Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-023-01682-2 OPEN

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The role of peers in promoting energy conservation among Chinese university students

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Guiding individuals to adopt pro-environmental behaviors is critical to achieving carbon neutrality goals. Public policy targeted at a small number of people may be amplified by interpersonal interaction, making peer effect a potentially useful tool for accelerating problem solving. However, previous studies have paid insufficient attention to the influence of peers on university students' energy-saving behaviors. This paper attempts to examine the effect using a large-scale survey dataset conducted on students from Xiamen University in China and the classical linear-in-means model. The result shows that peers' pro-environmental behaviors have positive effect on individuals. The heterogeneity of the influence and the potential mechanisms are also explored. This paper contributes to very important and still growing literature dealing with contagion processes in pro-environmental behaviors. The policy implication is that the government should make full use of the peer effect to maximize the benefits of energy-conservation campaigns.

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Introduction

For China to achieve its carbon neutrality goal, promotion of pro-environmental behavior among consumers is essential. Nevertheless, existing carbon emission reduction measures are skewed to the production side. Consumers' poor energy-saving initiatives and low willingness to pay for pollution reduction make it more difficult for policymakers to find feasible and efficient means of regulating consumption emissions. This is a particularly serious problem for university students, who are the future leaders of the energy transition toward sustainability, and whose behavior has a leading effect on the entire society, thus an urgent solution is required.

Peer effect refers to the phenomenon that the attitudes, values, or behaviors of an individual are influenced by the behaviors of members within a peer group. As one of the widely used nudge strategies, it is likely to be a helpful tool in addressing the challenges of promoting environmentally friendly behavior faced by China and other countries because it implies a contagion effect, in which the prosocial decisions of group members influence the subsequent behavior of others. For university students, the peer effect may play a more pronounced role since peer influence culminates in a person's life course during this time (Arnett et al., 2011). Fellow students become their closest contacts and play an essential part in the formation of values and behaviors. This is especially true for Chinese university students, whose education and management are organized in the basic unit of their major studies. Students of the same major need to attend classes and participate in activities together. We, therefore, are interested in the following research question: Would a university student be positively influenced if his or her fellow majors demonstrate active energy-conservation behaviors?

After reviewing the existing literature, we find that, although peer effect is of great research value (Wolske et al., 2020), the existence has been disputed by scholars (Carrell et al., 2009; Duncan et al., 2005; Griffith and Rask, 2014). Few studies have examined the effect of social influence on energy-saving behavior. Moreover, studies focusing on peer effect in school often explore the impact from roommates, which reflects only the tip of the iceberg of peer influence. Influences from the broader context are rarely discussed (Yakusheva et al., 2014). Evidence on whether peer effects help drive energy-saving behaviors among college students is urgently needed, and this paper is dedicated to adding to this perspective.

With the help of a large-scale survey dataset from a prestigious university in China and the classical linear-in-means model, this paper seeks to identify the causal effect of peer influence on energy-saving behavior. Peers of the same major are approximately randomly assigned since students cannot decide their companions, with whom they have an inevitable amount of contact. Our research shows that peers' energy-saving behavior has positive spillover effects on individuals. The marginal contribution of this study is as follows:

(1) Large-scale face-to-face interviews were conducted among approximately 3000 university students, with the aim of exploring their energy cognition level and clarifying motivations for energy conservation. As Manski (1993) stated, "*The only ways to improve the prospects for (peer effect) identification are to develop a tighter theory or to collect richer data. I have no thoughts to offer on tighter theory but I see much that we can do to collect richer data.*"
(2) We enrich the literature about peer effects on energy-saving behavior. The findings provide new insights into understanding the relationship between peer effect and green behavior. University students are the leaders of the future energy revolution. It is crucial to understand how peers affect a university student's energy-saving behavior: Yakusheva et al. (2014) argue that, "*if the behavior is subject to social contagion, harnessing the power of social networks could help policymakers propagate an intervention through a group of individuals tied to each other within some social context, thus multiplying its overall impact.*"
(3) Policy suggestions are put forward based on the conclusion of the study. Our estimates support the idea that public policies promoting energy-saving behavior can have a multiplier effect through interpersonal interaction. Students can be encouraged by peers to actively practice pro-environmental behaviors. If that is the case, the government should make full use of the peer effect to maximize the benefits of energy-conservation campaigns, which are conducive to the realization of China's carbon neutrality vision and the UN's sustainable development goal 13: Climate Action.

Literature review

Research on peer effect. Psychology research has long demonstrated the effectiveness of social norming (Hyland-Wood et al., 2021). Peer effects that arise from social norms are studied over a wide range of topics. Gong, Lu, and Song (2021) focued on education output. (Earnhart and Ferraro, 2021) studied wastewater treatment facilities' discharge behavior. Fluhrer and Kraehnert (2022) explored subjective well-being. Van Hoorn et al. (2016), Charlier et al. (2021) examined prosocial behavior. Eisenberg et al. (2013) studied mental health. Kremer and Levy (2008) researched the misconduct of university students. De Giorgi et al. (2020) investigated consumption. Ling et al. (2021) probed household waste separation. Moncada et al. (2021) chose distributed energy resources adoption. Bucciol et al. (2019) analyzed waste sorting, and Adaman et al. (2011) studied CO_2 emissions reduction.

Manski (1993) pointed out that three reasons may exist for the convergence of individual and group behavior. The first reason is the endogenous effect. An individual's behavior is influenced by the related behavior of other individuals in a reference group. This is the peer effect that we care about. The second reason is a result of the exogenous or contextual effect. An individual's behavior is influenced by the characteristics of other members of the group. The third reason is the correlated effect, where individuals in the group behave similarly because they have similar unobserved characteristics or are affected by the same environment. The former is the relevant group factor, which is commonly referred to as the sample selection problem. The latter is the common environmental factor. Mouw (2006) held that a natural experiment based on randomly assigned peers is a helpful method to solve the self-selection problem and this is considered the most advantageous method to capture the network causal effect. In reality, it is hard to find relationships that are randomly assigned and last over time to study peer effects. Many studies use university roommates, who can be regarded as approximately randomly assigned, to estimate the peer effect, (Yakusheva et al., 2014; Mcewan and Soderberg, 2006; Guo et al., 2015).

Roommates are only a tiny part of the social network of a university student. And over time, students' societal range is likely to extend beyond dormitory. Foster (2006), Mcewan and Soderberg (2006), Lyle (2007) indicated that studies on the peer effect of roommates' academic achievement often reach fragile and unstable conclusions. In view of this, this paper attempts to consider the influence a more extensive range of peers creates. University students studying within the same major cannot

determine their peers,, which help us to identify the causal effects of peer influence.

Research on energy-conservation behavior. Existing research has extensively explored the factors influencing individuals' energy-saving intention and behavior. Lacroix and Gifford (2018) regarded climate change risk perception to be the strongest predictor of the frequency of energy-saving behavior. Webb et al. (2013) applied a modified version of the self-determination theory and goal-directed behavior model to explain households' energy-saving behaviors. Mi et al. (2021) indicated that psychological motivation significantly influences energy-saving behavior. Huo et al. (2021) believed that as the income level of residents increases, they are more inclined to buy energy-saving appliances. Alvi and Khayyam (2020) showed that residents in the capital cities of Bangladesh and Pakistan hold pessimistic perceptions aboutclimate change and water conservation. Nawaz et al. (2022) analyzed the impact of social norms on energy-conservation behavior. Wang et al. (2021) held that past energy-saving experiences enhance energy-saving willingness.

Some scholars have studies the effectiveness of specific strategies aimed at promoting household energy conservation. (Ho et al., 2022) regarded video games as being a novel technological aid to environmental education. Lu et al. (2018) showed that WeChat has the best effect in reducing monthly energy use, but this effect lasts only for a short time. The use of stickers has a more lasting energy savings effect. Kang et al. (2012) discovered that residents' energy-conservation behavior improved after they were provided with relevant information and participated in pertinent publicity activities. Ornaghi et al. (2018) demonstrated the effectiveness of specific information interventions in promoting energy savings in naturally ventilated offices. Cardella et al. (2022) stressed that information nudges are useful in increasing the adoption of voluntary green-power plans.

At present, most studies on peer influence on consumers' energy behavior have mainly focused on the purchase of solar photovoltaic equipment and automobiles. Mundaca and Samahita (2020) showed that some scholars provide evidence of the existence of peer effects and regard it as an important factor driving the likelihood to adopt. Balta-Ozkan et al. (2015) find significant regional spillovers from photovoltaic deployments in the UK. Graziano and Gillingham (2015), Müller and Rode (2013), Rode and Weber (2016) reported that the closer the devices and social relationships are, the stronger the peer effect. Inhoffen et al. (2019) highlighted that the more solar radiation, the stronger the peer effect. Peer effects affect new car purchases as well. Goetzke and Weinberger (2012) revealed that consumers are more likely to buy new cars if their nearest neighbor or someone else in the same area does. Nolan et al. (2008) showed that peer effects appear to be a critical determinant of the diffusion of new energy technologies or behaviors. The actions of others influence individual and collective energy decisions. In some cases, these social impacts are even more potent than factors such as cost, convenience, education level, and effectiveness. (Brent et al., 2020) established that peer comparison can lead to water conservation. (Cerda Planas, 2018) acknowledges that peer effect would drive society toward lower levels of pollution.

Through the literature review, we find that most studies on the influencing factors of energy-saving behavior regard social norms as an essential component. Prosocial peers help to form good social norms. The literature also affirms the basic trend that members of the reference group affect an individual's energy-related behaviors. However, few studies have noted the impact of peers studying the same major on university students' energy-saving behaviors. This research gap is exactly what this paper is devoted to exploring. We put forward the following hypothesis: If a university student's peers in the same major exhibit frequent energy-saving behaviors, he/she will be positively influenced.

Data and methodology. This study employs the dataset of the University Students' Cognition of Energy and Environment Survey (CSCES) in analyzing the impact of peer effect in energy-saving behavior. CSCES is designed to explore the energy knowledge, energy-saving awareness, behavior and other low-carbon-related themes among Chinese university students. There are more than 240 items in the questionnaire. Several discussion and modification sessions were conducted prior to the implementation of the survey to ensure good content validity. A pre-survey of 100 samples was also undertaken. CSCES was formally implemented in Xiamen University from December 2020 to April 2021 by the China Institute for Studies in Energy Policy (CISEP), covering all schools and grades of the university. Face-to-face interviews combined with computer-aided technology are used to ensure the data quality. 2993 effective samples were collected.

The peers who interact with university students usually come from the same dormitory, class, major, school, and grade. Among them, there are remarkable intersections between students of the same major. They need to attend classes, take exams and participate in activities together. Therefore, based on the identification of university students' social networks, this paper examines the influence of peers in the same major on an individual.

Here is the process of how we construct the peer group. All the interviewees come from Xiamen University. In the survey, each respondent is asked the following four questions: What is your current stage of education? Which grade are you in? Which school are you from? and What is your major? Those students who answer these four questions exactly the same were considered to be from the same major. Students' energy-saving behaviors were assessed individually, and then we manually matched each student with his/her peer in the same major and calculated the mean score of his/her peer.

The reason we regard the constructed peer effect as a good measure is as follows. Students are not able to choose their peers in the same major with whom they have a lot of interaction. This allows us to adopt the strategy of eliminating sample self-selection through randomly selected peers. Referring to Alvarez-Cuadrado et al. (2016), this paper sets the minimum reference group size as 5. There are 1617 valid samples and the reference group sizes are from 5 to 33, with the mean value of 12.58 and the median value of 10. The university typically has 30 students in an undergraduate major and 8 students in a graduate major. This indicates that the sample size of peers we draw captures the overall profile of peers well. Besides, CSCES adopted a stratified random sampling technique. Firstly, the sample size of each school was determined according to the proportion of students in that school of Xiamen University, and then simple random sampling was adopted in each school. This means that the sample is drawn at random from the population and if the class sizes are bigger, more students in that major are likely to be chosen as respondents.

The widely applied classical linear-in-means model first developed by Manski (1993) propose that a student's outcome is a linear function of the mean of his peers' outcome. Hoxby and Weingarth (2005) considered that most of the other popular models of peer effects are defined based on behavior, as opposed to the specification of an equation, making it difficult to explain. In view of this, this paper uses the classical linear-in-means model to estimate the peer effect, as shown in Eq. (1). In this model, individual result (Y_i) depends on individual characteristics (X_i)

and peer average outcome ($peer_{-i}$) except individual i. The model includes the education stage, school, grade, and major as control variables to control common environmental factors. The coefficient (α_1) is the estimated peer effect, which represents the magnitude of change in the energy-saving behavior of individual i when the behavior of the peer improves by one unit on average. Considering the correlation of the energy-saving behaviors of students in the same major, we use standard errors clustered at the major level.

For robustness, in section "Robustness test" we also try to control for the influence of peer characteristics in exogenous effects. Although the dependent variable is discrete, we use the OLS estimation method because it has a high estimation accuracy following Deschenes et al. (2020). We also provide the result of the ordered probit model and ordered logit model in robustness analysis, considering that the dependent variable is ordered data.

$$Y_i = \alpha_0 + \alpha_1 peer_{-i} + X_i\beta + \varepsilon_i \quad (1)$$

In this study, the dependent variable (*sav*) is the score of student i's energy-saving behavior, and the core explanatory variable (*peer*) is the mean score of the energy-saving behavior of peers. The variable *sav* is obtained by summing up five items, all of which imply an effort aimed at reducing energy consumption and complying with the definition of energy conservation. They are as follows: I have formed the habit of buying energy-saving products; I turn up the cooling temperature of the air conditioner to save energy; I turn down the water temperature of the heater to save energy; I turn off the air conditioner and lights when the room is not in use; and when accessing food in the refrigerator, I try to minimize the opening time. Each respondent is asked whether the above statements fit with his/her daily routine. There are five options for each item: completely in line, relatively in line, sometimes in line sometimes not, not so much in line, not at all in line, corresponding to 1-5. The dependent variable ranges from 5 to 25. The larger the value, the more active the energy-saving behavior. The result of confirmatory factor analysis suggests that there is good internal consistency reliability and these five variables really are similar enough to each other to be joined, with the value of Cronbach's alpha being 0.78 and construct reliability being 0.78. Control variables are divided into individual and family characteristics. Individual characteristics include gender, year of birth, religious belief, marital status, political affiliation whether as a student cadre, school, education stage, grade, and major. These variables are expressed as *gender*, *birthyear*, *relig*, *marital*, *polit*, *leader*, *school*, *major*, *grade*, and *degree* respectively.

Family characteristics include the province where the family is located, registered permanent residence, category of family residence, ownership of family house, the level of family income in the local level, the number of family property owned, whether the family has a car, the father's educational level, the mother's educational level, the father's political status, and the mother's political status. Each variable is denoted as *province*, *hukou*, *livtyp*, *houstyp*, *incomty*, *housnum*, *car*, *edu_f*, *edu_m*, *polit_f*, and *polit_m* respectively. The variance inflation factor of all explanatory variables is in the range of [1.03, 6.77], less than 10, indicating that there is no need to worry about strict multicollinearity problem. The definition of the variables is shown in Table S1 (shown in the Supplementary information) and the descriptive statistics are presented in Table 1. The mean and median of the variables *sav* and *peer* are around 20, implying that the students demonstrate a certain degree of energy-saving behavior, but there is still considerable room for improvement, as the explained variables take values in the range of 5 to 25. The sample is evenly distributed between male and female students, with 22% having been student leaders. An average respondent is 22 years old, non-religious, unmarried, a member of the Communist Youth League, has not been a member of a student cadre, is an undergraduate student, lives in the county, lives in his own house, has an average family income in the local area, has 2 houses with 2 cars in the family, and has parents with a mass political status. These characteristics are consistent with the current features of a general Chinese university student, showing good representativeness.

Table 1 Descriptive statistics.

Variables	N	SD	p50	min	max
sav	1617	3.250	20	5	25
peer	1617	1.367	19.22	14.67	23.75
gender	1617	0.490	2	1	2
birthyear	1617	2.177	1999	1989	2004
relig	1617	0.350	1	1	3
marital	1617	0.0740	1	1	2
polit	1617	0.523	2	1	5
leader	1617	0.413	0	0	1
grade	1617	1.075	2	1	5
degree	1617	0.515	1	1	3
livtyp	1617	1.138	3	1	4
hukou	1617	0.878	2	1	5
houstyp	1617	2.239	1	1	7
incomtyp	1617	1.094	3	1	6
housnum	1617	1.244	2	1	7
car	1617	0.836	2	1	6
polit_f	1617	1.274	1	1	6
polit_m	1617	1.283	1	1	6

Table 2 Baseline regression results.

	(1)	(2)	(3)	(4)
peer	0.313***	0.278***	0.301***	0.271***
p-value	0.000	0.001	0.001	0.001
95%-CI	[0.149,0.477]	[0.121,0.435]	[0.135,0.467]	[0.112,0.430]
SE	(0.082)	(0.079)	(0.083)	(0.080)
Control	NO	YES	YES	YES
N	1617	1617	1617	1617

Robust standard errors clustered at the major level are shown in parentheses. ***$p < 0.01$. Column (1) contains no control variables. Column (2) adds individual characteristics as control variables. Column (3) adds household characteristics as control variables. Column (4) adds both individual and household characteristics as control variables and the fixed effect of education stage, school, grade and major are controlled, which is taken as the benchmark regression result. The estimation method is OLS. The dependent variable is the score of individual's energy-saving behavior.

Empirical results and discussion

Baseline regression. The regression results are shown in Table 2. No control variables are included in column (1), and the core explanatory variable is positive at the significance level of 1%, indicating that when the peer's average energy-saving behavior increases by one standard deviation, the individual's behavior improves 0.132 standard deviations (0.313*1.367/3.250). Column (2) is the estimated result of the model after including individual characteristics as control variables. Column (3) is the result after adding family characteristics as control variables. Column (4) is the result after adding the control variables of individual and family characteristics simultaneously, which is taken as the benchmark regression result in this paper. The *p*-value of the White test indicates that the null hypothesis of homoskedasticity cannot be rejected at the 5% level of significance. The *p*-value for Ramsey's regression specification error test is 0.7019, indicating that no evidence is found to reject the null hypothesis of no omitted variables.

Table 3 Heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)
peer	0.317**	0.236***	0.353***	0.205	0.415***
p-value	0.030	0.008	0.004	0.137	0.000
95%-CI	[0.032,0.602]	[0.063,0.409]	[0.122,0.584]	[−0.067,0.477]	[0.227,0.603]
SE	(0.143)	(0.087)	(0.115)	(0.136)	(0.094)
inter_1					-0.298***
p-value					0.002
95%-CI					[−0.480,-0.117]
SE					(0.091)
Control	YES	YES	YES	YES	YES
N	1617	1617	1617	1617	1617

Robust standard errors clustered at the major level are shown in parentheses. **$p < 0.05$, ***$p < 0.01$. All models control individual and household characteristics variables and the fixed effect of education stage, school, grade and major. The estimation method is OLS. The dependent variable is the score of individual's energy-saving behavior. The following tables are the same.

Table 4 Heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)
peer	0.264***	0.166	0.212	0.239***	0.464***
p-value	0.001	0.514	0.111	0.003	0.000
95%-CI	[0.117,0.410]	[-0.339,0.671]	[-0.050,0.475]	[0.084,0.393]	[0.221,0.707]
SE	(0.074)	(0.252)	(0.131)	(0.077)	(0.122)
inter_2					-0.021**
p-value					0.014
95%-CI					[−0.038,-0.004]
SE					(0.009)
Control	YES	YES	YES	YES	YES
N	1398	219	323	1294	1617

Robust standard errors clustered at the major level are shown in parentheses. **$p < 0.05$, ***$p < 0.01$.

The core explanatory variable remains significant at 1% level in column (4), indicating that when the average energy-saving behavior of peers increases by one standard deviation, the behavior of an individual increases by 0.114 standard deviations (0.271*1.367/3.250). We detect that students coordinate their energy-saving behaviors with their surrounding partners. The possible reason for this is that individuals who are embedded into social groups exhibiting positive energy-conservation behavior tend to conform to that group's prescribed norms to gain approval from social peers (Yakusheva et al., 2014). Section "Further discussion: mechanism analysis" explores and discusses this mechanism.

Heterogeneity analysis

Males or females. Considering that individuals are influenced by their peers to varying degrees, and that groups with different characteristics produce peer effects of different magnitudes, we explore the heterogeneity of the peer effect in section "Robustness test". This can help policymakers identify the individuals most vulnerable to peer influence to maximize the multiplier effect of social interactions. As shown in Table 3 columns (1) and (2), after regression by gender, the peer effect is significant for both males and females. Although the coefficient of core explanatory variables is larger in the male sample, the overlap is found after comparing the confidence intervals of coefficient values. In addition, after introducing the interaction of gender and peer energy-saving behavior, the interaction term is not significant. The *p*-value of 1000 times Bootstrap is 0.241, and the *p*-value of the Fischer combined test is 0.237. This indicates that no significant difference is found between males and females, which is consistent with the finding of (Khayyam et al., 2021) that climate change mitigation and adaptation behavior are unaffected by gender.

Different grades. We take students in grade 3 and above as high grades and students in grades 1 and 2 as low grades. Table 3 columns (3) and (4) show the regression estimation results for high- and low-grade students, respectively. It is found that the peer effect is significant for high-grades students but not for low-grades students. One possible explanation is that the peer effect takes time to work. Senior students become more familiar with each other and interact more frequently, showing a more prominent peer influence.

Whether depressed. The questionnaire asks the respondents whether they have ever been depressed in the past month. If respondents answer sometimes, often, or always, they are defined as having high levels of depression recently. If the answer is never or rarely, their recent depression level is defined as low. The interaction term (denoted as *inter_1*) of level of depression (1 for high-level depression, 0 for low level) and peers' average initiative of energy-saving behavior is constructed, and the results are shown in column (5) of Table 3. It is found that the interaction term is significantly negative. That is, people with low levels of recent depression are more likely to be positively affected by peers' energy-saving behaviors than people with high levels of depression. The possible reason is that depressed individuals are relatively isolated and have less contact with the outside world, making them less influenced by their peers.

Table 5 2SLS estimation.

	(1)	(2)	(3)	(4)
peer	0.402***	0.402***	0.400***	0.400***
p-value	0.000	0.000	0.000	0.000
95%-CI	[0.207,0.597]	[0.197,0.607]	[0.195,0.605]	[0.195,0.605]
SE	(0.099)	(0.105)	(0.104)	(0.104)
Control	YES	YES	YES	YES
N	1617	1617	1617	1617

Robust standard errors clustered at the major level are shown in parentheses. ***$p < 0.01$.

Level of environmental concern. Columns (1) and (2) of Table 4 are the estimation results of positive environmental value viewers and general environmental value viewers, respectively. We define a positive environmental value viewer as an individual who regards environmental protection, pollution prevention, and harmony with nature as being important. It is found that the peer effect is significant for the group with positive environmental values but not for the other group. Columns (3) and (4) are subsample regressions according to an individual's level of attention to energy issues. We notice that the peer effect is not significant for those who never pay attention to energy issues but significant at a 1% level for people concerned with energy issues. It can be seen that the more positive an individual's environmental value, and the higher their level of environmental concern, the more likely they are to be affected by the energy-saving behavior of peers, which is in agreement with the finding of (Lucas et al., 2018).

Peer composition difference. Putnam (2007) showed that peer composition difference influences the magnitude of peer effect. When an individual is in a group with large peer differences, social isolation is likely to occur, which reduces the individual's sense of belonging, trust, intimacy, and enthusiasm to participate in group activities. In this paper, we construct an interaction term (denoted as inter_2) using a combination of the variance and mean of peer energy-saving behaviors to explore the effects of differences in peer composition. The results are shown in column (5) of Table 4, and the coefficient we are interested in is significantly negative, suggesting that peer composition differences do make a difference. The greater the difference in peer energy-saving behavior, the smaller the positive impact on the individual, which coincides with the results of Putnam (2007).

Robustness test. This section tests whether baseline regression results are robust using various approaches. According to the analysis in the literature review, considering that the contextual effect and correlated effect may still interfere with the estimation of the true causal effect, we control for possible confounding factors. The instrumental variables approach is commonly used to mitigate the endogeneity problem, and we believe we have found the ideal instrumental variables and thus we give the estimation results of the instrumental variables approach. Different setting of reference group size varies the sample from 1,617 to 488, and thus the corresponding robustness analysis is provided.

Using instrumental variable estimation. The behavior of an individual may influence the behavior of his/her peers, i.e., reverse causality problems may exist. In addition, although the baseline regression has controlled for important control variables, there is still the risk of unobservable omitted variables causing estimation bias. Considering the likely problems, we use the instrumental variables method to verify the robustness. The appropriate instrumental variables (*iv*) need to satisfy the following criteria: the only channel through which the variables *iv* affect *y* is by affecting *peer*. A peer's family may exert influence on individual i by influencing the peer. Thus, the low-carbon awareness and behavior of individual i's peer's family are good instrumental variables. In the survey, each interviewee is asked whether his/her personal circumstance match the description of the following statements: My family thinks I should opt for a low-carbon lifestyle; My family thinks I should opt for environmentally friendly take-out containers; My family uses environmentally friendly take-out containers. Does it match perfectly, match fairly, match sometimes, match less, or not match at all? The more it matches the description, the higher the score. The three instrumental variables adopted in this paper are the average score of individual i's peer's family's low-carbon expectations for individual (denoted as *iv1*), average score of individual i's peer's family's expectations for individual environmentally friendly take-out containers (*iv2*), and average score of individual i's peer's family's use of ecologically friendly take-out containers (*iv3*).

The correlation coefficients between the three variables and the core explanatory variable are 0.538, 0.552, and 0.522, respectively, which are all significant at the level of 1%. revealing that the three instrumental variables strongly correlate positively with the possible endogenous variable *peer*. In addition, it can be seen from the regression results of the first stage that instrumental variables have good explanatory power over the endogenous variables, with *p*-values of 0.000. The *F* statistic of the first stage is 40.41. Kleibergen-Paap RK Wald F statistic is 259.656, which strongly rejects the null hypothesis that the three variables are redundant instrumental variables.

The result of the two-stage least squares estimation is presented in column (1) of Table 5. The Kleibergen-Paap rk LM test strongly rejects the unidentified null hypothesis. The *p*-value of the over-identification test is 0.7337, failing to provide evidence that instrumental variables are not exogenous. We further investigate the correlation between instrumental variables and endogenous variables. Shea's Partial R-Sq. is 0.3572, and the *F* statistic is 259.656, much higher than 10. Supposing the significance level of endogenous explanatory variables in the structural equation is carried out in the Wald test of 5% nominal size, and the acceptable true significance level is not more than 5%, the null hypothesis of weak instrumental variables can be rejected. Therefore, it is reasonable to assume that there are no weak instrumental variables.

For the sake of robustness, the maximum likelihood method with limited information is used, which is less sensitive to weak instrumental variables, and the result is shown in column (2) of Table 5. One can find that the coefficient estimates are very close to column (1). The *p*-value of the DWH endogeneity test is 0.1033. The Chi-square statistic of the endogeneity test is 2.196, and the *p*-value is 0.1384. This suggests that the endogenous explanatory variable problem is somewhat insignificant.

Table 6 Changing the minimum group size.

	(1)	(2)	(3)	(4)	(5)	(6)
peer	0.125***	0.182***	0.245***	0.344***	0.369***	0.438***
p-value	0.010	0.003	0.000	0.000	0.000	0.000
95%-CI	[0.030,0.219]	[0.064,0.301]	[0.118,0.371]	[0.187,0.501]	[0.193,0.546]	[0.213,0.664]
SE	(0.048)	(0.060)	(0.064)	(0.078)	(0.088)	(0.110)
Control	YES	YES	YES	YES	YES	YES
N	2497	2151	1893	1437	1221	933
	(7)	(8)	(9)	(10)	(11)	(12)
peer	0.427***	0.390**	0.404**	0.318*	0.199	−0.011
p-value	0.001	0.020	0.022	0.061	0.394	0.971
95%-CI	[0.194,0.661]	[0.068,0.713]	[0.064,0.743]	[−0.016,0.651]	[−0.289,0.687]	[−0.689,0.667]
SE	(0.113)	(0.156)	(0.163)	(0.159)	(0.226)	(0.304)
Control	YES	YES	YES	YES	YES	YES
N	843	773	696	660	530	488

Robust standard errors clustered at the major level are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

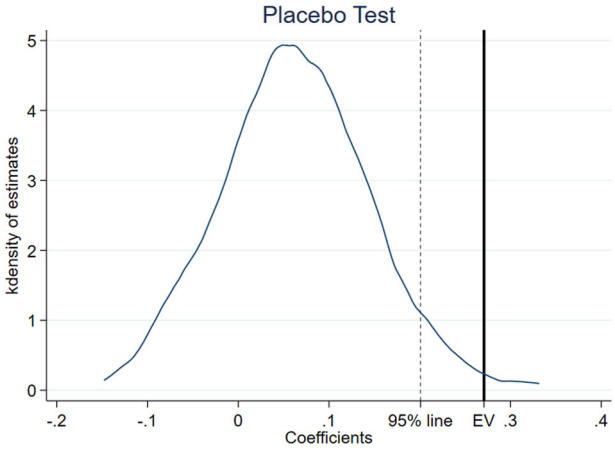

Fig. 1 Placebo test. Note: "EV" means estimated value.

Changing the minimum reference group size. In this section, we change the minimum group size to test the robustness of the results. As shown in Table 6, columns (1)–(12) correspond to the results of the group with a minimum size of 2–4, 6–14, respectively. It is found that when the minimum group size is less than 13, the coefficients are significant, but they are not significant when the group size is more than 13. It is worth noting that the sample size gradually decreases with the increase in the minimum group size. Since the survey is conducted by stratified random sampling, it is hard to ensure that many students of the same major are selected. Therefore, the effective sample size becomes smaller and it is challenging to obtain significant estimation results when the minimum size of the reference group is set too large.

Reflection problem: control the correlated effect. In this section, the placebo test is used to control the influence of shared environmental factors. Our approach is to randomly assign students from other majors in the same school to the individual, i.e., construct pseudo peers and perform regression analysis. After repeating the random process 500 times, Fig. 1 is drawn, with dotted lines representing 95% quantile values of the 500 simulations and solid lines denoting coefficient estimates in the baseline regression. Since the latter is greater than the former, we believe that the shared environment of the school does not confuse the peer effect.

Reflection problem: control the exogenous effects. To further control the exogenous effect, we incorporate some characteristics of the peers and their families into the control variables. These variables include the mean of peers' responsibility, the mean of peers' environmentally friendly attitude, the mean of peers' energy-saving intention, and the mean of the educational level of the peers' parents. The results are listed in column (1) of Table 7, and significant peer effects can still be observed.

Regression only for first-year students. Column (2) in Table 7 is the result of estimation for first-year students only. The parameter of primary interest is not significant, which is in line with expectations. The first-year students entered the university in mid-September 2020. By the beginning of the survey (December 2020), these students had not been with their peers for a long time, and the peer influence was not yet obvious. This may to some extent guarantee that the significant results observed in the baseline regression are not caused by chance.

Changing the estimation method. Since the dependent variable can be seen as ordered data, ordered probit and ordered logit model are also used to test whether the coefficient significance is robust. The results are shown in columns (3) and (4) of Table 7, and the peer effects are both significant at the significance level of 1%. The magnitude of the coefficient does not reflect the marginal effect and is not comparable with the baseline regression.

Further discussion: mechanism analysis. The influence mechanism of peer effect can be divided into direct and indirect influence. Direct influence refers to peers' ability to pass on specific knowledge in a particular field (Griffith and Rask, 2014). Indirect impact, as defined by Stinebrickner and Stinebrickner (2006), refers to peers' ability to affect an individual's values and attitudes.

To explore the possible mechanism, this section analyzes the influence of peers' energy-saving behavior on an individual's energy-saving knowledge, energy-saving willingness, awareness of the importance of energy-saving, and social responsibility. We define peer influence generated by energy-saving knowledge embedded in peer networks as the direct influence. Moreover, the further influence of peer by afftecting social responsibility, awareness of the importance of energy-saving, and willingness to save energy is defined as the indirect influence. The definitions of variables are presented in Table S1. The higher the value, the more positive the respondent's attitude toward energy conservation. The variable social responsibility is measured by the sum of the scores of four questions. Confirmatory factor analysis shows

Table 7 Other robustness tests.

	(1)	(2)	(3)	(4)
peer	0.217**	−0.009	0.089***	0.164***
p-value	0.045	0.963	0.000	0.000
95%-CI	[0.005,0.429]	[−0.382,0.365]	[0.039,0.139]	[0.079,0.248]
SE	(0.106)	(0.185)	(0.026)	(0.043)
Control	YES	YES	YES	YES
N	1617	525	1617	1617
Adj.*R*-square	0.028	0.077		

Robust standard errors clustered at the major level are shown in parentheses. **$p < 0.05$, ***$p < 0.01$. The estimation method for the first two columns is OLS and maximum likelihood estimation for the last two columns.

Table 8 Mechanism analysis.

	(1)	(2)	(3)	(4)
peer	0.062**	0.064***	0.045***	0.190**
p-value	0.047	0.002	0.010	0.012
95%-CI	[0.001,0.123]	[0.024,0.105]	[0.011,0.078]	[0.043,0.337]
SE	(0.031)	(0.020)	(0.017)	(0.074)
Control	YES	YES	YES	YES
N	1617	1617	1617	1617
Adj.*R*-square	0.011	0.041	0.066	0.032

Robust standard errors clustered at the major level are shown in parentheses. **$p < 0.05$, ***$p < 0.01$. The estimation method is OLS. The dependent variables in columns 1–4 are: energy-saving knowledge, energy-saving willingness, awareness of the importance of energy-saving, and social responsibility.

that the load of each factor is not less than 0.70, Cronbach's alpha is 0.90, the Construct Reliability is 0.90, and the Convergent Validity is 0.70, indicating that there is a good internal consistency reliability and these four questions indeed measure the same construct. Regression results are shown in Table 8 columns (1)–(4). The coefficient estimates we are interested in are all positive at a significance level of at least 5%, showing the presence of a positive influence, which is in line with the findings of the above literature.

Conclusion and policy implications

To achieve the mission of carbon neutrality, promoting public participation in carbon emission reduction activity is critical and requires urgent solutions (Lin and Zhu, 2019). Social interaction has long been recognized as an important source of reducing free-riding in public good provision. Incentives from peers may become an important way for university students to form a green lifestyle. This paper contributes to a very important and still growing body of literature dealing with contagion processes in pro-environmental behaviors. We find that the energy-saving behavior of university students is significantly affected by randomly assigned peers. When companions' energy-saving behavior increases by one standard deviation, the individual's behavior improves 0.132 standard deviations. Such initiative is highly commendable, since consumers' preferences not only determine consumption but also have a guiding effect on the production decisions on the supply side. We also discover that peer effect can be divided into direct influence and indirect influence. The former is generated by the knowledge related to energy-saving embedded in the peer network, and the latter is further developed by influencing an individual's social responsibility, awareness of the importance of energy-saving, and willingness to save energy. Peer influence is heterogeneous. Individuals in different grades, with varying levels of depression, environmental concerns, and peer composition are subject to varying levels of peer influence.

The policy recommendations are presented below: (1) This paper adds to the literature that considers social networks as complementary to market mechanisms. Considering the evidence of peer effect found in this study, the government should make full use of the peer effect to maximize the benefits of energy-conservation campaigns. (2) Targeted efforts should be made to groups prone to peer influence, such as senior students, organizations with more personal interaction, as well as those with a low level of depression, and people who attach importance to environmental protection. (3) This paper supplements the discussion on energy-conservation education and management for university students. According to the findings of the mechanism analysis in this paper, universities should strengthen training in energy-conservation knowledge, promote environmentally friendly values, and increase students' awareness and willingness to save energy to better leverage the peer effect.

This paper has the following limitations: The dataset is collected from only one university in China. Whether the findings can be generalized to other schools needs to be further explored. In addition, this paper is focused on the peer effect of energy-saving behaviors. The peer effects for other environmentally friendly behaviors, such as green consumption, needs to be investigated. This provides avenues for future research.

Data availability

The datasets that support the findings of this study are available from the corresponding author on reasonable request.

Received: 6 October 2022; Accepted: 13 April 2023;
Published online: 05 May 2023

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Acknowledgements

This paper is supported by National Natural Science Foundation of China (Key Program, No 72133003).

Competing interests

The authors declare no competing interests.

Ethical approval

All procedures performed in this study were in accordance with the ethical standards of the Xiamen university. Ethical clearance and approval were granted by Xiamen University.

Informed consent

Informed consent was obtained from all participants, which was delivered and collected together with the questionnaire.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-023-01682-2.

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