**Low-carbon behavior approaches for reducing direct carbon emissions:
household energy use in a coastal city**

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Abstract: Household carbon emissions from energy use are rapidly increasing in conjunction with growing urbanization; their reduction is critical for local urban climate improvement and the sustainable development of cities. Low-carbon behavior is proved as a key element determining residents' lifestyle. Understanding how that behavior affects household energy use will be useful in promoting low-carbon households. In this study, Xiamen, a coastal city was divided into areas at high and low risk of flooding. We used the path analysis method—integrated with behavior and socioeconomic factors—to explore the mechanisms of low carbon behavior effects on household direct energy use and related carbon emissions. We found that socioeconomic conditions combined with low-carbon behavior had direct and indirect impacts on household

carbon emissions. Low-carbon behavior in the high-risk area contributed most to reducing carbon emissions. Education level was the important factors in the low-risk area. Government-led policies encouraging low-carbon behavior were effective in reducing household carbon emissions in the high-risk area. However, in low-risk areas, education about a low-carbon lifestyle is an effective means for reducing carbon emissions.

Keywords: household energy usage; low carbon behavior; socioeconomic condition; coastal city; integration

1. Introduction

Energy usage is soaring worldwide. Rapid urbanization is raising the demand for new services and energy. As indicated by the Intergovernmental Panel on Climate Change, about 70% of energy demand will derive from cities (IPCC, 2007). According to the United Nations, city populations will increase by 2.5 billion residents by 2050. As a consequence of increasing energy consumption, the CO₂ produced will exert a direct or indirect effect on local and global climate change.

Household CO₂ emissions, including greenhouse gases (GHG), have continued to increase (Lin et al., 2013; Zhang et al., 2015). In China, emissions from buildings are the second-largest source of energy carbon emissions. Because of the increasingly serious impact of climate changes, vigorous measures are required to diminish the associated environmental burden (Ivanova et al., 2015). In this regard, studies have

examined strategy development for reducing household carbon emissions.

Previous studies have highlighted the large proportion of energy consumption and associated carbon emissions that arise from the household sector. Research efforts have focused on the relationship between building construction characteristics and operation energy consumption. Links between city morphology, urban form and energy use have been identified (Wong et al., 2016).

With respect to socioeconomic factors, studies investigated energy use with a focus on the application of sustainable green approaches related to the social conditions of local residents. The green behavior of inhabitants and their social relationships have been assessed in terms of recycling and the probability of establishing standards regulating energy-conservation measures.

Energy-use behavior (choosing the type of energy consumed) in the United States currently affected policymaker decisions; this situation will have an impact on the future use of fuels (Kahn, 2015). In China, around 26% of total household energy consumption and 30% of CO₂ emissions are associated with residential lifestyles and related economic activities (Wei et al., 2007). Raising awareness about the need to save energy is considered an effective means toward carbon reduction (Bai and Liu, 2013). Accordingly, it is necessary to investigate residents' behavior with regard to diminishing household carbon emissions.

Comprehensive explanation in terms of energy saving behavior integrated with socio-economic condition supply a new and valuable way to explore the potential household building operation energy carbon emission (HCE, hear after 'emission')

reduction except from the view of building construction characteristics, building surrounding natural conditions (Ye et al., 2011; Ye et al., 2013). In this paper, based on detailed information about household operation energy consumption activities, we applied this approach to analyze the impact of low carbon behaviors on energy conservation. This research will help provide the first-hand data and novel method to develop policies of raising public awareness regarding environmental protection.

2. Study area

Xiamen, is a major city on the southeastern coast of China. The administrative area of the city is 1565 km², which includes a sea area of 390 km². The population was 3.81 million in 2014. With the fast urbanization rate, the built-up area in Xiamen expanded rapidly from 44.9 to 230 km². Simultaneously, household areas in Xiamen increased from 31.6 million ton in 1991 to 240 million to 399 million in 2010. As an important contributor of urban carbon emissions, annual per-family emissions from household energy use greatly increased from 1368.72 kg in 2008 to 3585.12 kg in 2014(Ye et al., 2015).

In the present study, we examined a climate-risk region in Xiamen. We distinguished high- and low-risk areas (Fig. 1). The population of the high-risk area was 717,056, constituting 19.86% of the city's total population. The high-climate-risk area covers 15,699.52 ha—almost one-tenth of the total area. Coastal areas account for over 50% of the global city population; thus, buildings in such areas, especially in climate-risk regions, need to avoid making additional carbon emissions. Based on the

current state of residents' energy savings, low-carbon behavior, and socioeconomic conditions in Xiamen, we attempted in this study to determine their direct and indirect impacts on direct carbon emissions from household energy use.

Fig.1.

3. Methods

3.1. Climate-risk areas

We made a close examination of the risk areas in Xiamen; those areas are ones that are potentially subject to sea-level rises and storm tides. First, we used a high-precision digital topographic map (1:5000) with 10×10 -m horizontal precision to build a digital elevation model (DEM) by means of ArcGIS 10.0 software. Second, we defined a 1.2-m sea-level rise and typhoon storm tide once per 100 years as an extreme climate condition. Third, we determined the flooded area caused by this condition according to the following criteria: (1) DEM cells with an elevation less than or equal to an extreme sea level caused by the extreme climate condition—with locations adjacent to the sea or connected to cells of equal or lower level adjacent to the sea; (2) DEM cells with missing or inadequate protective seawalls or levees. Fourth, after we identified the flooded area, we overlaid a map of the city of Xiamen with the flooded-area map to obtain areas of high and low flood risk (Fig. 1).

3.2. Social questionnaire design

Social questionnaire investigation was established in December 2014. The subject households were selected by random sampling from 29 communities of

Xiamen city. For each residential building in the sample, we collected data of energy consumption, building quality, socio-economic condition and energy saving behavior of the family members. After screening 600 questionnaires, we found 564 to be valid.

3.2.1 Low-carbon behavior questionnaire design

We developed nine types of low-carbon behavior to measure their influences. Some scored some self-reported low-carbon behavior items were scored by using a five-point agreement scale. We used detailed data to assess the responses to questions about ideal indoor air conditioner temperature set in summer and winter and how much the respondents would spend to improve indoor comfort in summer.

3.2.2 Socioeconomic condition questionnaire

The information on family size was extracted directly from the questionnaire results. Household income level was represented by monthly family income; assigned household education level as the person with the highest level in that household; recorded the age of each family member during the interview, and calculated the average age.

3.2.3 Energy consumption questionnaire

Household energy usage (including cooking, warming, cooling, and lighting, but not transportation) were investigated. We assessed energy consumption from the investigated energy usage quantity or the money residents paid for energy consumption.

3.3. The calculation of carbon emission

We focused on two major household sources of direct carbon emissions,

residential electrical consumption and domestic fuels (coal, propane, petroleum gas, coal gas) for lighting, cooling or heating the floor. The study area was divided into at high and low risk of flooding. Residential transportation energy carbon emission boundary is hard to define according to these two specific climate risk area, then residential transportation energy consumption was not in our energy data panel. In addition, food, waste treatment and housing (construction and demolishment) were not in the data panel either.

To account for variation in energy consumption, we transform all kind of energy consumption and expenditures into carbon emission data. The amount of the carbon emissions from each fuel is significantly influenced by its consumption and its carbon content. The following equation gives an accounting framework for converting energy use into carbon dioxide emissions.

$$CE_F = \sum_i^n (C_{ei} \times G_{ei} \times I_{ei}) \quad (1)$$

Where CE_F is the total energy carbon emission from coal Gas, LPG and coal consumption; C_{ei} are the energy consumption amounts (kg or m³); G_{ei} are the energy i capacity conversion factors (MJ/Tt or MJ/Mm³—set at 111MJ/m³ for LPG, 29.31MJ/kg for coal); I_{ei} are the energy carbon emission conversion factors (kgC/GJ) which means energy carbon containment per unit. The carbon containment parameter is set at 27.63gC/GJ.

Although there were no carbon emissions during electricity use, electricity was the secondary product fits original generating matter such as coal, natural gas and refined

petroleum products etc.

The original matter and its carbon content were used to calculate electricity consumption and its carbon emission. The formula is as follows:

$$CF_{EL} = \frac{W_{electricity} \times W_{coal} \times G_{coal} \times I_{coal}}{1 - \beta} \quad (2)$$

Note: $W_{electricity}$ is the electricity consumption (kWh); W_{coal} is the coal applied to electricity production (kg/kWh); G_{coal} is the coal energy transfer coefficient (MJ/Tt) (electricity in Xiamen is mainly supplied by fossil fuel combustion); I_{coal} is the coal carbon containment.

3.4. Correlation analysis

We calculated the correlation coefficients of low-carbon awareness and socioeconomic factors to identify the interrelationships among these factors; we also assessed whether multiple collinearities existed among the studied variables prior to path analysis. In addition, we used rank correlation (Spearman coefficient).

3.5. Path analysis

Path analysis is a statistical technique used to examine the comparative strength of direct and indirect relationships among variables within a hypothesized model (Wright, 1934). Relationships among variables consist of direct and indirect effects. Direct effects go directly from one variable to another; indirect effects occur when the relationship between two variables is mediated by one or more other variables. In statistics, a positive effect signifies that as the value of one variable increases (or decreases), so does the value of the other variable. The strength of the effect of an exogenous variable on an endogenous one is represented by a standard path

coefficient, for which absolute values <0.10 indicate a small effect, ~ 0.30 a medium effect, and >0.50 a large effect.

After we identified the interrelationships among the variables based on general logic and Spearman correlation coefficients, we built a hypothesized path analysis model that displayed the network of all variables. We evaluated the goodness-of-fit of the model to the data using a non-significant χ^2 value, root mean square error of approximation (RMSEA), normalized fit index (NFI), comparative fit index (CFI), and global fit index (GFI).

4. Results

4.1.State of residential household

The average of the residential buildings is characterized by 4 individuals; average age 34 years, floor area 99 m², family income 4258 Yuan (China's official currency, RMB), completed education 13.6 years in one family. Of the selected households, there were 64 houses built before 1990, 133 houses during 1990s, 295 houses during 2000s and 72 houses after 2010. This is typical of the construction age spread in Xiamen city.

The average household income, education level, family age and floor area are 4089 (yuan), 13.5 (years), 33 (years) and 94.68 (m²) in low-risk area, which are lower than those in high-risk area (4441 yuan, 13.8 years, 35 years and 103.72 m², respectively).

The average household energy usage carbon emission per month in Xiamen city

is 299kg. Though the total emission was lower in low-risk area (291kg) than that in high-risk area (307kg), the unit emission was opposite. Specifically, carbon emissions were 990g and 970g per area per membership in lower risk area and high-risk area.

4.2.Descriptive statistics

The socio-economic condition of samples was consistent with the demographic characteristics of Xiamen's resident population (Table 1). We selected three low-carbon behavior items for the path analysis to explore their relationships with socioeconomic conditions. Those three items were represented by the following questions: (1) how much the respondent cared about using energy-saving devices; (2) the ideal indoor air conditioner temperature the respondent would set in summer; and (3) how much the respondent would spend to improve indoor comfort in summer. Here, question 1 represents low-carbon awareness (LCAW), question 2 low-carbon implementation action (LCAC), and question 3 the ability to overcome barriers during low-carbon implementation (low-carbon ability or LCAB).

Table 1

The range of the means of items for all the families was 3.08–4.04; it was 3.03–4.09 for the high-risk area and 3.13–4.01 for the low-risk area. On the five-point scale, we took a mean score >3.0 to be high. It is evident in the graphs that regardless of climate risk area, low-carbon awareness had the highest score; low-carbon implementation action was second and the ability to overcome barriers during low-carbon implementation third (Fig.2).

Fig.2.

4.2 SEM (Structural equation modeling) analyses

Tables 2–4 show the direct, indirect, and total effects of the variables on HEC. The indices assessing goodness-of-fit of the model appear in Tables 2–4. It is evident that the χ^2 test was significant for the entire region and high- and low-risk areas (respectively, $\chi^2 = 13.98$, $p < 0.001$; $\chi^2 = 19.94$, $p < 0.001$; $\chi^2 = 15.48$, $p < 0.001$). The CFI exceeded 0.95, and the RMSEA was below the recommended threshold of 0.05 for the three areas (Hu and Bentler, 1999). The final path model and standardized coefficients among the variables are depicted in Figs. 3–5.

Fig. 3.

4.2.1 Direct effects

For the entire city, in terms of the absolute values of standard path coefficients, the order of direct effects was family size > floor area > overcome barriers > awareness > education level > implementation. For the high-risk area, the order of direct effects was the same as for the entire city (Fig. 4). It was different for the low-risk area, where it was family size > floor area > education level > income > awareness > overcome barriers > implementation (Fig. 5).

Fig.4.

Fig.5.

The variable coefficients showed that only family size had an upper-moderate direct effect on emissions. There were very small effects from implementation in the entire and high-risk areas and also from implementation and overcome barriers in the low-risk area.

4.2.2 Indirect effects

In the entire and high-risk areas, all the variables except awareness and implementation had an indirect effect on emissions. Among those variables, family size had a low-moderate indirect effect in high-risk area; the others had a very small indirect effect.

In the high-risk area, family size influencing through floor area, through income and floor area had positive effects on emissions; through awareness posed negative effects on emissions. The total indirect effects of the studied factors had a coefficient of 0.11.

In contrast to the entire and high-risk areas, no low-carbon behavior variables in the low-risk area exerted indirect effects. In the low-risk area, education had an indirect effect on emissions. The total indirect effects of the studied factors had a coefficient of 0.10 (Figs. 3–5).

4.2.3 Total effects

The total effects equaled the direct plus indirect effects. As shown in Table 2, for the entire risk region, among the studied energy-saving awareness and socioeconomic factors, the absolute values of the standard path coefficients of family size were >0.3 ; this represents a upper-moderate total effect. The coefficients of floor area, education

level, awareness, and overcome barriers were between 0.1 and 0.3, indicating a low-moderate total effect. However, the coefficients of income, age, and implementation were <0.1 , which represents a very small total effect.

Table 2

Table 3

Table 4

Compared with the entire city, for the high-risk area, according to absolute values of the standard path coefficients, education level, income, and age, reflected the different order. In the low-risk area, coefficients indicated that education level, income, floor area and awareness had a lower-moderate effect; overcome barriers, implementation, and age had a very small total effect, which was different from that in the entire city and the high-risk area.

5. Discussion

5.1. Influencing factors

In this investigation, we identified the factors that affect household energy carbon emissions in the climate-risk areas. The factors were socioeconomic factors, low-carbon behavior, and the combined effect of those factors. We found that in addition to family socioeconomic conditions, low-carbon implementation, low-carbon awareness, and energy-saving ability affected emissions. Socioeconomic conditions were usually integrated with low-carbon behavior to influence emissions.

The high- and low-risk areas are geographically separate, and there we analyzed various emission driving mechanisms in Xiamen. Generally, the variables which had effects on emissions in the high-risk area, showed the similar effects for the whole city. Furthermore, the variables in the high-risk area had stronger influences than they had in the low-risk area. This indicates that the high-risk area had a greater impact on emissions than the low-risk area.

5.2.Direct impacts

For the entire and high-risk areas, family size and floor area had the strongest direct impact on emissions, which is in accordance with our previous research results (Ye et al., 2011). In the high-risk area, other socioeconomic factors had a low impact on emissions. However, implementation and overcome barriers ranked third and awareness fourth in terms of impact on emissions. Low-carbon behavior had a strong direct effect on emissions; this demonstrates that energy-saving awareness and behavior are widely encouraged among residents, especially in the high-risk area (Long et al., 2014).

The low-risk area exhibited a different order with direct impact factors. After family size and floor area, education and income were the third and fourth major impacts on emissions. Household income was another factor for emission increase, as identified in other studies (Liu et al., 2011). In a low-risk area, if there is substantial potential of family income increase, there is also great potential for increased carbon emissions. This represents a major obstacle to reducing emissions in low-risk areas. Education level is considered a major factor for emission reduction in low-risk areas.

Therefore, education has been recommended as an effective method for mitigating household energy use.

Although income and education level are relatively low in low-risk area, they are closely related to carbon emissions. Whereas, low-carbon, awareness and action exhibit close relationship with carbon emission in high-risk area, where income, education level are relatively high. Human physical demand satisfaction degree usually is the basis for psychology demand desire. When income is relatively low, it may become an obstacle to hamper the process of psychology demand satisfaction. Only with the increment of income, the environmental, ecological awareness will produce strong impacts on carbon reduction.

5.3. Indirect impacts

Our results indicate that some socioeconomic factors had indirect effects on emissions by influencing other socioeconomic factors or low-carbon behavior. When studying the impact of low-carbon behavior on emissions, it is necessary to integrate socioeconomic conditions with low-carbon behavior factors. In high-risk areas, low-carbon behavior exhibited a more obvious indirect impact on emissions than in low-risk areas. It has been suggested that improving low-carbon behavior performance by positive government feedback represents an effective carbon mitigation course for high-risk areas, for instance, the residential tariff pricing reform has strengthened the expect of low carbon emission. In low-risk areas, education was an important factor as an indirect impact on emissions, although its actual impact was very low. It would appear that greater investment in education would be an effective means of carbon

reduction for low-risk areas.

5.4. Total impacts

For the entire and high-risk areas, floor area had the second-highest total impact on emissions; however, in the low-risk area, it had a lower impact. Most buildings in the high-risk area were located close to the coast and had a relatively large floor area. Owing to the important effect of floor area on emissions, urban planners should be recommended to design relatively small floor areas in high-risk areas.

We found that in the high-risk area, energy-saving behavior, such as controlling the temperature of air conditioners, was not an impact factor. Improving awareness of energy-saving behavior among residents is a challenge. However, energy-saving awareness has an impact on emissions: the government should thus consider making efforts to encourage energy-saving behavior among residents (Yao et al., 2014).

Compared with the high-risk area, the impetus to reduce carbon emissions, energy-saving ability, and energy awareness were weaker in the low-risk area. Education level had a powerful impact in the low-risk area. Therefore, we would recommend that reducing emissions be achieved by improving the education level toward altering energy-consumption attitudes and spending habits. Residents well informed of the knowledge and value of carbon management have a strong willingness to practice low-carbon action. Furthermore, structural, regulatory and cultural will ensure low-carbon actions enforcement.

6. Conclusion

In this study, a typical coastal residential area in China was divided into areas at

high and low risk of flooding. In those two areas, we examined the different emission driving mechanisms related to socioeconomic and low-carbon behavior. The details of these mechanisms can help inform effective carbon-reduction strategies related to energy-saving behavior.

The main influences on emissions varied greatly between the high- and low-risk areas. The factors determining emission in the high-risk area were similar to those determining emissions in the entire city. Low-carbon behavior had stronger direct effects in the high-risk than in the low-risk area. Therefore, the government needs to develop effective rules or encouragement strategies to promote low carbon behavior. In contrast, the socioeconomic factors of education level had greater effects on emissions in the low-risk than in the high-risk area. Low-carbon consumption and living patterns may be encouraged through education to mitigate energy CO₂ emissions (Dai et al., 2012).

We combined socioeconomic conditions and psychological awareness to thoroughly explore the effects of behavior on emissions. We found that socioeconomic conditions had confounding effects on energy-saving behavior. In particular, we determined that family size in the high-risk area, education in the low-risk area were associated with energy-saving behavior and reducing emissions.

For Xiamen city, the ‘Beauty Xiamen construction planning’ has been implemented since 2014. Greenhouse and low-carbon building construction are of critical importance for planning implementing successfully. Optimal strategy between governments and residents should be conducted in the process of implementing

energy-saving and emission-reduction action to promote friendly environment for coastal region and its climate-risk resistance ability.

The goal of reducing carbon emissions is life improvement. Well-being should not be a tradeoff for residents making low-carbon decisions (Kalvelage et al., 2014). Residents in high-risk areas spent more on having a comfortable living habitat than on energy-saving behavior. Future studies need to address life-quality improvement and the relationship between energy-saving behavior and low-carbon city building.

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Fig.1.Climate risk region in Xiamen city

Fig.2. Level of the residents' low-carbon behavior

Note: Here, 'LCAW' represents low-carbon awareness, while 'LCAC' and 'LCAB' represent low-carbon implementation action, and the ability to overcome barriers

during low-carbon implementation respectively.

‘XM’ represents the whole area. ‘HR’ represents high risk area while ‘LR’ represents low risk area.

Fig. 3. Path analysis model for the entire region

Note: Squares indicate the observed variables, and circles or ellipses the unobserved variables measured using the observed variables. e1, e2, e3, e4, e5, and e6 are residual factors that were not included in the model. Solid lines indicate positive effects, dashed lines negative effects, line widths the magnitude of the effects, and arrows their direction.

A triple asterisk indicates that the coefficient is significant at the 0.001 level, a double asterisk significant at the 0.01 level, and a single asterisk significant at the 0.05 level.

‘LCAW’ represents low-carbon awareness, while ‘LCAC’ and ‘LCAB’ represent low-carbon implementation action, and the ability to overcome barriers during low-carbon implementation respectively.

‘HCE’ represents household building operation energy carbon emission.

Fig.4. Path analysis model for high-risk area

Note: Squares indicate the observed variables, and circles or ellipses the unobserved variables measured using the observed variables. e1, e2, e3, e4, e5, and e6 are residual factors that were not included in the model. Solid lines indicate positive effects, dashed lines negative effects, line widths the magnitude of the effects, and arrows their direction.

A triple asterisk indicates that the coefficient is significant at the 0.001 level, a double asterisk significant at the 0.01 level, and a single asterisk significant at the 0.05 level.

‘LCAW’ represents low-carbon awareness, while ‘LCAC’ and ‘LCAB’ represent low-carbon

implementation action, and the ability to overcome barriers during low-carbon implementation respectively.

‘HCE’ represents household building operation energy carbon emission.

Fig.5. Path analysis model for low-risk area

Note: Squares indicate the observed variables, and circles or ellipses the unobserved variables measured using the observed variables. e1, e2, e3, e4, e5, and e6 are residual factors that were not included in the model. Solid lines indicate positive effects, dashed lines negative effects, line widths the magnitude of the effects, and arrows their direction.

A triple asterisk indicates that the coefficient is significant at the 0.001 level, a double asterisk significant at the 0.01 level, and a single asterisk significant at the 0.05 level.

‘LCAW’ represents low-carbon awareness, while ‘LCAC’ and ‘LCAB’ represent low-carbon

implementation action, and the ability to overcome barriers during low-carbon implementation respectively.

‘HCE’ represents household building operation energy carbon emission.

Table 1 Summary of sample demography (N=564)

Background		Xiamen city		High-risk area		Low-risk area	
		Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Family size	1	8	1.4	3	1.1	5	1.7
	2	52	9.2	33	12.2	19	6.5
	3	181	32.1	88	32.6	93	31.6
	4	153	27.1	66	24.4	87	29.6
	5	101	17.9	48	17.8	53	18
	6	49	8.7	22	8.1	27	9.2
	7	11	2	5	1.9	6	2
	8	6	1.1	4	1.5	2	0.7
	9	1	0.2	0	0	1	0.3
	10	1	0.2	0	0	1	0.3
	12	1	0.2	1	0.4	0	0
Income	<4000	172	30.5	86	31.9	86	29.3
	4000-8000	266	47.2	113	41.9	153	52
	8000-15000	93	16.5	49	18.1	44	15
	15000-20000	21	3.7	14	5.2	7	2.4
	≥20000	12	2.1	8	3	4	1.4
Age	<25	36	6.4	9	3.3	27	9.2
	25-35	351	62.2	164	60.7	187	63.6
	36-45	142	25.2	79	29.3	63	21.4
	46-55	14	2.5	7	2.6	7	2.4
	>55	21	3.7	11	4.1	10	3.4
Education	Illiterate	3	0.5	2	0.7	1	0.3
	Primary school	18	3.2	12	4.4	6	2
	High school	213	37.8	111	41.1	102	34.7
	College	303	53.7	128	47.4	175	59.5
	Master or above	27	4.8	17	6.3	10	3.4
Floor area	<60	70	12.4	31	11.5	39	13.3
	60-89	180	31.9	74	27.4	106	36.1
	90-119	151	26.8	59	21.9	92	31.3
	120-139	85	15.1	63	23.3	22	7.5
	≥140	78	13.8	43	15.9	35	11.9

Table 2 Effects of socio-economic/low-carbon behavior variables on HCE in the entire region

Dependent variables	Independent variables	Direct effects	Indirect effects	Total effects
HCE	Family size	0.41	0.08	0.49
	Age	-	0.02	0.02
	Income	-	0.08	0.08

	Education	0.12	0.06	0.18
	Floor area	0.24	-0.03	0.21
	LCAW	-0.14	-	-0.14
	LCAB	0.16	-0.03	0.13
	LCAC	-0.02	-	-0.02
	Chi-square=13.975 (P<0.001)			
Model fit indices	Comparative Fit Index (CFI) =0.997			
	RMSEA=0.017			

Note: ‘LCAW’ represents low-carbon awareness, while ‘LCAC’ and ‘LCAB’ represent low-carbon implementation action, and the ability to overcome barriers during low-carbon implementation respectively.

‘HCE’ represents household building operation energy carbon emission.

Table 3 Effects of socio-economic/low-carbon behavior variables on HCE in high-risk area

Dependent variables	Independent variables	Direct effects	Indirect effects	Total effects
HCE	Family size	0.4	0.11	0.51
	Age	-	-0.02	-0.02
	Income	-	0.09	0.09
	Education	0.1	0.03	0.13
	Floor area	0.23	-0.03	0.2
	LCAW	-0.19	-	-0.19
	LCAB	0.22	-0.05	0.17
	LCAC	0.05	-	0.05
	Chi-square=19.924 (P<0.001)			
Model fit indices	Comparative Fit Index (CFI) =0.985			
	RMSEA=0.035			

Note: ‘LCAW’ represents low-carbon awareness, while ‘LCAC’ and ‘LCAB’ represent low-carbon implementation action, and the ability to overcome barriers during low-carbon implementation respectively.

‘HCE’ represents household building operation energy carbon emission.

Table 4 Effects of socio-economic/low-carbon behavior variables on HCE in low-risk area

Dependent variables	Independent variables	Direct effects	Indirect effects	Total effects
HCE	Family size	0.38	0.05	0.43
	Age	-	0.01	0.01
	Income	0.13	0.05	0.18
	Education	0.18	0.1	0.28
	Floor area	0.2	-0.06	0.14
	LCAW	-0.1	-	-0.1
	LCAB	0.08	-	0.08
	LCAC	-0.07	-	-0.07
Chi-square=15.475 (P<0.001)				
Model fit indices	Comparative Fit Index (CFI) =0.997			
	RMSEA=0.019			

Note: ‘LCAW’ represents low-carbon awareness, while ‘LCAC’ and ‘LCAB’ represent low-carbon implementation action, and the ability to overcome barriers during low-carbon implementation respectively.

‘HCE’ represents household building operation energy carbon emission.