The Effect of Social Influence on Farmers' Intention to Buy Flood Insurance: The Evidence from Randomized Controlled Trial in Hue, Vietnam

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Abstract

Non-life insurance is considered important for people in poverty because it protects them from risks, such as crop failure. However, the reality is that people in poverty, who need insurance most, do not have insurance. Therefore, there are studies about the factors that encourage them to buy insurance, and some found that social influence, such as the recommendation from family members or friends, has an impact on the intention to buy insurance. In this context, our study focuses on social influence as a determinant of buying insurance, and conducted randomized controlled trial (RCT) in Hue city in Vietnam by using a household survey of farmers. The main purpose of our study is to examine whether the information that the respondents' closest neighbor has insurance, namely the weaker type of social influence, has an impact on the intention to buy insurance. As a treatment, the interviewers randomly let the respondents know that their closest neighbor bought flood insurance, and ask whether the respondents would like to buy the insurance or not . Namely, they are only given the information about the neighbor's choice and asked questions. Consequently, the data analysis shows that the information that their closest neighbor bought flood insurance has a positive effect on the intention to buy it. The result suggests the necessity of the change in the way to sell insurance.

1 Introduction

Natural hazard is getting more serious around the world due to climate change. Flood is a typical hazard whose damage will be worsened by climate change. Climate Central（2014）reported that 147 to 216 million people would live below sea level or regular flood levels by the end of the 21st century and eight out of ten large countries most at risk are in Asia（New

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York Times, 2014）. Although wealthy countries such as Netherlands can manage the risk by using advanced technology, poor Asian countries cannot afford to introduce it. One of such countries is The Socialist Republic of Vietnam. Floods in Vietnam affect 929,635 people and the annual damage is estimated as 2,295.35 million dollars on average (Luo, Winsemius, and Ward, 2015). To cope with the problem, The Vietnamese government aims to reduce exposure to floods through resettlement and dike. However, the resettlement policy ends up to worse-off households because livelihood support was not taken in sufficient level while most people did not have adequate assets to finance the settlement. Dike infrastructure also has difficulty solving the problem. For instance, dike in Long Xuen which is located near Mekong Delta was constructed without considering the future climate change. According to the survey by Bangalore, Smith and Veldkamp (2016) , the dike was already inadequate to protect city from current floods. In addition, dike is not a realistic way to protect remote and sparsely populated areas since it is not cost-effective. Since the current strategy does not go well, this paper insists that the alternative support is required.

Insurance is one of the effective solutions, because suffered people can cover up the financial loss due to natural disasters when they actually happen. Certainly, informal insurance can contribute to compensating for the loss, but informal insurance is financed by local community and it does not work well in the case of the natural disaster which affects the entire region because no one would be able to cover other's damage. As a result, its impact is uncertain and it alone is not enough for the recovery. Hence, these days the Vietnamese government attempts to raise the insurance subscription rate, but its policies to achieve the goal has not been so successful yet. Therefore, it is important to find the determinants of buying insurance in order to encourage people who are exposed to the disaster risks to buy flood insurance.

The previous studies found out that social influence, the recommendation from an individual's family members or friends, increased the probability of buying the insurance. However, they did not examine whether social influence has an impact on the intention to buy insurance even if the respondents know less about the neighbors' situations. Therefore, our study focuses on the "follow effect", weaker type of social influence, as a determinant of the intention to buy the insurance, and surveys its effect by randomized controlled trial. The follow effect is different from social influence in that the follow effect is the effect of the information of others' choices, not the recommendation from others. The treatment of RCT in the survey is to inform the respondents that their closest neighbor bought flood insurance. After the respondents in treatment group are informed about it, they are asked whether they want to buy it or not. On the other hand, the respondents in the control group are asked whether they want to buy the insurance without getting any information about their neighbors' choices. The data analysis found out the information that their closest neighbor has insurance increased the probability of buying insurance. In the next section, the analyses of the previous studies will be firstly explored.

2 Previous Studies about Social Influence on Insurance Demand

It is important to buy insurance as a measure to lower the vulnerability to risks from natural disaster. However, for those who are vulnerable to those risks due to poverty, it is not common to buy insurance as a measure to protect themselves. This is a dilemma. In order to to take the way out of it, a lot of research on the determinants of purchasing insurance has been conducted.

For example, Binh et al (2017) did research on flood insurance demand through choice experiment at farm villages in Mekong Delta, Vietnam. He found that the followings had significant impact on the decision to buy insurance: the contents of insurance (e.g. insurance coverage, premium), and the characteristics and perception of people insured (e.g. his wealth, risk perception toward flood, flood experience). The study used flood insurance as a sample insurance, and found these determinants through the logit model. However, the study did not examine other social factors such as peer pressure.

Other researchers shed more light on the social influence than on the insurance itself or the characteristics of the insured. Lo (2013) did a household survey of people living in Brisbane in Australia and found that "peer pressure", being encouraged to buy flood insurance by their family members or friends, increases the likelihood of purchasing insurance. His econometric analysis, on the other hand, rejected a significant impact of their risk perceptions and their income on the decision to buy insurance. This study used the regression model, and the dependent variable was whether the respondents had insurance or not. The peer pressure was defined as "the perception of how other members of the community and family and friends would respond to the household's decision about purchasing flood insurance, as suggested in an official issue paper ."(Lo 2013, 72) The question asked was "my family or friends think I should insure my house against flooding," and the respondents chose answer from five choices(strongly disagree, somewhat disagree, neither disagree nor agree, somewhat agree, strongly agree)

Furthermore, Lo et al (2015) tried to disclose how people affect others' decision to buy insurance through the regression analysis in Tianjin, one of the largest cities next to Yangtze River in China. The regression analysis has proved that the following three social variables, not risk perception or flood experience, increase the intention to make preparation of the insurance: 1.social expectation (My family or friends would encourage me to prepare for urban flood hazards.), 2.social relationships (There are good relationships with others.), 3.institutional trust (When floods happen, my community would help me cope with that situation.)

However, the studies have flaws. The first is reverse causality. In the studies by Lo (2013) and Lo et al (2015), the dependent variable was whether the respondents have insurance or not, and the respondents answered the question about social influence based on their subjective observation. If those insured were asked how much the family or friends recommended insurance, they would overestimate the level of the recommendation, because they answer the question based on the fact that the respondents actually bought the insurance. On the other hand, if those who were not insured were asked the same question, they would underestimate the level of the recommendation, because they answer based on their perception that their family or friends

did not recommend insurance enough for the respondents to buy it. As a result, it is estimated that there is a threat of reverse causality in the previous studies by Lo (2013) and Lo et al (2015) The second is omitted variable biases. The question regarding the recommendation from the family members or friends is based on the subjective observation, so it is possible that their answers are influenced by unobserved psychological factors.

Social influence as a determinant of purchase has been also discussed in consumer behavior theory. For instance, Leibenstein (1952) advocated the presence of "network effect" in purchase decision making. Network effect assumes that others' behavior or intention influences that of individual consumers when they buy things. He separated the effect into "bandwagon effect" and "snob effect", based on whether the effect is positive or negative. Bandwagon effect means that the more people consume goods, the more likely those who still don't use are to decide to buy them and snob effect vice versa. Coleman (1990) put more emphasis on social influence of personal connections with others on the decision to buy goods. He claimed that, for customers, a high reputation of the goods scored by their friends or family is the guarantee of the goods' quality or utility.

Based on the concept of network effect introduced by Leibenstein (1952) and Coleman (1990), our paper introduces a new concept which is different from social influence or bandwagon effect. That is "follow effect". In this paper the "follow effect" is defined as follows: the positive effect on the intention of buying insurance by giving the respondents the information that "the closest neighbor bought the same insurance." Therefore, our research has two main goals: to prove the presence of "follow effect" in flood insurance purchase and to improve the validity of the previous studies which is regarded to social influence on insurance.

The first purpose is to examine the "follow effect" on buying insurance in Vietnam. As mentioned in the former part, a lot of research tried to clarify the determinants of buying insurance and some focus on social influence. In the previous research, the meaning of social influence is expected to have an impact on individual decision making on buying insurance due to the significant effect of recommendation from other people. However, "recommendation" is just a mere part of "social influence". This paper suggests that there is another type of social influence that was undistinguished from the social influence of recommendation. For instance, when an individual needs to make decision on buying insurance, he/she might take into account whether people around him/her bought the same insurance or not because the fact that the neighbor has insurance guarantees the quality of the insurance. In other to examine the overlooked social influence, we established a model to see the "follow effect". Our hypothesis is that the "follow effect", which is the weaker social influence than the recommendation of insurance, also has an impact on the individual's decision to buy insurance.

The second purpose is to improve the internal validity of the previous studies such as Lo (2013) and Lo et al (2015), by using RCT. The previous studies by Lo (2013) and Lo et al (2015) did not reveal the causal relationship because of the endogeneity embedded in the model. Firstly, as mentioned before, it is possible that their models have reverse causality between the dependent variable and the variable related to social influence. Furthermore, the question asked

was "my family or friends think I should insure my house against flooding," but the answer might be influenced by unobservable variables such as personal characteristics, which causes omitted variable bias. Therefore, by using randomized controlled trial, it enables us to prevent reverse causality and other threats to the internal validity. The next section explores the method which was used in our research.

3 Method

Samples and Survey

This section explains the detailed information about RCT and the survey. The treatment in the survey is to tell the respondents that their closest neighbor bought flood insurance. After the treatment, they are asked whether they want to buy it or not. On the other hand, the respondents in the control group were asked whether they want to buy the insurance without telling any information of their neighbors. Therefore, the only difference between the treatment group and the control group is that the respondents in the treatment group know that their closest neighbors have flood insurance, if the the treatment is randomly assigned. In accordance with Binh et al(2017), which conducted a similar survey in Vietnam, the survey uses flood insurance as a sample insurance. The survey also mainly targeted farmers, because they they are exposed to the high risk of financial loss due to floods and can benefit most from flood insurance. In the survey, the respondents were informed of the content of the sample flood insurance, such as deductible, premium, coverage, and providers, as the Figure 1 shows . The sample insurance is said to be the most popular one according to Binh et al(2017). The questions of the treatment and other control variables are based on Binh et al(2017).

Table 1: The insurance that was shown to the respondents

Insurance policy	flood+waterlog+whilrwind
Insurance provider	private insurance company
Coverage	VND 3 million per $1000m^2$
Deductible	25%
Premium	VND 40000 per $1000m^2$

In the end, 278 samples were collected through a household survey conducted in three villages of Hue city in Vietnam: Quang Loi, Phu My, and Vinh Thanh. The villages are located in the area where there is danger of flood.

Model

Based on the sample collected, the effect of the treatment is estimated by the regression, the probit model, and the logit model. The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 Treatment_i + \underbrace{\beta_2 X_{2i} + \cdots + \beta_k X_{ki}}_{control\ variables=C} + u_i$$

Y_i is the dummy variable, which equals 1 when the interviewees intend to buy the flood insurance when they are asked. $Treatment_i$ is the treatment dummy variable, which equals 1 when the interviewers tell the respondents that their closest neighbor has that insurance. As a result, it is possible to see the causal relationship between social influence and the intention to buy the insurance. Other control variables are shown on `https://1drv.ms/b/s!AgYLU4vopIav6DriTrugwWnpYcG3`.

The probit model and the logit model is similar to the regression model. As for the probit model,

$$Pr(Y_1 = y_1, Y_2 = y_2, \cdots, Y_n = y_n | Treatment_i, X_{2i}, \cdots, X_{ki}, i = 1, \cdots, n) = \prod_{i=1}^{n} p_i^{y_i}(1-p_i)^{1-y_i}$$

where p_i is the probability that $Y_i = 1$ conditional on $Treatment_i, X_{2i}, \cdots, X_{ki}, i = 1, \cdots n$. If $Y_i = 1$ when $Y_i^* = \beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki} + \varepsilon_i > 0$ and Y_i=0 when $Y_i^* \leq 0$, the derivation of p_ii is as follows;

$$\begin{aligned}
p_i &= Pr(Y_i = 1 | Treatment_i, X_{2i}, \cdots, X_{ki}) \\
&= Pr(Y_i^* > 0 | Treatment_i, X_{2i}, \cdots, X_{ki}) \\
&= Pr(\beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki} + \varepsilon_i > 0 | Treatment_i, X_{2i}, \cdots, X_{ki}) \\
&= Pr(-(\beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki}) < \varepsilon_i | Treatment_i, X_{2i}, \cdots, X_{ki}) \\
&= Pr[\frac{-(\beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki})}{\sigma} < \frac{\varepsilon_i}{\sigma} | Treatment_i, X_{2i}, \cdots, X_{ki}] \\
&= 1 - \Phi(\frac{-(\beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki})}{\sigma}) \\
&= \Phi[(\beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki})]
\end{aligned}$$

where the derivation is based on the assumption that the residual follows the normal cumulative distribution and the distribution is symmetry. As a result, the log likelihood function becomes

$$\begin{aligned}
& ln[f_{probit}(Y_1 = y_1, Y_2 = y_2, \cdots, Y_n = y_n | Treatment_i, X_{2i}, \cdots, X_{ki}, i = 1, \cdots, n)] \\
= & \sum_{i=1}^{n} y_i ln[\Phi(\beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki})] \\
& + \sum_{i=1}^{n} (1 - y_i) ln[1 - \Phi(\beta_0 + \beta_1 Treatment_i + \cdots + \beta_k X_{ki})]
\end{aligned}$$

The MLE maximizes this log likelihood function. On the other hand, in the logit model, the

estimation method is almost the same, but the $p_i = \frac{1}{1+e^{-(\beta_0+\beta_1 Treatment_i+\cdots+\beta_k X_{ki})}}$, because it is assumed that the residual follows the logistic cumulative distribution.

4 Results

Before conducting the analyses, it is necessary to examine whether the treatment was randomly assigned, even though the assignment itself was random. In order to ensure the random assignment, t-test is firstly used. If it is concluded that the average demographic conditions of the treatment group and the control group are the same, it is reasonable to assume the validity of the random assignment. The Table 2 summarizes the demographic information and the results of the t-tests.

The patterns of almost all the variables are the same between the treatment group and the control group. However, there are few variables the pattern of which differ between the treatment group and the control group. The first variable that contradicts the random assignment is *agriproduct_4*, which equals 1 when the respondents produce the crops that is not included in our questionnaire. The second variable is *cellphone*, which equals 1 when the interviewees have cellphones, and the last variable is *floodexperience_3* dummy, which equals 1 when they never experienced floods. Secondly, the F-test on the result of regressing $Treatment$ on the control variables shows no correlation between $Treatment$ and the control variables as Table 3 shows. The F-statistic is 1.199, so the null hypothesis that all the control variables have no effect on $Treatment$ is not rejected at 10% significance level.

Table 2: The demographic description of the sample

	Treatment		Control			Treatment		Control	
	mean	sd	mean	sd		mean	sd	mean	sd
age	53.54	14.00	53.82	14.11	experiencelevel	2.99	1.57	2.97	1.47
annualexpenditure	39094.37	29240.51	46282.45	53706.37	flooddamage__0	0.75	0.44	0.67	0.47
intername__1	0.11	0.31	0.07	0.26	*cellphone	0.81	0.39	0.72	0.45
intername__2	0.11	0.31	0.13	0.33	saving	0.27	0.44	0.26	0.44
intername__3	0.09	0.29	0.07	0.26	debt	0.29	0.45	0.26	0.44
intername__4	0.16	0.37	0.15	0.36	gender	0.54	0.50	0.45	0.50
intername__5	0.15	0.36	0.19	0.39	education	8.02	5.45	7.81	5.90
intername__6	0.19	0.39	0.21	0.41	working	0.96	0.18	0.96	0.21
intername__7	0.06	0.23	0.06	0.24	numofjob	1.44	0.55	1.46	0.56
intername__8	0.02	0.14	0.01	0.12	village1	0.23	0.42	0.23	0.42
intername__9	0.12	0.33	0.11	0.31	village2	0.42	0.49	0.40	0.49
family	4.44	2.04	4.33	1.87	village3	0.36	0.48	0.37	0.48
marrage	0.94	0.24	0.90	0.31	toilettype3	0.90	0.30	0.90	0.30
children	2.11	1.79	1.99	1.66	prijobname	0.75	0.43	0.82	0.39
annualexpenditure	39094.37	29240.51	46282.45	53706.37					
*agriproduct__4	0.01	0.08	0.04	0.21					
agriproduct__0	0.00	0.00	0.00	0.00					
agriproduct__1	0.70	0.46	0.73	0.45					
agriproduct__2	0.49	0.50	0.47	0.50					
agriproduct__3	0.03	0.17	0.04	0.21					
ownhouse	0.97	0.17	0.97	0.17					
ownland	157.92	191.53	172.10	293.13					
farmland	3400.37	5070.31	3149.51	4178.77					
TVs	1.03	0.31	1.02	0.28					
fridge	0.75	0.45	0.70	0.46					
motorbikes	1.68	1.36	1.77	1.20					
livestock	0.77	0.42	0.84	0.37					
ownpoultry	22.13	60.63	31.11	92.92					
owncows	0.44	2.26	0.52	2.49					
ownpigs	3.80	7.75	4.55	11.75					
insurance__1	0.77	0.42	0.79	0.41					
insurance__2	0.98	0.14	0.98	0.15					
floodexperience__1	0.25	0.43	0.31	0.46					
floodexperience__2	0.85	0.36	0.89	0.31					
*floodexperience__3	0.10	0.30	0.04	0.19					
N	142		136			142		136	

"*" means the failure to reject the null hypothesis
that the treatment group and the control group have the same distribution of the samples
More detailed information is shown in the Appendix

Table 3: The regression of Treatment on other control variables

	(1) Treatment
floodexperience__3	-0.417 (-1.83)
cellphone	-0.0975 (-1.11)
agriproduct__4	0.347* (2.15)
family	-0.000229 (-0.01)
children	-0.00399 (-0.13)
annualexpenditure	0.000000824 (0.92)
ownhouse	0.0342 (0.16)
fridge	-0.128 (-1.51)
motorbikes	0.0356 (0.85)
floodexperience__1	0.0406 (0.30)
floodexperience__2	-0.0914 (-0.50)
age	0.001000 (0.35)
village1	-0.0146 (-0.10)
village2	0.00194 (0.01)
saving	0.0160 (0.17)
debt	-0.0530 (-0.65)
gender	-0.106 (-1.49)
_cons	0.650 (1.33)
N	278
F	1.199 (Prob>F = 0.2032)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The following analysis controls these three variables to improve the estimation, although the F-test does not reject the null hypothesis. This is because $E(u|Treatment, C) = E(u|C)$ under the model $y = \beta_0 + \beta_1 Treatment + C + u$, where $Treatment$ is the dummy variable for the treatment and C are the control variables such as $agriproduct\_\_4$, $cellphone$, and $floodexperience\_\_3$ in this case.

The mathematical explanation is as follows. In the normal cases where treatment is randomly assigned, the effect of the treatment can be estimated through $E(y|Treatment = 1) - E(y|Treatment = 0)$. However, the sample collected might violate this random assignment to some extent because of $agriproduct\_\_4$, $cellphone$, and $floodexperience\_\_3$. The solution is to control them. If $E(u|x, C) = E(u|C)$ holds,

$$\begin{aligned}
E(y|Treatment = 1, C) &= \beta_0 + \beta_1 \times 1 + \underbrace{E(u|x, C)}_{=E(u|C)} \\
E(y|Treatment = 0, C) &= \beta_0 + \beta_1 \times 0 + \underbrace{E(u|x, C)}_{=E(u|C)} \\
E(y|Treatment = 1, C) - E(y|Treatment = 0, C) &= E(y_{Treatment=1} - y_{Treatment=0}|C) = \beta_1
\end{aligned}$$

Therefore, It is proved that the RCT is valid as long as these variables are controlled. As a result, the control variables are used in the following analysis to improve the estimation, but it is concluded that the randomization does not fail.

Table 4: The results of the econometric analysis

	(1) Regression(1)	(2) Regression(2)	(3) Probit	(4) Logit
main				
Treatment	0.135**	0.142***	0.363**	0.588**
	(0.059)	(0.052)	(0.158)	(0.257)
(Marginal Effect at means)			0.138	0.138
floodexperience__3	-0.114	-0.118	-0.293	-0.470
	(0.122)	(0.189)	(0.308)	(0.501)
cellphone	0.074	-0.073	0.199	0.320
	(0.071)	(0.076)	(0.185)	(0.301)
agriproduct__4	-0.223	-0.320*	-0.584	-0.935
	(0.189)	(0.185)	(0.488)	(0.784)
family		-0.015		
		(0.021)		
children		0.025		
		(0.024)		
annualexpenditure		-0.000		
		(0.000)		
ownhouse		0.036		
		(0.173)		
toilettype3		0.092		
		(0.106)		
floodexperience__1		-0.056		
		(0.093)		
floodexperience__2		-0.110		
		(0.131)		
age		-0.004*		
		(0.002)		
education		0.001		
		(0.005)		
village1		0.005		
		(0.115)		
village2		0.041		
		(0.108)		
saving		-0.091		
		(0.081)		
debt		-0.055		
		(0.069)		
gender		0.025		
		(0.060)		
N	278	278	278	278
R^2	0.031	0.387		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table 4 shows the results of the analyses with the regression, the logit model, and the probit model. The first column is the result of the regression. Controlled with several variables which were mentioned before, the coefficient of the treatment is significant at the 5% significance level. The similar result is reported in the column (2), which is the result of the regression with more control variables. The robustness is also checked by the probit model and the logit model which is reported in the column (3) and (4) of Table 2. The marginal effects of the treatment variable based on the logit model and the probit model at means are also shown in Table 2. In the end, all the coefficients of the treatment dummy is significant at the 5% level and the treatment effect is similar. The treatment increases the probability of the intention of joining the insurance by about 13%. Therefore, our hypothesis that the choices of neighbors (social influence) affect the probability of the intention to buy the insurance is verified.

5 Discussion and Conclusion

Although formal insurance has a significant effect on flooding damages, we are facing with the reality that its subscription rate fluctuates at a very low level in developing countries. There are increasing number of studies on factors that motivates people to get the insurance. However, a few questions are not solved through those researches yet. That is, the existence of “ follow effect ”, and the problems of endogeneity. We therefore tackle with these issues by conducting RCT in Hue city in Vietnam. We collected a random sample of 278 households in three villages of Hue city in Vietnam: Quang Loi, Phu My, and Vinh Thanh, which are located at flood prone area.

As a consequence, our research shows three important implications. First, we elucidated the "follow effect" on getting insurance. That is to say, people are inclined to buy insurance more if their closest neighbor already had the same one. The key point is that we premise people are not exposed to any peer pressure to buy it from them. Second, we successfully proved that the result has the internal validity due to the RCT. Thus, the causal relationship between the "follow effect" and the decision making of buying insurance is confirmed.

A lot of studies have done research on the determinants of purchasing goods. For example, the bandwagon effect was confirmed empirically by Coleman (1990). In the area of insurance, Lo (2013) and Lo et al (2015) found that the recommendation from family members or friends increases the probability of buying insurance. However, our study proved a completely new path to the purchase of insurance, namely the follow effect. The result gives us a suggestion for increasing the insurance subscription rate. It implies that it is inefficient to sell insurance to each individual randomly. Rather, insurance providers should launch a campaign and sell it to residents in some compounds collectively to maximize the "follow effect". In addition to this study's result, Binh et al.(2017) found out the characteristics of the insurance which the farmers favor and the characteristics of those who are more likely to buy insurance. Therefore, by using our study's result and Binh et al.(2017) result, it is possible to promote the purchase of flood insurance in Vietnam.

Binh et al.(2017) mentioned that few people buy flood insurance even if the people are offered the most popular type of flood insurance. However, GDP per capita in Vietnam increased from $ 433 in 2000 to $ 2186 in 2016 and the proportion of the population living on less than $1.25 per day in Vietnam also declined from 20.7% in 2010 to about 13.5 % in 2014 according to the World Bank. It is reasonable to say that Vietnamese economy is growing very rapidly. Therefore, more people will have savings in the near future, and the demand on flood insurance will also become larger. That is why our study is useful in order to accelerate the spread of flood insurance.

However, there are still some challenges in our research. Firstly, we suppose that the cause of " follow effect " is the implicit guarantee of the insurance quality secured by neighbors' act. However, it is remained to be checked by other studies whether the hypothesis is correct or not. Furthermore, the intention does not always lead to the real purchase of insurance. Ajzen(1991) empirically demonstrated that behavioural achievement depends on the intention to perform the behaviour and the behavioural control, which is the abilities and the resources that an individual has to achieve some behaviour. Therefore, the fact that the RCT affects the intention to buy insurance means that the RCT partly influences the actual behaviour. However, our study did not deal with the behavioural control. In our case, the behavioural control refers to financial restrictions and other obstacles. More research should be done on how much impact the follow effect has on the real purchase.

The last thing to keep in mind is the external validity. Our research was done in a limited area of Hue. Therefore, it is possible that the external validity is threatened. However, the external validity can be inferred based on the comparison between the data of the whole population and the data collected in our survey. For example, GDP per capita of Vietnam in 2016 is about $ 2186 dollars according to the World Bank, and the average annual income of the respondents is 53,503,000 VND, which is about $ 2,356. As a result, it is reasonable to extend the result of the study to some extent, because the data collected was not very different from the data collected from the whole population.

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