Does Internet use help increase residents' participation in programs to improve the dwelling environment? Evidence from China

Xueting Wang[a,b], Feng Qiu[c], Junbiao Zhang[a,b], Qingmeng Tong[d]

a. College of Economics & Management, Huazhong Agricultural University, Wuhan, China,
b. Hubei Rural Development Research Center, Wuhan, China
c. Department of Resource Economics and Environmental Sociology, University of Alberta, Alberta, Canada
d. School of Economics and Business Administration, Central China Normal University, Wuhan, China

E-mail:

Xueting Wang: wangxtwork@163.com

Feng Qiu: feng.qiu@ualberta.ca, Corresponding author.

Junbiao Zhang: zhangjb513@126.com, co-corresponding author.

Qingmeng Tong: cntqm@163.com

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Abstract: Currently, dwelling environment improvement remains a major problem in development countries. Promoting individuals' active participation is one of the keys to ensuring the dwelling environment improvement. In this article, we develop a theoretical analytical framework to show how Internet use influences residents' decisions to use flush type sanitary toilet and adopt centralized disposal of domestic waste. The model considers participation decisions of heterogenous individuals, with the decision to use Internet assumed to be endogenous. This study employs 11,523 household surveys data from the China Family Panel Studies (CFPS) in 25 provinces in China. In the empirical analysis, a recursive bivariate probit model that accounts for potential endogeneity of Internet use and selection bias is employed to analyze the impacts of Internet use on residents' use of flush type sanitary toilets and adopt centralized disposal of domestic waste. The results reveal that Internet use exerts a positive and statistically significant impact on the likelihood of using flush type sanitary toilets and adopting centralized disposal of domestic waste. The findings also show that education level, family income, political identity, and environmental cognition positively and significantly influence the probability of a resident using Internet and the likelihood of using flush type sanitary toilets and adopting centralized disposal of domestic waste. The results of this study may link Internet use and DEIP participation and provide a new reference for developing countries to promote the improvement of dwelling environment.

Keywords: Internet use; dwelling environment improvement programs; residents' participation;

recursive bivariate probit model; China

1. Introduction

Improving the residential living environment is a global challenge, especially in developing countries, due to the rapid population growth, changes in lifestyles, improved living standards and increased everyday waste (Yuan et al., 2018; Jiang et al., 2020). In recent years, a huge amounts of domestic pollutants such as domestic garbage, sewage and latrines excreta have been improper disposed, causing great damage to the environment as well as health and welfare of Chinese residents (Sun and Shang, 2015). For example, improper disposal of domestic waste will not only produce "white pollution", but also lead to the volatilization of toxic and harmful gases, and cancer, deformity and other diseases (Liu and Huang, 2014); Extensive use of unsanitary toilets has seriously polluted the dwelling environment due to the improper treatment of feces, and also has led to many water-borne diseases such as diarrhea, malaria and other mosquito and fly infectious diseases such as encephalitis B (WHO, 2005).

Growing evidences have shown that a pleasant dwelling environment is important for individuals to improve quality of life, promote health, enhance subjective well-being and life satisfaction (Welsch, 2006; Bougherara et al., 2007; Zhang et al., 2017; Yuan et al., 2018). Hence, the central and local governments have made substantial efforts and also set up many environmental projects (e.g., toilet revolution, river chief system, environmental information disclosure program, eco-compensation programs) to improve the quality of dwelling environment. These practices have also made certain effect (Chen et al., 2017; Wang et al., 2019; Zhang and Li, 2020; Li et al., 2020). One project that has to be mentioned is the dwelling environmental improvement program (DEIP). DEIP is proposed by Chinese government in response to the increasingly serious problem of dwelling environment pollution. It encourages and requires all sectors of the community to participate in dwelling environmental management, so as to provide ecological, healthy and sustainable living environment for residents.

Residents, as the most important participants in the process, strongly influence the project's continuity and its smooth implementation and also the continuity of the environmental benefits obtained from the DEIP. It is particularly important and essential to explore the drivers that promote the residents to participate in DEIP. The existing studies have focused on various factors including demographic characteristics (Saphores et al., 2012), household resource endowment (Videras et al., 2012; Liu and Huang., 2014; Ling and Xu, 2020), psychological factors (Carfora et al., 2017), institutional constraints (Li et al., 2019). However, the impact of the Information and Communication Technology (ICT) on residents' participation in DEIP has been ignored.

In the era of digital economy, ICT has undergone intense development and has been widely used over the past decades (Niebel, 2018). The Internet also has become an important ICT in the modern world. The Internet world stats[1] reports that 59.6% of the global population has become Internet users by the end of May 2020. Like many other countries, China has experienced a significant increase in the number of Internet users since 2000. As of March 2020, the number of Chinese Internet users was 904 million, with an Internet penetration rate of 64.5%[2]. Internet users has an increase of 881.5 million over the end of 2000, with an average annual growth rate

[1] https://www.internetworldstats.com/.

[2] Data source: China Internet Network Information Center, https://www.cnnic.net.cn/hlwfzyj/hlwxzbg/

of 21.15% (CNNIC, 2019). The rapid popularization of Internet use has exerted subtle influence on individual behaviors, living habits and values, because it creates a wide array of opportunities for facilitating the transmission, feedback, and sharing of information (Kim and Orazem, 2017; Niebel, 2018; Zhou et al., 2019; Gong et al., 2020). For example, people can quickly search for comprehensive information interest on the Internet, express their views on public Internet platforms. Furthermore, those social interactions will in turn affect individual perceptions and behaviors (Zhang et al., 2019a, 2019b, 2020). Previous theoretical literature on ICTs and environmental behaviors tends to focus on reducing carbon emissions generated by human activities and households' electricity consumption (e.g., Bastida et al., 2019; Gong et al., 2020). However, the quantitative studies investigating the impact of internet use on individual participation in DEIP are still lacking. This study is trying to fill this gap by examining how and to what extent the internet use affects individual participation in two practices of DEIP, centralized disposal of domestic waste and flush toilets.

This study contributes to the literature by developing an information economics-based analytical framework of "ICT → residents → DEIP participation", which combines individual internet use and the participation in DEIP. It is worth noting that the decision of internet use might be endogenous in predicting environmental behaviors.

In addition, Internet use is not randomly distributed, and Whitacre et al. (2014a) find that selection bias may exist in the use of Internet. Therefore, previous studies have used propensity score matching (PSM) to solve the problem. However, a well-known shortcoming of the PSM approach is that it addresses the issue of selection bias by controlling for only observable factors, without accounting for unobservable factors like innate abilities and motivations. In addition, previous studies did not attempt to develop a coherent conceptual framework that links Internet use to sanitary toilet use and adopting centralized disposal of domestic waste. To the extent that residents self-select into using or not using Internet, we use a recursive bivariate probit model to deal with potential endogeneity and selectivity bias, thus accurately estimating the quantitative effect of Internet use on residents' participation in DEIP. Moreover, various identification strategies are applied to assure the robustness of results.

Another important contribution of this paper is to incorporate regional factors into the empirical investigation of the impact of Internet use on individual DEIP participation. Specifically, we consider the different impacts of Internet use on residents' DEIP participation in urban and rural areas, as well as areas at different levels (e.g., well developed areas, developed areas, and less developed areas). As we all know, in China and even many other developed or developing countries, there are great differences for Internet development level between different regions, due to the different policy, infrastructure, economic development conditions. Therefore, it is necessary to discuss the regional heterogeneity of the relationship between Internet use and residents' DEIP participation. The findings of our study may provide policy implications for improving dwelling environment and promote the health and well-being of residents in developing countries.

2. Conceptual background and theoretical mechanism

2.1 Conceptual background

The Chinese government started DEIP which aimed at improving residential living environment about 20 years ago. The program was launched in urban and rural areas in 1996 and 2012, respectively. The DEIP involves multiple targets (e.g., infrastructure construction, dwelling environment management, promotion of residents' environmental awareness), a series of tasks (e.g., domestic waste management, domestic sewage treatment, latrines excreta management, construction and improvement of management and protection mechanism), multiple entities (e.g., central government, local governments, residents, financial bureaus, the Ministry of Housing and Urban-Rural Development, the Ministry of Environmental Protection), and multiple benefits (e.g., environment, economic, and social).

To promote the implementation of DEIP, the Chinese government has invested 139.811 billion yuan[3] in garbage treatment (CUCSY, 2018) and 447.619 billion yuan in sewage treatment (CSYE, 2018). The program has also helped to build 7968 harmless domestic garbage treatment plants (NBS, 2018) and 17,552 sewage treatment plants (CSYE, 2018) nationwide from 2007 to 2017. Ministry of Housing and Urban-Rural Development (MOHURD) has proposed that the dwelling environment of urban and rural communities will be significantly improved, and people's sense of access, happiness and security will be significantly enhanced by 2020. Further, we will basically achieve the goal of "clean, comfortable, safe and beautiful" dwelling environment in urban and rural communities, and initially establish a long-term mechanism of "co-creation" by 2022 (MOHURD, 2019).

Figure 1 shows the changing trend of the Internet penetration rate in urban and rural areas, the harmless disposal rate of domestic waste and the popularization rate of harmless sanitary

[3] 1 yuan=0.14 $.

toilets since 2007. Specifically, the Internet penetration rate, the harmless disposal rate of domestic waste and the popularization rate of harmless sanitary toilets are all steadily increasing, and the three are almost in sync. The difference is that the harmless disposal rate of domestic waste is significantly higher than the popularization rate of harmless sanitary toilets, which reveals that there is still a great room for progress in the popularization and use of sanitary toilet compared with the management of domestic waste. Figure 2 demonstrates a positive correlation between the Internet penetration rate and the harmless disposal rate of domestic waste as well as the popularization rate of harmless sanitary toilets since 2007, indicating that Internet use may have a positive effect on the management of domestic waste and the improvement of sanitary toilet, which provides a clue for the following empirical research.

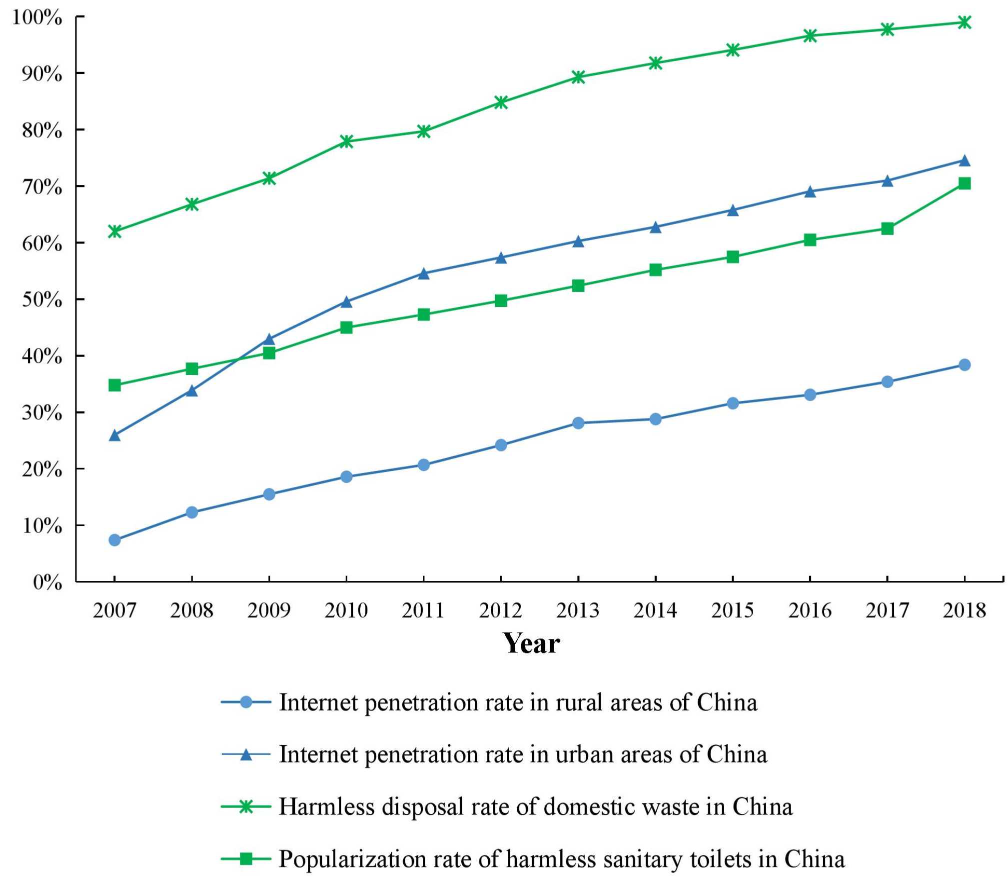

Fig. 1. The changing trend of the Internet penetration rate, the harmless disposal rate of domestic waste and the popularization rate of harmless sanitary toilets

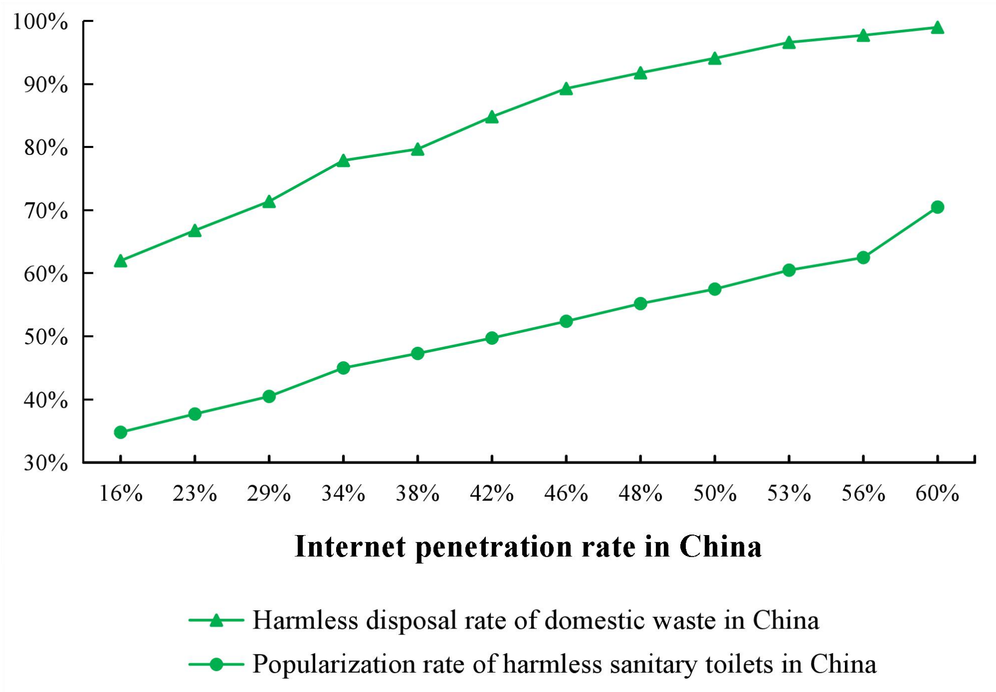

Fig. 2. The relationship between the Internet penetration rate in urban and rural areas, the harmless disposal rate of domestic waste and the popularization rate of harmless sanitary toilets

2.2 Theoretical mechanism

The path mechanism by which Internet use affects residents' participation in the DEIP is complex. Generally speaking, the Internet use may have an impact on residents' participation in the DEIP through the following four mechanisms. First, Internet use can lead people to a more efficient, green and environmentally friendly lifestyle. In recent years, the Internet is intimately intertwined with almost every aspect of life and has a more profound impact on people's values and behaviors. A study by Gong et al. (2020) found that Internet plays an increasingly important role in the cultivation of individuals' environmental protection behaviors such as the garbage classification management.

Second, Internet use has accelerated the dissemination of laws and knowledge related to environmental protection and influenced individuals' environmental improvement behaviors through information diffusion, feedback and sharing (Zhang et al., 2019b; Gong et al., 2020). As the main carrier of information technology, Internet has greatly changed the way of information dissemination, improved the efficiency of information dissemination and broadened the scope of information dissemination (Lio and Liu, 2006; Niebel, 2018; Zhang et al., 2019a; Zhou et al., 2019). The rapid dissemination and diffusion of Internet information allows individuals to learn more about the importance (e.g., improving community appearance, promoting individual health) and effective measures (e.g., centralized disposal of domestic garbage, using flush toilet) of improving the dwelling environment in a very short time (Zhang et al., 2019a; Zhang et al., 2020), thus promoting update of environmental knowledge and participation in the DEIP. In addition, Internet use allows individuals to quickly and timely access to a large amount of information related to environmental pollution including those environmental hot events. The easier access of information will refresh and awaken their environmental awareness (Zareie et al., 2016; Asongu et al., 2018), hence stimulate residents' subjective initiative to participate in the DEIP. For example, on February 28, 2015, a documentary named "Under the Dome" quickly exploded across China's mainstream media. By 0:00 on March 1, 2015, the total click-through rate of the documentary had exceeded 31 million on major video websites in China[4]. It aroused people's great vigilance of environmental issues and made them realize the urgency of participating in environmental protection. Other evidence also suggested that Internet use can

[4] Data source: http://soft.zol.com.cn/509/5090185.html

enhance individuals' environmental risk perception (Zhang et al., 2020), and enhance awareness of participation in environmental improvement.

Third, Internet use greatly promotes the social interaction between individuals and the outside world, and promote individuals' participation in DEIP by expanding social networks. Individuals can build social networks and form a circle of friends far beyond their daily lives through Internet use, thus promoteing more residents to understand and participate in DEIP by huge environmental information sharing (Gong et al., 2020). Furthermore, social interaction will enhance demonstration effect or imitation effect, and then encourage individuals to participate in DEIP. This kind of effect is particularly obvious in China's "relational society".

Finally, Internet use can enhance residents' health awareness, thus indirectly promoting their participation in DEIP. A growing body of studies show that the Internet has been widely used to search for health information and to conduct telemedicine (Koo et al., 2016; Liobikienė and Bernatonienė, 2018; Alkhatlan et al., 2018; Hämeen–Anttila et al., 2018; Parajuli and Doneys, 2017). As people's health awareness and knowledge are improved, they become more aware of the harm to human health caused by environmental pollution. As a result, Internet use may increase users' aversion to environmental damage and promote DEIP participation.

Summarizing the above discussion, Internet use can lead individuals to a more environmentally friendly lifestyle, accelerate the diffusion of knowledge and information related to environment, promotes the social interaction and expand their social networks, and enhance personal health awareness, which may indicate that there is a positive relationship between Internet use and individuals' participation in DEIP. Therefore, the rest of this paper attempts to use data from a nationwide Chinese survey to investigate the relationship between Internet use and individuals' DEIP participation to further enrich the relevant literature.

3. Data and Econometric Model

3.1 Analytical model

According to the assumption of rational economic man, whether or not to participate in DEIP and use the Internet are the two choices made by residents by maximizing the potential net utility. However, the expected net utility is unobserved since it is subjective. What can be observed in the data are actual decisions. To operationalize the decision problem, Y^{*}_{ik} stands for the unobserved or latent variable. In this study, the observed variable Y_{ik} can be used to represent a resident's decision to participate in DEIP (Y_{ik}=1), or not to participate (Y_{ik}=0).

Given that the primary goal of the empirical analysis is to examine how individual and household characteristics X_i influence a resident's decision to use Internet I_i, as well as to analyze the impact of the characteristics and Internet use on DEIP participation, the resident's participation decision can be expressed as the following function,

$$\begin{aligned} Y^{*}_{ik} &= \alpha I_i + \beta X_i + \mu_{ik} \ , \\ Y_{ik} &= 1 \ \ if \ \ Y^{*}_{ik} > 0 \end{aligned} \qquad (1)$$

Where Y_{ik} is a binary indicator variable which equals 1 if the individual i chooses to adopt centralized disposal of domestic waste (k=1) and use sanitary toilet (k=2), if the expected net utility (Y^{*}_{ik}) from participation in DEIP is positive, and 0 otherwise; I_i is a dummy variable for the choice of Internet use; α , β and γ are parameters to be estimated; μ_{ik} and ε_i are error terms assumed to be normally distributed.

Individuals will choose to use Internet, if the expected net utility derived from Internet use (I^*_{i1}) is greater than that from not using Internet (I^*_{i0}). Individuals are then assumed to choose to use Internet if the difference in net utility is positive, that is, $I^*_i = I^*_{i1} - I^*_{i0} > 0$. However, I^*_i cannot be directly observed but can be expressed as a function of observed elements in the following latent variable function:

$$I^*_i = \gamma Z_i + \varepsilon_i \text{ , } I_i = 1 \quad if \ I^*_i > 0, \tag{2}$$

where I_i equals 1, if individuals chooses to use Internet, and 0 otherwise; Z_i represents a vector of factors that influence a resident's decision to choose to use Internet; γ is a vector of parameters to be estimated, and ε_i is the error term assumed to be normally distributed.

If the same unobserved factors (e.g., resident's innate awareness and ability, motivation to improving the environment) influence both the error term (ε_i) in the Internet use equation and the one (μ_{ik}) in the DEIP participation equation, there will be a problem of selection bias, resulting in a correlation of the two error terms in the two specifications, such that $\text{cov}(\mu_i, \varepsilon_i) = \rho_{\mu\varepsilon}$. In this case, any standard regression technique such as probit or logit model applied to estimated equation (1) produces biased results when $\rho_{\mu\varepsilon} \neq 0$. Thus, rigorous assessment of the effect of Internet use on residents' participation in DEIP should take into account the endogeneity of Internet use variable.

Given our interest in estimating both the marginal effects and average treatment effects of Internet use on participating in DEIP, this study employs a recursive bivariate probit (RBP) model in the empirical analysis (Lanfranchi and Pekovic, 2014; Thuo et al., 2014). The RBP model estimates the Internet use choice equation and the participation equation simultaneously, using full information maximum likelihood (FIML) method.

In estimating the RBP model, the variables in the vector X_i in equation (1) and Z_i in the equation (2) are allowed to overlap. However, identification of the bivariate probit model requires a valid instrument that explains Internet use, meanwhile it is uncorrelated with the outcome variable (i.e., participation in DEIP). In our study, we use the provincial Internet penetration as an identifying instrument. In fact, residents in areas with high Internet penetration rate are more likely to use Internet in China. Therefore, the provincial Internet penetration rate is highly related to residents' choice of Internet use but should not influence their decisions to participate in DEIP. In addition, the RBP model will produce a Wald test statistic rho (ρ) which estimates the correlation between the error terms μ_{ik} of the two equations. If the ρ of the error terms μ_{ik} is significantly different from 0, it indicates the presence of endogeneity bias or selection on the unobservable (Jones, 2007).

We also estimate the average treatment effect (ATT) using the method proposed by Chiburis et al. (2011) to provide a better understanding of the causal effects of Internet use on the likelihood of participating in DEIP. The ATT is calculated using the following expression:

$$ATT = \frac{1}{N_I}\sum_{i=1}^{N_i}\left\{\Pr(Y_{ik}=1 \mid I_i=1) - \Pr(Y_{ik}=0 \mid I_i=1)\right\}$$

where N_I denotes the total number of treated samples, $\Pr(Y_{ik}=1 \mid I_i=1)$ represents the predicted participation probability for Internet use in an observed context, while $\Pr(Y_{ik}=0 \mid I_i=1)$ represents the predicted probability that a resident using Internet (in a counterfactual context) will not participate.

3.2 Variables

3.2.1 Dependent variable

Our dependent variable is residents' participation in DEIP, which is measured using two proxy variables: the use of flush toilet and centralized disposal of domestic garbage. Specifically, according to the questionnaire of 2014 CFPS, they were measured with questions "What type of toilet is the most commonly used in your home?" and "Where is the main dump of your garbage?" respectively. The detailed data processing methods are as follows: For the type of toilet, we regard those with answers such as "indoor flush toilet", "outdoor flush toilet" and "flush toilet" as the samples of "using flush toilet", and assign them as 1, Otherwise 0. For the disposal of domestic garbage[5], we regard those with answers "public garbage cans/bins", "garbage cans in the residential passageway" and "collected by specially assigned persons" as the samples of "centralized disposal of domestic garbage", and assign them as 1; Conversely, we regards those with answers "nearby ditches", "around houses", "soil cesspit", "pour everywhere" and others as the samples of "not centralized disposal of domestic garbage", and assign them as 0.

3.2.2 Independent variable

we focus on the impact of Internet use on the residents' participation in DEIP. Therefore, we select whether to use Internet and Internet use intensity as proxy variables of Internet use. Two

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[5] "dumping" refers to direct dumping, which refers to the place where the garbage in the home is thrown out, such as the domestic garbage is poured into the river near the residence. If the garbage is packed in a garbage bag at home, after going out, the garbage bag is thrown on the open space beside the road, which is regarded as "pouring everywhere".

questions, "Do you use the Internet"[6], and "In general, how many hours do you spend on the Internet in your spare time every week"[7], are used to measure above two proxy variables in CFPS 2014. Whether to use Internet is a 0-1 variable. If respondents use the Internet, it is assigned a value of 1, otherwise 0. Internet use intensity is measured by the actual hours of Internet use every week.

3.2.3 Covariates

We have also controlled several covariates in the estimation. Existing studies revealed that individual factors (e.g., age, gender, and educational level), family endowments (e.g., income and health condition) as well as environmental awareness all contribute to predicting individuals' environmental improvement behaviors (Wesselink et al., 2017; Czajkowski et al., 2017; Li et al., 2019; Zhang et al., 2019). Therefore, this study also includes respondents' gender, age, education level, political status, registered permanent residence, health condition, relative income, and environmental awareness as covariates in the model. In addition, several dummy variables are also included to control for regional fixed effects. The model variables and summary statistics are described in Table 1.

Table 1. Basic information of sample

Variables	Full samples（N=11523）	Urban sample（N=5849）	Rural samples（N=5674）

[6] "access to the Internet" refers to the access to the Internet through telephone line, local area network, wireless network and other means.

[7] The "general situation" refers to the normal living conditions, rather than some special periods or experiences.

	Frequency/ Mean	percentage（%）	Frequency/ Mean	percentage（%）	Frequency /Mean	percentage（%）
Dependent variables						
Whether to use flush type sanitary toilet:						
Yes	5825	50.55	4313	73.74	1512	26.65
No	5698	49.45	1536	26.26	4162	73.35
Whether to adopt centralized disposal of domestic waste:						
Yes	7230	62.74	5041	86.19	2189	38.58
No	4293	37.26	808	13.81	3485	61.42
Whether to use Internet:						
Yes	2807	24.36	2068	35.36	739	13.02
No	8716	75.64	3781	64.64	4935	86.98
Internet use time（hour/week）	2.7617	—	4.1912	—	1.2881	—
Independent variables						
Gender：Male	6069	52.67	2831	48.40	3238	57.07
Female	5454	47.33	3018	51.60	2436	42.93
Age（years）	49.9232	—	49.1942	—	50.6746	—
Education（years）	7.5285	—	8.9386	—	6.0749	—
Heath condition（1~7 score）	5.6796	—	5.8131	—	5.5421	—
Household size	3.7138	—	3.4034	—	4.0338	—
Per capita net family income：						
Minimum 25%	2609	22.64	852	14.57	1757	30.97
Middle and lower 25%	2498	21.68	968	16.55	1530	26.97
Middle and higher 25%	2794	24.25	1456	24.89	1338	23.58
Top25%	3622	31.43	2573	43.99	1049	18.49
Political identity：						
Yes	1153	10.01	732	12.51	421	7.42
No	10370	89.99	5117	87.49	5253	92.58
Environmental cognition（0~10 score）	6.7461	—	7.1528	—	6.3269	—
Recognition of the importance of the Internet（1~5 score）	1.9192	—	2.2501	—	1.5782	—
Region:						
LDA	6512	56.51	2893	49.46	3619	63.78
DA	2877	24.97	1560	26.67	1317	23.21
WDA	2134	18.52	1396	23.87	738	13.01

Note：“Political identity” refers to whether the respondent is a member of the Communist Party of China.

3.3 Data collection and sample

The dataset used in this study is from a household survey, China Family Panel Studies (CFPS), which is conducted by the Institute of Social Science Survey, Peking University. CFPS is a nationally representative longitudinal survey of Chinese communities, families, and individuals, designed to obtain dynamic data related to social, economic, demographic, educational and health changes. The survey is implemented every two years, covering 25 provinces, municipalities, and autonomous regions, excluding Hongkong, Macao, Taiwan, Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan. The survey data of 2014 are used in our analysis because some key variables (i.e., DEIP participation) are covered. The samples are further divided into three groups based on the level of regional development: well developed areas (WDA), developed areas (DA), and less developed areas (LDA). We match the data of family database with that of adult database (questionnaire respondents) one by one in CFPS for research purposes. The final dataset has a total of 11,523 valid samples. Table 2 shows the regional distribution of samples.

Table 2. The regional distribution of samples

Region	Province	Sample size	Percentage（%）	Total samples
Well developed areas (11 provinces)	Beijing	114	10.53	2134
	Jiangsu	243	2.07	
	Shandong	586	5.46	
	Shanghai	863	11.65	
	Tianjin	74	3.72	
	Zhejiang	254	2.00	
Developed areas (8 provinces)	Anhui	257	10.62	2877
	Fujian	133	4.28	
	Guangdong	1027	2.31	
	Guangxi	242	2.88	
	Hubei	198	1.00	
	Hunan	334	2.23	
	Jiangxi	204	1.15	
	Sichuan	482	8.91	

Less developed areas (6 provinces)	Gansu	1213	2.10	6512
	Guizhou	238	1.72	
	Hebei	629	2.90	
	Henan	1343	1.77	
	Heilongjiang	429	4.18	
	Jilin	230	0.99	
	Liaoning	1224	2.11	
	Shanxi	493	5.09	
	Shaanxi	266	7.49	
	Yunnan	332	0.64	
	Chongqing	115	2.20	
Total		11523	100%	11523

4. Results and Discussion

4.1 Mean differences in characteristics between IU and NIU

Table 1 shows that 24.36% of the respondents have used the Internet, and the average use time is 11.34 hours per week. The proportion of respondents using flush type sanitary toilets is 50.55%, while that of adopting centralized disposal of domestic waste is 62.74%. The average age of respondents is 49.92 years, and the average years of schooling is about 7.53. Table 3 reports the descriptive results of the mean differences in the characteristics between Internet users (IU) and non-Internet users (NIU). The results indicate that respondents in the IU group significantly differs from that in NIU group. More specifically, the IU are younger and better educated, and they have a higher possibility of achieving high family income and environmental cognition. As shown in Table 3, the IU are more likely to use flush type sanitary toilets and adopt centralized disposal of domestic waste than the NIU, suggesting that Internet use may be the key to understanding individuals' participation in the DEIP. The differences in most variables are significant between IU and NIU groups, implying that the IU group systematically differs from the NIU group. Specifically, the Internet is not used randomly by the IU group. Thus, we need to employ RBP model to solve selection bias due to observable and unobservable confounding factors.

Table 3 Mean Differences in Characteristics between Internet Users and non-Internet Users

Variables	Internet users (n=2807)	non-Internet users (n=8716)	Diff.
Sanitary toilet	0.766（0.008）	0.421（0.005）	0.345***（0.010）
Domestic waste	0.848（0.007）	0.557（0.005）	0.290***（0.010）
Gender	0.512（0.009）	0.531（0.005）	－0.019*（0.011）
Age	37.765（0.221）	53.839（0.136）	－16.074***（0.270）
Education	11.415（0.064）	6.277（0.045）	5.138***（0.087）
Health condition	6.098（0.017）	5.545（0.012）	0.553***（0.024）
Household size	3.437（0.030）	3.803（0.020）	－0.366***（0.039）
Per capita net family income (control group: Minimum 25%)			
Middle and lower 25%	0.135（0.006）	0.243（0.005）	－0.108***（0.009）
Middle and higher 25%	0.229（0.008）	0.247（0.005）	－0.018*（0.009）
Top25%	0.555（0.009）	0.237（0.005）	0.318***（0.010）
Political identity	0.151（0.007）	0.084（0.003）	0.067***（0.006）
Environmental cognition	7.955（0.041）	6.357（0.030）	1.598***（0.058）
Urban or rural areas	0.737（0.008）	0.434（0.006）	0.303***（0.010）
Region (control group: LDA)			
DA	0.261（0.008）	0.246（0.005）	0.015（0.009）
WDA	0.257（0.008）	0.162（0.004）	0.095***（0.008）
Importance of Internet	3.736（0.023）	1.334（0.010）	2.402***（0.021）
Sample size	11523	11523	11523

4.2 Results for SUBP Estimates

First, we present estimates from a seemingly unrelated bivariate probit (SUBP) model to justify the use of the RBP model. The main reason for estimating the SUBP model is to ascertain whether the decision of Internet use is associated with the outcome variables through some unobserved heterogeneities (e.g., personal characteristics and hobbies). The SUBP model estimation requires that the variable of Internet use is drooped from the participation equation. We use Stata 15.0 software to run the SUBP model to estimate individual participation behaviors. The results are shown in Table 4. The *p*-values for two specifications are both extremely small and reject the null hypothesis that $\rho'_{\mu\varepsilon}$ =0, suggesting the unobserved heterogeneities of both decisions are correlated. In addition, the sign of $\rho'_{\mu\varepsilon}$ are positive both in model 1 and model 2, indicating that Internet use and participation in DEIP are complementary decisions (Thuo et al., 2014). To control the endogeneity and obtain unbiased estimates, we use RBP model to estimate participation behavior and Internet use equations simultaneously (Lanfranchi and Pekovic, 2014).

Table 4. Estimation Results of SUBP Model for Joint Decisions of Internet use and Participation in DEIP

	Model 1		Model 2	
	Internet use	Sanitary toilet	Internet use	Domestic waste
Gender	0.010（0.040）	－0.170*** （0.030）	0.012（0.040）	－0.221***（0.030）
Age	-0.075*** （0.009）	－0.021*** （0.006）	－0.075*** （0.009）	－0.011* （0.006）
Age squared	0.000*** （0.000）	0.000*** （0.000）	0.000*** （0.000）	0.000** （0.000）
Education	0.102*** （0.007）	0.068*** （0.004）	0.102*** （0.007）	0.059*** （0.004）
Health condition	0.070*** （0.020）	0.009（0.013）	0.065*** （0.020）	0.017（0.013）
Household size	0.009（0.013）	0.018** （0.008）	0.007（0.013）	－0.040***（0.008）
Per capita net family income (control group: Minimum 25%)				
Middle and lower 25%	0.225*** （0.071）	0.228*** （0.044）	0.218*** （0.071）	0.190*** （0.041）
Middle and higher 25%	0.249*** （0.068）	0.469*** （0.042）	0.248*** （0.068）	0.344*** （0.040）
Top25%	0.568*** （0.067）	0.917*** （0.044）	0.558*** （0.067）	0.589*** （0.043）
Political identity	0.201*** （0.066）	0.230*** （0.049）	0.202*** （0.067）	0.138*** （0.051）
Environmental cognition	0.027*** （0.008）	0.018*** （0.005）	0.027*** （0.008）	0.014*** （0.005）
Urban or rural areas	0.267*** （0.042）	1.030*** （0.030）	0.274*** （0.042）	1.134*** （0.030）
Region (control group: PDA)				
GDA	0.174*** （0.046）	1.333*** （0.038）	0.173*** （0.046）	0.646*** （0.034）
SDA	0.240*** （0.051）	0.909*** （0.039）	0.240*** （0.051）	1.186*** （0.049）

Importance of Internet	0.527*** (0.014)		0.528*** (0.014)	
Constant	-1.375*** (0.264)	-1.723*** (0.177)	-1.379*** (0.265)	-0.934*** (0.182)
Log-likelihood	-7685.542		-7799.301	
$\rho_{\mu\varepsilon}$	0.189*** (0.028)		0.135*** (0.029)	
Wald test: $\rho'_{\mu\varepsilon}=0$	43.907***, with Prob=0.000		21.126***, with Prob=0.000	
Sample size	11523		11523	

Note: *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. Robust standard errors are in parentheses.

4.3 Results for RBP Estimates

The estimates of RBP model are presented in Table 5. The lower part of Table 5 show that the correlation coefficients $\rho_{\mu\varepsilon}$ in model 3 and model 4 are both significantly different from zero, suggesting the existence of selection bias caused by unobserved factors. Moreover, the negative correlation coefficient $\rho_{\mu\varepsilon}$ indicate negative selection bias, suggesting that residents who are less likely to participate in the DEIP are more likely to choose to use Internet. Furthermore, the results of the Wald test for $\rho'_{\mu\varepsilon}=0$ in model 3 and model 4 are significant, indicating the null hypothesis that Internet use is exogenous can be rejected. That is, residents' decision to use Internet and participate in DEIP are made jointly. To sum up, it is appropriate to use RBP model to estimate the impact of Internet use on residents' participation in DEIP.

Table 5. The RBP Estimates for the Impact of Internet Use on Participation in DEIP

	Model 3		Model 4	
	Internet use	Sanitary toilet	Internet use	Domestic waste
Internet use		0.582*** (0.075)		0.631*** (0.078)
Gender	0.010 (0.040)	-0.169*** (0.030)	0.008 (0.040)	-0.220*** (0.029)
Age	-0.073*** (0.010)	0.008 (0.007)	-0.073*** (0.010)	0.019*** (0.007)
Age squared	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)
Education	0.102*** (0.007)	0.056*** (0.004)	0.102*** (0.007)	0.047*** (0.004)

Health condition	0.062*** (0.020)	0.004 (0.013)	0.062*** (0.020)	0.013 (0.013)
Household size	0.004 (0.013)	0.020** (0.008)	0.004 (0.013)	-0.037*** (0.008)
Per capita net family income (control group: Minimum 25%)				
Middle and lower 25%	0.199*** (0.071)	0.220*** (0.044)	0.195*** (0.071)	0.181*** (0.040)
Middle and higher 25%	0.230*** (0.068)	0.450*** (0.042)	0.222*** (0.068)	0.323*** (0.040)
Top25%	0.535*** (0.067)	0.853*** (0.045)	0.534*** (0.067)	0.520*** (0.044)
Political identity	0.202*** (0.067)	0.188*** (0.050)	0.201*** (0.067)	0.095* (0.052)
Environmental cognition	0.028*** (0.008)	0.012** (0.006)	0.028*** (0.008)	0.009* (0.005)
Urban or rural areas	0.284*** (0.042)	0.995*** (0.031)	0.284*** (0.042)	1.096*** (0.031)
Region (control group: LDA)				
DA	0.168*** (0.046)	1.321*** (0.038)	0.166*** (0.046)	0.630*** (0.034)
WDA	0.228*** (0.051)	0.887*** (0.039)	0.222*** (0.051)	1.159*** (0.049)
Importance of Internet	0.533*** (0.014)		0.534*** (0.014)	
Constant	-1.390*** (0.266)	-2.496*** (0.203)	-1.393*** (0.266)	-1.753*** (0.211)
Log-likelihood	-7656.698		-7768.195	
$\rho_{\mu\varepsilon}$	-0.120*** (0.049)		-0.193*** (0.050)	
Wald test: $\rho'_{\mu\varepsilon} = 0$	5.816**, with Prob=0.016		13.834***, with Prob=0.000	
ATT	13.231*** (0.018)		11.967*** (0.017)	
Sample size	11523		11523	

Note: Asterisk *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. Robust standard errors are in parentheses.

4.4 Determinants of Internet use and DEIP participation decision

The second and fourth column in Table 5 presents results from first-stage estimates of the RBP model, showing the determinants of Internet use. Similar results are obtained from two model specifications. The two coefficients of age are negative and significant, indicating that an increase in age reduces the probability of using Internet. The lower probability of using Internet for older residents is probably due to the lack of necessary technology and Internet knowledge, as well as the poor learning ability. The education is positively and significantly associated with Internet use in the two model specifications, suggesting that residents with higher education level are more likely to use Internet. Consistent with the conclusion from Deng et al. (2019) and Gong et al. (2020), family income tends to increase the probability of using Internet. Political identity and environmental cognition are able to encourage Internet use. The results also suggest that Internet use is significantly related to location, that is, urban residents are more likely to use Internet than rural residents.

The results of drivers predicting using flush type sanitary toilet and adopting centralized disposal of domestic refuse are shown in the third column and fifth column of Table 5. The estimates of most interest indicate that Internet use exerts positive and statistically significant impact on both using flush type sanitary toilet and adopting centralized disposal of domestic waste. The possible explanations lie in that Internet use can accelerate the diffusion of laws, knowledge and information related to environment, as well as promote the social interaction, expand social networks and enhance personal health awareness, thus leading to a more environmentally friendly lifestyle and higher possibility of participating in the DEIP.

The other coefficient estimates are presented in the third and fifth column of Table 5. The coefficient of the gender variable is negative and significant, indicating that females are more likely to use flush type sanitary toilet and adopt centralized disposal of domestic waste rather than male residents. It might be that females are more likely to live an elegant life and inclined to pursue a healthy and green lifestyle, thus having a higher standard for dwelling environment and preference for participation in the DEIP. The coefficient of education and income are all significant and positive, indicating that residents with higher education level and more family income are more likely to use flush type sanitary toilet and adopt centralized disposal of domestic waste.

4.5 Marginal Effects and Average Treatment Effects

Given that the estimated coefficients of the explanatory variables in Table 5 cannot be directly interpreted, we also calculate the marginal effects to provide a better understanding of how internet use and other covariates influence DEIP participation. The results presented in Table 6 reveal that Internet use increases the probability of using flush type sanitary toilets and participating in centralized disposal of domestic waste by 14.3% and 15.8%, respectively. Among other variables, males tend to be 4.1% and 5.5% less likely to use flush type sanitary toilets and adopt centralized disposal of domestic waste than females, respectively. Residents with higher education level are 1.4% and 1.2% more likely to use flush type sanitary toilets and participate in centralized treatment of domestic waste. Residents with Top 25% of per capita net family income are 20.9% and 13% more likely to use flush sanitary toilets and adopt centralized disposal of domestic waste. As for different regions, residents in urban areas are 24.4% and 27.5% more likely to use flush type sanitary toilets and adopt centralized disposal of domestic waste respectively, compared with those in rural areas. Meanwhile, residents in WDA are 21.8% and 29.1% more likely to use flush type sanitary toilets and participate in centralized disposal of domestic waste, compared with those in LDA. But in DA, the proportion is 32.43% and 15.79%, respectively.

Table 6. Marginal effects of RBP model estimation on the marginal probability of participating in DEIP (in %)

Variables	Sanitary toilet	Domestic waste
Internet use	14.293^{***}（0.075）	15.811^{***}（0.020）

Gender	－4.143*** （0.007）	－5.496*** （0.007）
Age	0.188（0.002）	0.480*** （0.002）
Age squared	0.001（0.000）	－0.003（0.000）
Education	1.368*** （0.001）	1.178*** （0.001）
Health condition	0.092（0.003）	0.323（0.003）
Household size	0.494** （0.002）	－0.927*** （0.002）
Per capita net family income (control group: Minimum 25%)		
Middle and lower 25%	5.397*** （0.011）	4.538*** （0.010）
Middle and higher 25%	11.044*** （0.010）	8.093*** （0.010）
Top25%	20.942*** （0.010）	13.043*** （0.011）
Political identity	4.616*** （0.012）	2.390* （0.013）
Environmental cognition	0.302** （0.001）	0.229* （0.001）
Urban or rural areas	24.415*** （0.006）	27.478*** （0.006）
Region (control group: LDA)		
DA	32.428*** （0.008）	15.786*** （0.008）
WDA	21.770*** （0.009）	29.060*** （0.011）
Sample size	11523	11523

To the extent that marginal effects only estimate the partial effects of Internet use on using flush toilets and adopting centralized disposal of domestic waste in case of changing Internet use variable from zero to one, we further employ the approach suggested by Chiburis et al. (2011) to estimate the average treatment effects (ATT) to provide a better and more comprehensive understanding of the effects of Internet use on residents' participation decision. We use bootstrap replications to reduce sampling noise (Chiburis et al. 2011). Unlike the mean differences presented in Table 3, these ATT estimates account for selection bias arising from the fact that Internet users and non-Internet users are systematically different in terms of both observed and unobserved characteristics. The results are presented in the lower part of Table 5. Our findings show that Internet use significantly increases the probability of using flush type sanitary toilets and adopting centralized disposal of domestic waste by 13.2% and 12%, respectively. The results are similar to what obtained from the RBP model estimation, again demonstrating the positive effect of internet use on DEIP participation.

4.6 Regional Heterogeneity

To gain insight into the heterogeneity of locations/regions regarding the impact of Internet use on DEIP participation, we further divide the samples into urban and rural, and three different development areas to estimate the same model. The results presented in Table 7 generally reveal that Internet use exerts different impact on residents' participation in DEIP for different regions. In urban areas, Internet use has a positive and statistically significant impact on residents' participation in both practices of DEIP, while the impact is significant only for adopting centralized disposal of domestic waste in rural areas. Unlike the centralized disposal of domestic waste, flush type sanitary toilets have higher demand for supporting infrastructures such as water supply system, sewer or sewage treatment infrastructures that are seriously deficient in rural areas. Therefore, the influence of Internet use on residents' use of flush type sanitary toilets has been greatly weakened.

For areas with different development levels, the impact of Internet use on DEIP participation are also different. Specifically, Internet use has a positive and significant impact on residents' participation in DEIP in LDA, but no significant impact is found for the influence of Internet use on using flush type sanitary toilets in DA. The possible explanation is that, compared with poor development areas, the infrastructure is better and the popularization of sanitary toilets is also higher in DA, hence the impact of Internet use on using flush type sanitary toilets is obviously weakened. In WDA, the reason why Internet use has no significant impact on residents' participation in DEIP is the same with DA.

Table 7. Heterogeneity of the impact of Internet use on residents' participation in DEIP in different areas

Group	Sanitary toilet		Domestic waste		Sample size
	RBP	Marginal effect（%）	RBP	Marginal effect（%）	
Group by urban and rural areas					
Urban areas	0.645***（0.094）	15.664***（0.023）	0.828***（0.094）	14.370***（0.014）	5849
Rural areas	0.216（0.132）	4.872（0.030）	0.397***（0.114）	12.880***（0.037）	5674
Group by the level of regional development					
WDA	0.230（0.166）	5.058（0.036）	0.262（0.232）	3.420（0.030）	2134
DA	0.247（0.152）	6.936（0.029）	0.337**（0.163）	8.876**（0.043）	2877
LDA	0.778***（0.106）	17.112***（0.023）	0.825***（0.097）	22.954**（0.027）	6512

4.7 Robustness Test

To further ensure the reliability of the conclusion, we will test the robustness of the previous estimation results, the following three strategies are used: (1) changing the measuring method of the independent variable, that is, we replace the variable of Internet use with the Internet use time. Since the Internet use time is a continuous variable, we use the two-stage instrumental variable method (IV-probit) to estimate the impact of Internet use time on residents' participation in DEIP, the results presented in the second and third column in Table 8 show that Internet use time exerts a positive and significant impact on residents' using flush type sanitary toilet and adopting centralized disposal of domestic waste. (2) changing the measuring method of the instrumental variable. We also replace individual perception of importance of Internet access information with provincial Internet penetration in the model, the results presented in fourth and fifth column in Table 8 reflect that Internet use still has a positive and significant impact on residents' DEIP participation. (3) changing the econometric model. This study refers to Lokshin and Sajaia (2011) and employs an IV-probit method to explore the impact of Internet use on DEIP participation. The results presented in Table 8 and Table 9 show that the coefficient of Internet use is significant and positive, demonstrating the consistent result and conclusion. All results of the robustness tests support that the significant effect of Internet use on DEIP participation is robust.

Table 8. Robustness test results after replacing independent variable and tool variable

Variables	Model 5（IV-probit）		Model 6（RBP）	
	Sanitary toilet	Domestic waste	Sanitary toilet	Domestic waste
Internet use	—	—	0.958***（0.137）	0.660***（0.151）
Internet use time	0.046***（0.006）	0.052***（0.007）	—	—
Gender	-0.179***（0.030）	-0.231***（0.030）	-0.166***（0.030）	-0.220***（0.030）
Age	0.015*（0.008）	0.029***（0.008）	0.025***（0.009）	0.020**（0.009）
Age squared	-0.000（0.000）	-0.001***（0.000）	-0.000（0.000）	-0.000（0.000）
Education	0.058***（0.004）	0.048***（0.004）	0.047***（0.005）	0.046***（0.005）
Health condition	0.008（0.014）	0.017（0.013）	0.001（0.013）	0.013（0.013）
Household size	0.024***（0.008）	-0.033***（0.008）	0.022***（0.008）	-0.037***（0.008）
Per capita net family income (control group: Minimum 25%)				
Middle and lower 25%	0.223***（0.043）	0.185***（0.040）	0.214***（0.043）	0.181***（0.040）
Middle and higher 25%	0.452***（0.042）	0.325***（0.041）	0.434***（0.042）	0.322***（0.040）
Top25%	0.850***（0.045）	0.515***（0.045）	0.796***（0.049）	0.515***（0.047）
Political identity	0.210***（0.054）	0.115**（0.055）	0.160***（0.050）	0.0957*（0.053）
Environmental cognition	0.012**（0.006）	0.009（0.005）	0.008（0.006）	0.009（0.005）
Urban or rural areas	0.991***（0.031）	1.093***（0.031）	0.952***（0.035）	1.092***（0.034）
Region (control group: LDA)				
DA	1.321***（0.035）	0.631***（0.034）	1.294***（0.040）	0.629***（0.035）
WDA	-2.706***（0.041）	1.126***（0.049）	0.857***（0.041）	1.159***（0.050）
Constant	-2.706***（0.226）	-2.025***（0.230）	-2.931***（0.237）	-1.785***（0.262）
Wald chi2	38.83, with	27.77, with	13.99, wih	3.38, with

	Prob=0.000	Prob=0.000	Prob=0.000	Prob=0.066
Sample size	11523	11523	11523	11523

Table 9. Robustness IV-probit model

Variables	Model 7（IV-probit）	
	Sanitary toilet	Domestic waste
Internet use	0.634***（0.084）	0.713***（0.088）
Gender	-0.169***（0.030）	-0.220***（0.030）
Age	0.009（0.007）	0.022***（0.007）
Age squared	0.000（0.000）	-0.000*（0.000）
Education	0.055***（0.004）	0.045***（0.004）
Health condition	0.003（0.014）	0.012（0.013）
Household size	0.021**（0.008）	-0.037***（0.008）
Per capita net family income (control group: Minimum 25%)		
Middle and lower 25%	0.221***（0.043）	0.183***（0.040）
Middle and higher 25%	0.451***（0.042）	0.324***（0.040）
Top25%	0.849***（0.044）	0.513***（0.044）
Political identity	0.183***（0.054）	0.086（0.055）
Environmental cognition	0.012**（0.006）	0.008（0.005）
Urban or rural areas	0.993***（0.030）	1.095***（0.030）
Region (control group: LDA)		
DA	1.322***（0.035）	0.629***（0.034）
WDA	0.887***（0.040）	1.161***（0.048）
Constant	-2.554***（0.208）	-1.847***（0.211）
Wald chi2 of exogeneity	8.08, with Prob=0.005	19.82, with Prob=0.000
Sample size	11523	11523

5. Conclusions and Policy implications

5.1 Conclusions

This article is aimed at examining the impact of Internet use on residents' participation in DEIP in China. Specifically, based on the survey data of 11,523 observations from 25 provinces in China, we develop a dynamic model to investigate how Internet use as well as individual and family characteristics influence residents' decision to participate in DEIP (i.e., use flush type sanitary toilet and adopt centralized disposal of domestic waste). At the same time, a recursive bivariate probit model is employed to address potential selectivity bias that arises from both observed and unobserved heterogeneities. The main results are as follows:

(1) Regarding a quantitative relationship, Internet use exerts a positive and significant influence on residents' participation in DEIP. The results from the marginal effect show that Internet use increases the probabilities of adopting centralized disposal of domestic waste and using flush type sanitary toilet by 15.8% and 14.3%, and the results from average treatment effect also indicate that Internet use significantly increases the probability of adopting centralized disposal of domestic waste and using flush type sanitary toilet by 12.0% and 13.2%. After a variety of robustness tests, the estimated results are stable and consistent.

(2) Regarding heterogeneous impacts, the estimates show residents in urban areas are 24.4% and 27.5% more likely to use flush type sanitary toilets and adopt centralized disposal of domestic waste, compared with those in rural areas. Meanwhile, residents in WDA are 21.8% and 29.1% more likely to use flush type sanitary toilets and adopt centralized disposal of domestic waste, compared with those in LDA. But for DA, the marginal effect of proportion is 32.4% and 15.8%, respectively.

5.2 Policy implications

Based on the above findings, we can derive some policy implications. Improving the residential living environment remains a major challenge for developing countries. The rapid spread of the Internet has created new opportunities to eradicate this problem. Our findings indicate that

Internet adoption can help increase residents' use of flush type sanitary toilet and adopt centralized disposal of domestic waste, which is helpful for improving the residential living environment, thus improving their quality of life, promote health and enhance subjective well-being and life satisfaction (Zhang et al., 2017). However, this study finds that the Internet adoption propensity of residents located in rural and poor development and general development areas is lower than that of residents located in urban and superior development areas. Similarly, residential living environment is serious in some rural and poor development areas. Thus, governments of developing countries should increase their investment in Internet infrastructure in remote areas. For example, governments should increase the number of base stations in rural and poor development areas and provide residents with free training in Internet use. Moreover, the results further show that age, education level, health condition, and family income are significantly related to individual Internet use. For example, our results suggest that an increase in age will reduce the probability of using Internet; residents with higher education level are more likely to use Internet. Regarding the spatial heterogeneity, Internet use has a positive impact on residents' participation in DEIP in LDA, and increases the probability of adopting centralized disposal of domestic waste and using flush type sanitary toilet by 23.0% and 17.1%, respectively.

5.3 Limitations and future research direction

This study has certain deficiencies that future research can further address. Specifically, (1) this study focuses on the quantitative impacts of the Internet use on residents' participation in DEIP, and future research can further empirically analyze the channels through which Internet use affects residents' participation; (2) the Internet involves a wide range of content, and future research can further explore the quantitative impacts of specific content on the Internet on residential living environment improvement; and (3) the relationship between Internet use and residents' DEIP participation may be dynamic, and future research can use panel data to explore this relationship.

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