interestingly, our results indicate that low-income households with monthly per capita incomes less than 3000 RMB consume less electricity than their counterparts in the medium income category, which is statistically significant and consistent in both winter and summer months. However, there are no significant differences in electricity consumption between the households in the high-income category with monthly per capita incomes greater than 8000 RMB and those in the medium-income category. Additionally, there are no statistically significant differences in electricity consumption among households located on middle floors (floor level 2–8), those on high floors (floor level >8), or those on the top floor. However, we do find evidence that households on the first floor may consume more electricity, especially in winter months, which might result from limited solar access in winter months.

5. Discussion

The results of this study suggest clear effects of neighborhood-level urban form, especially physical density measured by floor area ratio, on household electricity consumption. It is interesting to note that the effect of neighborhood density on energy consumption may be completely different in different seasons and for households located in different types of dwelling units. Our multi-level regression results suggest a positive relationship between density (floor area ratio) at the neighborhood-level and summer electricity consumption, which supports the theory that denser built environments significantly contribute to the heat island effect [20,44,45]. However, the significant positive effect of density only exists for households located in slab and tower apartments, which makes sense because slab and tower apartment are located in dense urban neighborhoods. Thus, increasing physical density can exacerbate the heat island effect in these neighborhoods, which in turn increases household cooling energy demands in the summer. On the other hand, when it comes to single-family houses, the effect of physical density on household electricity consumption during the summer becomes negative, which is still consistent with the results of previous studies in the United States which are composed of single-family houses [11,26]. Based on these studies, the hypothesized link between density and electricity consumption is explained through a different mechanism in low-density neighborhoods with single-family houses: Stone and Norman [26] claim that urban residential development with lower densities contribute more surface energy to the formation of the heat island effect than higher density residential developments, since larger lawns associated with low-density residential development are a significant contributor to surface heating. Additionally, higher physical densities also contribute to more mutual shading between buildings, which is a very important factor during the summer in terms of reducing household energy consumption for single-family houses [46,47]. It is also worthwhile to note that we did not find any significant effect of neighborhood density on household electricity consumption during winter months, which is consistent with the results of Wilson's study [11], even though electricity is the primary source for heating homes in Ningbo. This might stems from the possible trade-offs of density effects of building cooling energy demands: on the one hand, neighborhood with higher density has been associated with lower thermal losses in winter months [23], which can in turn reduce the heating loads in buildings; on the other hand, denser neighborhoods also suffer from less solar gains in winter months.

According to our regression results, building age does not significantly influence residential household electricity consumption; this result might stem from most of the households we surveyed living in apartments that were built after China's housing reform; since that time, there have been very limited differences in insulation across new buildings. Additionally, there exists no significant difference in electricity consumption for households located in slab and tower apartments, which are the two dominant dwelling types in Chinese cities; the effect of dwelling types on residential electricity consumption is lower compared to the findings of previous studies. These findings may indicate that, because of unique features associated with building age and dwelling type in Chinese cities, the effects of building characteristics on residential energy consumption might be less noticeable in China, comparing with findings from previous studies in other countries (e.g., [10,25,31,32,47]).

Furthermore, in contrast with existing research, the average age of adults is found to have a negative relationship with household electricity consumption. This finding is consistent with more nuanced results from studies about occupant electricity consumption behavior in Chinese cities, which reveal that older occupants exhibit a more frugal behavior than their younger counterparts [16].

There are still several limitations in this study. First, our models only include building age as a proxy for the building-level energy efficiency measure. The explanatory power of our model might be improved if we could include several detailed building-level characteristics that affect energy efficiency such as building geometry (e.g., surface-to-volume ratio[10]), glazing ratio[11] and the insulation of walls and windows. There is also a promising research opportunity in which one can explore urban form effects at household-, building-, and neighborhood-levels using a three-level hierarchical model. Furthermore, urban form might influence building energy consumption through different paths, which might include solar access, external shading, natural ventilation, and the heat island effect [12,48,49]. Future research could consider constructing or refining existing urban form metrics, which measure these different aspects in a specific way, thus analyzing energy-related trade-offs among these effects. Third, the external validity of this study is still limited since it focuses on a single city in a single climate zone. Future research should evaluate various options for density in the context of different urban forms in different climates, so as to find urban form strategies that produce net benefits for building energy efficiency in each climate. In addition, future building energy performance simulation should focus more on seasonal effects of urban form on building energy consumption. It is also worthwhile to investigate the association between urban form and embodied energy consumption, so as to fully understand the net effects of urban form on building energy consumption (both the operational and embodied energy consumption).

6. Conclusions and policy implications

This study uses a unique dataset to examine the impact of urban form on residential electricity consumption in Ningbo,

[10] Surface-to-volume ratio is also known as the surface area to volume ratio. It is the amount of surface area per unit volume of a building, which is often used to measure a building's compactness.

[11] Glazing ratio is also known as the window-to-wall ratio. It measures the percentage area determined by dividing a building's total glazed area by its exterior envelope wall area. It is an important variable affecting building energy efficiency.

China. The results suggest a clear role of urban form in affecting residential electricity consumption. Neighborhood density, which is measured by floor area ratio, is associated with household electricity consumption in summer months when controlling for other important demographic, socioeconomic, behavioral, and property-related covariates. The effects of neighborhood density on residential electricity usage are different in different seasons and for households located in different types of dwelling units. Neighborhood density could significantly influence household electricity consumption during summer months, while we did not find any linkages between neighborhood density and household electricity usage in winter months. For households located in slab and tower apartments, there exists a positive relationship between neighborhood density and electricity consumption in summer months since increasing physical density exacerbates the heat island effect in these neighborhoods. However, for single-family houses located in low-density neighborhoods, increasing neighborhood density could significantly reduce residential electricity consumption in summer months, which can be explained by more mutual shading, decreased amount of exposed surface, and reduced surface heating.

This study has several implications for policy and practice concerning energy-efficient buildings and neighborhoods. In order to promote low-carbon buildings in China's "hot summer and cold winter" climate zone, incentives and policies are needed not only for buildings and households, but also for neighborhood environments and urban form. For local policy makers and planners, the effects of urban form (especially physical density) on building energy consumption should be distinctly considered for different seasons and for different dwelling types. Neighborhood design guidelines could also include detailed seasonal strategies for different types of dwelling units and neighborhoods. For instance, in terms of controlling residential energy consumption through the lens of urban form, heat island mitigation strategies (e.g., area-based tree canopy requirements and vertical greening) should be very important for residential neighborhoods composed of slab and tower apartments in summer months. For low-density single-family neighborhoods, regulating floor area ratio to ensure more mutual shading between buildings, and external shading from trees might be an effective measure to improve building energy performance in summer.

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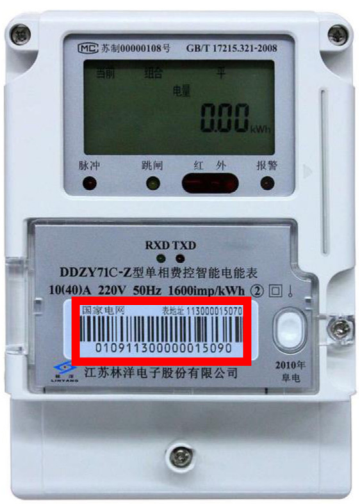
Appendix A.

Household survey instrument[1]
Date: ____________ Time: ____________ Questionnaire #____________
Neighborhood: _____________Neighborhood ID: _____________Surveyors: _______________

Part 1:
1) Household address: ____
2) How many floors are in this building? Do not include basements or parking levels. _________
(Answer must be in the range from 1 up to 100)
3) On which floor is this housing unit located? ________________
(Answer must be in the range from 1 up to 100)
4) Building type of this housing unit: _______________________
1. Tower apartment
2. Slab apartment
3. Single-family house
4. Other, please specify: _________________________________
5) Electricity meter ID: _________________________________
(Please record the identification number of the electricity meter of the household. See picture below for reference)



Part 2:
6) How long has your household lived in this housing unit?
1. Less than a year
2. 1 to 2 years
3. More than 2 years
7) In what year was this housing unit built? ____
(Answer must be in the range from 1900 up to 2015; if the survey respondent cannot provide exact information, ask the property manager of the neighborhood where the housing unit is located)
8) What is the total floor area in this housing unit (in square meter)? _____________________
(Answer must be in the range from 1 up to 999)
9) This housing unit has _____________ bedrooms, __________ living rooms and dining rooms.
(Answers must be counts in the range from 1 up to 10)
10) On average, how much is your monthly electricity bill (in RMB[2])? Your best estimate is okay.
____
11) What is the main space heating equipment for this household?
____
1. Radiant Floor Heating using electricity
2. Radiant Floor Heating using natural gas
3. Electric heating facility (air conditioning, electric heater)
Part 3:
12) Please provide the following information about the family members living in this housing unit:

Family Member	Sex	Age	Work or not	Family Member	Sex	Age	Work or not
1				6			
2				7			
3				8			
4				9			
5				10			

13) Which of the following categories best describes the average monthly income for all the adults living in this housing unit?
1. Less than 3000 RMB per month
2. 3000 to 8000 RMB per month
3. More than 8000 RMB per month
14) Which of the following categories best describes the homeownership of your household for this housing unit?
1. Renter
2. Owner
15) Air-conditioner count in this housing unit: ______________________
16) Refrigerator count in this housing unit: _________________________
17) Washing machine count in this housing unit: ____________________
18) Electric water heater count in this housing unit: __________________
19) Gas water heater count in this housing unit: _____________________
20) Solar power water heater count in this housing unit: _______________
21) Computer count in this housing unit: ___________________________
22) Television count in this housing unit: ___________________________
Part 4:
Please indicate if your household has the following conditions or takes the following actions:
23) Turn off all the lights when you leave a room for more than thirty minutes.
1. Never 2. Sometimes 3. Always
24) Your household uses energy-saving bulbs for lighting.
1. None of the light bulbs in this housing unit are energy-saving bulbs.
2. Some of the light bulbs in this housing unit are energy-saving bulbs.
3. All the light bulbs in this housing unit are energy-saving bulbs.
25) Your household regularly maintains the air-conditioner(s) in this housing unit. (e.g. clean the condenser, change the air filter, etc.)
1. Never 2. Sometimes 3. Always
26) Your household sets the room temperature higher than 26°C when using the air-conditioner(s) in summer.
1. Never 2. Sometimes 3. Always
27) Your household turns off major household appliances (e.g. televisions, computers, wireless router, etc.) when they are not in use.
1. Never 2. Sometimes 3. Always
28) Does this housing unit have tree shade?
1. No 2. Yes
29) Is your neighborhood adjacent to water bodies (e.g. rivers, lakes, etc.)?
1. No 2. Yes

Notes: [1]The complete survey instrument was initially in Chinese; for brevity, we only translated the main survey components to English as a reference.
[2]RMB is the official unit of official currency in China.

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