Doctoral Thesis

The Diffusion of Agricultural Information in Real and Virtual Communities: Evidence from Shrimp Farmers in Developing Countries

(現実コミュニティと仮想コミュニティにおける農業情報の普及：開発途上国のエビ養殖業者の事例から)

李　根雨

Abstract

The diffusion of information on good farming practices plays a key role in improving agricultural productivity and promoting rural welfare in developing countries. Traditionally, the main channels to disseminate information to farmers have been the governments of developing countries through their extension officers. Nevertheless, the lack of information remains one of the reasons for farmers to adopt wrong or inefficient practices. Moreover, the problem of spreading inaccurate information also persists (WB, 2007).

The studies find that social network targeting (henceforth, SNT) is a method to increase farmers' adoption of new technology (Banerjee et al., 2013; Beaman et al., 2015; Kim et al., 2015). However, it remains unclear as to what type of targeting method one should use in disseminating information in terms of delivering accurate information.

Moreover, they do not reveal the reason why people share information with others. Literature on psychology or social networks have studied communication among the community of practices (CoPs), which are groups that consist of individuals who are engaged in the same industry or related work, and found that direct reciprocity is one of the reasons why people share information (Lave, 1991; Lave & Wenger, 1991; Wasko, 2005; Wenger, 1998). Others show that indirect reciprocity, which is the feeling of obligation to help others if they are helped by someone, also plays a role (Nowak and Sigmund, 2005). However, most of these studies rely on self-report recall data of personal communications and consequently, the data points are limited. Further, examples are drawn from developed-country settings, and thus the applicability of these findings to developing-country agriculture is not guaranteed.

This dissertation considers a case of shrimp farmers in Vietnam and Thailand to answer the remaining questions. As shrimp diseases spread rapidly from an infected shrimp with a virus to another shrimp in the same pond, and all the shrimp may die within a few days, obtaining appropriate and timely information is vital for shrimp farmers to reduce the risk of

shrimp diseases. To reduce the risk of shrimp diseases, veterinary drugs are used by shrimp producers, but these often contain substances harmful to the human body such as chloramphenicol, enrofloxacin, and ciprofloxacin. Thus, there have been attempts by the governments of developing countries and international communities to disseminate good aquaculture practices. Better management practices (BMPs) is one of them. According to NACA (2016), well-designed and well-implemented BMPs support smallholder shrimp aquaculture to increase productivity by reducing the risk of shrimp disease outbreaks. I investigated whether the BMPs reduce the use of harmful substances in shrimp farming, taking a case of Vietnam. Using the laboratory-tested objective data on the use of prohibited substances, I found that receiving BMPs training has a significant and positive effects on reducing the use of these drugs. This finding suggests the importance of considering effective ways to spread the information of BMPs among farmers.

Regarding one of remaining questions mentioned in the second paragraph, this dissertation compares targeting methods. To construct data for the analysis, I conducted a workshop on BMPs to 36 shrimp farmers in December 2016. The participants are selected using three targeting methods and divided into three groups based on the methods. Treatment group 1 includes farmers selected by simple random sampling (SRS), while treatment group 2 includes individuals chosen by systematically unaligned random sampling (SURS) using individual location information. Treatment group 3 is selected using SNT. In August 2017, I conducted a follow-up survey to investigate how well farmers' knowledge of BMPs improved in comparison to the status before our treatment. I found that: (1) SRS shows the highest increase in BMPs knowledge in comparison to other treatments; (2) SURS shows lower improvement in BMPs knowledge than SRS. On the other hand, unlike other groups, treated farmers in SURS increase their neighbors' scores; and (3) SNT increases information sharing between villagers in the treated village. However, untreated farmers, who receive information from treated farmers of the SNT group, have a lower improvement score in their BMPs knowledge.

Furthermore, to reveal the motivation of information exchanges between shrimp farmers in virtual community of practices (VCoPs), this dissertation considers a case of one Facebook group, which share a common farming crop and the majority of the members are shrimp farmers. One way to find this out is to examine whether a norm of reciprocity plays a role in facilitating information exchange even in a virtual space. Particularly, indirect reciprocity, rather than direct reciprocity, may be an important motivation for the information exchange with other VCoP members (Jung, 2017; Nowak and Sigmund, 2005; Wasko, 2005). I construct a monthly panel data to addresses the Facebook group member's motivation for information exchange between January 2015 and May 2017. I found that: (1) members who have previously asked questions are more active in sharing information than people who have never asked; (2) other members' positive expressions to previous information shared (such as clicking likes) promote future information sharing; (3) the act of information sharing by one's peer promote his/her own information sharing, and (4) the more the member shares information in the past, the more s/he asks information today. These findings suggest that reciprocity does play a significant role in motivating information exchange even in the VCoPs, similar to CoPs. I also confirm that professional reputation is one of the motivations for information sharing and that there is a positive effect of peer's prosocial behavior.

Based on these findings, it can be concluded that in a real community, the SNT targeting method seems to be a way to disseminate information to more people, and SURS targeting method may be suitable to enhance the knowledge level of their neighbors. However, both methods are less likely to deliver accurate information than SRS because of bias generated by those samplings. Regarding the motivation of information exchanges between farmers in a virtual community, I clarify that reciprocity and professional reputation play important roles in enhancing professional knowledge exchange even in VCoPs. If the members in a VCoP have a common motivation, information exchange can be activated, and such active exchange of information will lead to the growth of the community.

This dissertation makes a contribution to suggest effective targeting methods to transmit information to more people or to spread accurate information by comparing various targeting methods, such as sampling using location information or social networks, which are rarely used in the analysis of development economics. Furthermore, this dissertation clarifies that reciprocity and professional reputation play important roles in enhancing professional knowledge exchange, even in VCoPs using large-scale data from a virtual community. If the members in a VCoP have a common motivation, information exchange can be activated, and such active exchange of information will lead to the growth of the community. As the adoption rate of information and communication technology increases, the demand for E-farming for the effective and efficient dissemination of agricultural information in developing countries may increase. The results of this dissertation will be useful for disseminating accurate information and promoting E-farming in various countries.

Acknowledgement

First and above all, I praise God, the almighty for giving me the opportunity and granting me the capability to proceed successfully. Without his graces and blessings, this achievement would not have been possible.

I would like to express my sincere gratitude to my advisor **Professor Aya Suzuki** for the continuous support of my Ph. D study and related research. I hold her in esteem and want to be a person of character like her.

Besides my advisor, I would like to thank the rest of my thesis committee, **Professor Todo Yasuyuki**, **Professor Masahide Horita**, **Professor Riki Honda**, and **Professor Maiko Sakamoto**, not only for their insightful comments and encouragement, but also for the challenging question which incented me to widen my research from various perspectives.

My sincere thanks also extends to **Professor Yue Yaguchi**, **Professor Vu Hoang Nam**, and **Professor Nattapong Puttanapong** for their support, advice, guidance, valuable comments, and suggestions.

I thank my colleagues and lab-mates **Tada Tamao**, **Takeda Takaki**, **Dr. Yu Ri Kim**, **Dr. Seong Yoon Choi**, **Eunjin Ryu**, and **Sijia Zhao**. Their support, encouragement, and credible ideas have been great contributors in the completion of the thesis.

Thanh Binh Tran, **Truong Hong Quan**, **Trang Duong**, **Nhu Lo**, **Nguyen Ngoc Nhi**, **Hoang Son**, and **Yokuyok Ruengwatanaporn** —have done their best to undertake research in Vietnam and Thailand. I am extremely grateful to them.

Somyung Church, The University of Tokyo, Yosida Institute, and the Japan Society for the Promotion of Science —have all lent their support to me during times in which I needed encouragement and fortitude. Thank you very much.

Last but not the least, I thank my parents **Hyunsoon Kim** and **Sunggyu Kim**, in-laws **Hyeja Han** and **Jiyang Wie**, other family members **Mika Tanaka**, **Seungjun Kim**, **Jieun Lee**, **Daejun Kim**, **Gayoung Lee**, **Yongjin Choi**, **Mihye Wie**, **Sanghoon Lee**, and **Eunhye Wie**, my nephew **Onew Choi**, my niece **Sena Kim**, friends **Hyunggu Kang**, **Jaesung Jang**, and **Sehoon Kim**, and my beloved wife **Zieh Wie** who is the most beautiful woman in the universe —whom I very much appreciate. Words fail to capture the extent of gratitude I owe and feel.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AC	Anonymous Chosen game
AMPE	Average Marginal Probability Effects
AR	Anonymous Random game
BC	Betweenness Centrality
BMPs	Better Management Practices
CIPRO	Ciprofloxacin
CML	Chloramphenicol
CoPs	Community of Practices
DD	Difference in Difference
ENR	Enrofloxacin
EU	European Union
EUT	Expected Utility Theory
FAO	Food and Agriculture Organization of the United Nations
ICT	Information and Communication Technology
LCMS	Liquid Chromatography Mass Spectrometry
MHLW	Japanese Ministry of Health, Labor and Welfare
NACA	Network of Aquaculture Centers in Asia-Pacific
NB	Negative Binomial
OTC	Oxytetracycline
PPB	Parts Per Billion
PT	Prospect Theory
RC	Revealed Chosen game
RR	Revealed Random game
SNS	Social Network Service
SNT	Social Network Targeting
SRS	Simple Random Sampling
SURS	Systematically Unaligned Random Sampling
UNEP	United Nations Environment Program
US	United States
VCoPs	Virtual Community of Practices
WWF	World Wildlife Fund

1. Introduction

1.1. Background

The diffusion of information on good farming practices plays a key role in improving agricultural productivity and promoting rural welfare in developing countries. Traditionally, the main channels to disseminate information to farmers have been the governments of developing countries through their extension officers. Nevertheless, the lack of information remains one of the reasons for farmers to adopt wrong or inefficient practices. Moreover, the problem of spreading inaccurate information also persists (WB, 2008). Holmstrom et al. (2003) conducted interviews with shrimp farmers along the Thai coast in 2000 and found that 88 percent of the farmers interviewed adopted wrong practices, such as using antibiotics simultaneously with probiotics. This is considered to be the result of lack of information on aquaculture practice.

To overcome such problems, recent literature has focused on the role of farmers' social network on obtaining information. The studies find that social network targeting (henceforth, SNT) is a method to increase farmers' adoption of new technology (Banerjee et al., 2013; Beaman et al., 2015; Kim et al., 2015). However, it remains unclear as to what type of targeting method one should use in disseminating information in terms of delivering accurate information.

Moreover, they do not reveal the reason why people share information with others. Literature on psychology or social networks have studied communication among the community of practices (CoPs), which are groups that consist of individuals who are engaged in the same industry or related work, and found that direct reciprocity is one of the reasons why people share information (Lave, 1991; Lave & Wenger, 1991; Wasko, 2005; Wenger, 1998). Others show that indirect reciprocity, which is the feeling of obligation to help others if they are helped by someone, also plays a role (Nowak and Sigmund, 2005). However, most of these studies rely on self-report recall data of personal communications and consequently, the data points are limited. Further, examples are drawn from developed-country settings, and thus the applicability of these findings to developing-country agriculture is not guaranteed. Therefore, this dissertation attempts to overcome these limitations on studying SNT and the motivation of information exchange between farmers by using panel data from real communities in Vietnam and from a Facebook group of Thai shrimp farmers.

1.2. Objectives and Research Questions

To examine how farmers exchange agricultural information among each other, I consider a case of shrimp farmers in Vietnam and Thailand in this dissertation. This industry is selected as shrimp farming is characterized by the importance of information and high embeddedness among farmers. Shrimps are very sensitive aquatic animals and their farming practice is challenging. As shrimp diseases spread rapidly from an infected shrimp with a virus to another shrimp in the same pond, and all the shrimp may die within a few days, obtaining appropriate and timely information is vital for shrimp farmers to reduce the risk of shrimp diseases. Moreover, if a disease occurs on one farm, it spreads rapidly from the source to neighboring farms which share the same water source. In light of these facts, it appears that cooperation or information sharing among residents using the same canal is essential to prevent shrimp diseases and increase individual productivity. However, through a fieldwork in southern Vietnam, I found that shrimp farmers in the region were reluctant to share information on shrimp cultivation with their neighboring farmers owing to limited experience in shrimp farming or weak ties. Thus, this dissertation considers a case of shrimp farmers in southern Vietnam and aims to suggest a targeting method to select a treatment group of farmers who are active in sharing information, and disseminate information accurately to both treated and non-treated farmers.

To construct data for finding the targeting method, a baseline survey was conducted in the Ca Mau province in southern Vietnam in September 2016 to collect information from 167 farmers. The data include information on farmers' social networks, psychological characteristics, and the knowledge level of better management practices (BMPs), as well as their socio-economic characteristics. Treated farmers were selected using three targeting methods and were divided into three groups based on the methods. Treatment group 1 includes farmers selected by simple random sampling (SRS), while treatment group 2 includes individuals chosen by systematically unaligned random sampling (SURS) using individual location information. Treatment group 3 is selected using SNT. Farmers in SNT group have higher betweenness centralities than untreated farmers in the same village. The reason why this study employs betweenness centrality for SNT is that an individual with high betweenness centrality is an intermediary who plays an important role in the connection between other people in the same network. The individual has a large influence on information transfer through the network and is called a gatekeeper. Theoretically, providing information to the gatekeeper allows us to pass information to the highest number of people in the network (Brandes, 2008; Freeman, 1977; Grund, 2015). Using the data, I examine which targeting method (1) improves the knowledge of good practices of the treated the most; (2) enhances information sharing with their neighbors the most, and (3) improves the farming knowledge of those who receive information from the treated.

Furthermore, this dissertation considers a case of one Facebook group in Thailand, which shares a common farming crop and the majority of the members are Thai shrimp farmers, and aims to reveal the motivation of information exchanges between farmers in the virtual community. Facebook groups are considered as a virtual community of practices (VCoPs), which is similar to CoPs, but the members of VCoPs tend to be distributed throughout a country or the globe, and many of them may not meet face-to-face with the other members (Wasko, 2005).

In the middle of 2000, the number of social network service (SNS) users in Thailand increased tremendously. Currently, shrimp farmers in Thailand are actively sharing information with other farmers through SNS and are exchanging their farming knowledge by forming VCoPs in SNSs. As it is easy to access information and as it allows farmers to obtain the information they need instantly, information sharing in the VCoPs is considered to be helpful for solving problems caused by lack of information, as mentioned above.

While these SNS communities are considered to be an advanced form of agricultural extension systems (called "E-farming") which promote information exchange in developing countries, there is a dearth of literature that examines how communications actually take place among the members. One concern for promoting this type of communities is the question of how active will information exchange be, particularly as interpersonal ties between the members in VCoPs are typically weak in comparison to real communities in villages where a social network is very dense. One method to identify this is to examine whether a norm of reciprocity plays a role in facilitating information exchange even in a virtual space.

1.3. Outline of the Thesis

The remainder of the thesis proceeds as follows. Before my intervention to disseminate BMPs knowledge to Vietnamese shrimp farmers, I identified the impact of BMPs on reducing antibiotic use. The study is introduced in Chapter 2. Chapter 3 compares targeting methods to reveal the method to diffuse accurate information in a real community. In Chapter 4, I explain the reason why farmers share their knowledge in a virtual community. Finally, Chapter 5 concludes the study.

This dissertation makes a contribution to suggest effective targeting methods to transmit information to more people or to spread accurate information by comparing various targeting methods, such as sampling using location information or social networks, which are rarely used in the analysis of development economics. Furthermore, this dissertation clarifies that reciprocity and professional reputation play important roles in enhancing professional knowledge exchange, even in VCoPs using large-scale data from a virtual community. If the members in a VCoP have a common motivation, information exchange can be activated, and such active exchange of information will lead to the growth of the community. As the adoption rate of information and communication technology increases, the demand for E-farming for the effective and efficient dissemination of agricultural information in developing countries may increase. The results of this dissertation will be useful for disseminating accurate information and promoting E-farming in various countries.

2. The Determinants of Detecting Veterinary Drugs Residues: Evidence from Shrimp Farmers in Southern Vietnam

2.1. Introduction

The Food and Agriculture Organization of the United Nations (FAO) has released statistics showing that developing countries account for about 78 percent of total shrimp exports (FAO, 2016). For developing countries, semi-intensive and intensive shrimp aquaculture are profitable businesses, and means of acquiring foreign currency. The producing countries use veterinary medicinal drugs to mitigate the risk of crop failures due to shrimp viral diseases, but such inputs contain substances harmful to the human body such as chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline. Accordingly, the EU, Japan, and the US, the major importers of shrimps, have been raising the standards of quarantine inspections on shrimps from developing countries (UNIDO, 2013).

Unless the exporting countries can change the situation, their market share relative to countries with a reputation for drug-free shipments will decline, and it is expected to hold back the economies of the producing countries (Suzuki & Vu, 2013; UNIDO, 2013). Further, another serious problem is the effect of waste water on the residents in surrounding villages as farmers discharge water to canals (Dierberg & Kiattisimkul, 1996; Jackson, Preston, & Thompson, 2004; Pham et al., 2010; Senarath & Visvanathan, 2001; Taya, 2003; Tzachi et al., 2004). According to Taya (2003), this is an important issue for village people who use river water for domestic and agricultural purposes.

The difficulty in changing the situation lies in the fact that shrimps are mainly produced by small-scale farmers in many of the Asian countries, except in the case of Indonesia. As the producers are numerous and dispersed, it is hard to control their farming practices. Collectors, who purchase shrimps from smallholders and sell to exporters, often mix shrimps from many farmers to fill a container; this makes it even harder to trace the source of problems (Suzuki & Vu, 2016).

Shrimp aquaculture in Vietnam has been growing discernibly since the Doi Moi.[1] Between 1986 and 2013, the country's shrimp exports increased from 20 000 tons to 358 000 tons; in terms of dollar value, it rose from $75 million to over $3 billion over the same period. This represents nearly an 18-fold increase in volume and a 40-fold increase in monetary value, testifying to the remarkable growth achieved by the Vietnamese shrimp industry (FAO, 2016). However, despite the high growth, the number or rate of refusals to Vietnamese shrimps imports continues to grow as shown in Figure 2.1, mainly due to the overuse of veterinary drugs (UNIDO, 2013).

To understand why this issue persists, this study first needs to understand what leads to the use of these prohibited substances among small-scale producers. While there are studies examining the determinants of chemical inputs in agriculture (such as Liu & Huang, 2013), empirical studies in an aquaculture context are few and tend to rely on subjective data or use inappropriate methodologies. Thus, this study focuses on a case of small-scale farmers in southern Vietnam and examine the determinants of antibiotic use in shrimp farming.

The study interviewed 201 shrimp farmers randomly selected from the population list in a district in Ca Mau province in southern Vietnam in 2015 and collected shrimp samples from each household's pond for the screening of residual drugs. The district has a total of 1 546 shrimp farms, and my sample is equivalent to about 13 percent. The drug residue tests were conducted in a laboratory at Can Tho University in 2016. Out of the 201 farms included in the sample, the tests revealed residual veterinary drugs exceeding acceptable limits set by the Japanese Ministry of Health, Labor and Welfare (MHLW) standard[2] in 40 farms' shrimps. I also collected data on the farmers' socio-economic characteristics, social networks, farm

---

[1] Doi Moi is the Vietnamese for the English renovation. The economic reform of Vietnam initiated in 1986 with the goal of creating a socialist-oriented market economy (World Library Foundation, n.d.).

[2] If the MHLW detects an amount of oxytetracycline residue from shrimp samples above 200 ppb, they reject these shrimp imports. The MHLW rejects shrimp imports depending on the presence of chloramphenicol, enrofloxacin, and ciprofloxacin residues (The Japan Food Chemical Research Foundation, 2015).

characteristics, sales performance, risk and time preferences, and farming behaviors by Better Management Practices (henceforth, BMPs). I conducted Logit and Tobit regressions using cross-sectional data to examine whether results of the residue tests were significantly associated with particular farmers' characteristics and farm management practices, as mentioned above.

This study finds that: (1) receiving BMPs training has a significant and positive effect on reducing residual drugs; (2) if farmers trust information on the treatment of shrimp diseases from extension officers, this relationship has a significant and positive effect on reducing residual drugs; and (3) farmers with experience of shrimp disease outbreaks reduce use of antibiotics, which contain veterinary drugs because of distrust in the efficacy of these drugs. My contribution is threefold: (1) I found the above results using objective data on the use of prohibited substances from farmers' pond samples; (2) I showed that social networks and experience matter in the use of these prohibited substances; and (3) I showed that psychological parameters such as time and risk preferences matter in the veterinary drug residues.

The remainder of the study proceeds as follows. In Subchapter 2.2, I review relevant extant literature on veterinary substance abuse in Thailand, risk preferences and pesticide use by cotton farmers in China, and the impact of BMPs on shrimp farming. Subchapter 2.3 describes Vietnam's shrimp industry, the data used herein, presents summary statistics, and experimental designs for eliciting farmers' risk preferences and distinguishing hyperbolic consumers from other survey respondents. Subchapter 2.4 describes the estimation methods used, and the results are presented in Subchapter 2.5. Finally, Subchapter 2.6 concludes the study.

2.2. Previous Literature and Hypotheses

2.2.1. Previous Literature

Currently, there is a dearth of literature examining the determinants of chemical input use in agriculture. Holmstrom et al. (2003) and Liu and Huang (2013) are most relevant to my study, and thus are described below.

The closest comparator to this study is provided by Holmstrom et al. (2003), who conducted interviews with shrimp farmers along the Thai coast in 2000. The interviews were based on a questionnaire regarding management practices and the use of chemicals on farms. Their data reveals that norfloxacin, oxytetracycline, and enrofloxacin are the antibiotics most widely used by Thai shrimp farmers. A large proportion of shrimp farmers, 74 percent (56 out of 76 farmers), use those antibiotics in pond management to prevent and treat shrimp diseases. Based on the interviews, Holmstrom et al. (2003) find that farmers who have experienced shrimp disease outbreaks tend to use greater quantities of antibiotics than farmers who are not experienced in this respect. Furthermore, they find that the age of ponds is also associated with antibiotic use: older ponds were at greater risk of disease outbreaks. In other words, farmers who have recently established farms are less likely to use antibiotics than farmers who have longer-established farms, because they have a lower risk of suffering from shrimp disease outbreaks. Also, they point out that 88 percent of the farmers they interviewed used antibiotics simultaneously with probiotics. One interpretation of such behavior is that a large number of farmers have insufficient or inaccurate information on the effects of antibiotics and probiotics (Holmstrom et al., 2003). While this study exhibits similarities with my aims and objectives, Holmstrom et al. (2003) do not employ inferential quantitative methods such as regression analysis; they rely solely on farmers' subjective answers to questions regarding the use of antibiotics and pesticides. Thus, their answers may not generalize well beyond these subjectively ascertained answers. By contrast, my study provides objective indicators for drug residues.

Another important study in this domain is Liu and Huang (2013), which revealed a relationship between Chinese cotton farmers' risk preferences and pesticide use—to combat *Bacillus thuringiensis*—using primary data collected by the Center for Chinese Agricultural Policy (CCAP) in four provinces (Shandong, Hebei, Henan, and Anhui) in 2006. These data consist of detailed information about 320 farmers' inputs to and outputs from cotton plots, experiences of pesticide poisoning, and risk preferences. Their methodology was mainly based on the experimental design of Tanaka, Camerer, and Nguyen (2010). Results therein revealed that more risk-averse farmers applied greater amounts of pesticides in an effort to minimize infestation risks, while more loss-averse farmers tended to use fewer pesticides. In terms of the latter group, the authors note that loss aversion was conceptualized and characterized in terms of aversion to negative health impacts incurred because of pesticide poisoning, rather than aversion to economic (cotton yield) losses (Liu & Huang, 2013).

A guide for good aquaculture practice, called better management practices (BMPs), was developed by the international community, spearheaded by the World Bank, the Network of Aquaculture Centers in Asia-Pacific (NACA), the World Wildlife Fund (WWF), FAO, and the United Nations Environment Program (UNEP). The purpose of BMPs is to improve farmers' management practices, delivering increased profitability and environmental performance through more efficient use of resources (Khiem et al., 2010; Mantingh and V.H., 2008; NACA, 2006, UNIDO, 2013).

In particular, NACA has implemented BMPs in several countries, such as Indonesia, Thailand, and Vietnam. According to NACA (2016), well-designed and -implemented BMPs support smallholder shrimp aquaculture to 1) increase productivity by reducing the risk of shrimp disease outbreaks, 2) mitigate the impacts of farming on the environment, 3) improve food safety and the quality of shrimp farm products, and 4) improve the social benefits from shrimp farming and its social acceptability and sustainability. BMPs are likely to play a significant role in enhancing the quality of shrimp, as well as the welfare of farmers.

During the 2004 crop, NACA implemented a project to promote BMPs as a useful disease control method in Vietnam—in Ca Mau, Nghe An, Ha Tinh, Quang Ninh, and Khanh Hoa provinces. To promote BMPs to these pilot farming communities, they provided advice on pond preparation, stocking practices, pond management, and health management for shrimp farmers and distributed materials about BMPs to the farmers. Overall, pilot farmers accepted a solution for shrimp health problems that involved no use of antibiotics or other chemicals. The farmers also recognized the importance of keeping records on management practices and started to keep records concerning water quality and shrimp health status (NACA, 2006). NACA's analysis shows the differences between the shrimp mortality experiences of pilot farmers who followed BMPs and the experiences of a comparison (control) group during the production cycle. Their results reveal that the application of BMPs by farmers significantly decreases shrimp mortality, and that pilot farmers' productivities are considerably higher than farmers who do not follow BMPs (NACA, 2006).

In summary, these studies point out that the use of chemicals seems to correlate with farmers' prior experiences of shrimp disease outbreaks, the age of shrimp ponds, risk and time preferences of famers, and experience of BMPs training.

2.2.2. Hypotheses

Based on the previous studies, I specify the following hypotheses.

Hypothesis 1:

The BMPs training decreases farmers' use of antibiotics, because farmers who follow BMPs can control shrimp diseases without antibiotics.

Hypothesis 2:

More risk-averse farmers will use greater amounts of antibiotics in their ponds to minimize the risk of shrimp mortality.

Hypothesis 3:

Farmers with inconsistent time preferences ("hyperbolic consumers," as explained below) will overuse antibiotics because they tend to buy on impulse.

Hypothesis 4:

Farmers who nominate extension officers as the most reliable information source on treating shrimp diseases or know more shrimp input sellers will not use products that contain prohibited elements because they are able to get more and various information on products from multiple sources.

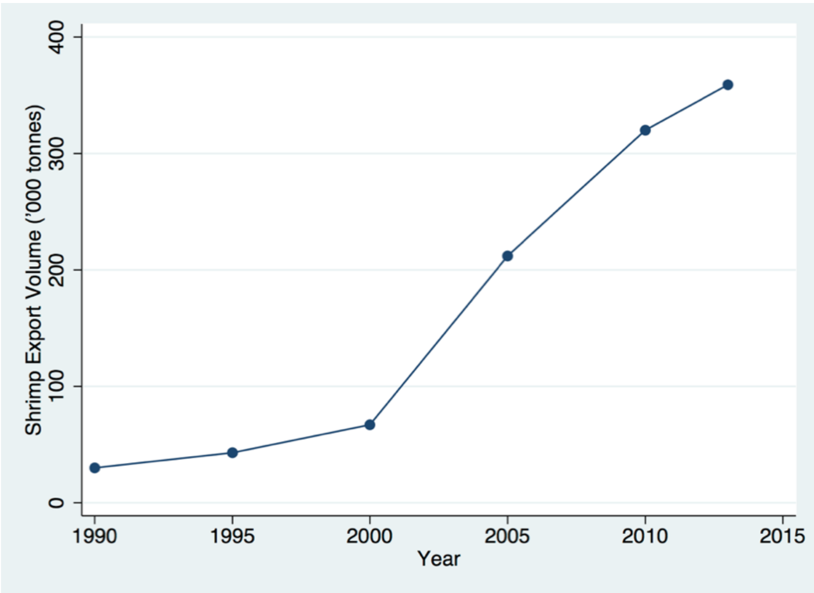
As mentioned in Subchapter 2.1, residual quantities of four substances form the basis of my hypothesis testing, i.e., chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline.[3]

[3] The residual drugs may come from different sources such as antibiotics, industrial feeds, shrimp seeds, and so on. Therefore, it is possible to detect these residuals even if farmers do not use antibiotics.

2.3. Study Context, Data, and Summary Statistics

2.3.1. Vietnamese Shrimp Industry and Port Rejection Rates

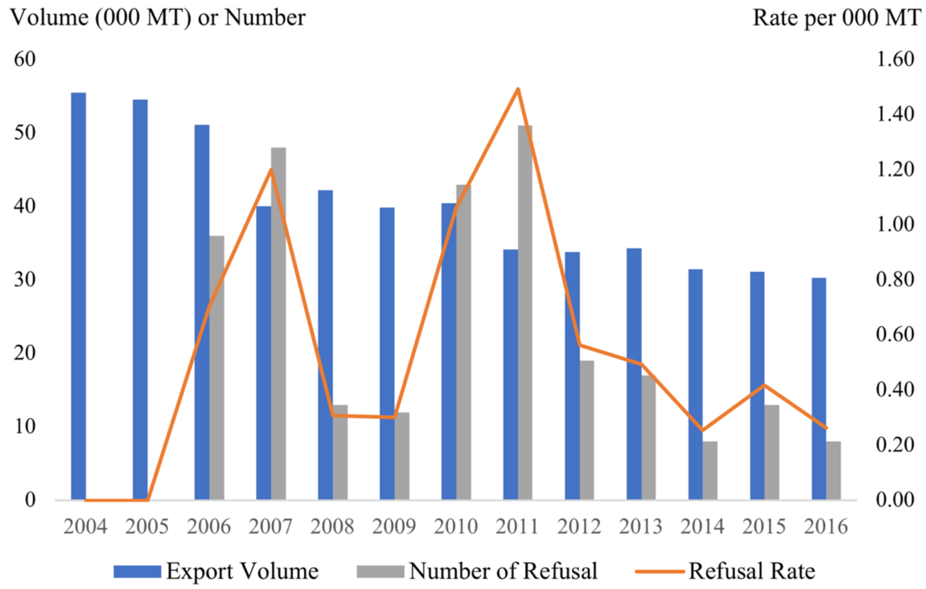
Since market liberalization, the Vietnamese government has fostered a more strategic approach to shrimp aquaculture. Consequently, in 2013, Vietnam was ranked as the largest exporter of shrimp in the world (UNIDO, 2013; FAO, 2016). Figure 2.1 shows the trend in the country's shrimp exports between 1990 and 2013. During this period, Vietnamese shrimp exports increased from 20 000 tons to 358 000 tons. This represents nearly an 18-fold increase in volume, and shrimp farming has become a multi-billion-dollar industry.



Source: Based on FAO

Figure 2. 1. Vietnam's Shrimp Exports between 1990 and 2013

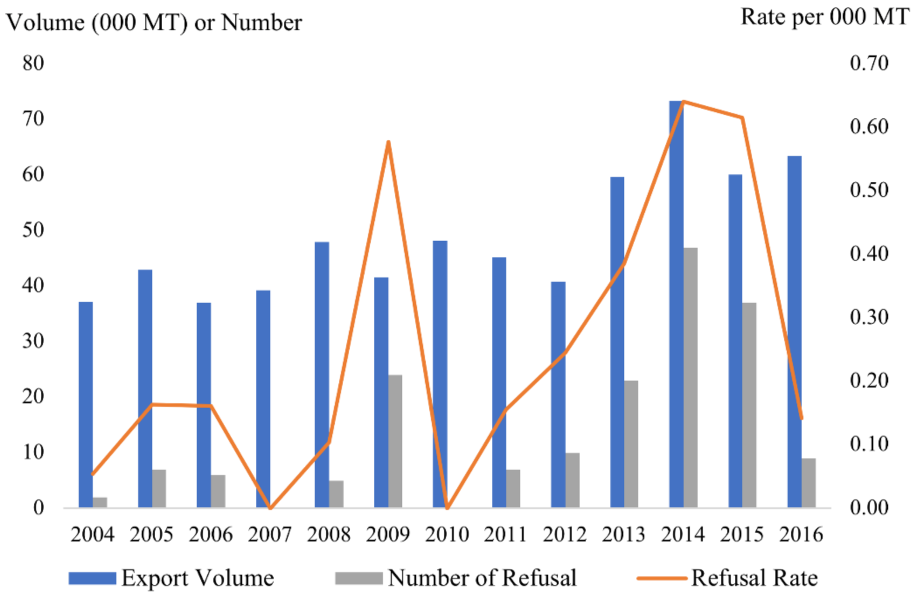
Figure 2.2 shows that the volume of Vietnamese Shrimp exports to Japan and the US, and the number or rate of Vietnamese shrimp refusals for veterinary drug Residues in those countries. The refusal rate per thousand metric tons peaked at 1.49 in 2011 and then dropped to 0.56 in 2012. In 2016, the rate further decreased to 0.26. In 2004, the volume of Vietnamese shrimp imports into Japan was higher than those in the US but began to decline gradually from 2006. In 2016, Vietnam exported shrimp to Japan amounted to 30 thousand metric tons, only half of US imports. The reason for the decline in exports of Vietnamese shrimp destined to Japan seems to be related to the fact that Japan's total shrimp imports have decreased by half in the past two decades (SEAFOOD NEWS.COM, 2014).



Notes: The refusal rates are estimated by dividing the number of cases by the volume of exports.
Source: The volume of Vietnam's shrimp export is calculated based on MAFF, and the refusals of shrimp entry lines for veterinary drug residues is calculated based on MHLW data

Figure 2. 2. The Volume of Vietnam's Shrimp export to the Japan, and the Number and Rate of Vietnamese Shrimp Refusals for Veterinary Drug Residues in those Countries

As shown in Figure 2.3, the US imports of shrimp from Vietnam increased sharply between 2012 and 2014, and the US imports of Vietnamese shrimp in 2014 reached 73 thousand metric tons, up 78 percent from 2012. During the same period, the number of the US refusals of Vietnamese shrimp contaminated with banned drugs also increased about 5-fold in 2014 compared to 2012. The refusal rate due to veterinary drug residues at the US is relatively small compared to Japan. The rate per thousand tons peaked at 0.64 in 2014 and then dropped to 0.16 in 2016. Overall, the Vietnamese shrimp industry has unequivocally grown regarding quantity, yet it appears that a number of problems remain, such as veterinary drug residues, that diminish the quality profile of this growth.



Notes: The refusal rates are estimated by dividing the number of cases by the volume of exports.
Source: The volume of Vietnam's shrimp export is calculated based on NOAA data, and the refusals of shrimp entry lines for veterinary drug residues is calculated based on FDA data

Figure 2. 3. The Volume of Vietnam's Shrimp export to the US, and the Number and Rate of Vietnamese Shrimp Refusals for Veterinary Drug Residues in those Countries

2.3.2. Shrimp Survey

Figure 2.4 presents my study site, Ca Mau province, which is located in the southernmost part of Vietnam and is surrounded by water on three sides. The province attained and maintained a shrimp industry by virtue of its geographical advantages. In an effort to grow the industry, they created 9 650 hectares of industrial shrimp farming area, and intensive shrimp farming area in this province reached about 98 600 hectares in 2016, which was nearly 18 percent of the total area in Ca Mau province (see Figure 2.5). As a result, the province is currently the largest shrimp producer in Vietnam with output of more than 145 000 tons in 2016, which is 23 percent of the country's total shrimp production. The value of the province’s shrimp exports is about $1 billion in 2016, representing around 30 percent of Vietnam’s total shrimp exports (VASEP, 2017).

Source: Based on GADM (2015)

Figure 2. 4. The Map of Vietnam

Source: From own survey

Figure 2. 5. Bird's Eye View of Ca Mau

To examine the determinants of antibiotic use by shrimp farmers in Vietnam, I conducted a household survey in Ca Mau province in 2015, collecting information from 201 households.[4] Concomitantly, shrimp samples were taken from the ponds of these 201 households and screened for residual antibiotics. The respondents were chosen randomly among shrimp farmers, who live in a district of the Ca Mau province, using population lists that were obtained from the Ca Mau provincial government. The district has a total of 1 546 shrimp farms, and my sample is equivalent to about 13 percent. The data include information on farmers' social networks, farm characteristics, sales performance, and behavior regarding BMPs, as well as their socio-economic characteristics. The cornerstone of these data is the results from laboratory tests for antibiotic residues. I chose four substances for the purposes of drug residue testing: chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline.[5] The tests were conducted in the food safety laboratory of the Department of Aquatic Nutrition and Product Processing in the College of Aquaculture and Fisheries, Can Tho University. Shrimp samples were collected directly from farmers' ponds by university staff and transported in ice-cold storage boxes. Residues were analyzed using liquid chromatography–mass spectrometry (LCMS). The results revealed that chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline were indeed detected in the shrimp produced by 13 households, 22 households, 15 households, and 11 households, respectively. Specifically, and importantly, substances found in 40 samples exceeded amounts allowed by the MHLW standard, as shown in Table 2.1. Out of 201 samples, 147 samples are used for my regression analysis because of missing data on farm characteristics, BMPs, and so on. The number of samples is reduced, but the percentage of detected and undetected is almost the same as the result of testing 201 samples.

[4] This survey was granted permission by Ca Mau Department of Agriculture and Rural Development.
[5] This was based on advice from industry experts, as these are the most frequently tested and detected substances at the ports of developed countries.

Table 2. 1. The Number of Shrimp Farms where Veterinary Drugs were detected above the MHLW Standard

Substances	Undetected	Share	Detected	Share
201 Samples analyzed using LCMS				
Veterinary drug	161	80%	40	20%
Chloramphenicol (CML)	188	94%	13	6%
Ciprofloxacin (CIPRO)	186	93%	15	7%
Enrofloxacin (ENR)	179	89%	22	11%
Oxytetracycline (OTC)	190	95%	11	5%
147 Samples used for Regression Analysis				
Veterinary drug	118	80%	29	20%
Chloramphenicol (CML)	135	92%	12	8%
Ciprofloxacin (CIPRO)	137	93%	10	7%
Enrofloxacin (ENR)	131	89%	16	11%
Oxytetracycline (OTC)	140	95%	7	5%

Notes: I collected one sample per farm. Residues were analyzed using LCMS. The MHLW allows less than 200 ppb of oxytetracycline residues. The MHLW rejects shrimp imports depending on the presence of chloramphenicol, enrofloxacin, and ciprofloxacin residues.

Source: From own survey

Table 2.2 summarizes 147 respondents' socio-economic characteristics, farm characteristics, and sales performance. The average age of interviewees is about 50 years old, and most of them are male. On average, they have completed eight years of formal school education and resided for 44 years in each commune. A significant difference is found in shrimp farming experience which is higher in the non-detection group. This result suggests that more experienced farmers use less veterinary drugs. Unlike Holmstrom's finding mentioned in sub-section 2.1, the rate of farmers who experienced shrimp disease in the detection group is lower than that of the non-detection group. This is statistically insignificant but notable. Farm size, number of ponds, and seed price are not very different between these groups. Seed density, however, is slightly higher for the "detected" group. The shrimp seed cost variable is created by multiplying three variables, which are shrimp farm size, shrimp seed density, and shrimp seed price. We find that the cost of shrimp feed per hectare is higher for the "undetected" group relative to the "detected" group, but the difference is not statistically significant. Other components of farming costs and revenue per hectare are also not importantly different between the two groups.

Table 2. Socio-economic and Farm Characteristics, and Sales Performance

		(a) Undetected		(b) Detected		Dif.
Variable	Unit	Obs	Mean	Obs	Mean	(a) - (b)
Socio-economic Characteristics						
Gender	Female=0	118	0.94	29	0.90	0.04
	Male=1		[0.24]		[0.31]	(0.05)
Age	Years	118	48.62	29	52.28	-3.66
			[11.99]		[11.04]	(2.45)
Education	Years	118	7.89	29	8.07	-0.18
			[2.94]		[3.21]	(0.62)
Length of residence in commune	Years	118	43.67	29	44.76	-1.09
			[16.68]		[16.92]	(3.47)
Non-farm activities	No=0	118	0.18	29	0.10	0.07
	Yes=1		[0.38]		[0.31]	(0.08)
σ (Risk aversion)	Index	118	5.42	29	5.83	-0.40
			[1.28]		[0.66]	(0.25)
λ (HC)	No=0	118	0.46	29	0.48	-0.02
	Yes=1		[0.50]		[0.51]	(0.10)
Farm & Sales Performance						
Shrimp farming experience	Years	118	8.56	29	5.86	2.69*
			[8.07]		[5.05]	(1.57)
Previous disease outbreaks	No=0	118	0.68	29	0.59	0.10
	Yes=1		[0.47]		[0.50]	(0.10)
Total farm land	ha	118	1.31	29	1.44	-0.13
			[1.66]		[1.80]	(0.35)
Shrimp farm size	ha	118	1.27	29	1.44	-0.17
			[1.57]		[1.80]	(0.34)
# of ponds	Number	118	2.95	29	2.97	-0.02
			[2.28]		[1.59]	(0.45)
Shrimp seed density	Piece/m^2	118	70.54	29	78.10	-7.57
			[77.56]		[96.66]	(16.91)
Shrimp seed price	VND/piece	118	95.17	29	97.27	-2.10
			[20.21]		[11.44]	(3.90)
Cost of shrimp seed	Million VND/ha	118	62.10	29	65.32	-3.22
			[76.42]		[69.80]	(15.58)
Cost of shrimp feed	Million VND/ha	118	369.85	29	221.66	148.19
			[597.59]		[251.28]	(113.59)
Cost of permanent labors	Million VND/ha	118	19.08	29	11.16	7.92
			[62.40]		[35.39]	(12.06)
Cost of casual labors	Million VND/ha	118	5.04	29	4.29	0.75
			[17.16]		[15.65]	(3.50)
Revenue	Million VND/ha	118	272.87	29	218.86	54.02
			[499.66]		[260.39]	(96.00)

Notes: Standard deviations are reported in brackets. Standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.3 illustrates respondents' social network characteristics and their behaviors regarding BMPs. The farmers in the non-detection group know more buyers, seed sellers, and input sellers than do farmers in the detection group. 75 percent of the farmers in the non-detection group answered that they had received BMPs training. This is about 17 percent higher than the detection group, and the difference between the two groups is statistically significant at the 0.01 level. Nearly 85 percent of farmers in both groups do not know the exact names of prohibited elements and which inputs contain these elements.

Table 2. 2. Social Network Characteristics and Better Management Practices

		(a) Undetected		(b) Detected		Dif.
Variable	Unit	Obs	Mean	Obs	Mean	(a) - (b)
Social Network						
# of shrimp buyers	Number	118	7.82	29	6.34	1.48
			[6.21]		[7.06]	(1.32)
# of shrimp seed sellers	Number	118	4.69	28	4.32	0.37
			[5.91]		[4.11]	(1.18)
# of shrimp input sellers	Number	118	4.25	29	4.03	0.22
			[5.35]		[3.82]	(1.05)
Better Management Practices						
BMPs training	No=0	118	0.75	29	0.59	0.17*
	Yes=1		[0.43]		[0.50]	(0.09)
Knowledge on antibiotics	No=0	118	0.19	29	0.10	0.08
	Yes=1		[0.39]		[0.31]	(0.08)
Knowledge on products	No=0	118	0.11	29	0.07	0.04
	Yes=1		[0.31]		[0.26]	(0.06)
Recording water quality	No=0	118	0.16	29	0.10	0.06
	Yes=1		[0.37]		[0.31]	(0.07)
Recording seed use	No=0	118	0.47	29	0.41	0.05
	Yes=1		[0.50]		[0.50]	(0.10)
Recording input use	No=0	118	0.34	29	0.34	-0.01
	Yes=1		[0.48]		[0.48]	(0.10)
Recording feed use	No=0	118	0.47	29	0.45	0.03
	Yes=1		[0.50]		[0.51]	(0.10)
Recording sales price	No=0	118	0.37	29	0.38	-0.01
	Yes=1		[0.49]		[0.49]	(0.10)
Recording sales volume	No=0	118	0.30	29	0.31	-0.01
	Yes=1		[0.46]		[0.47]	(0.10)

Notes: Standard deviations are reported in brackets. Standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Lastly, Table 2.4 describes the informants whom respondents rely on to obtain information on shrimp cultivation technologies and shrimp disease control; in each case respondents were permitted to select only one answer. Regarding shrimp cultivation technology, 90 percent of all respondents stated that they obtained information from their friends, with only 4 percent of respondents depending on extension officers. Concerning shrimp disease treatment information, most people also responded that they acquired this information from their friends. However, the number of respondents depending on extension officers in this respect increased 16 percent compared to the previous question. Furthermore, I observed a difference between the two groups in terms of the degree of reliance on extension agents to obtain information. For both shrimp cultivation and treatment of diseases, the share of farmers relying on extension officers is higher for the undetected group.

Table 2. 3. Types of Information Sources for Shrimp Cultivation in each Household

	Undetected	Detected	Total
Shrimp Cultivating Technology			
Friends	104 (88%)	29 (100%)	133 (90%)
Input seller	3 (3%)	0 (0%)	3 (2%)
Extension officer	6 (5%)	0 (0%)	6 (4%)
Others	5 (4%)	0 (0%)	5 (3%)
Total	118 (100%)	29 (100%)	147 (100%)
Treating Diseases			
Friends	84 (71%)	24 (83%)	108 (73%)
Input seller	6 (5%)	1 (3%)	7 (5%)
Extension officer	22 (19%)	2 (7%)	24 (16%)
Family	1 (1%)	0 (0%)	1 (1%)
Others	5 (4%)	2 (7%)	7 (5%)
Total	118 (100%)	29 (100%)	147 (100%)

Source: From own survey

2.3.3. Risk Preferences

Several studies posit that farmers' risk preferences play a significant role in agricultural decision-making (Feder, 1980; Just et al., 1983; Liu & Huang, 2013). Liu and Huang (2013) empirically test the correlation between Chinese cotton farmers' risk preferences and pesticide use (to combat Bt) and find that more risk-averse farmers use greater quantities of pesticides. Based on their findings, I assume that shrimp farmers' risk preferences have significant effects on the use of veterinary drugs.

To elicit individual risk preferences, either prospect theory (henceforth, PT) or expected utility theory (henceforth, EUT) approaches can be employed. PT adopts three parameters, such as risk aversion, loss aversion, and nonlinear probability weighting, for determining the shape of the utility function. On the other hand, EUT uses risk aversion as the sole parameter. Agricultural economists have debated which theory is most suitable to capture farmers' risk preferences (Kahneman & Tversky, 1979; Liu & Huang, 2013; Moscardi & Janvry, 1977; Tanaka et al., 2010). This study adopts Suzuki's approach, which follows EUT instead of PT, favoring the simplicity of this method to elicit individual risk preferences in order to create risk-aversion indices for farmers (Suzuki, 2015).

Each farmer's risk-aversion index is based on the results of a survey-based risk preference game (see Table 2.5). This risk preference game has six stages and two options, namely, projects A and B, with different probabilities of receiving prizes. To elaborate, farmers who choose project A, definitely win (100 percent chance) a prize at each stage, while if farmers select project B, they have a fifty-fifty chance of winning the reward. Apart from stage six, the amount of the prize associated with project B is higher than project A, but the risk is also higher. Because their decisions are considered irrational, I drop those observations where project B is chosen in stage 6. The risk-averse index, then, is as follows:

$$\sigma = \sum_{s=1}^{n} V_s \tag{2.1}$$

where s denotes each stage of the risk preference game; V_s equals 1 if project A is chosen at stage s, and zero otherwise; and σ is the risk-averse index. The index ranges from 1 (least risk-averse) to 6 (very risk-averse). Table 2.2 indicates that farmers in the non-detection group have lower risk-averse indexes σ than the detection group. In other words, it appears that farmers in the detection group tend to avoid risks more than do the non-detection group. However, this difference between the two groups is not statistically significant.

Table 2. 4. Risk Preference Game

	Project A	**Project B**	
	You obtain for sure:	50% chance of obtaining:	50% chance of obtaining
S1	1 million VND	2 million VND	0 VND
S2	1.2 million VND	2 million VND	0 VND
S3	1.4 million VND	2 million VND	0 VND
S4	1.6 million VND	2 million VND	0 VND
S5	1.8 million VND	2 million VND	0 VND
S6	2 million VND	2 million VND	0 VND

2.3.4. Hyperbolic Discounting

Hyperbolic discounting has an advantage in terms of explaining an individual's time-inconsistent preferences (Ainslie, 1996). For that reason, the number of studies that adopt hyperbolic discounting functions is increasing (Angeletos et al., 2001; Kubota & Fukushige, 2009; Laibson, 1996; Morimoto, 2009). Furthermore, Morimoto (2009) identified differences between hyperbolic consumers (time inconsistency) and non-hyperbolic consumers (time consistency) vis-à-vis spending behavior, using panel data from a household survey in Japan. According to Morimoto (2009), the hyperbolic consumer is inclined to spend money on impulse even if s/he has a saving plan for the future. On the other hand, non-hyperbolic consumers are more likely to adhere to personal spending plans and saving schemes.

To demarcate hyperbolic consumers, I tested respondents using a time preference game, which is pioneered by Tversky and Kahneman (1986) and Benzion et al. (1989) among others, and extended by Ashraf et al. (2006) (Table 6). This game has ten stages in two series and two options—project A and B—associated with different paydays and different amounts of money. In series 1, a player who chooses project A receives an immediate prize in each stage. If the player prefers project B, the award is paid three months from now. Overall, the amount of money associated with project B is higher than project A, and the difference of payment between project A and B shows how much the respondent will be compensated for the time they wait to receive the payment. Thus, the earlier the respondent switches from project A to B, the more patient s/he is. If s/he chooses project B from S1, it shows that the person is very patient. I dropped the observations who switched from project B to A because their choices are considered irrational.

Series 2 has the same conditions as series 1, but the payment is three months later for project A and six months later for project B. If the respondent's switching point from project A to B is different between Series 1 and 2, his/her time preference is inconsistent over time, and we call him/her a "hyperbolic consumer," following Ashraf, et al. (2006) among others.

Based on the results of this game, I use a dummy variable for indicating whether a farmer is a hyperbolic consumer or not as follows:

$$\lambda = \begin{cases} 1 \text{ if } \dfrac{U(a)}{U(b)} > \dfrac{U(c)}{U(d)} \\ 0 \text{ otherwise} \end{cases} \tag{2.2}$$

where $U(a)/U(b)$ is a discount factor for series 1; $U(c)/U(d)$ is a discount factor for series 2; λ is the hyperbolic consumer dummy, equal to one if series 1's discount factor is greater than series 2's and 0 otherwise. Table 2.2 shows that 47 percent of the farmers are hyperbolic consumers. Among the non-detection group, this is about 2 percent lower, although the difference between the two groups is not statistically significant.

Table 2. 5. Hyperbolic Discounting

Series 1	**Project A** Today (a)	**Project B** 3 months later (b)
S1	2 million VND	2.2 million VND
S2	2 million VND	2.4 million VND
S3	2 million VND	2.6 million VND
S4	2 million VND	2.8 million VND
S5	2 million VND	3 million VND
S6	2 million VND	3 million VND
S7	2 million VND	3.4 million VND
S8	2 million VND	3.6 million VND
S9	2 million VND	3.8 million VND
S10	2 million VND	4 million VND
Series 2	**Project A** 3 months later (c)	**Project B** 6 months later (d)
S1	2 million VND	2.2 million VND
S2	2 million VND	2.4 million VND
S3	2 million VND	2.6 million VND
S4	2 million VND	2.8 million VND
S5	2 million VND	3 million VND
S6	2 million VND	3.2 million VND
S7	2 million VND	3.4 million VND
S8	2 million VND	3.6 million VND
S9	2 million VND	3.8 million VND
S10	2 million VND	4 million VND

2.4. Empirical Strategy

Using the combined data from the household survey and the screenings for residual antibiotics, I first evaluate the average marginal probability effects (AMPE) in the Logit model to test the hypotheses stated above:

$$\Pr\left(Y_{ijk} = 1\right) = \beta_0 + \beta_1 SC_{ijk} + \beta_2 FP_{ijk} + \beta_3 BMP_{ijk} + \beta_4 SN_{ijk} + \beta_5 \lambda_i + \varepsilon_{ijk} \qquad (2.3)$$

where i denotes individual, j denotes veterinary drug, and k denotes commune; Y_j is the detection dummy for each veterinary drug j (chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline) equal to one where a sample is found to contain more than the amount permissible by the MHLW and 0 otherwise; *SC* captures individual i's socio-economic characteristics and *FP* is individual i's farming characteristics and sales performance relevant to the abuse of antibiotic j; *BMP* is a dummy variable for the BMPs training; *SN* refers to individual i's social network characteristics, such as how many shrimp input sellers individual i knows. *SN* also contains the extension officer dummy. The dummy equals to one where individual i nominates extension officers as a reliable information source on treating shrimp diseases and 0 otherwise; λ is the hyperbolic consumer dummy variable, and ε_{ijk} is the error term.

Next, equations (4) and (6) are estimated using the Tobit model, because my dependent variable is a mixture of observations with zero and positive values (Cameron & Trivedi, 2010). Among the four substances tested, for three (i.e., chloramphenicol, enrofloxacin, and ciprofloxacin), any amount detected is subject to rejection, while for oxytetracycline there is a threshold for rejection set by the MHLW. I therefore created an index that shows the total number of substances detected, and also used the quantity of oxytetracycline as dependent variables. The regressions are as follows:

$$\sum_{j=1}^{n} Y_{ijk} = \beta_0 + \beta_1 SC_{ijk} + \beta_2 FP_{ijk} + \beta_3 BMP_{ijk} + \beta_4 SN_{ijk} + \beta_5 \sigma_i + \beta_6 \lambda_i + \mu_k + \varepsilon_{ijk} \quad (4)$$

$$Y_{iok} = \beta_0 + \beta_1 SC_{iok} + \beta_2 FP_{iok} + \beta_3 BMP_{iok} + \beta_4 SN_{iok} + \beta_5 \sigma_i + \beta_6 \lambda_i + \mu_k + \varepsilon_{iok} \quad (5)$$

where o denotes oxytetracycline; $\sum_{j=1}^{n} Y_{ijk}$ is the total number of substances detected—for example, if two of the four drugs are detected, the value is two—the variable's minimum (maximum) value is zero (four); and Y_{iok} denotes the amount of oxytetracycline residue—if the substance is not detected the value is zero parts per billion (ppb). σ is the risk-averse index of individual i; μ_k is commune fixed effect.

2.5. Estimation Results

The study evaluates AMPE in the Logit model to examine the determinants of chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline residues. In order to avoid bias due to perfect prediction, both commune dummy variables and the variable for risk aversion are excluded from the analyses. The AMPE results shown in Table 2.7 indicate that the probabilities of detecting any drug and chloramphenicol residues increase as the age of respondents increases. The result in column (2) shows that the probability of detecting chloramphenicol decreases as the size of shrimp farm increase. The use of expensive feeds has positive and significant effects on lowering the probability of detecting chloramphenicol and enrofloxacin. In magnitude, the probability of the two antibiotic residues decreases by about 0.1 percent as the expenditure on feeds increases by 1 million VND per hectare. The following results support hypotheses 1 and 4. The BMPs training dummy indicates a negative and significant impact on chloramphenicol residues: receiving this training decreases the probability of detecting any drug residues by 13 percent. Where farmers nominate extension officers as the most reliable information source on treating shrimp diseases, the probability of detecting any drug residue decreases by 18 percent and, again, this decrease is statistically significant. While the dummy extension officer is insignificant in the models (2) to (5), it shows significance in the model (1). This is likely to be because the number of observations who are detected (i.e., the dependent variable is 1) is more in the model (1) than in other models, and this allows us to have enough variations in the data to show the trend more clearly.

Table 2. 6. Determinants of the Veterinary Drug Residue: Average Marginal Probability Effects (AMPEs) from the Logit Model

Dependent variable	Dummy drug	Dummy CML	Dummy ENR	Dummy CIPRO	Dummy OTC
	(1)	(2)	(3)	(4)	(5)
Respondent's age	0.01*	0.004***	0.002	0.001	-0.001
	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
Years of education	0.01	-0.002	0.001	0.00003	-0.003
	(0.01)	(0.007)	(0.01)	(0.01)	(0.01)
Shrimp farming experience	-0.01	-0.01	-0.001	-0.002	-0.003
	(0.01)	(0.01)	(0.004)	(0.002)	(0.004)
Shrimp seed density/m^2	0.0005	0.0002	0.0003	-0.0001	0.0001
	(0.0005)	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Shrimp farm land	0.001	-0.06*	0.01	0.01	0.001
	(0.02)	(0.04)	(0.01)	(0.01)	(0.01)
Shrimp seed price/piece	0.001	0.0004	-0.00001	-0.0001	0.0002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Cost for feeding/ha	-0.0002**	-0.0001*	-0.00005*	-0.00002	-0.00003
	(0.0001)	(0.0001)	(0.00003)	(0.00001)	(0.00002)
Previous disease outbreaks	-0.10	0.06	-0.10*	-0.07	-0.01
	(0.07)	(0.07)	(0.06)	(0.05)	(0.03)
BMPs training	-0.13*	-0.09*	-0.07	-0.07	-0.002
	(0.07)	(0.05)	(0.06)	(0.05)	(0.05)
λ (HC)	-0.02	-0.03	-0.04	-0.05	0.05
	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)
No. shrimp input sellers	-0.001	0.001	0.001	0.001	-0.002
	(0.01)	(0.003)	(0.004)	(0.003)	(0.002)
Dummy extension officers	-0.18*	-0.09	-0.11	0.04	
	(0.10)	(0.06)	(0.09)	(0.07)	
Commune fixed effect	No	No	No	No	No
Observations	147	147	147	147	147
Pseudo R2	0.16	0.31	0.10	0.10	0.08

Notes: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Dummy drug is a dummy variable for detecting any drug residues. The dummy equals to 1 if any of those such as chloramphenicol, chloramphenicol, enrofloxacin, and oxytetracycline is detected to contain more than the MHLW permissible amount of the drugs. Otherwise, it is 0. CML is the abbreviation for chloramphenicol, ENR is the abbreviation for enrofloxacin, CIPRO is the abbreviation for ciprofloxacin, OTC is the abbreviation for oxytetracycline.

Tables 2.8 and 2.9 show the marginal effects from estimating the Tobit model in terms of equations (4) and (5), respectively. The total number of antibiotics detected is the dependent variable in Table 2.8. The amount of oxytetracycline residues is explained by independent variables in Table 2.9. Tables 2.8 and 2.9 contain different models for each column because there are several explanatory variables that seem to be correlated with the error term, which may cause the endogeneity problem. The study, thus, divide models of equations (4) and (5) into four, respectively, and test whether the level of significance and the sign would change by adding these variables step by step. Depending on the model, both tables include different explanatory variables as listed below. Column (1) includes variables for individual *i*'s socio-economic characteristics, farm characteristics, and sales performance, but excludes the dummy variable for BMPs, risk-aversion index, hyperbolic consumer dummy, and individual *i*'s social network features. Column (2) excludes the risk-aversion index, hyperbolic consumer dummy, and individual *i*'s social network features. Column (3) excludes individual *i*'s social network characteristics only. The models in columns (4) contain all of the variables in equations (2) and (3).

In Table 2.8, the marginal effects from Tobit shown in all columns confirm that the total number of detected veterinary drugs increases by 0.004 as the age of respondents increases by 1 year. The dummy variable for receiving BMPs training is statistically significant in column (4) and decreases the number of antibiotics detected by about 0.21. While it may seem small considering that the maximum of the dependent variable is 4, we should note that this is for a subpopulation where the detected value is positive. Thus, it means that for those who are already tested positive, which is 21% of the sample (Table 2.1), if they participate in a BMP training, the number of substance detected will be reduced by 0.21. The dummy for extension officers decreases the total number of antibiotics detected by 0.23, which is statistically significant at 10 percent level. Similar to the results in Table 2.7, these results directly support hypotheses 1 and 4. In addition, the explanatory variables such as shrimp farming experience and previous disease outbreaks experience are statistically significant in reducing the total number of antibiotics detected. On the other hand, the dummy for extension officers, risk aversion, and hyperbolic consumer variables are insignificant. This result indicates that hypotheses 2, 3, and 4 were not supported.

Table 2. 8. The Sum of Veterinary Drugs: Marginal Effects from the Tobit Model

Dependent variable	Total number of antibiotics detected (0-4)			
	(1)	(2)	(3)	(4)
Respondent's age	0.01*	0.01*	0.01	0.01
	(0.004)	(0.004)	(0.004)	(0.004)
Years of education	0.02	0.02	0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Shrimp farming experience	-0.02**	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Shrimp seed density/m^2	0.0004	0.001	0.0004	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)
Shrimp farm land	0.04	0.04	0.03	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
Shrimp seed price/piece	-0.001	-0.0001	0.0001	-0.0001
	(0.002)	(0.003)	(0.003)	(0.003)
Cost for feeding/ha	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Previous disease outbreaks	-0.16	-0.20*	-0.22*	-0.22*
	(0.12)	(0.12)	(0.12)	(0.11)
BMPs training		-0.20	-0.18	-0.21*
		(0.13)	(0.13)	(0.13)
σ (Risk aversion)			0.08	0.06
			(0.05)	(0.05)
λ (HC)			-0.03	-0.02
			(0.11)	(0.11)
No. shrimp input sellers				-0.01
				(0.01)
Dummy extension officers				-0.23*
				(0.13)
Commune fixed effect	Yes	Yes	Yes	Yes
Observations	147	147	147	147
Pseudo R2	0.08	0.09	0.10	0.11

Notes: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Nine communes exist in our data set. I compute marginal effects for the left-truncated mean, $E(y|x,y>0)$. 118 censored observations at the number of antibiotics detected=0. Marginal effects for dummy variables (disease outbreak, BMPs training, HC) are discrete change from the base level.

Unlike other antibiotics which the MHLW rejects shrimp import depending on the presence of the substances, in the case of oxytetracycline, the MHLW permits the import if the concentration is less than 200ppb. Therefore, the model which uses the amount of oxytetracycline as the dependent variable focuses on reducing the amount. The amount of oxytetracycline detected ranges from 0 to 1,667 ppb. The results shown in Table 2.9 indicates that having a prior experience of shrimp disease outbreaks decreases the amount of oxytetracycline residue by about 40 ppb. The BMPs training dummy shown in all columns has a negative effect on the use of oxytetracycline, but the result is statistically insignificant. In Column (4), the dummy for extension officers indicates that the amount of oxytetracycline detected is reduced by about 45.26 ppb, which is statistically significant at 10 percent level.

Table 2. 9. The Amount of Oxytetracycline Residue: Marginal Effects from the Tobit Model

Dependent variable	Amount of OTC detected			
	(1)	(2)	(3)	(4)
Respondent's age	-1.03	-1.04	-1.03	-0.93
	(0.81)	(0.82)	(0.81)	(0.77)
Years of education	-0.93	-1.07	-1.06	-0.36
	(3.83)	(3.85)	(3.84)	(3.68)
Shrimp farming experience	-1.36	-0.83	-0.78	-0.51
	(1.42)	(1.44)	(1.39)	(1.24)
Shrimp seed density/m^2	0.07	0.10	0.10	0.09
	(0.12)	(0.13)	(0.13)	(0.13)
Shrimp farm land	3.24	2.23	2.07	-0.25
	(4.57)	(4.39)	(4.40)	(4.50)
Shrimp seed price/piece	0.24	0.36	0.37	0.34
	(0.45)	(0.43)	(0.44)	(0.45)
Cost for feeding/ha	-0.02	-0.02	-0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.01)
Disease outbreak	-37.84*	-43.44*	-42.52*	-40.71*
	(22.56)	(22.48)	(22.38)	(22.32)
BMPs training		-36.10	-35.27	-40.04
		(25.91)	(25.94)	(25.64)
σ (Risk aversion)			0.61	-0.57
			(7.23)	(6.98)
λ (HC)			4.52	8.48
			(20.61)	(20.77)
No. shrimp input sellers				-1.44
				(0.46)
Dummy extension officers				-45.26*
				(26.03)
Commune fixed effect	Yes	Yes	Yes	Yes
Observations	147	147	147	147
Pseudo R2	0.04	0.04	0.04	0.04

Notes: Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. OTC is the abbreviation for oxytetracycline. Nine communes exist in our data set. The amount of OTC detected ranges from 0 to 1,667 ppb. The MHLW rejects shrimp shipments when the concentration of oxytetracycline exceeds 200 ppb. I compute marginal effects for the left-truncated mean, $E(y|x,y>0)$. 120 censored observations at the amount of OTC detected=0. Marginal effects for dummy variables (disease outbreak, BMPs training, HC) are discrete change from the base level.

2.6. Chapter Summary

Solving problems arising from veterinary drug residues is considered an important strategy to improve both shrimp producers' welfare and food safety for consumers. To optimize appropriate intervention strategies, determinants of drug use should be identified, and the impact of existing management efforts should be measured. Although many shrimp-exporting and -importing countries have maintained interest in this issue, few studies have attempted to quantitatively examine these determinants or estimate these impacts.

Therefore, I conducted a survey to collect information from 201 farmers in Vietnam and used 147 of them to verify my hypotheses in Subchapter 2.2.2. Based on regression analyses of these data I note that: (1) receiving BMPs training had a positive and significant effect on reducing veterinary drug residues; (2) where farmers trust information on the treatment of shrimp diseases from extension officers this has a significant and positive effect on preventing the use of prohibited substances. Unlike the study of Holmstrom et al. (2003), my results suggest that farmers with prior experience of shrimp disease outbreaks use smaller quantities of antibiotics. Therefore, arguably, farmers distrust the efficacy of antibiotics because prior experience of using these drugs did not reduce shrimp mortality as expected. Overall, this study contributes to revealing the determinants of detecting veterinary drugs residues in shrimp farming in multiple (social, economic, psychological) dimensions.

Further, almost all the farmers in my sample did not know the exact names of elements that are prohibited, or which inputs contain these elements. Judging from these findings, it can be presumed that farmers' lack of knowledge about antibiotics led to an increase in veterinary drug use despite the fact that the farmers had kept records of input use.

Based on my findings, I suggest that BMPs are likely to play significant roles in reducing port rejections arising from the presence of veterinary drug residues. Thus, a way of spreading the effects of BMPs training to other farmers who do not currently receive this training should be considered. This is likely to decrease farmers' use of veterinary drugs. Moreover, I propose that efforts to improve producers' knowledge about antibiotics and chemicals is necessary to decrease port rejection rates given the results herein concerning inadequate knowledge. Taken together, optimizing management interventions will enhance the economic and environmental sustainability of shrimp farming.

3. Comparison of Targeting Methods for the Diffusion of Farming Practices: Evidence from Shrimp Producers in Vietnam

3.1. Introduction

The diffusion of information on good farming practices plays a key role in improving agricultural productivity and promoting rural welfare in developing countries. Traditionally, the main channels to disseminate information to farmers have been the governments of developing countries through their extension officers. Nevertheless, the lack of information remains one of the reasons for farmers to adopt wrong or inefficient practices. Moreover, the problem of spreading inaccurate information also persists (The World Bank, 2007).

To overcome such problems, recent literature has focused on the role of farmers' social network on obtaining information. Banerjee et al. (2013) examine how participation in a microfinance program diffuses through social networks. They find that participation in a microfinance program is significantly higher when first-informed individuals about the program have higher community centralities. Beaman et al. (2015) examine the impact of network-based targeting on the diffusion of agricultural information. They find that information does not spread to people who are far from treated farmers in their social networks.

While existing studies have revealed the impact of social networks on the diffusion of information or technologies, it remains unclear as to what type of targeting method one should use in disseminating information in terms of delivering accurate information. This study uses individual-level data to identify a targeting method which can diffuse accurate agricultural information to farmers. This study examines which targeting method (i) improves the knowledge of good practices of the treated and their neighbors the most, (ii) enhances information sharing with their neighbors the most, and (iii) improves the farming knowledge of those who receive information from the treated.

To test these research questions, I consider a case of shrimp farmers in Vietnam. Shrimp farming is a profitable business for smallholders in developing countries. However, it is also challenging and farmers frequently experience crop failures due to shrimp viral diseases (UNIDO, 2013). To reduce the risk of shrimp diseases, veterinary drugs are used by shrimp producers, but these often contain substances harmful to the human body, such as chloramphenicol, enrofloxacin, and ciprofloxacin. Thus, there have been attempts by the Vietnamese government and international communities to disseminate good aquaculture practices to Vietnamese shrimp farmers, BMPs being one of them. According to NACA (2016), well-designed and well-implemented BMPs support smallholder shrimp aquaculture to increase productivity by reducing the risk of shrimp disease outbreaks. Furthermore, my study regarding BMPs in Chapter 1 identifies that receiving BMPs training has a significant and positive effect on reducing the use of these drugs.

A baseline survey was conducted in the Ca Mau province in southern Vietnam in September 2016 to collect information from 173 farmers. The data include information on farmers' social networks, psychological characteristics, and the knowledge level of BMPs, as well as their socio-economic characteristics. 40 shrimp farmers were invited to my BMPs workshop in December 2016 to disseminate BMPs to the farmers. 36 of the 40 invited farmers participated in the workshop. The participants were selected using three targeting methods and were divided into three groups based on the methods. Treatment group 1 includes farmers selected by SRS, while treatment group 2 includes individuals chosen by SURS using individual location information. Treatment group 3 is selected using SNT. Farmers in the SNT group have higher betweenness centralities than untreated farmers in the same village. The reason why this study employs betweenness centrality for SNT is that an individual with high betweenness centrality is an intermediary who plays an important role in the connection between other people in the same network. The individual has a large influence on information transfer through the network and is called a gatekeeper. Theoretically, providing information to the gatekeeper allows us to pass information to the highest number of people in the network (Brandes, 2008; Freeman, 1977; IBM, 2017). In August 2017, I conducted a follow-up survey to investigate how well farmers' knowledge of BMPs improved in comparison to the status before our treatment.

Using the balanced panel data and cross-sectional data, this study employs the difference in difference (DD), two-way fixed effects models, and control function estimator to test the research questions mentioned above. As a result, this study identifies that SRS shows the highest increase in BMPs knowledge in comparison to other treatments. Second, SURS shows a lower improvement in BMPs knowledge than SRS. On the other hand, unlike other groups, treated farmers in SURS increase their neighbors' scores. Third, SNT increases information sharing between villagers in the treated village, but untreated farmers who receive information from treated farmers of the SNT group have a lower improvement score in their BMPs knowledge.

These findings can conclude that SNT appears to be a method to disseminate information to more people, and SURS may be suitable to enhance the knowledge level of neighboring farmers. However, both the methods are less likely to deliver accurate information than SRS owing to the bias generated by the samplings.

The remainder of the study proceeds as follows. Subchapter 3.2 describes Vietnam's shrimp industry, BMPs, reviews relevant extant literature on social network analyses, and a reciprocity index. Subchapter 3.3 describes and explains the data used herein, presents the summary statistics, and describes my workshop and targeting methods. Subchapter 3.4 describes the estimation methods used and the results are presented in Subchapter 3.5. Finally, Subchapter 3.6 concludes the study.

3.2. Previous Literature

3.2.1. Vietnam's Shrimp Industry and Better Management Practices

As a means of acquiring foreign currency, the Vietnamese government has been encouraging shrimp farming among farmers in southern Vietnam since market liberalization. Between 1990 and 2013, Vietnamese shrimp exports increased almost 18-fold in volume and 40-fold in monetary value. These figures suggest that the Vietnamese shrimp industry has achieved quantitative growth (FAO, 2016; UNIDO, 2013).

However, the problem of small farmers abandoning shrimp farming due to crop failures caused by shrimp viral diseases continues. Farmers use antibiotics to mitigate the risk of crop failures due to shrimp diseases, but such inputs contain substances harmful to the human body, such as chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline. Due to the residual antibiotics, the port rejection rate, or the share of Vietnamese shrimps that are rejected at the ports of importing countries, continues to grow. In addition, water pollution is occurring in rivers used for agriculture and as drinking water as some farmers discharge water in their ponds to the rivers without removing residual antibiotics (NACA, 2016; Suzuki & Vu, 2016; Taya, 2003; UNIDO, 2013).

To solve these problems, there have been attempts by the Vietnamese government and NACA to disseminate a guide for good aquaculture practices called BMPs. The purpose of BMPs is to improve farmers' management practices, and delivering increased profitability and environmental performance through the more efficient use of resources (Khiem, Simon, Nguyen, & Vo, 2010; Mantingh & V.H., 2008; NACA, 2016; UNIDO, 2013). According to NACA (2016), the application of BMPs by farmers significantly decreases shrimp mortality, and the pilot farmers' productivities are considerably higher than farmers who do not follow BMPs. Moreover, the analyses in chapter 2 identifies that receiving BMPs training has a significant and positive effect on reducing the use of those drugs mentioned in the paragraph above. Reviewing the studies on BMPs, the spread of these practices appears to increase the output of small farmers and reduce port rejections arising from the presence of antibiotic residues.

3.2.2. Social Network Targeting

In developing countries, extension officers perform a role in transferring new techniques and information to farmers (Anderson & Feder, 2004). However, the provision of services through such official channels may be limited by reasons such as farmers' capabilities and residential areas. As a method to overcome such shortcomings, many studies in development economics have suggested peer learning or social learning for disseminating information to a wide range of farmers (Foster & Rosenzweig, 1995; Liverpool-Tasie & Winter-Nelson, 2012; Magnan, Spielman, Lybbert, & Gulati, 2015; Songsermsawas, Baylis, Chhatre, & Michelson, 2016).

Furthermore, recent studies have employed social network analysis to investigate the peer effects on agricultural information dissemination or technology adoption. According to Valente (2010), while random sampling is not suitable for measuring peer effects as sampling removes individuals from the social context, network analysis is useful for measuring the influence of a relationship on an individual's behavior. To investigate the spread of a microfinance program through social networks in each village, Banerjee et al. (2013) collected social network data from 43 villages in south India. They measured the eigenvector centrality[6] of the leader of each village using network data. Their result suggests that participation in a microfinance program is significantly higher when the village leaders have higher eigenvector centralities.

[6] The eigenvector centrality is a measure to indicate how important a node is in the sense of iterative paths through a network.

Beaman and Dillon (2018) employed network-based targeting to observe who benefit and who is excluded from the information transferred through social networks. They conducted social network census in 52 villages and selected farmers with the highest degree[7] or the highest betweennesses in each village as a treatment group. They provided short training on composting to farmers selected by the social targeting methods and random sampling, and provided informational placards about composting. Through a field experiment they found that information does not spread to people who are far from treated farmers in their social networks. However, they did not find that aggregate knowledge about composting differed across those targeting methods.

Kim et al. (2015) introduced their public health interventions to randomly selected villagers, villagers with the most social ties, or nominated friends of random villagers to assess which targeting methods produce the highest cascade or spillover effects, and hence maximize population-level behavior change. They found that the treatment group which included nominated friends increased the adoption of nutritional intervention by 12.2 percent in comparison to random targeting. On the contrary, targeting the most connected individuals did not increase adoption of either of the interventions. These results imply that targeting using the inherent characteristics of human social networks is a method to enhance the spread of intervention effects.

The existing studies reveal the impact of social networks on the diffusion of information. However, these studies do not provide answers on the best method to disseminate accurate information, although there is a concern that information dissemination through peers, not experts, may spread inaccurate information (Anderson & Feder, 2004). Therefore, this study compares various targeting methods to identify methods to accurately provide agricultural information to more farmers.

[7] The degree refers to the number of links to whom the node is connected.

3.3. Data Collection, Targeting Methods, and Workshop

3.3.1. Research Questions and Summary Statistics

Based on previous studies, this study poses three research questions. To test the research questions, this study considers a case of shrimp farmers in Vietnam and uses individual-level data to identify a targeting method which can diffuse accurate agricultural information to farmers.

Research Question 1

What are the targeting methods to improve the knowledge of good practices of the treated and their neighbors the most?

Research Question 2

What are the targeting methods to enhance information sharing with their neighbors the most?

Research Question 3

What are the targeting methods to improve the farming knowledge of those who receive information from the treated the most?

3.3.2. Summary Statistics

The study chooses four villages in the Phu Tan district, Ca Mau province as the study area as the province is currently the largest shrimp producer in Vietnam with an output of more than 145,000 tons in 2016, which is 23 percent of the country's total shrimp production. The value of the province's shrimp exports was approximately $1 billion in 2016, representing approximately 30 percent of Vietnam's total shrimp exports (VASEP, 2017). In the region, I conducted household surveys before and after a workshop as a part of the research project between the University of Tokyo and Foreign Trade University, Hanoi, Vietnam. As shown in Figure 3.1, the workshop for the dissemination of information on BMPs was held through a project in December 2016 in collaboration with the Ca Mau Province Office of the Ministry of Rural and Agricultural Development, Vietnam. A baseline survey was conducted for Vietnamese shrimp farmers in October 2016, and a follow-up survey was conducted in July 2017, collecting information from 173 households. In both the surveys, a farmer who is in-charge of shrimp farming in each family was requested to answer several questions regarding BMPs, which I prepared (see appendix 1 for the BMPs problems). The minimum (maximum) score is zero (17).

Figure 3. 1. Timeline

Table 3.1 summarizes 173 respondents' basic, psychological, and network characteristics, as well as their BMPs knowledge level. Overall, we observe that farmers have similar characteristics across villages. The average age of the interviewees is approximately 49 years old, and 86 percent of them are male. On an average, they have completed 8 years of formal school education and two people in their family are between the ages 16 and 60 years. The reason for choosing the range of 16 to 60 years is that they are likely to engage in income activities and participate in family decisions (WB, 2004).

As will be explained elaborately in Subchapter 3.3.2, I conducted the BMPs workshop for selected farmers in Villages A, B, and C, inviting them through different methods depending on the village. Village D is a pure control group. There is no notable difference in the basic characteristics between the villages, and the only difference in the statistics of shrimp production is the cost of shrimp farming. The cost of Village D is 4.85 billion VND, which is nearly 4 billion VND lesser than the average of other villages. In the BMPs test conducted in 2016, the average of Village B was approximately 1.7 points higher than those of other villages. Subsequent to my intervention in December 2016, the difference in the BMPs test scores between the treated villages (Villages A to C) and the untreated village (Village D) is much greater than in 2016. The other differences are that the average of Village A's logged reciprocity is lower than the other villages by 5, and considering the out-degree, the average of the treated villages, excluding Village C, decline from 2016. Village C's betweenness centrality increased largely in 2017 in comparison to 2016. This is owing to fact that the betweenness centrality of the treated in Village C increased significantly after the intervention. The average of their betweenness centralities rose from 2.92 to 48.19.

Table 3. 1. Basic, Farming, and Psychological Characteristic of each Village in 2017

	Village A (SRS)		Village B (SURS)		Village C (SNT)		Village D (Control)	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Basic Characteristic								
Gender (Male = 1)	53	0.81	34	0.97	51	0.84	35	0.83
		[0.39]		[0.17]		[0.37]		[0.38]
Age	53	50.17	34	52.00	51	44.16	35	47.89
		[9.79]		[12.57]		[12.86]		[15.65]
Years of Education	53	7.70	34	7.26	51	8.49	35	8.26
		[2.59]		[2.69]		[2.63]		[2.42]
No. HM16 to 60	53	1.91	34	2.44	51	1.84	35	2.11
		[0.99]		[1.24]		[0.81]		[1.25]
Shrimp Production								
Farther Shrimp Farmer	53	0.23	34	0.09	51	0.25	35	0.11
(Yes=1)		[0.42]		[0.29]		[0.44]		[0.32]
Years of Shrimp Farming	53	6.25	34	6.24	51	6.94	35	6.97
		[3.65]		[3.04]		[3.00]		[2.88]
Shrimp farm size (ha)	53	0.60	34	0.57	51	0.58	35	0.63
		[0.37]		[0.36]		[0.42]		[0.42]
Cost (billion VND)	53	9.16	34	8.62	51	9.82	35	4.85
		[6.75]		[7.51]		[6.68]		[6.88]
Treatment	53	0.28	34	0.24	51	0.25	35	0.00
		[0.45]		[0.43]		[0.44]		[0.00]
Test score of BMP in 2016	53	1.58	34	3.44	51	2.00	35	1.54
(0 to 17)		[2.48]		[3.54]		[2.74]		[2.63]
Test score of BMP in 2017	53	11.64	34	12.79	51	10.02	35	8.34
(0 to 17)		[3.29]		[2.14]		[3.17]		[5.58]
Psychological Characteristic								
Logged Reciprocity	53	5.85	34	11.15	51	10.91	35	11.13
		[0.79]		[0.12]		[1.56]		[0.16]
Risk Aversion (1 to 6; 6 most risk averse)	53	5.85	34	5.97	51	5.47	35	5.54
		[0.79]		[0.17]		[1.36]		[1.31]
Network Characteristics								
Out-degree Centrality 2016	53	0.68	34	0.91	51	0.57	35	1.77
		[1.09]		[1.06]		[1.02]		[1.14]
Out-degree Centrality 2017	53	0.02	34	0.00	51	1.84	35	2.14
		[0.14]		[0.00]		[1.16]		[1.03]
Betweenness Centrality 2016	53	5.02	34	2.71	51	2.55	35	7.46
		[11.18]		[6.06]		[4.67]		[9.67]
Betweenness Centrality 2017	53	7.51	34	4.44	51	29.25	35	11.31
		[12.33]		[0.11]		[42.63]		[13.74]

Notes: Standard deviations are reported in brackets. Cost = cost of shrimp seed + cost of shrimp feed+ cost of permanent labors + cost of casual labors. Out-degree is measured using a question "To whom (only shrimp farmer) do you advise on shrimp cultivation?". Betweenness centrality is measured using a question "From whom (only shrimp farmer) do you obtain advice on shrimp cultivation?".

Another method of dividing farmers into groups is based on the canals they use. By nature, shrimp farming has a large potential for spillovers. As each farmer is connected through canals, one's action affects his/her neighbors. Even if one farmer faithfully implements water quality management of the pond following the BMPs guidelines, his/her shrimp pond may be contaminated by the behavior of the neighbors using the same canal. Therefore, to prevent shrimp diseases and increase productivity, cooperation among residents using the same canal is necessary. To analyze this aspect, I examine the relation between the status of shrimp harvest in 2017 and the BMPs score of canal groups in Table 3.2. Using the shrimp farming data of 2017, respondents are divided into a "harvest failure" group and a "successful harvest" group. The failure group includes farmers who put shrimp seeds into their ponds in 2017, but did not earn any revenue by selling shrimp that year. The other group includes farmers who sold their own shrimps and earned revenue in 2017. In total, there were 26 canals which the farmers in our sample use, and each farmer uses only one canal. The number of farmers who use the same canal varies from 1 to 19, with a mean of 6.65. The canal score *Min, Mean, Max,* and *SD* represent the score for canal groups which each respondent belongs to. While the mean, maximum, and standard deviation of the canal score are not statistically different between the two groups, a statistically significant difference is found in the canal score *Min*, which is higher in the successful group. This result implies that increasing the BMPs knowledge level of a farmer with the lowest level knowledge and using the same canal is likely to affect the productivity improvement of farms in the same cluster.

Table 3. 2. The Test Score of the BMPs in 2016

	(a) Harvest Failure		(b) Successful Harv.		Diff
Variable	Obs	Mean	Obs	Mean	(a)-(b)
Canal Score Min	109	0.00	54	0.17	-0.17*
		[0.00]		[0.91]	(0.09)
Canal Score Mean	109	14.39	54	14.57	-0.19
		[2.50]		[2.92]	(0.44)
Canal Score Max	109	5.98	54	6.48	-0.50
		[1.80]		[2.00]	(0.31)
Canal Score SD	109	5.28	54	5.18	0.10
		[1.09]		[1.17]	(0.19)

Notes: Standard deviations are reported in brackets. Standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Min is the abbreviation for minimum, Max is the abbreviation for maximum, SD is the abbreviation for standard deviation.

3.3.3. Targeting Methods and Workshop

The study implements a social network census in four villages in the Ca Mau province to ask all farmers in the village about the name of the farmers seeking advice on shrimp cultivation. As shown in Table 3.3, in 2016, 72 out of 80 farmers (90 percent) in Village A, 46 out of 52 farmers (88 percent) in Village B, 63 out of 76 farmers (83 percent) in Village C, and 47 out of 74 farmers (64 percent) in Village D were interviewed by me. In comparison to other villages, the number of respondents in Village D is relatively small, but as mentioned in Subchapter 3.3.2, there is generally no notable difference between the characteristics of these villages. Nevertheless, this study should be careful when interpreting the estimation results using the sample as the difference in the response rates may introduce participation bias into our experiment.

Using the network information, a social network map of each village is drawn as shown in Figure 3.2. The direction of the arrows in those directed graphs indicates that each farmer nominates other farmers as his/her advisers. Nodes with a betweenness centrality of one or higher are displayed in red, and nodes with a value of zero are displayed in blue. The size of the nodes indicates how high the betweenness centrality of each node is. The betweenness centrality is as follows:

$$BC_i(g) = \sum_{k \neq j : i \notin \{k,j\}} \frac{P_i(kj)/P(kj)}{(n-1)(n-2)/2} \quad (3.1)$$

where $BC_i(g)$ is the betweenness centrality of a node i and n is the number of nodes in a network; $P_i(kj)$ denotes the shortest paths between a node k and j that i lies on. $P(kj)$ denotes the total number of shortest paths between k and j (Freeman, 1977; Jackson, 2008).

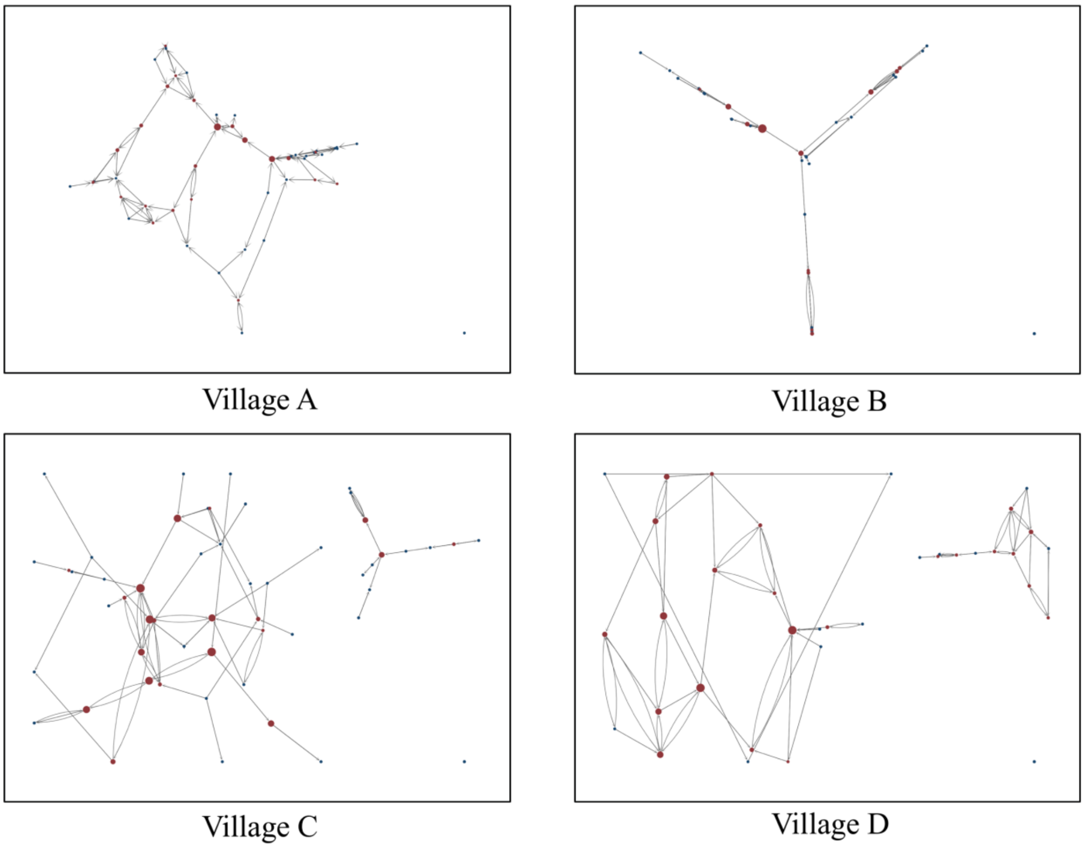
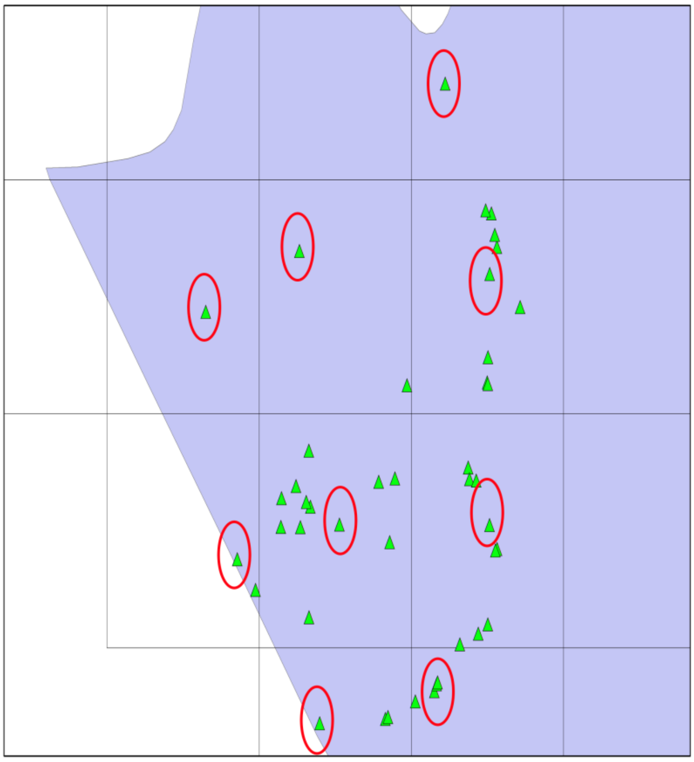


Figure 3. 2. The Social Network of each Village

To select treatment groups to participate in my workshop, villages are randomly assigned to be among one of the targeting methods, such as SRS, SURS, and SNT. According to Rogers (1962), the critical point, at which the adoption rate is accelerating, is approximately 16 percent in theory. Thus, I choose approximately 16 percent of all farmers in each village as my workshop participants. First, SRS is assigned to Village A. 15 shrimp farmers are randomly selected from the population list in the village. Second, SURS is assigned to Village B. As depicted in Figure 3.3, I created a polygon grid on the map of Village B, and then marked the location of each farm on the map. The grid size is set at 1.5 km x 1.5 km as it is the size most suitable for choosing approximately 16 percent of the farmers in the village. Among the farmers in this village, the workshop participants are randomly selected in each block. The reason why the study employs SURS is that selecting a treatment group for each block appears to be the solution to the geographical obstacles mentioned below. The geographical features of the villages in the Ca Mau province are divided into several clusters due to the canals. Thus, it is challenging to visit other farms in the same village due to the canal, which may be an obstacle to the spread of information. Third, SNT is assigned to Village C. The treatment group includes farmers whose betweenness centrality is in the top 20 percent of all the farmers in the village. A prerequisite for the use of betweenness centrality in targeting is the response of most of the network members as the centrality may change depending on the response rate of members. As 83 percent of the farmers in Village C responded to my network census in 2016, the value obtained from the survey appears to be close to the centrality of the whole network. Accordingly, I employ betweenness centrality for SNT. Another reason for using centrality in this study is that an individual with high betweenness centrality is an intermediary who plays an important role in the connection between other people in the same network. Finally, Village D is set as a pure comparison group, which means that none of the villagers are invited to my workshop.



Note: 1.5km x 1.5km grid

Source: From own survey

Figure 3. 3. The Systematically Unaligned Random Sampling (SURS)

As shown in Figure 3.4, a workshop on BMPs was held in the Ca Mau province on December 31, 2016. Table 3.3 summarizes that all the invited farmers in the SRS group, 8 out of 9 invited farmers in the SURS group, and 13 out of 16 invited farmers in the SNT group participated in my workshop. The participants were provided a leaflet on BMPs, water test kits, and a book to record water quality tested by the kit (see appendix 2), as well as a lecture on BMPs. There is a difference between the invitees and participants. As four farmers, who were invited but did not participate in my workshop, did not respond to the follow-up survey, they are excluded from the sample used for the analysis of the study. Thus, this study estimates the average effect of the treatment on the treated to find answers to the research questions mentioned previously.

Source: From own survey

Figure 3. 4. BMP Workshop

Table 3. 3. Number of Invitees and Participants

	Targeting Method	Total # of farmers	# of Respondents (Baseline)	# of Respondents (Follow-up)	Invited	Participated
Village A	SRS	80	72	53	15	15
Village B	SURS	52	46	34	9	8
Village C	SNT	76	63	51	16	13
Village D	N/A (control)	74	47	35	N/A	N/A

Source: From own survey

In August 2017, a follow-up survey was conducted to measure changes in the knowledge level of BMPs and the adoption rate of water quality test kits. As shown in Table 3.3, among 228 respondents who responded to the baseline survey, 55 were excluded from the sample as they refused to respond to the follow-up survey or abandoned shrimp farming. While no one started using the kit after my intervention, the knowledge level showed a change. Most of the neighbors in the treatment group increased their BMPs knowledge level. This result indicates that my intervention had a spillover effect. In particular, the SURS village appears to have the highest spillover effect of my intervention as the BMPs knowledge level of all untreated farmers in the SURS village increased after my intervention.

3.3.4. Reciprocity

Apart from the common variables, I collected information to measure farmers' reciprocity. The literature on psychology or social networks has found that reciprocity is an important motive for information exchange in communities of practice (Lave, 1991; Lave and Wenger, 1991; Wasko, 2005; Wenger, 1998). Ethan and Schechter (2012) introduce an approach to measure reciprocity using variants of the dictator game, such as anonymous random game, revealed random game, anonymous chosen game, and revealed chosen game. The game is played in pairs. Each pair consists of a dictator and a recipient. The dictator receives 14,000 Guaranies and decides how much is to be shared with the recipient. The relationship between sharing in the four games and the four motives is as follows:

$$T_i = \begin{bmatrix} \tau_i^{AR} \\ \tau_i^{AC} \\ \tau_i^{RR} \\ \tau_i^{RC} \end{bmatrix} = \begin{bmatrix} B_i \\ B_i + D_i \\ B_i + S_i \\ B_i + D_i + S_i + R_i \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}, \tag{3.2}$$

where i indexes an individual, T_i is the column vector of transfers made by the individual i, B is undirected altruism, D is directed altruism, and S is sanctions; τ indicates how much money the dictator gives to each recipient in each game. The reciprocity of individual i is equal to

$$R_i = \tau_i^{RC} - (\tau_i^{AC} - \tau_i^{AR} + \tau_i^{RR}) = \tau_i^{RC} - (B_i + D_i + S_i). \tag{3.3}$$

To measure individual reciprocity, I adopt their approach and conduct an experiment similar to that described above. However, the results may be different from their result as the dictators of my experiment receive play money instead of real money. This may have effects as the dictators may send more money to recipients in comparison to the case when the game is played using real money.

3.4. Econometric Strategies

3.4.1. Regression Analyses

Using various estimation methods, this study empirically analyzes the research questions mentioned in Subchapter 3.3.1. Balanced panel data is used in Equation (3.4)–(3.7), and cross-sectional data is used in Equation (3.8)–(3.10).

Since the study by Ashenfelter and Card (1985), the DD approach has become a popular method to estimate the causal effects of policy interventions (Ashenfelter & Card, 1985; Bertrand, Duflo, & Mullainathan, 2004; Wooldridge, 2007). According to Wooldridge (2007), the approach removes biases from the permanent difference between treatment and control groups, and from comparisons over time in the treatment group. Therefore, to estimate the effects of my treatment by comparing the treated and untreated, the DD estimation and two-way fixed effects with the DD are assessed by grouping the treatment groups into one group, rather than dividing them by targeting methods. The regression is as follows:

$$Y_{it} = \alpha + \beta_1 dT_{i\,or\,j} + \beta_2 X'_{it} + \gamma_1 T_t + \gamma_2 T_t \cdot dT_{i\,or\,j} + \eta_i + \lambda_t + \varepsilon_{it}, \qquad (3.4)$$

where the subscript i indexes the individual, j indexes the informer, and t indexes time. In the models for Question (i) and (iii), Y denotes the BMPs test score of individual i in t year, and the dependent variable *Y* for Question (ii) refers to individual *i*'s out-degree[8]—the variable's minimum (maximum) value is zero (three); dT_i is a dummy variable for my treatment which equals to one if individual *i* participates in my workshop and zero otherwise. In the model for Question (iii), dT_j equals to one if a farmer *j*, who provides BMPs information to individual *i* participates in my workshop; X' refers to individual *i*'s time-variant characteristics, such as *i*'s farming and household characteristics, and the risk-averse index (see Subchapter 3.3) is added only to the model for Question (ii). The index ranges from 1 (least risk-averse) to 6 (very risk-averse); *T* is a dummy variable indicating time which equals one if the intervention is performed and zero otherwise; η is the unobserved individual effect, λ is the time fixed effect, and u is the error term. The DD estimate $\hat{\gamma}_2$ can be expressed as follows:

$$\hat{\gamma}_2 = (\bar{Y}_{i,TRE,POST} - \bar{Y}_{i,TRE,PRE}) - (\bar{Y}_{i,COM,POST} - \bar{Y}_{i,COM,PRE}). \quad (3.5)$$

where the subscript *TRE* indicates that the individual is in the treatment group and *COM* is that the individual belongs to the comparison group. The *PRE* and *POST* subscripts represent before and after the treatment, respectively.

Second, this study assesses the difference in treatment effects between groups using DD estimation and fixed effect models with the DD estimate. The regression model is as follows:

$$Y_{it} = \alpha + \beta_1 dT_{i\ or\ j} + \beta_2 X'_{it} + \gamma_1 T_t + \delta_1 G_{i\ or\ j} + \delta_2 G_{i\ or\ j} \cdot dT_{i\ or\ j} + \delta_3 G_{i\ or\ j} \cdot T_t + \delta_4 G_{i\ or\ j} \cdot dT_{i\ or\ j} \cdot T_t + \eta_i + \lambda_t + \varepsilon_{it}, \quad (3.6)$$

[8] Out-degree is the number of outgoing links from a node to others.

where *G* is a categorical variable for targeting methods: 1 for SRS, 2 for SURS, 3 for SNT, and 4 for the pure comparison group. The DD estimate δ_4 is

$$\hat{\delta}_4 = (\bar{Y}_{i,TRE,G,POST} - \bar{Y}_{i,TRE,G,PRE}) - (\bar{Y}_{i,COM,G,POST} - \bar{Y}_{i,COM,G,PRE}) \tag{3.7}$$

where the subscript *G* represents SRS if the DD estimate is for SRS. In the case of the estimate for SURS, *G* indicates SURS.

Third, as a robustness check, the study employs the DD estimate again. Unlike Equation (3.4), in this model, the variable for targeting methods *G* is multiplied by the dummy for the treatment *dT*. The dependent variable *Y* is individual *i*'s BMPs test score or out-degree after my treatment. Using the cross-sectional data, this study estimates regressions of the form

$$Y_{i,POST} = \alpha + \delta_1 G_{i\ or\ j} + \delta_2 G_{i\ or\ j} \cdot dT_{i\ or\ j} + \varepsilon_i. \tag{3.8}$$

The DD estimate δ_2 is

$$\hat{\delta}_2 = (\bar{Y}_{i,TRE,G} - \bar{Y}_{i,TRE,G}) - (\bar{Y}_{i,COM,G} - \bar{Y}_{i,COM,G}). \tag{3.9}$$

Furthermore, this study employs a control function estimator to estimate the effect of treatment after controlling the major variables. In addition to time-variant variables, time-invariant variables are added to the right-side of this model. The regression model is as follows:

$$Y_{i,POST} = \alpha + \beta_1 X'_{i,POST} + \beta_2 Z'_{i,POST} + \delta_1 G_{i\ or\ j} + \delta_2 G_{i\ or\ j} \cdot dT_{i\ or\ j} + \theta Y_{i,PRE} + \varepsilon_i \quad (3.10)$$

where Z' represents individual i's time-invariant or omitted characteristics in fixed effects models, such as i's gender, age, years of education completed, and farming experience. In the model for Question (ii), the variable for logged reciprocity is added. Variable reciprocity is used only for cross-sectional regression as the data on reciprocity of farmers was collected only in 2017. The dependent variable in this model is how many people does individual i provide information on shrimp cultivation to. Therefore, to avoid endogeneity problems, reciprocity is measured based on donating behavior, not information-sharing behavior. The method for obtaining the variable is described in Subchapter 3.3.4.

3.4.2. Correlation Matrix

Table 3.4 presents the correlation matrix of all the independent variables used in the above models. The highest correlation is found between the continuous numerical variable for individual i's age and the dummy for father's occupation; however, it is only -0.38. The correlation between the categorical variable for targeting methods and other variables is less than 0.2. Most of the other correlations between the other controls are also lower than 0.2. Therefore, among the explanatory variables used in my analyses, there is no high correlation between the variables.

Table 3. 4. Correlation Matrix of All Independent Variables

	Group	Treated	Treated advisor	Gender	Age	Education	Years of Shrimp Farming	Father Shrimp Farmer	No. of HM16 to 60	Shrimp farm size (ha)	Risk Aversion (1 to 6)	Logged Reciprocity
Group	1.00											
Treated	-0.21	1.00										
Treated advisor	-0.03	0.18	1.00									
Gender	-0.003	-0.07	0.08	1.00								
Age	-0.14	-0.04	-0.05	-0.03	1.00							
Education	0.12	0.01	0.02	0.17	-0.26	1.00						
Years of Shrimp Farming	0.10	-0.02	0.04	0.09	0.14	0.07	1.00					
Father Shrimp Farmer	-0.05	0.16	-0.05	-0.10	-0.38	0.13	-0.08	1.00				
No. HM16 to 60	0.01	0.01	-0.11	0.01	0.07	-0.01	-0.004	-0.13	1.00			
Shrimp Farm Size (ha)	0.02	0.07	0.01	-0.02	-0.05	0.22	0.17	-0.04	-0.03	1.00		
Risk Aversion (1 to 6)	-0.15	-0.03	-0.12	-0.04	0.08	-0.14	-0.03	-0.02	0.08	-0.15	1.00	
Logged Reciprocity	-0.03	0.05	0.05	-0.03	0.13	0.11	0.04	-0.16	0.002	0.04	0.27	1.00

3.5. Estimation Results

3.5.1. Effect of Each Targeting Method on the Knowledge of BMPs of the Treated

Tables 3.5 and 3.6 show the estimation results for Question (i) using panel data and cross-sectional data, respectively. The dependent variable in the table is the BMPs test score of individual *i*.

In Columns (1) and (2), we consider the treatment of BMPs information workshop as one and examine the average effect of the treatment on the treated. We find that the coefficient of interaction term between treatment and time is insignificant, suggesting that the treatment did not have significant effect on BMPs score on an average. Column (1) of Table 3.5 shows the result of the DD estimation, indicating that the score after my intervention is 8.67 higher than the score in 2016, which is statistically significant at the 1 percent level. Column (2) is a fixed effects model with time-variant characteristics added to the independent variables used in Column (1). The result of the DD estimate in Column (2) is similar to that in Column (1).

Column (3) in Table 3.5 shows the result of the DD estimation to assess the difference in treatment effects between groups, and the result of the model with other explanatory variables added to the variables in Column (3) appears in Column (4) in Table 3.5. Village D, a pure comparison group, is used as the base level in the regressions. Coefficients on the interaction between group and time show that treated groups (i.e., SRS, SURS, and SNT) improved on BMPs scores in 2017 on an average and the effects are higher than the pure control village. Considering the SRS and SURS groups, the effects are statistically significant at 1% and 5% level, respectively. When we observe the treatment effects on treated farmers (i.e., interaction terms between group, treatment, and time), we find that most of them, except SURS in Column (3), are insignificant. This means that while farmers in the treated groups improved the score on an average, the increase was not significantly different between the treated and untreated farmers within the same village. Essentially, the negative coefficients suggest that the increase was less for the treated. In particular, for the SURS group, the increase for the treated was 2.59 points lesser than the untreated (but the impact was still 0.57 more than the pure control group). The results suggest that there is a spillover effect between the treated and non-treated farmers within the treated villages. Except for SURS, the differences between the treated and untreated farmers in other groups are not statistically significant. Overall, the results shown in Column (4) are similar to those in Column (3). From the results of the two columns, it can be mentioned that the spillover effects from the treated to untreated are largest for the SRS group, followed by the SURS and SNT groups.

Table 3. 5. Effect of each Targeting Method on the Knowledge of BMPs of the Treated: Panel Data

Dependent Variable: i's BMPs test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.67***	8.79***	6.80***	7.00***
	(0.39)	(0.41)	(0.93)	(0.97)
SRS*Time			3.31***	3.26***
			(1.14)	(1.15)
SURS*Time			3.16**	2.81**
			(1.12)	(1.18)
SNT*Time			1.28	1.03
			(1.16)	(1.17)
i's Treated*Time	0.06	-0.08		
	(0.77)	(0.77)		
SRS**i*'s Treated*Time			-0.17	-0.31
			(1.29)	(1.32)
SURS**i*'s Treated*Time			-2.59*	-2.54
			(1.55)	(1.54)
SNT**i*'s Treated*Time			-0.23	-0.10
			(1.11)	(1.10)
Father Shrimp Farmer		-0.48		-0.43
		(0.61)		(0.60)
No. HM 16-60		0.43		0.29
		(0.30)		(0.28)
Farm Size		-1.00		-1.36
		(1.06)		(1.09)
Constant	2.06***	1.77*	2.06***	2.30**
	(0.17)	(1.03)	(0.16)	(1.00)
Joint-significance	0.00	0.00	0.00	0.00
Observations	346	346	346	346
R-squared	0.79	0.80	0.81	0.81
Number of id	173	173	173	173

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively.

Table 3.6 summarizes the estimation results using cross-sectional data. The standard errors are clustered at the canal level. All the columns in the table indicate that the effect in the SRS group is approximately 0.80 lesser than that in the SURS group. These results are statistically significant at the 0.01 level. Similar to the results in Table 3.5, the differences between the treated and untreated farmers within the group are not statistically significant, except for the SURS group. The spillover effects from the treated to untreated farmers appear the highest in the SURS group, followed by the SRS and SNT groups.

Table 3. 6. Effect of each Targeting Method on the Knowledge of BMPs of the Treated: Cross-sectional Data

Dependent Variable:	DD2	CFE1	CFE2
i's BMPs test score	(1)	(2)	(3)
Score 2016		0.17	0.11
		(0.11)	(0.12)
SRS	3.74***	3.62***	3.73***
	(0.80)	(0.76)	(0.77)
SURS	4.58***	4.37***	4.54***
	(0.82)	(0.90)	(0.93)
SNT	1.68**	1.55*	1.50**
	(0.82)	(0.76)	(0.72)
SRS**i*'s Treated	-1.55	-1.44	-1.10
	(1.58)	(1.69)	(1.59)
SURS**i*'s Treated	-0.55	-0.92***	-0.90***
	(0.34)	(0.32)	(0.28)
SNT**i*'s Treated	-0.03	-0.19	-0.32
	(0.94)	(0.65)	(0.57)
Father Shrimp Farmer		0.74	0.37
		(0.65)	(0.68)
No. HM 16-60		0.02	-0.00
		(0.17)	(0.18)
Farm size, t-1		0.05	-0.15
		(0.83)	(0.81)
Gender			1.24
			(0.94)
Age			-0.02
			(0.03)
Year of Education			0.17
			(0.10)
Years of Shrimp Farming			0.01
			(0.08)
Constant	8.34***	7.94***	6.94***
	(0.73)	(0.92)	(2.26)
Joint-significance	0.0001	0.0004	0.0006
Observations	173	173	173
R-squared	0.16	0.18	0.22

Notes: Standard errors in parentheses are clustered at the canal level. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively.

3.5.2. Effect of Each Targeting Method on Information Sharing with Neighbors

The dependent variable in Tables 3.7 and 3.8 is the out-degree of individual *i*, which refers to how many farmers she/he provides the BMPs knowledge to. Each table has a column which contains a variable for the risk-aversion index and a column which does not contain it. As the variable may cause an endogeneity problem, I show the results of both the models.

Column (1) in Table 3.7 shows the result of the DD estimation, indicating that the increase in the out-degree of the treated farmer group is 0.05 lesser than the untreated farmer group. The results of the DD estimates in the three columns are statistically insignificant and similar in magnitude. In Columns (4)–(6), we find the interaction terms between group and time to be statistically significant at the 1% level for all groups. In particular, it is negative and statistically significant for the SRS and SURS groups, while it is positive and statistically significant for the SNT group. It means that information sharing was reduced in the SRS and SURS villages, while it was enhanced in the SNT village after the treatment. We also observe that the effects on treated farmers are insignificant (i.e., coefficients on the interaction terms between group, treatment status, and time), indicating that the effect of the treatment to enhance information sharing was not different between the treated and untreated farmers within the same group. Considering these results, we can state that after the treatment, information sharing was enhanced most in the SNT group, 0.87 higher than the pure control village, while the degree of information sharing was reduced for the SRS and SURS groups relative to the pure control group. This result is interpreted as reflecting the features of each targeting method. As the treated in SNT were originally active people in communicating with their neighbors, they became more active in sharing new information with their neighbors. The treated farmers in SRS and SURS, selected regardless of their communicative participation, have a lower betweenness centrality in 2016 (before my intervention) of 2 and 9 respectively, than those treated in SNT. The figure leads us to presume that the treated in the SRS and SURS groups were originally not as active as the treated in the SNT group in communicating with their neighboring farmers. During the fieldwork, I found that many farmers were reluctant to share farming information with other farmers. Many farmers mentioned that “because shrimp is very sensitive, if some problem occurs in my neighbors’ ponds due to my advice, I cannot take responsibility.” Thus, it may be that those with lower betweenness centrality strengthened this behavior of hiding information when they received new information, while those with higher betweenness centrality continued to spread information to others.

Table 3. 7. Effect of each Targeting Method on Information Sharing with their Neighbors: Panel Data

Dependent Variable:	DD1	FE with DD1	FE with DD1&Risk	DD2	FE with DD2	FE with DD2&Risk
i's out-degree	(1)	(2)	(3)	(4)	(5)	(6)
Time	0.08	0.10	0.08	0.37	0.43*	0.42*
	(0.13)	(0.13)	(0.13)	(0.24)	(0.24)	(0.24)
SRS*Time				-0.95***	-0.97***	-0.97***
				(0.30)	(0.29)	(0.29)
SURS*Time				-1.41***	-1.42***	-1.43***
				(0.32)	(0.31)	(0.31)
SNT*Time				0.87***	0.90***	0.89***
				(0.31)	(0.31)	(0.31)
i's Treated*Time	-0.05	-0.09	-0.07			
	(0.30)	(0.31)	(0.30)			
SRS**i*'s Treated*Time				-0.35	-0.43	-0.41
				(0.33)	(0.32)	(0.32)
SURS**i*'s Treated*Time				0.41	0.50	0.51
				(0.37)	(0.39)	(0.39)
SNT**i*'s Treated*Time				0.30	0.28	0.29
				(0.44)	(0.47)	(0.46)
Father Shrimp Farmer		0.36**	0.34*		0.30*	0.29*
		(0.18)	(0.18)		(0.15)	(0.16)
No. hm 16-60		0.01	-0.002		0.11	0.10
		(0.07)	(0.07)		(0.07)	(0.07)
Farm Size, t-1		0.01	0.01		0.35	0.35
		(0.44)	(0.43)		(0.30)	(0.30)
Risk Aversion			-0.10			-0.05
			(0.09)			(0.06)
Constant	0.94***	0.82**	1.42**	0.94***	0.40	0.71
	(0.06)	(0.35)	(0.64)	(0.05)	(0.26)	(0.47)
Joint-significance	0.92	0.96	0.98	0.13	0.07	0.08
Observations	346	346	346	346	346	346
R-squared	0.00	0.02	0.02	0.38	0.40	0.40
Number of id	173	173	173	173	173	173

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively. Out-degree is measured using a question "To whom (only shrimp farmer) do you advise on shrimp cultivation?".

In Table 3.8, we again observe that the group dummies of SRS and SURS are statistically significant at the 1% level and negative across models. Controlling for the out-degree of 2016, farmers in the SRS and SURS groups decrease the out-degree in 2017 by approximately 2 units relative to the pure control village. SNT dummies are insignificant across the models. The effects on the treated farmers are also insignificant in most of the cases, except for SUR in Column (1). Overall, it can be stated that the effects on treated farmers were not different from those on untreated farmers within the village. In order to examine whether reciprocity plays a role in facilitating the out-degree, I included the variable for logged reciprocity in Column (5). It shows that if a person has a higher degree of reciprocity, she/he is likely to have a lower out-degree by approximately 0.08 units. This result is intuitive as having a higher degree of reciprocity means that the person offers something to others if she/he receives something from others.

Table 3. 8. Effect of each Targeting Method on Information Sharing with their Neighbors: Cross-sectional Data

Dependent Variable: i's out-degree	DD2 (1)	CFE1 (2)	CFE2 (3)	CFE3 (4)	CFE4 (5)
Out-degree 2016		0.16***	0.18***	0.18***	0.18***
		(0.05)	(0.06)	(0.06)	(0.06)
SRS	-2.12***	-1.97***	-2.00***	-2.01***	-2.00***
	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)
SURS	-2.14***	-1.98***	-2.05***	-2.05***	-2.05***
	(0.14)	(0.16)	(0.16)	(0.17)	(0.16)
SNT	-0.43	-0.24	-0.21	-0.20	-0.23
	(0.36)	(0.34)	(0.36)	(0.37)	(0.35)
SRS* i's Treated	-0.03	-0.02	0.06	0.06	0.07
	(0.02)	(0.08)	(0.13)	(0.13)	(0.12)
SURS* i's Treated	8.84E-16*	-0.02	-0.02	-0.03	-0.02
	(4.42e-16)	(0.08)	(0.10)	(0.09)	(0.10)
SNT* i's Treated	0.52	0.41	0.36	0.36	0.39
	(0.36)	(0.47)	(0.46)	(0.46)	(0.43)
Score 2016		0.02	0.02	0.02	0.02
		(0.02)	(0.02)	(0.02)	(0.02)
Father shrimp farmer		0.10	0.16	0.15	0.13
		(0.13)	(0.14)	(0.13)	(0.14)
No. hm 16-60		-0.09	-0.09	-0.09	-0.09
		(0.07)	(0.07)	(0.07)	(0.07)
Farm size, t-1		0.24**	0.31**	0.31**	0.30**
		(0.12)	(0.14)	(0.15)	(0.14)
Gender			0.32*	0.32*	0.30
			(0.18)	(0.19)	(0.19)
Age			0.002	0.002	0.003
			(0.005)	(0.005)	(0.005)
Year of education			-0.02	-0.02	-0.02
			(0.02)	(0.02)	(0.02)
Years of Shrimp Farming			-0.02	-0.02	-0.02
			(0.01)	(0.01)	(0.01)
Risk Aversion				0.02	
				(0.06)	
Reciprocity					-0.08***
					(0.03)
Constant	2.14***	1.85***	1.70***	1.57***	2.59***
	(0.14)	(0.17)	(0.35)	(0.46)	(0.44)
Joint-significance	0.00	0.00	0.00	0.00	0.00
Observations	173	173	173	173	173
R-squared	0.63	0.66	0.67	0.67	0.67

Notes: Standard errors in parentheses are clustered at the canal level. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively. Out-degree is measured using a question "To whom (only shrimp farmer) do you advise on shrimp cultivation?".

3.5.3. Effect of Each Targeting Method on the Knowledge of BMPs of their Neighbors

The dependent variable in Tables 3.9–3.11 is BMPs test score of individual i, which is the same as the dependent variable for Question (i). The major difference between the models for Questions (i) and (iii) is that the models for Question (iii) employ the dummy variable dT_j for the treatment of informer j. To confirm the flow of information in each village, I asked farmers, "To whom (only shrimp farmer) do you advise on shrimp cultivation?." As the direction of selection is from an informer j to an individual i (information receiver), the explanatory variable dT_j can be treated as exogenous, which is not correlated with the error term of individual i.

The results in Columns (1) and (2) in Table 3.9 imply that treated informers have negative effects on the test score of individual i, although it is insignificant. However, when the treatment is separated into different groups as in Columns (3) and (4), we observe that it is positive for the SRS and SURS groups, and negative for the SNT group (i.e., interaction terms between groups, j's treatment status, and time). These coefficients show direct effects of spillovers from the treated to untreated farmers and is particularly strong in the SURS group, which is 2.9 and statistically significant at the 5% level. General spillovers can be observed from the interaction terms between group and time in the same columns, and these are positive and statistically significant for SURS and SRS. In addition to these general spillover effects, when a person's direct informer is treated, the BMPs score increases by 2.9 within the SURS group.

Table 3. 9. Effect of each Targeting Method on the Knowledge of BMPs of their Neighbors: Panel Data

Dependent Variable: *i*'s test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.71***	8.84***	6.80***	7.02***
	(0.38)	(0.38)	(0.93)	(0.63)
SRS*Time			3.20***	3.16***
			(1.12)	(1.13)
SURS*Time			2.30**	1.95
			(1.13)	(1.19)
SNT*Time			1.90	1.69
			(1.18)	(1.17)
j's Treated*Time	-0.27	-0.36		
	(0.82)	(0.82)		
SRS**j*'s Treated*Time			0.30	0.05
			(1.42)	(1.38)
SURS**j*'s Treated*Time			2.90**	2.92**
			(1.16)	(1.38)
SNT**j*'s Treated*Time			-1.65	-1.66
			(1.13)	(1.14)
Father shrimp farmer		-0.51		-0.42
		(0.60)		(0.57)
No. hm 16-60		0.42		0.32
		(0.30)		(0.28)
Farm size, t-1		-1.04		-1.31
		(1.05)		(1.12)
Constant	2.06***	1.82*	2.06***	2.22**
	(0.17)	(1.05)	(0.16)	(1.01)
Joint-significance	0.00	0.00	0.00	0.00
Observations	346	346	346	346
R-squared	0.79	0.80	0.81	0.81
Number of id	173	173	173	173

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. *j* indexes informer. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively.

All columns in Table 3.10 again indicate that the test scores of individuals who receive information from the treated in SURS are 1.69–2.96 points higher than those informed by the untreated in the group. These results are statistically significant at the 5% level. The DD variables for the treated informer *j* in SRS and SNT have negative effects on their receivers' test scores and are not significant. These results are consistent with the panel models and confirm that the direct spillover effects are strong in the SURS group.

Table 3. 10. Effect of each Targeting Method on the Knowledge of BMPs of their Neighbors: Cross-sectional Data

Dependent Variable: *i*'s test score	DD2 (1)	CFE 1 (2)	CFE 1 (3)
Score 2016		0.18*	0.13
		(0.10)	(0.12)
SRS	3.47***	3.32***	3.55***
	(0.87)	(0.79)	(0.77)
SURS	4.30***	3.96***	3.999***
	(0.83)	(0.90)	(0.91)
SNT	1.76*	1.69*	1.79**
	(0.91)	(0.87)	(0.84)
SRS**j*'s Treated	-0.91	-0.53	-0.59
	(0.96)	(1.10)	(1.03)
SURS**j*'s Treated	1.69***	1.96***	2.96**
	(0.40)	(0.44)	(0.90)
SNT**j*'s Treated	-0.20	-0.45	-0.94
	(1.25)	(1.24)	(1.21)
Father shrimp farmer		0.58	0.19
		(0.77)	(0.75)
No. hm 16-60		-0.03	-0.04
		(0.20)	(0.21)
Farm size, t-1		-0.01	-0.18
		(0.83)	(0.79)
Gender			1.63*
			(0.95)
Age			-0.03
			(0.03)
Year of education			0.16
			(0.11)
Year of Shrimp Farming			-0.002
			(0.09)
Constant	8.34***	8.06***	7.06***
	(0.62)	(0.99)	(2.42)
Joint-significance	0.0001	0.002	0.001
Observations	173	173	173
R-squared	0.16	0.18	0.22

Notes: Standard errors in parentheses are clustered at the canal level. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. *j* indexes informer. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively.

Table 3.11 shows the results using samples, including untreated farmers, only to show the direct spillover effects from treated to untreated farmers. In addition to direct spillover effects, when a person's direct informer is treated, the BMPs score increases by 2.3 within the SURS group. On the contrary, the BMPs score decreases by 2.2, if an untreated farmer nominates a treated farmer of the SNT as an advisor.

Table 3. 11. Effect of each Targeting Method on the Knowledge of BMPs of their Neighbors: Panel Data & Untreated Farmers Only

Dependent Variable: *i*'s test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.66***	8.76***	6.80***	6.97***
	(0.43)	(0.44)	(0.93)	(0.98)
SRS*Time			3.08**	3.06**
			(1.20)	(1.21)
SURS*Time			2.30*	2.59**
			(1.18)	(1.43)
SNT*Time			1.96	1.80
			(1.23)	(1.23)
j's Treated*Time	0.06	-0.11		
	(1.03)	(1.06)		
SRS**j*'s Treated*Time			1.46	1.46
			(1.17)	(1.10)
SURS**j*'s Treated*Time			2.30*	2.25
			(1.18)	(1.43)
SNT**j*'s Treated*Time			-1.99	-2.17
			(1.50)	(1.52)
Father shrimp farmer		-0.45		-0.21
		(0.63)		(0.63)
No. hm 16-60		0.32		0.24
		(0.34)		(0.32)
Farm size, t-1		-1.16		-1.40
		(1.11)		(1.15)
Constant	2.04***	2.07*	2.04***	2.35**
	(0.20)	(1.13)	(0.19)	(1.07)
Joint-significance	0.00	0.00	0.00	0.00
Observations	274	274	274	274
R-squared	0.78	0.79	0.81	0.81
Number of id	137	137	137	137

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. *j* indexes informer. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively.

3.5.4. Robustness Checks

Table 3.12 describes the results of the robustness checks for Questions 1 and 3. In the table, the variables used in the estimations of Questions 1 and 3 are analyzed together. The table shows that the results are similar to those in Tables 3.5 and 3.9. The variables *Group*i's Treated*Time* are statistically insignificant. While the variable *SURS*j's Treated*Time* is not significant in Column (4), the variable is statistically significant in Column (3) and the magnitude is similar to the result in Table 3.9. These show that even after controlling for the treatment effects on treated farmers, direct spillover effects from the treated informer to an untreated farmer in the SURS group is high.

Table 3. 12. Effect of each Targeting Method on the Knowledge of BMPs of the Treated and their Neighbors: Panel Data

Dependent Variable: *i*'s test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.71***	8.84***	6.80***	7.01***
	(0.42)	(0.42)	(0.93)	(0.97)
SRS*Time			3.25***	3.25***
			(1.19)	(1.20)
SURS*Time			2.90**	2.54**
			(1.16)	(1.22)
SNT*Time			1.86	1.63
			(1.21)	(1.21)
i's Treated*Time	-0.01	-0.02		
	(0.78)	(0.78)		
j's Treated*Time	-0.27	-0.35		
	(0.83)	(0.84)		
SRS**i*'s Treated*Time			-0.21	-0.32
			(1.26)	(1.26)
SURS**i*'s Treated*Time			-2.32	-2.28
			(1.58)	(1.57)
SNT**i*'s Treated*Time			0.23	0.38
			(1.19)	(1.20)
SRS**j*'s Treated*Time			0.33	0.09
			(1.36)	(1.28)
SURS**j*'s Treated*Time			2.30*	2.31
			(1.18)	(1.42)
SNT**j*'s Treated*Time			-1.70	-1.75
			(1.21)	(1.23)
Constant	2.06***	1.82*	2.06***	2.32**
	(0.17)	(1.05)	(0.16)	(1.03)
Time-variant Charac.	No	Yes	No	Yes
Observations	346	346	346	346
R-squared	0.79	0.80	0.81	0.82
Number of id	173	173	173	173

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. *j* indexes informer. SRS, SURS, and SNT is the abbreviation for the Simple Random Sampling, the Systematically Unaligned Random Sampling, and the Social Network Targeting, respectively.

3.6. Chapter Summary

The study uses individual-level data to identify a targeting method which can diffuse accurate agricultural information to farmers. The data includes information on farmers' social networks, psychological characteristics, and the knowledge level of a good practice called BMPs, as well as their socio-economic characteristics.

On December 31, 2016, I held a workshop for disseminating BMPs. The participants were selected using three targeting methods and were divided into three groups based on the methods, such as SRS, SURS, and SNT. In August 2017, a follow-up survey was conducted to investigate how well farmers' knowledge of BMPs improved in comparison to the status before my intervention.

Using primary data, this study tested my research questions mentioned in Subchapter 3.3.1, and found that: (1) while the treatment effect on treated farmers was weak or insignificant for most of our models, the SRS targeting method increases BMPs knowledge for all farmers in the village the most, followed by the SURS targeting method; (2) the SNT targeting method increases the degree of information sharing among villagers the most, while other targeting methods reduces information sharing; and (3) the SURS targeting method increases the BMPs knowledge of the information advisees of the treated farmers the most. These findings suggest that in order to spread accurate information to a wider group of farmers, the SRS and SURS targeting methods are better than the SNT targeting method. While the SNT targeting method is found to increase information sharing among farmers, the extent that the information is disseminated depends on the existing social network, and thus may not reach a wider group of farmers. Furthermore, the study found that reciprocity has a negative correlation with sharing information with many people. Reciprocity means helping others for mutual benefits. Therefore, it is presumed that people with strong reciprocity tend to be passive in information sharing. Considering the case of my study site, there are many factors which hinder frequent information exchanges among farmers, such as (i) the geographical characteristics that separate farmers from each other, (ii) information exchange using smart phones that is still not popular, and (iii) there is a strong traditional norm that people are not willing to exchange information, particularly about shrimp farming. These factors may have supported the effectiveness of the SURS targeting method that is based on geographical distance in my case.

My findings shed light on the effective targeting methods for information diffusion. First, SURS may be suitable to enhance the knowledge level of neighboring farmers. However, I need to interpret the result carefully as systematic sampling tends to introduce bias into the sample rather than SRS. Second, while the SNT group is more active in informing BMPs knowledge to other farmers than other groups, the direct and indirect treatment effects of the SNT group on the diffusion of accurate information may be smaller than those of the other groups. I presume that this is suggesting that the person with high betweenness centrality tends to receive and send a substantial amount of information through various channels and focuses on exchanging information frequently without distinguishing the quality of information.

Finally, I should note that there are several limitations to this study. One limitation is that the study does not handle regional or industrial heterogeneities. As my field experiment was conducted in only four villages, the estimation results may be due to the combined effects of the characteristics of each village and each targeting rather than the net effect of each targeting method. Therefore, a further study should be conducted in more regions and industries to clarify my research issues by eliminating the heterogeneities. My findings suggest effective targeting methods to transmit information to more people or to spread accurate information to the untreated as well as the treated. It is hoped that they will contribute to improving farming practices in developing countries.

4. Motivation for Information Exchange in a Virtual Community of Practice: Evidence from a Facebook Group for Shrimp Farmers

4.1. Introduction

Information plays an important role in decision-making, and farming decisions in developing countries are no exception. The information may be on farming technique, market information, or climatic conditions. Studies have found positive effects of various media in disseminating information, such as the introduction of mobile phones and the market information system in many African countries (Muto and Yamano, 2009; Aker and Mbiti, 2010; Jack and Suri, 2014). While agricultural extension officers have been a traditional distribution channel of agricultural information for farmers, information from peers also matters for technology adoption; thus, social networks play an important role in disseminating agricultural information (Conley and Udry, 2010; Maertens and Barett, 2012).

However, information is not cost-less, and why people share information with others is not well understood. The literature on psychology or social networks has studied communication among communities of practice (CoPs), namely groups that consist of individuals engaged in the same industry or related to the work, finding that direct reciprocity is one of the reasons why people share information (Lave, 1991; Lave and Wenger, 1991; Wasko, 2005; Wenger, 1998). Others show that indirect reciprocity, which is the feeling of obligation to help others if being helped by someone, also plays a role (Nowak and Sigmund, 2005). Reputation and peer effects can be other reasons (Wasko, 2005; Fehr, Kirchsteiger, and Riedl, 1993; Gächter, Nosenzo, and Sefton, 2013). However, most of these studies rely on self-reported recall data of personal communications and consequently the data points are limited. Further, examples are drawn from developed-country settings, and thus the applicability of these findings to developing-country agriculture is not guaranteed.

This study attempts to overcome these limitations by studying the motivation for information exchange by using the records of communications via Facebook over two and a half years. I examine the case of a Facebook group mostly comprising farmers, which shares a common farming crop. Facebook groups are considered to be virtual communities of practice (VCoPs). Although VCoPs are similar to CoPs, their members tend to be distributed nationally or globally, and many of them may not meet face to face with other members (Wasko, 2005). While these SNS communities are considered to be an advanced form of extension systems (called "e-farming") that promote information exchange in developing countries, there is a dearth of literature on how communications actually take place among members. One concern with promoting this kind of community is how active information exchange will be, particularly because the interpersonal ties between members in VCoPs are typically weak compared with real communities in villages where the social network is dense. One way in which to find this out is to examine whether a norm of reciprocity plays a role in facilitating information exchange even in a virtual space. In particular, indirect reciprocity,[9] rather than direct reciprocity, may be an important motivation for information exchange with other VCoP members (Jung, 2017; Nowak and Sigmund, 2005; Wasko, 2005).

I construct a monthly panel dataset between January 2015 and May 2017 to understand a Facebook group member's motivation for information exchange. Based on Poisson and negative binomial regressions, I find that: (1) members who have previously asked questions are more active in sharing information than people who have never asked; (2) other members' positive expressions to previous information shared (such as clicking likes[10]) promote future information sharing; (3) the act of information sharing by one's peer promotes his/her own information sharing; and 4) the more the member shared information in the past,

[9] Indirect reciprocity occurs when a person helps strangers, either in response to their kindness to third parties or after receiving kindness from others (Apeldoorn and Schram, 2016).

[10] Facebook has provided a like button function to users since February 2009. The Facebook like button enables users to interact with posts shared by friends and advertisements. Those users usually click the button to visually indicate that they agree or enjoy a shared post (Facebook Help Center, 2017).

the more s/he asks for information today. These findings suggest that reciprocity plays a significant role in motivating information exchange in VCoPs, similar to in CoPs. I also confirm that professional reputation is a motivation for information sharing and that there is a positive effect of a peer's pro-social behavior.

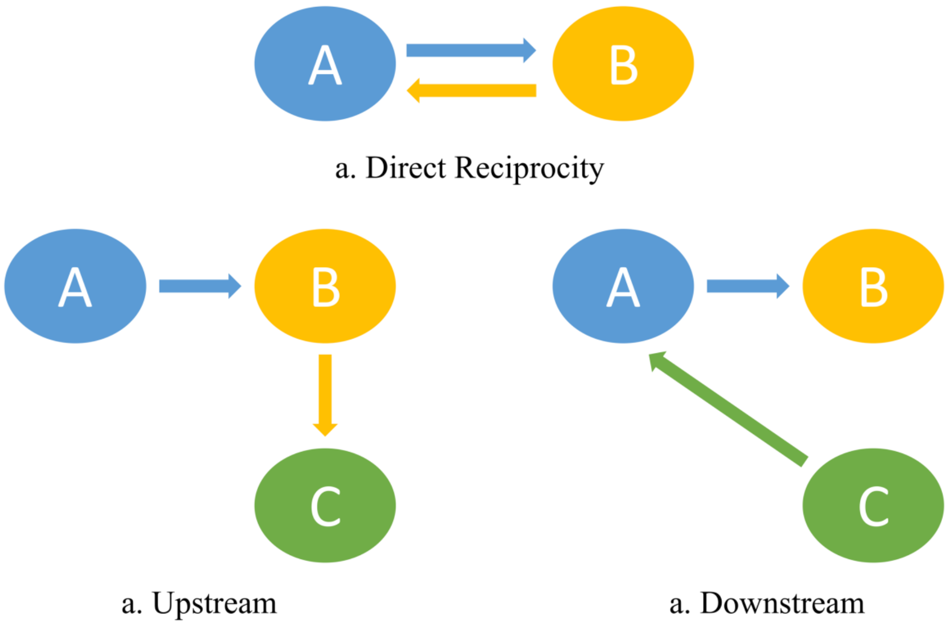
The contribution of this study is threefold. First, by using the records of communication among members, this study verifies that reciprocity is an important motivation for information sharing and inquiries in VCoPs, as in CoPs. Second, it provides evidence on whether peer effects exist in online communities. Third, this study documents the case of an online CoP, which is functioning effectively to provide useful information to members.

The rest of the study is organized as follows. Subchapter 4.2 reviews the relevant literature on the motivation for information-sharing behavior in cyberspace and describes the Facebook group's role and features. Subchapter 4.3 describes my hypotheses. In Subchapter 4.4, I explain the data used herein, present summary statistics, and describe the variables used to elicit the reciprocities and peer effects among members. Subchapter 4.5 describes the estimation methods used, and the results are presented in Subchapter 4.6. Finally, Subchapter 4.7 concludes.

4.2. Description of a VCoP

4.2.1. Previous Literature

According to Nowak and Sigmund (2005), indirect reciprocity can be divided into upstream and downstream reciprocity, as shown in Figure 4.1. Upstream reciprocity is built on a recent positive experience. Individual B, who has just received help from A, helps C. Downstream reciprocity is based on reputation. Individual A has helped B and therefore receives help from C. As mentioned in Subchapter 4.1, in a virtual community, most members do not meet with each other. Moreover, they may not remember some of those who helped them because they often receive help from a large number of people in a short period.[11] Taking these matters into account, it seems that it is insufficient to explain the motivation for information exchange in VCoPs only with direct reciprocity. Thus, this study suggests that indirect reciprocity such as downstream and upstream reciprocity should be considered to identify the motivation.



Source: Nowak and Sigmund (2005)
Figure 4. 1. Direct and Indirect Reciprocity

The study by Wasko et al. (2005) is the most relevant to my study. They collected data from an electronic network of a legal professional association in the United States and examined how individual motivations and social capital influence knowledge contribution.[12] Since participation in the network was not anonymous, they assumed that knowledge contribution to the system would have a positive impact on the professional reputation of the

[11] In my data, the average number of comments to questions is about 20. This average is the result excluding zero comments.
[12] The virtual network of practice for its members, offered by the association, is similar to a web-based bulletin board and the exchange of information on this network is open to all members (Wasko, 2005).

individual who shared the information. The study employed the volume of the contribution and helpfulness of the contribution[13] as dependent variables and found that members aware that knowledge contribution helps their professional reputation are more active in sharing and that participation occurs irrespective of expectations of direct reciprocity from others. While the study is crucial to understanding the motivation for individual knowledge-sharing behavior among online community members, Wasko et al.'s (2005) model does not take into account time effects (e.g., social capital accumulated over many years can affect current knowledge sharing) because they used cross-sectional data.

In contrast to Wasko et al.'s study of sharing information among specific online community members, Jung (2017) examined why people share knowledge with unspecified individuals in cyberspace by using game theory. Based on social exchange theory (Cook and Rice, 2003; Homans and Merton, 1961), the author hypothesized that the pro-social behavior of helping others online is motivated by self-interest such as reward maximization and cost minimization. Thus, the study set rewards such as mental satisfaction and reputation and costs such as time and effort. According to Jung (2017), in the model without the application of social capital, if an individual gains utility greater than zero $u = reward - cost > 0$ when s/he provides knowledge to other players, the person chooses to share her/his knowledge with others. Otherwise, s/he chooses not to share if $u < 0$. In the model with the application of social capital, the player selects knowledge sharing if the social capital $f(x)$ accumulated until the previous round and the profit from sharing knowledge with others in this round are greater than zero (i.e., when $u + f(x) > 0$). Otherwise, the player chooses not to share if $u + f(x) < 0$. The advantage of Jung's study is that it considered the impact of social capital on knowledge sharing over time. However, those hypotheses were not tested with empirical evidence.

[13] The author rated responses as very helpful, helpful, somewhat helpful, and not helpful (Wasko, 2005).

Fehr, Kirchsteiger, and Riedl (1993) examined peer effects in pro-social behavior by using a three-person gift exchange experiment. The game has one employer and two employees. First, the employer decides the wage to give to employees and then employees choose how much effort to make sequentially. The study revealed that the second employee's choice is determined by the effort choice of the first employee. This finding suggests that the pro-social behavior of an individual is influenced by whether his/her peer chooses pro-social behavior first (see also Gächter, Nosenzo, and Sefton, 2013).

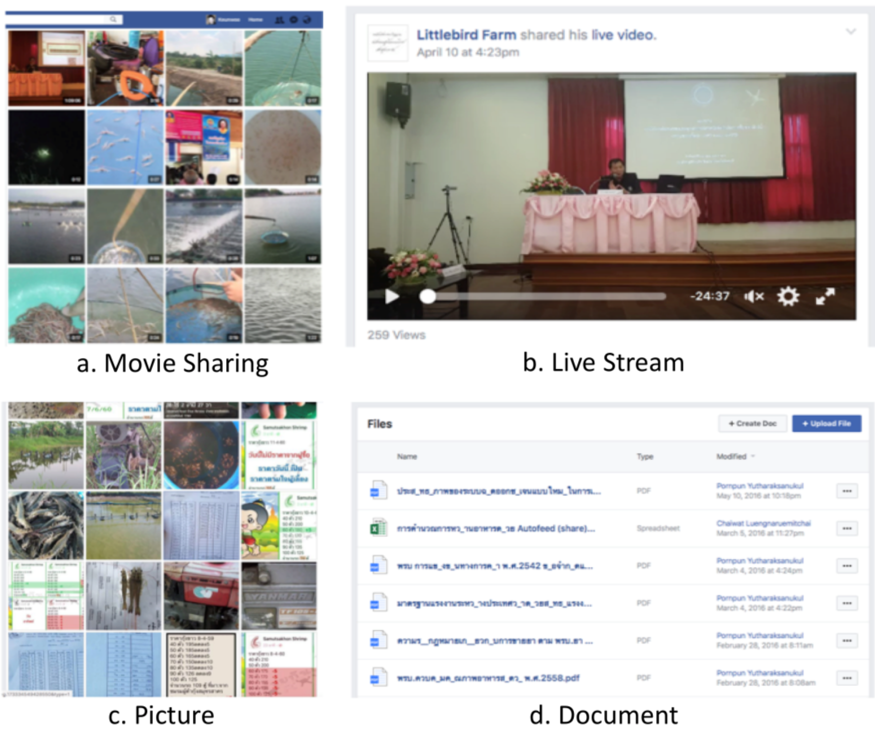
Although these studies reveal that reciprocity is an important component of pro-social behavior, their analyses are incomplete as they did not empirically examine the motives of pro-social behavior or use panel data to observe how individual behavior changes over time. Thus, how the interaction between VCoP members influences their pro-social behavior and how their behaviors change over multiple periods remain open questions. To answer these questions, this study uses panel data on a VCoP.

4.2.2. Information Exchange among Facebook Group Members

To identify the motivation for information exchange in VCoPs, this study investigates the activities of a particular VCoP, which is kept anonymous for privacy reasons. It is a closed Facebook group founded in 2011 by a shrimp farmer and it has been managed by nine farmers. To join the group, the applicant must be a Facebook user and must be added by an existing member. By the end of May 2017, the group had a membership of over 18,000 and nearly 13 000 posts. As shown in Figure 4.2 , group members usually create posts to share their expertise in shrimp cultivation or to ask other users issues relating to shrimp farming. Hence, regarding membership and activity, it seems that the group is a representative example of a VCoP.

Source: Based on a Facebook group data

Figure 4. 2. Inquiry and Share in a Facebook Group



Source: Based on a Facebook group data

Figure 4. 3. Knowledge Sharing Method in a Facebook Group

According to Taya (2003), shrimp diseases such as white spot syndrome virus and early mortality syndrome spread rapidly once they occur. When a shrimp is infected with a virus, it quickly spreads to other shrimp in the same pond, and all the shrimp may die within a few days. Thus, obtaining appropriate and timely information is vital for shrimp farmers to reduce the risk of shrimp diseases (Suzuki, 2016). As information exchange is important in shrimp farming, this network has been maintained effectively over time.

Table 4.1 shows the number of members in the Facebook group. In the middle of 2017, it had 18,271 subscribers, which is equivalent to 60% of the total shrimp farms in the country (FAO, 2017).[14] Annual and monthly membership growth shows mostly a positive linear trend. The number of new members in 2016 was approximately equal to that in 2015. Rogers's (1962) diffusion of innovation theory argues that there is a critical point[15] at which the adoption of innovation is accelerated. It seems that group membership reached the critical point before 2016 because the slope of membership growth increased sharply between 2015 and 2016, which is similar to the slope after reaching a critical point in Rogers' diffusion s-curve (Rogers, 1962). Regarding monthly mean new membership, which is not reported here for brevity, the average in 2017 was about 5% higher than the monthly average in 2016 and the standard deviation in 2017 was smaller than that in 2016. If this trend continued until the end of 2017, it is highly likely that new membership in 2017 was more than the annual total in 2016.

[14] However, the actual percentage of farmers in this group in the total shrimp farmer population may be much lower since the group comprises traders, researchers, and public administrators as well as shrimp farmers.

[15] On the basis of innovativeness, adopters are classified into five adopter categories: innovators, early adopters, early majority, late majority, and laggards. The critical point is associated with the early adopters category, which has the highest degree of opinion leadership and strong influences the decisions of others in the same community (Rogers, 1962).

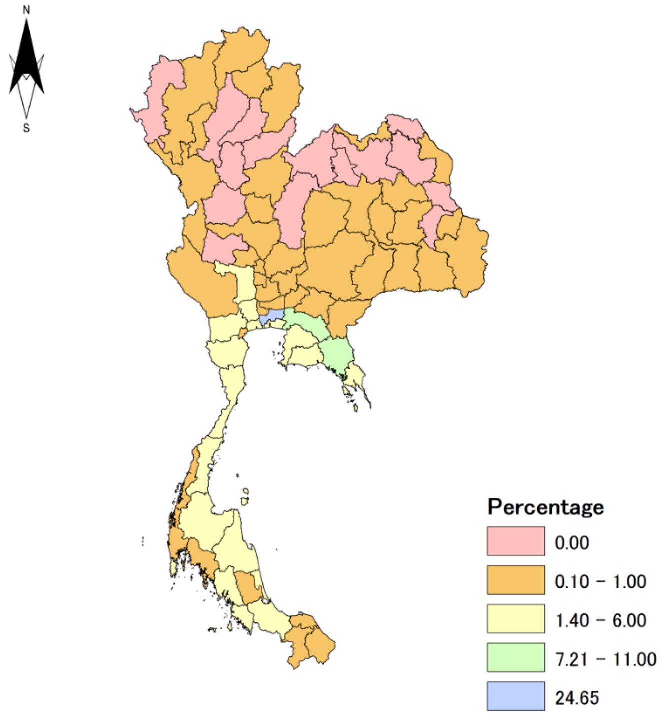
Table 4. 1. The Increase in the Membership for Facebook group

	2011	2012	2013	2014	2015	2016	2017
New Member	7	179	1,034	3,748	2,796	7,215	3,292
Cumulative Total	7	186	1,220	4,968	7,764	14,979	18,271

Notes: 2017 data is only for January to May.

Source: Based on a Facebook group data for 2011-2017

Figure 4.4 presents the group member distribution in Thailand. To draw the map, I randomly selected 1 000 people from the group members and extracted information on their residences from their Facebook profiles. There are five colors according to user concentration. Bangkok has the largest members with 24.65 percent, followed by Chantaburi and Chachoengsao. It seems that most users, who live in Bangkok, are engaged in foreign trade or intermediary agents related to shrimp aquaculture. Since the group started among farmers in Chantaburi, the percentage of users in Chantaburi is high. The large proportion of users in Chachoengsao is thought to be the geographical influence because Chachoengsao is located between Bangkok and Chantaburi. The percentage of users in the southern coastal areas, where shrimp farming is active, is the next, and inland users are less than one percent or zero.



Source: Based on a Facebook group data
Figure 4. 4. Membership Distribution

4.3. Hypotheses

To identify the motivation for information exchange in the Facebook group, I set the following six hypotheses based on previous studies. These hypotheses can be divided into two categories. Hypotheses 1 to 3 refer to information sharing by group members and Hypotheses 4 to 6 refer to information inquiries by group members.

I test Hypotheses 1 and 4 to verify whether reciprocity between the members of the Facebook group affect information sharing and inquiries, respectively. The aim of Hypothesis 2 is to test whether improvements in professional reputation promote information sharing in the Facebook group. Hypotheses 3 and 6 are tested to verify if there are peer effects on information sharing and inquiries between Facebook group members. Finally, I test Hypothesis 5 to confirm that the pro-social behavior of group members is correlated with encouraging members' inquiries.

Hypothesis 1:

Members of the Facebook group who have previously asked for information from other group members are more active in sharing information than those who have not.

Hypothesis 2:

When a person received a greater number of favorable ratings in the past, s/he is encouraged to share more information to other members of the group.

Hypothesis 3:

The sharing behavior of the peer who added the member to the group is correlated with the member's sharing behavior.

Hypothesis 4:

The more the member shared information in the past, the more s/he asks for information today.

Hypothesis 5:

The more the member received answers to previous questions from other members, the more s/he asks for information from group members today.

Hypothesis 6:

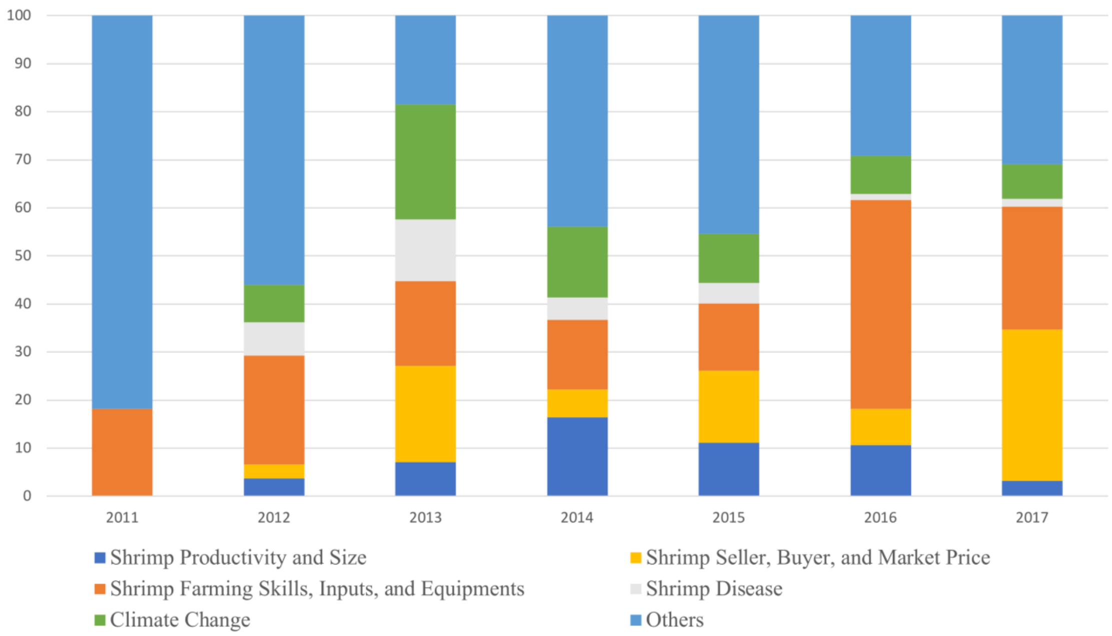
The inquiries of the peer who added the member to the group affects the member's inquiries.

4.4. Data

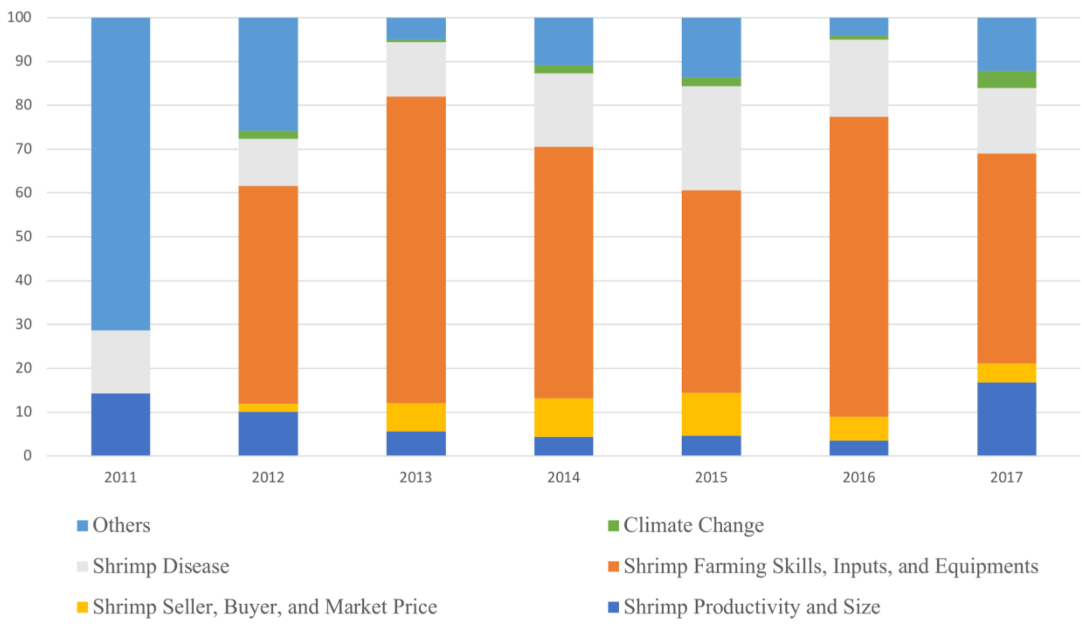
To identify the factors relating to information exchanges between group members, I collected data posted to the Facebook group between November 2011 and May 2017. In my regression analyses, I limited the sample to those who joined the group between 2011 and 2014 as I want to examine their communications between 2015 and 2017. Hence, I used only the 4,968 members who joined the group by the end of 2014 for my analysis. The data used for the analysis also included likes and comments[16] for each post, along with the 5,488 posts shared by them between January 2015 and May 2017.

I first divided all the posts from November 2011 to May 2017 into two categories according to their purpose of posting: information sharing and inquiries. During this period, 7,019 posts shared knowledge and 3 850 posts asked questions. I then divided each type into the six categories shown in Figure 4.5 based on their content. Both panels of this figure show that the "other" category, in which personal information dominates, was large initially but soon its share declined. This is because the initial purpose of the group was to promote friendship among alumni who graduated from the same university. Since 2012, posts about shrimp farming technologies, inputs, climate change, and shrimp diseases have been actively posted, and the Facebook group has become a CoP in shrimp farming. Overall, 15-45% of these posts have related to shrimp farming skills, inputs, and equipment, and this information not only improves productivity but also prevents shrimp diseases. In Panel b, the share of inquiries about shrimp farming skills was the largest, ranging from 46% to 70%, except for 2011. Moreover, questions about shrimp diseases consistently represented more than 10% of all questions. On the contrary, questions about sellers and buyers accounted for at most 4%, indicating that members mainly use the group to obtain information about practical skills rather than looking for a seller or buyer.

[16] Facebook users can type their opinion about other people's post or answers to other users' question by clicking the comment link under the post (Facebook Help Center, 2017).



a. Information Sharing Categories



b. Information Inquiry Categories

Source: Based on a Facebook group data for 2011-2017

Figure 4. 5. Sharing and Inquiry Categories

Table 4.2 summarizes the count data on each user's average monthly information sharing (*S*) and inquiries (*Q*). The variable *L* rows represent the statistics of likes for shared posts each year. The variable *C* rows display the statistics of comments for the question posts each year. From 2012 to 2014, I find that 11% to 19% of members shared information (*S* rows). However, this share dropped to 1–2% after 2015, indicating that as the number of members increased, many did not actively participate in the discussions. Similar to the decrease in the proportion of members who shared information, the average proportion of members who asked questions (*Q* rows) also fell, but this decreased more gradually relative to the speed of the decline in sharing. Furthermore, Table 4.2 implies that as the number of members increased, the number of likes on an information-sharing post rose dramatically whereas the number of comments on a question did not increase significantly.

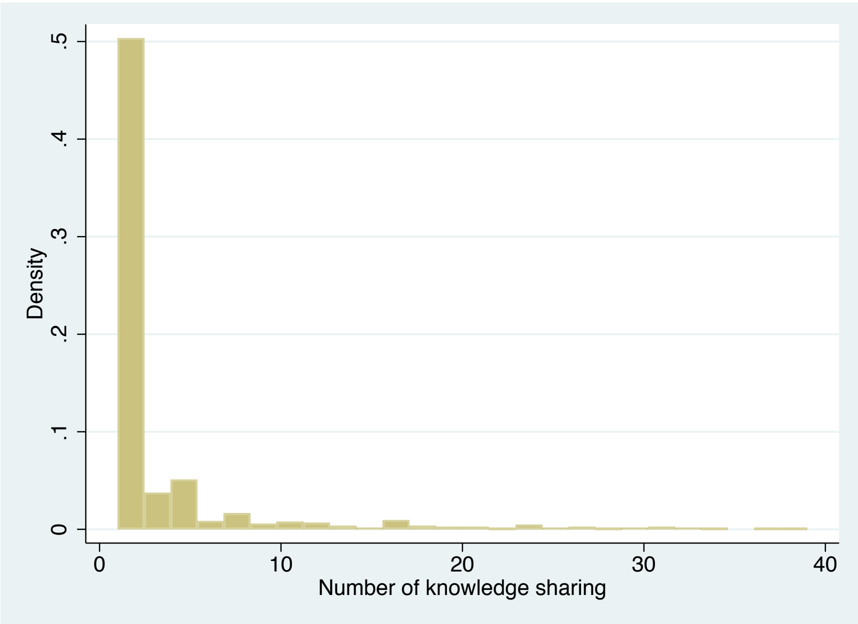
Table 4. 2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Jan to Dec 2012					
S	328	0.11	0.49	0.00	4.00
Q	121	0.11	0.41	0.00	3.00
L		6.32		0.00	10.00
C		11.68		0.00	33.00
Jan to Dec 2013					
S	1,125	0.19	1.77	0.00	57.00
Q	345	0.06	0.35	0.00	4.00
L		9.22		0.00	194.00
C		11.69		0.00	64.00
Jan to Dec 2014					
S	2,465	0.11	1.36	0.00	51.00
Q	1,302	0.02	0.21	0.00	8.00
L		28.21		0.00	480.00
C		10.12		0.00	128.00
Jan to Dec 2015					
S	1,313	0.02	0.46	0.00	30.00
Q	514	0.01	0.10	0.00	6.00
L		43.56		0.00	527.00
C		11.14		0.00	234.00
Jan to Dec 2016					
S	1,137	0.01	0.35	0.00	39.00
Q	970	0.005	0.08	0.00	4.00
L		56.90		0.00	569.00
C		12.78		0.00	177.00
Jan to May 2017					
S	647	0.01	0.35	0.00	37.00
Q	595	0.01	0.10	0.00	7.00
L		46.00		0.00	527.00
C		13.74		0.00	125.00

Note: *S*=information sharing, *Q*= information inquiry, *L*=the number of likes, and *C*=the number of comments. The number of obs for *S* and *Q* indicates the number of sharing and inquiry, respectively.

Source: Based on a Facebook group data for 2011-2017

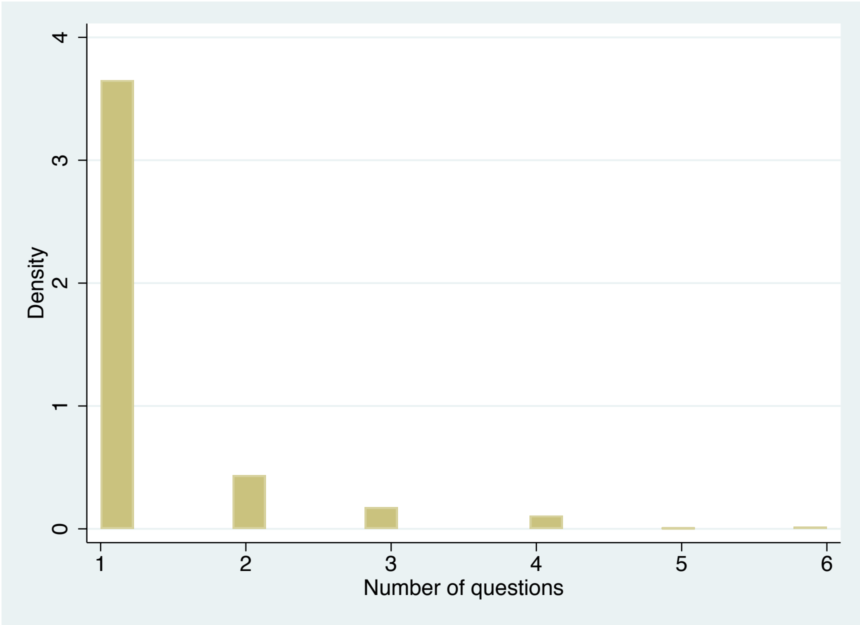
Figure 4.6 presents a histogram showing the information sharing by members during that period. I exclude those observations with zero shares, which have by far the highest density, to present the density of the other observations clearly. The distribution of the histogram is skewed to the right. The density is the highest at 0.5 for the observations that shared information between 1 and 2.4 times, followed by 0.05 for those that shared between 3.8 and 5.2 times and 0.04 for those that shared between 2.4 and 3.8 times. The density of all other frequencies is close to zero.



Source: Based on a Facebook group data for 2011-2017

Figure 4. 6. Number of Sharing

The histogram in Figure 4.7 illustrates the inquiries to other members during the same period. Again, I exclude observations with zero inquiries. Similar to Figure 4.4, the histogram is skewed to the right. The density of one question is extremely high at 3.65, followed by that of two questions at 0.44 and that of three questions at 0.17.



Source: Based on a Facebook group data for 2011-2017

Figure 4. 7. Number of Questions

4.5. Empirical Strategies

I empirically examine the determinants of information sharing and inquiries among Facebook group members by using the hypotheses set above. I first evaluate the two-way fixed effect Poisson regression with the number of shares as the dependent variable. I estimate

$$S_{it} = \beta_1 S_{it-1} + \beta_2 Q_{it-1} + \beta_3 L_{it-1} + \beta_4 S_{jt-1} + \alpha_i + \lambda_t + u_{it} \tag{4.1}$$

where the subscript i denotes the individual, j denotes i's social network partner who added i, and t is the month; S is the knowledge shared by i or j each month; Q denotes the number of questions that i asked each month; L refers to the average monthly number of likes that i obtained; α is the unobserved individual effect; λ is the time fixed effect; and u is the error term. According to Cameron and Trivedi (2013), the Poisson regression model is appropriate for counter-dependent variables. Because those dependent variables in Equations (4.1) and

(4.2) are counter variables, I employ a two-way fixed effect Poisson regression and take the behavioral changes of those members each month.

Next, I model the determinants of inquiries. I assume that the factors that encourage inquiries in the group are similar to the motivation for information sharing. The regression model is as follows:

$$Q_{it} = \beta_1 Q_{it-1} + \beta_2 S_{it-1} + \beta_3 C_{it-1} + \beta_4 AS_{jt-1} + \lambda_t + a_i + u_{it} \tag{4.2}$$

where *C* denotes the average monthly number of comments that *i* obtained.

Furthermore, the study employs pooled Poisson regressions for both the dependent variables mentioned above to increase the sample size and sample from the population at different points in time. However, the Poisson regression model does not address the problem of overdispersion often observed in count variables. In addition to the Poisson models, I therefore use negative binomial regression models such as the mean-dispersion model (NB1) and constant-dispersion model (NB2) for the overdispersed variables. All models include time dummies to account for monthly fluctuations in those dependent variables (Cameron and Trivedi, 2013). I also create two binary variables for information sharing and inquiries and examine the determinants of the probability of these behaviors. Equations (4.3) and (4.4) are estimated by using the average marginal probability effects in the two-way fixed effect Logit model:

$$\Pr(S_{it} = 1) = \beta_1 S_{it-1} + \beta_2 Q_{it-1} + \beta_3 L_{it-1} + \beta_4 S_{jt-1} + \lambda_t + a_i + u_{it} \tag{4.3}$$

$$\Pr(Q_{it} = 1) = \beta_2 Q_{it-1} + \beta_1 S_{it-1} + \beta_3 C_{it-1} + \beta_4 Q_{jt-1} + \lambda_t + a_i + u_{it} \tag{4.4}$$

where S is the dummy for each member's sharing in the VCoP, equal to one if the member shares information and zero otherwise, and Q is the binary variable for each member's inquiries, equal to one if the member asks other members any question and zero otherwise.

4.6. Estimation Results

4.6.1. Determinants of Information Sharing

I evaluate various models such as the fixed effect Poisson model, pooled Poisson model, pooled NB1, and pooled NB2 to examine the count variables for information sharing shown in Equation (4.1). The dependent variable in Table 4.3 is the information sharing of individual i. To compare the goodness-of-fit of the three pooled models, I perform the likelihood ratio test. The result of this test suggests that NB1 and NB2 have a better fit than the pooled Poisson model because both overdispersion parameters (α=0 and δ=0) are rejected. As the log likelihood of NB1 is higher than that of NB2, NB1 appears to be the most suitable pooled model.

In Column (1), there are statistically significant relationships between all the explanatory variables and the information sharing of individual i. The result of individual i's information sharing a month ago (Lag_S) indicates that the individual's shares this month increase by 0.05 units. Further, if an individual had increased the frequency of inquiries a month ago (Lag_Q), the difference in the logs of expected counts would be expected to increase by 0.24 units, while holding the other variables in the model constant. This result supports Hypothesis 1 about reciprocity, which is one of the motivations for information sharing. The variable Lag_L, which denotes the number of likes for a post posted by individual i a month ago, has a positive and significant impact on individual i's information sharing this month. This result is statistically significant and supports Hypothesis 2 relating to professional reputation. The significance levels and signs of the explanatory variables in

Column (1) are consistent in the other models in Table 4.3, except for information sharing by an individual's social network partner (*Lag_J_S*).

Table 4. 3. The Estimation Result of the Number of Information Sharing (2015-2017)

	FE Poisson	Pooled Poisson	Pooled NB1	Pooled NB2
VARIABLES	(1)	(2)	(3)	(4)
Lag_S	0.05***	0.19***	0.96***	0.17***
	(0.01)	(0.01)	(0.29)	(0.01)
Lag_Q	0.24***	0.84***	2.11***	0.89***
	(0.07)	(0.08)	(0.24)	(0.08)
Lag_L	0.003***	0.01***	0.03***	0.01***
	(0.001)	(0.001)	(0.004)	(0.001)
Lag_J_S	0.04**	0.01	-0.01	-0.01
	(0.02)	(0.03)	(0.02)	(0.01)
Constant		-4.30***	-4.63***	-3.57***
		(0.58)	(0.42)	(0.35)
Time Dummy	Yes	Yes	Yes	Yes
Observations	6,322	144,058	144,058	144,058
Number of *i*	218	4,968	4,968	4,968
Time Periods	29	29	29	29
Wald chi2(32)	1197.72	6180.03	575.35	5290.79
Pseudo R2		0.49	0.19	0.17
Log Likelihood	-2551.81	-8037.35	-4630.65	-4751.05
AIC	5167.61	16140.7		
α			19.84	
δ				4.14
LR test			chi2(1)=6813.39	chi2(1)=6572.60
			Prob>chi2=0.00	Prob>chi2=0.00

Note: Pooled NB1 is a mean-dispersion model, Pooled NB2 is a constant-dispersion model, *S*=information sharing, *Q*= information inquiry, *L*=the number of likes, and *J_S*= information sharing by j. In Column (1), robust standard errors in parentheses. In Columns (2), (3), and (4), standard errors in parentheses are adjusted for 4,968 clusters. * significant at 10%; ** significant at 5%; *** significant at 1%.

4.6.2. Determinants of Inquiries

Table 4 presents the results from estimating the Poisson models and negative binomial models based on Equation (4.2). The result of the likelihood ratio test for comparing the goodness-of-fit of the pooled models suggests that NB1 and NB2 have a better fit than the pooled Poisson model, and the result of the log likelihood indicates that NB1 is the most appropriate model among the pooled models.

In Column (1), there are statistically significant relationships between inquiries a month ago (*Lag_Q*) and the dependent variable for inquiries. The result for individual *i*'s inquiries a month ago (*Lag_Q*) indicates that the individual's inquiries this month increase by 0.32 units. Similar to the result of the fixed effect Poisson model, the result of NB1 in Column (3) shows that the explanatory variable (*Lag_Q*) has a positive and significant impact on the inquiries of individual *i*. In addition, the variable (*Lag_C*), which denotes the number of comments for a question posted by individual *i* a month ago, has a coefficient of 0.02, which is statistically significant at the 5% level. This means that for each one-unit increase in the number of comments received, the expected log count of inquiries increases by 0.02. This result is statistically significant and supports Hypothesis 5, which is that pro-social behavior by group members encourages their inquiries. On the contrary, the variable (*Lag_J_Q*) is not significant in all the models in Table 4.4. This result indicates that Hypothesis 6 is not supported.

Table 4. 4. The Estimation Result of the Information Inquiry (2015-2017)

VARIABLES	FE Poisson (1)	Pooled Poisson (2)	Pooled NB1 (3)	Pooled NB2 (4)
Lag_Q	0.32***	1.38***	3.00***	1.36***
	(0.06)	(0.09)	(0.21)	(0.08)
Lag_S	0.03	0.13***	0.50	0.13***
	(0.03)	(0.01)	(0.35)	(0.01)
Lag_C	0.004	0.02***	0.02**	0.02***
	(0.003)	(0.003)	(0.01)	(0.003)
Lag_J_Q	-0.11	-0.11	-0.30	-0.12
	(0.25)	(0.31)	(0.33)	(0.30)
Constant		-4.59***	-4.61***	-4.67***
		(0.21)	(0.18)	(0.19)
Time Dummies	Yes	Yes	Yes	Yes
Observations	7,105	144,058	144,058	144,058
Number of *i*	245	4,968	4,968	4,968
Time Periods	29	29	29	29
Wald chi2(32)	263.64	1275.77	1079.61	1245.88
Pseudo R2		0.15	0.10	0.10
Log Likelihood	-1557.42	-3733.31	-3422.56	-3441.21
AIC	3178.84	7532.63		
α			19.66	
δ				0.45
LR test			chi2(1)=621.52	chi2(1)=584.20
			Prob>chi2=0.00	Prob>chi2=0.00

Note: Pooled NB1 is a mean-dispersion model, Pooled NB2 is a constant-dispersion model, *S*=information sharing, *Q*= information inquiry, *C*=the number of comments, and *J_Q*= information inquiry by j. In Column (1), robust standard errors in parentheses. In Columns (2), (3), and (4), standard errors in parentheses are adjusted for 4,968 clusters. * significant at 10%; ** significant at 5%; *** significant at 1%.

4.6.3. Determinants of Information Sharing and Inquiries

Table 4.5 shows the marginal effects from estimating the Logistic model in terms of Equations (4.3) and (4.4). The dummy variable for information sharing is the dependent variable in Column (1) and the dummy variable for inquiries is the dependent variable in Column (2).

Most of the results in Table 4.5 are similar to those in Tables 3 and 4. A notable difference from Table 4.4 is that individual *i*'s information sharing a month ago (*Lag_S*) has a positive and significant effect on increasing the probability of individual *i*'s inquiries this month. In magnitude, the probability of inquiries by *i* increases by 1% as information sharing a month ago increases by one unit. Although this result does not confirm Hypothesis 4, it supports that reciprocity can affect inquiries in VCoPs.

Table 4. 5. Determinants of information sharing and inquiry: Average Marginal Probability Effects from the Fixed Effect Logistic Model (2015-2017)

VARIABLES	Sharing (1)	Inquiry (2)
Lag_S	0.22***	0.01**
	(0.006)	(0.005)
Lag_Q	0.05***	0.06***
	(0.02)	(0.02)
Lag_L	0.0003***	
	(0.0001)	
Lag_C		0.0002
		(0.001)
Lag_J_S	0.001	
	(0.002)	
Lag_J_Q		-0.03
		(0.04)
Time Dummy	Yes	Yes
Observations	6,264	7,105
Number of *i*	216	245
Time Periods	29	29
LR chi2(32)	278.99	196.83
Log Likelihood	-1235.54	-1283.06

Note: *S*=information sharing, *Q*= information inquiry, *L*=the number of likes, *C*=the number of comments, and J_S= information sharing by j, *J_Q*= information inquiry by j. Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

4.6.4 Robustness Checks

These estimation results may vary depending on the sample size and data collection period. Therefore, I retest my hypotheses by using data obtained from the 7 764 members who joined the group by the end of 2015. The data include their activity between January 2016 and May 2017.

Table 4.6 describes the results of the robustness checks. Columns (1) and (2) have dependent variables for information sharing. Columns (3) and (4) have dependent variables for inquiries. Column (1) shows results similar to those in Column (1) of Table 4.3 except for the variable *Lag_Q*. In Column (2), the variable *Lag_J_Q* is statistically significant at the 5% level unlike the result in Column (1) of Table 4.5. In Column (3), the results also slightly differ from the result of the model using data between 2015 and 2017. The explanatory variable *Lag_Q* is statistically significant in Column (1) of Table 4.4, whereas it is not significant in Column (3) of Table 4.6. Finally, Column (4) is the most different from the estimation results using data from 2015 to 2017 compared with the other columns in Table 4.6. Unlike the results in Table 4.5, none of the explanatory variables in Column (4) of Table 4.6 is significant.

Table 4. 6. Robustness Check (2016-2017)

	Sharing		Inquiry	
	FE Poisson	FE Logit	FE Poisson	FE Logit
	(1)	(2)	(3)	(4)
Lag_S	0.05***	0.03***	0.10	0.02
	(0.01)	(0.01)	(0.08)	(0.01)
Lag_Q	0.11	0.08**	0.08	0.02
	(0.11)	(0.04)	(0.06)	(0.03)
Lag_L	0.003***	0.0002		
	(0.001)	(0.0002)		
Lag_C			0.004	0.001
			(0.004)	(0.001)
Lag_J_S	0.06**	0.01*		
	(0.02)	(0.003)		
Lag_J_Q			-0.21	-0.03
			(0.33)	(0.08)
Constant				
Time Dummy	Yes	Yes	Yes	Yes
Observations	2,686	2,652	4,590	4,590
Number of *i*	158	156	270	270
Time Periods	17	17	17	17
Wald chi2(32)	454.11		56.85	
Log Likelihood	-1275.36	-662.47	-1271.88	-1967.83
AIC	2590.71		2583.75	

Note: *S*=information sharing, *Q*= information inquiry, *L*=the number of likes, *C*=the number of comments, and *J_S*= information sharing by j, *J_Q*= information inquiry by j. In Columns (1) and (3), robust standard errors in parentheses. In Columns (2) and (4), standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

4.7. Chapter Summary

Although VCoPs are used by many people in countries with Internet access, the motivation for and behavior of users' information exchange are still unclear. Therefore, the present study was undertaken to identify why people share their expertise in online communities, using data from a particular Facebook group. The study hypothesized that such behavior is motivated by reciprocity, professional reputation, and peer effects and tested the hypotheses by using various econometric models, including those that consider the time fixed effects.

As a result, I found that members who have previously asked questions are more active in sharing information than people who have not. This finding suggests that members' positive expressions such as clicking likes about posts promote information sharing. The results are robust to the various estimation methods employed, including models that consider the time fixed effects. Hypothesis 3, which stated that the information sharing of a social network partner has a positive effect on the sharing of an individual, was supported by the results of most models, except for the pooled NB1 regression.

In terms of inquiries, I was able to identify that people who had asked the question before were more active in asking the question. I also revealed that members who have previously shared information ask more frequently than members who have not shared. This behavior may come from reciprocity. Another finding is that the pro-social behavior of group members encourages members' inquiries, although the significance level is inconsistent across the models.

These findings clarify that reciprocity and professional reputation play important roles in enhancing professional knowledge exchange in VCoPs. If the members of a VCoP have a common motivation, information exchange can be activated, and such an active exchange of information will lead to the growth of the community.

Lastly, I should note several of the limitations of this study. One limitation is that I was not able to distinguish between direct and indirect reciprocity in virtual communities because of a lack of data. Therefore, an additional study should be conducted to examine the effects of direct and indirect reciprocity separately. Moreover, a model that includes psychological variables should be studied further to clarify the motivation for information sharing. My findings on the role of reciprocity and professional reputation suggest effective ways in which to activate information exchange among farmers. It is hoped that they will contribute to the better management of virtual communities, particularly with regard to designing e-farming interventions to improve farming practices in developing countries.

5. Conclusion

Solving problems arising from inaccurate information and the lack of information is considered an important strategy to improve both agricultural productivity and rural welfare in developing countries. Therefore, the present study identifies methods to disseminate accurate information in real communities and the reasons why people share their expertise in virtual communities.

In Chapter 2, to find a practice which can solve the problems of shrimp farming due to the use of antibiotics, this study interviewed 201 shrimp farmers randomly selected and collected shrimp samples from each household's pond for the screening of residual drugs. Using interview data and the test result, Logit and Tobit regressions were performed to investigate whether the results of the residue tests were significantly associated with particular farmers' characteristics and farm management practices. As a result, I find that: (1) receiving BMPs training has a significant and positive effect on reducing residual drugs; (2) if farmers trust information on the treatment of shrimp diseases from extension officers, this relationship has a significant and positive effect on reducing residual drugs; and (3) farmers with experience of shrimp disease outbreaks reduce the use of antibiotics, which contain veterinary drugs owing to the distrust in the efficacy of these drugs.

In Chapter 3, using 2-year panel data from a real community, I test which targeting method (1) improves the knowledge of BMPs of the treated the most; (2) enhances information sharing with their neighbors the most, and (3) improves the farming knowledge of those who receive information from the treated. To examine the questions, in 2016, I held a workshop for disseminating BMPs. The participants were selected using three targeting methods and were divided into three groups based on the methods, such as SRS, SURS, and SNT. In 2017, a follow-up survey was conducted to investigate how well farmers' knowledge of BMPs improved in comparison to the status before my intervention. I found that: (1) SRS shows the highest increase in BMPs knowledge in comparison to other treatments; (2) SURS shows lower improvement in BMPs knowledge than SRS. On the other hand, unlike other groups, treated farmers in SURS increase their neighbors' scores; and (3) SNT increases information sharing between villagers in the treated village. However, untreated farmers, who receive information from treated farmers of the SNT group, have a lower improvement score in their BMPs knowledge.

In Chapter 4, using a monthly panel dataset from a virtual community, the study examines that information exchange is motivated by reciprocity, professional reputation, and peer effects, and tests the hypotheses by using various econometric models, including those that consider the time fixed effects. In my regression analyses, based on Poisson and negative binomial regressions, I find that: (1) members who have previously asked questions are more active in sharing information than people who have never asked questions; (2) other members' positive expressions to previous information shared promote future information sharing; (3) the act of information sharing by one's peer promotes his/her own information sharing; and 4) the more the member shared information in the past, the more she/he asks for information currently.

In summary, my findings shed light on the effective targeting methods for information diffusion. SURS targeting appears to be a method to spread information to all residents, including those living in remote areas. However, I need to interpret the result carefully as systematic sampling tends to introduce bias into the sample rather than SRS. While the SNT group is more active in informing BMPs knowledge to other farmers than other groups, the direct or indirect treatment effects of the SNT group on the diffusion of accurate information may be smaller than those of the other groups. I presume that this is suggesting that the person with a high betweenness centrality tends to receive and send a substantial amount of information through various channels and focuses on exchanging information frequently without distinguishing the quality of information. Regarding the motivation of information exchanges between farmers, I clarify that reciprocity and professional reputation play important roles in enhancing professional knowledge exchange even in VCoPs. If the members in a VCoP have a common motivation, information exchange can be activated, and such active exchange of information will lead to the growth of the community.

Finally, I should note that there are several limitations to this study. First, the study for the targeting methods in real communities does not handle regional or industrial heterogeneities. Second, the study of the virtual community does not distinguish between direct and indirect reciprocity due to lack of data. Therefore, a further study should be conducted in more regions and industries to clarify my research issues by eliminating the heterogeneities, and examining direct reciprocity and indirect reciprocity effects separately.

References

Ainslie, G. (1996). *Breakdown of Will.* Cambridge: Cambridge University Press.

Anderson, J., & Feder, G. (2004). Agricultural Extension: Good Intentions and Hard Realities. *The World Bank Research Observer, 19*(1), 41-60.

Andrews, D., & Buchinsky, M. (2000). A Three-Step Method for Choosing the Number of Bootstrap Repetitions. *Econometrica, 68*(1), 23-51.

Angeletos, G., Laibson, D., Repetto, A., Tobacman, J., & Weinberg, S. (2001). The Hyperbolic Consumption Model: Calibration, Simulation, and Empirical, Evaluation. *Journal of Economic Perspectives*, pp. 47-68.

Apeldoorn, V., & Schram, A. (2016, April). Indirect Reciprocity; A Field Experiment. *PLOS ONE*.

Ashenfelter, O., & Card, D. (1985). Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs. *The Review of Economics and Statistics*, 648-660.

Banerjee, A., Chandrasekhar, A., Duflo, E., & Jackson, M. (2013). The Diffusion of Microfinance. *Science, 341*.

Beaman, L., & Dillon, A. (2018). Diffusion of Agricultural Information whithin Social Networks: Evidence on Gender Inequalities from Mali. *Journal of Development Economics*.

Beaman, L., Yishay, A., Magruder, J., & Mobarak, A. (2015). Can Network Theory-based Targeting increase Technology. *Working Paper*.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics*, 249-275.

Brandes, U. (2008). Social Network Analysis and Visualization. *IEEE Signal Processing Magazine*, 147-151.

Ca Mau Province. (2008). *Ca Mau Portal*. Retrieved November 25, 2016, from http://www.camau.gov.vn/wps/portal/camauportal

Cameron, A., & Trivedi, P. (2013). *Regression Analysis of Count Data* (Second Edition ed.). New York: Cambridge.

Cameron, C. A., & Trivedi, P. (2010). *Microeconimetrics Usin Stata, Revised Edition.* Texas: Stata Press.

Cook, K., & Rice, E. (2003). Social Exchange Theory . In J. D. (Ed.), *Handbook of Social Psychology* (pp. 53-76). New York: Kluwer Academic/Plenum.

Dierberg, F., & Kiattisimkul, W. (1996). Impacts and Implications of Shrimp Aquaculture in Thailand. *Environmental Management, 20*, 649-666.

Edwards, A., Edwards, C., Washi, S., & Myers, S. (2013). *The Communication Age: Connecting & Engaging.* SAGE Publications.

Ethan, L., & Schechter, L. (2012). Motives for Sharing in Social Networks. *Journal of Development Economics*, 13-26.

Facebook Help center. (2017). *Like and React to Posts*. Retrieved September 27, 2017, from Facebook: https://www.facebook.com

FAO. (2016). *Fishery commodities global production and trade (online query)*. Retrieved 11 21, 2016, from http://www.fao.org/fishery/statistics/global-commodities-production/query/en

FAO. (2017). *National Aquaculture Sector Overview-Thailand.* Retrieved October 1, 2017, from http://www.fao.org/fishery/countrysector/naso_thailand/en

Feder, G. (1980). Farm Size, Risk Aversion and the Adoption of new Technology under Uncertainty. *Oxford Economic Papers*(30(2)), pp. 263-283.

Fehr, E., Georg, K., & Arno, R. (1993). Does Fairness Prevent Market Clearing? An Experimental Investigation. *Quarterly Journal of Economics, 108*(2), 437-459.

Foster, A., & Rosenzweig, M. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy, 103*(6), 1176-1209.

Freeman, L. (1977). A Set of Measures of Centrality Based on Betweenness. *Sociometry*, 35-41.

Freeman, L. (1977). A Set of Measures of Centrality Based on Betweenness. *Sociometry*(40), 35-41.

Gächter, S., Nosenzo, D., & Sefton, M. (2013). Peer Effects in Pro-Social Behavior: Social Norms or Social Preferences? *Journal of the European Economic Association , 11*(3), 548-573.

Holmstrom, K., Graslund, S., Wahlstrom, A., Poungshompoo, S., Bengtsson, B.-E., & Kautsky, N. (2003). Antibiotic Use in Shrimp Farming and Implications for Environmental Impacts and Human Health. *International Journal of Food Science and Technology, 38*, 255-266.

Homans, G., & Merton, R. (1961). *Social Behaivor: its Elementary Forms.* New York: Harcourt Brace & World.

IBM. (2017). *Betweenness*. Retrieved from IBM Knowledge Center: https://www.ibm.com/support/knowledgecenter/en/SSXVXZ_2.1.7/com.ibm.i2.anb.doc/about_betweenness.html

Jackson, C., Preston, N., & Thompson, P. (2004). Intake and Discharge Nutrient Loads at Three Intensive Shrimp Farms. *Aquaculture Research, 35*, 1053-1061.

Jackson, M. (2008). *Social and Economic Networks.* New Jerey: Princeton University Press.

Jung, S. (2017). *A Discussion on Social Knowledge Sharing in Online Environment based on Social Exchange Theory and Social Capital: Applications of Game Theory and Agent-Based Model.* Hanyang University, Education Technology. Seoul: Hanyang University.

Just, E. R., Zilberman, D., & Hochman, E. (1983). Estimation of Multicrop Production Functions. *American Journal o Agricultural Economics*(65 (4)), pp. 770-780.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47*, pp. 263-292.

Khiem, N., Simon , B. R., Nguyen, M., & Vo, T. (2010). Upgrading Small-Holders in the Vietnamese Pangasius Value Chain (Odi Grant Number Ro334).

Kim, D., Hwong, A., Hughes, D., O'Malley, A., Fowler, J., & Christakis, N. (2015). Social Network Targeting to Maximise Population Behaviour Change: A Cluster Randomised Controlled Trial. *Lancet*, 145-54.

Kubota, K., & Fukushige, M. (2009). Rational Consumers. *Discussion Paper.*

Laibson , D. I. (1996). Hyperbolic Discount Function, Undersaving, and Savings Policy. *NBER Working Paper Series*(5635).

Lave, J. (1991). Situating Learning in Communities of Practice. In L. Resnick, J. Levine, & S. Teasley (Eds.), *Perspectives on Socially Shared Cognition* (pp. 63-82). Washington, DC: American Psychological Association.

Lave, J., & Wenger, E. (1991). *Situated Learning: Legitimate Peripheral Participation.* Cambridge, UK: Cambridge University Press.

Ligon, E., & Schechter, L. (n.d.). Motives for Shr.

Liu, E. M., & Huang, J. (2013). Risk Preferences and Pesticide Use by Cotton Farmers in China. *Journal of Development Economics*, 202-215.

Liverpool-Tasie, L., & Winter-Nelson, A. (2012). Social Learning and Farm Technology in Ethiopia: Impacts by Technology, Network Type, and Poverty Status. *Journal of Development Studies*, 1505-1521.

Luck, C. (2017). *Open Vs. Closed Groups on Facebook*. Retrieved September 28, 2017, from Chron: http://smallbusiness.chron.com/open-vs-closed-groups-facebook-62344.html

Magnan, N., Spielman, D., Lybbert, T., & Gulati, K. (2015). Leveling with Friends: Social Networks and Indian Farmers' Demand for a Technology with Heterogeneous Benefits. *Journal of Development Economics*, 223-251.

Mantingh, I., & V.H., N. (2008). Pre-Assessment of Pangasius Sector: Toward Sustainability. *Report commissioned by the Dutch Ministry of Agriculture*.

Morgan, M., & Grube, J. (1991). Closeness and Peer Group Influence. *Brithish Journal of Social Psychology*, 159-169.

Morimoto, S. (2009). Hyperbolic Discounting and Household Consumption: an Analysis based on a Large-scale Survey in Japan. *Behavioral Economics*(2), pp. 49-59.

Moscardi, E., & Janvry, A. (1977). Attitudes toward Risk among Peasants: An Econometric Approach. *American Journal of Agricultural Economics*(59 (4)), pp. 710-716.

NACA. (2006). Reducing the Risk of Aquatic Animal Disease Outbreaks and Improving Environmental Management o Coastal Aquaculture in Viet Nam. *Final report of the NACA/SUMA projects FSPS I* .

NACA. (2016, November 23). Retrieved from http://www.enaca.org/modules/cms/start.php?tag_id=24

NCAA. (2016). *Better Management Practices for Shrimp Aquaculture*. Retrieved November 23, 2016, from http://www.enaca.org/modules/cms/start.php?tag_id=24

Ngo, T. (2011). From Rice to Shrimp: Ecological Change and Human Adaptation in the Mekong Delta of Vietnam. In M. A. Stewart, & C. P. A. (Eds.), *Environmental Change and Agricultural Sustainability in the Mekong Delta* (pp. pp 271-285). New York: Springer Science+Business Media .

Nowak, M., & Sigmund, K. (2005, Oct 27). Evolution of Indirect Reciprocity. *Nature, 437*(7063), 1291-8.

Pham, T., Kroeze, C., Bush, S., & Mol, A. (2010). Water Pollution by Intensive Brackish Shrimp Farming in South-east Vietnam: Causes and Options for Control. *Agricultural Water Management*.

Poi, B. (2004). From the Help Desk: Some Bootstrapping Techniques. *The Stata Journal*, 312-328.

Rogers, E. M. (1962). *Diffusion of Innovations* (1 st ed. ed.). New York: Free Press of Glencoe.

SEAFOOD NEWS.COM. (2014, Dec 24). *Traders ask if era of shrimp as a mass commodity is over in Japan, as imports fall 50%.* Retrieved from SEAFOOD NEWS.COM: http://www.seafoodnews.com/Story/957178/Traders-ask-if-era-of-shrimp-as-a-mass-commodity-is-over-in-Japan-as-imports-fall-50-percent-

Sebora, T. C., & Cornwall, J. R. (1995). Expected Utility Theory Vs. Prospect Theory: Implications for Strategic Decision Makers. *Journal of Manageraial Issues*, pp. 41-61.

Senarath, U., & Visvanathan, C. (2001). ENvironmantal Issues in Brackish Water Shrimp Aquaculture in Sri Lanka. *Environmental Management, 27*, 335-348.

Songsermsawas, T., Baylis, K., Chhatre, A., & Michelson, H. (2016). Can Peers Improve Agricultural Revenue? 163-178.

Suzuki, A. (2015). Risk on Dynamic Behavior of Farmers in the Export Market: A Case from the Pineapple Industry in Ghana. *2014 AAEA Annual Meeting* . Minneapolis: The Agricultural & Applied Economics Association.

Suzuki, A., & Vu, H. (2016, March). Food Quality Awareness: Cases from Shrimp Producers in Thailand and Vegetable Producers in Vietnam. *IDE Discussion Paper, 569*.

Suzuki, A., & Vu, H. (2016). *Food Quality Awareness: Cases from Shrimp Producers in Thailand and Vegetable Producers in Vietnam.* IDE Discussion Paper.

Suzuki, A., & Vu, H. N. (2013, March). Status and Constraints of Costly Port Rejection: A Case from the Vietnamese Frozen Seafood Export Industry. *IDE discussion paper, 395*.

Tanaka, T., Camerer, F. C., & Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review*(100 (1)), pp. 557-571.

Taya, K. (2003). *Asia No Ebi Youshoku to Boueki (Shrimp Aquaculture and Trade in Asia) (in Japanese)*. Tokyo: Seizando.
Taya, K. (2003). *Asia No Ebi Youshoku to Boueki (Shrimp Aquaculture and Trade in Asia) (in Japanese)*. Tokyo: Seizando.
The Japan Food Chemical Research Foundation. (2015, February 20). *The MHLW Administrative Information*. Retrieved November 28, 2016, from http://www.ffcr.or.jp/zaidan/MHWinfo.nsf/ab440e922b7f68e2492565a700176026/7f4e59f635ff2d0149257df20019b161?OpenDocument

The World Bank. (2007). *Agriculture for Development.* Washington DC: The International Bank for Reconstruction and Development / The World Bank.

Tzachi, M., Lopez, I., Jones, E., Jackson, S., & Lawrence, A. (2004). Characterization of Intake and Effluent Waters from Intensive and Semi-intensive Shrimp Farms in Texas. *Aquaculture Research, 35*, 321-339.

UNIDO. (2013). *Meeting Standards, Winning Markets Regional Trade Standards Compliance Report East Asia 2013.* Vienna: United Nations Industrial Development Organization.
UNIDO. (2013). *Meeting Standards, Winning Markets Regional Trade Standards Compliance Report East Asia 2013.* Vienna: United Nations Industrial Development Organization.
Valente, T. (2010). *Social Networks and Health.* New York: Oxford University Press.

VASEP. (2017). *Available Fish Sources*. Retrieved November 3, 2017, from VASEP: http://seafood.vasep.com.vn/?ni=99&p=2&&go=search&key=ca%20mau

Viet Nam News. (2014, April 30). *Japan may stop Vietnamese shrimp imports*. Retrieved November 22, 2016, from http://vietnamnews.vn/economy/254296/japan-may-stop-vietnamese-shrimp-imports.html#9G8TwP7KTDFmCdrg.97

Wasko, M. (2005). Why Should I Share? Examining Social Capital and Knowledge Contribution In Electronic Networks of Practice. *MIS Quarterly, 29*(Special Issue on Information Technologies and Knowledge Management), 35-57.

Wenger, E. (1998). *Communities of Practice.* Cambridge, UK: Cambridge University Press.

Wooldridge, J. (2007). What's New in Econometrics? Lecture 10 Difference-in-Differences Estimation. *NBER Summer Institute.* NBER.

World Bank. (2004). *Economic Growth, Poverty, and Household Welfare in Vietnam.* Washington DC: World Bank.

World Library Foundation. (n.d.). *Đổi Mới*. Retrieved March 14, 2017, from Project Gutenberg Self-Publishing Press: http://self.gutenberg.org/articles/eng/Đổi_Mới?View=embedded's,%20newfoundland%20and%20labrador#1970s

Appendix 1. The Questionnaire for the Survey in Vietnam

Vietnam Shrimp Survey (Inducing Good Practices)

Foreign Trade University (FTU), Can Tho University (CTU), and Graduate School of Frontier Sciences, the University of Tokyo (UOT)

Objective of the Survey

This survey is a joint research between the Foreign Trade University (FTU), Can Tho University (CTU), and Graduate School of Frontier Sciences, the University of Tokyo (UOT), under a project title "Inducing Adoption of Good Practices for Small-scale Shrimp Growers in Southern Vietnam." It aims to understand the effective ways to support small-scale shrimp growers to adopt good practices to produce shrimps of higher quality. We have obtained a permission from the Camau Province to conduct the survey and promise that any information collected through the interviews will be used exclusively for the research purpose.

CP1	Respondent Name:	
CP2	Mobile phone number:	
CP3	Gender: 1=Male, =Female	
CP4	Age:	
CP5	Commune:	
CP6	Date interviewed: DDMMYY	
CP7	Interviewed by:	
CP8	Date data entered: DDMMYY	
CP9	Entered by:	
CP10	Date data checked: DDMMYY	
CP11	Checked by:	

1. General Information (GI)

GI1	Years of education completed	
GI2	Mother's years of education completed	
GI3	Father's years of education completed	
GI4	Can you speak English? 1=Yes fluently, 2=Yes with some difficulty, 3=No	
GI5	Can you read in English? 1=Yes fluently, 2=Yes with some difficulty, 3=No	
GI6	Can you write in English? 1=Yes fluently, 2=Yes with some difficulty, 3=No	
GI7	How many years have you lived in this commune?	
GI8	How many years have you cultivated shrimps?	
GI9	Who taught you shrimp production initially? 1=parents, 2=neighbors, 3=extension officers, 4=others (specify)	
GI10	Are your parent farmers? 1= Yes, 2= No	
GI11	If yes, how many hectares of farm land do they own?	ha
GI12	Do your parents keep livestock? 1= Yes, 2= No	
GI13	Do your parents cultivate shrimps? 1=Yes, 2=No	
GI14	Do you have siblings cultivating shrimps? 1=Yes, 2=No	
GI15	How many mobile phones do you own?	
GI16	Do you belong to a cooperative? 1=Yes, 2=No	
GI17	If yes, is it shrimp-related? 1=Yes, 2=No	
G18	Do you have a smart phone? 1=Yes, 2=No	
G19	Do you have a radio or television? 1=Yes, 2=No	
G20	Do you have a personal computer which is connected to internet? 1=Yes, 2=No	
G21	Do you have any family members who major in fishery aquaculture? 1=yes, 2=no	

2. Members of Your Household (those who share the same household income, Exclude the respondent him/herself; HM)

HH	Total number of household members besides you?		HH0to5	Number of kids between 0 and 5 yrs old?	
HH6to15	Number of kids between 6 and 15 yrs old?		HH16to60	Number of members between 16 and 60 yrs old (excluding you)?	
HH61	Number of memebers above 61 yrs old (excluding you)?		HH_job	Number of members with income-earning jobs (excluding you)?	
HH_income	If HH6 is not zero, how much is the average monthly income from those members (excluding you) in total?				

3. Land Used for Production (LS)

Plot ID	Size (ha)	Tenure status 1=own, 2=rented 3=other (specify)	If rented:					If owned, how was it obtained? 1=purchased, 2=bequeathed, 3=just walked in, 4=other(specify)	How is it used now? 1=agricultural production, 2=shrimp, 3=fallow, 4=other (specify)
			Pay by? 1=fixed rent, 2=share crop, 3=other (Specify)	If fixed rent, how much per year? (mVND)	If share cropped, what's your share?	How many years have you been renting it?	Residence of land owner 1=same commune, 2=same district, 3=same province, 4=other(specify)		
PID	LS1	LS2	LS3	LS4	LS5	LS6	LS7	LS8	LS9
1									
2									

LS10	Do you have land that is rented-out to someone? 1=Yes, 2=No				
LS11	If so, how large is it in total?	Ha	LS12	If so, for how much do you receive per year?	mVND

4. Production Activity

Ask about activities on each plot from Jan.-Dec. 2016, Jan.-July. 2017. E.g., if plot ID1 is used for rice for Jan- Mar and for shrimp for Apr-Jun, ask about both activities on the same plot.

For Agricultural Plots: Input Use (AI)

Plot ID	Production ID (a=1^{st} crop, b=2^{nd} crop, etc)	When		Crop ID (below)	Area under this crop (ha)	Seed use			Chemical fertilizer			Organic fertilizer			Total expenditure on other inputs (mVND)
		From (MM)	To (MM)			Qty	Unit	Price/unit (VND)	Qty	Unit	Price/unit (mVND)	Qty	Unit	Price/unit (mVND)	
PID	PRID	AI1	AI2	AI3	AI4	AI5	AI6	AI7	AI8	AI9	AI10	AI11	AI12	AI13	AI14

Crop ID: 1=lúa, 2=hoa quả, 3=rau, 4=Khác (ghi rõ)

For Shrimp Ponds: Input Use (SI)

Plot ID	Production ID (a=1^{st} crop, b=2^{nd} crop, etc)	When		Shrimp type	Shrimp Seed use			From whom (Major one)?	How many times have you bought from the same place?	Seed tested for disease? 1=Yes, 2=No	Feed Use					Other Inputs			
		From (MM)	To (MM)		Qty	Unit	Price/unit (VND)				Type	If industrial, name	Qty	Unit	Price/unit (mVND)	Type	Qty	Unit	Price/unit (mVND)
PID	PRID	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8	SI9	SI10	SI11	SI12	SI13	SI14	SI15	SI16	SI17	SI18

SI19.What type of shrimp do you grow? 1=Vannamei, 2=Black tiger	
SI20.From whom? (Major one) (Vannamai)	
SI21.How long have you been dealing with them? (years) (Vannamai)	
SI22.How many times have you bought from the same place? (Vannamai)	
SI23.Vannamai seed tested for disease?	
SI24.From whom? (Major one) (Black Tiger)	
SI25.How long have you been dealing with them? (years) (Black Tiger)	
SI26. How many times have you bought from the same place? (annual average) (Black tiger)	
SI27. Black tiger seed tested for disease?	
SI28. How do you finance payment for the seed? 1=in cash at purchase, 2= on credit from seller and pay at harvest, 3= borrow cash and pay at harvest, 4) others (Specify	
SI29. If SI28= 3, whom do you borrow it from? 1=bank, 2=family, relatives, or friends, 3=moneylender, 4=others (specify)	
SI30. Do you follow the recommended schedule? 1=yes, 2=no	
SI31. Do you use any drugs/ products as prophylactic? 1=yes, 2=no	
SI32. If SI31=yes, what kind of the drugs/ products? 1= Antibiotics; 2=Veterinary drugs, 3=Nutrient supplements, 4= handmade drugs, 5= other (record), 6= I don't know	
SI33, If SI31=yes, how often do you use? 1= Periodically, 2=Disease outbreaks in nearby ponds, 3=Disease announcement, 4=Other (record)	

Code for SI3: 1=Vannamei, 2=Black tiger, 3=White-leg, 4=Others (specify)
Code for SI8: 1= once, 2=twice, 3=3 times or more
Code for SI15: 1=fertilizer, 2=antibiotics, 3=veterinary medicine, 4=biological product
Code for SI7: 1=certified hatchery, 2=private hatchery, 3=local trader, 4=others (specify)
Code for SI10: 1= industrial feed, 2=homemade, 3=others (specify)

For Shrimp Ponds: Practices (SP)

Plot ID	Water source (Name of canal)	Any methods for more oxygen?	Is there a reservoir pond? 1=Yes, 2=No	When was this plot dried? MMYY or 99=never	Did you remove waste soil? 1= Yes, 2=No	How long was it dried? (Months)	How often do you take water from river?	How often do you discharge water to river?	Any disease outbreak? 1=Yes, 2=No	How long has this pond been cultivated (years)?	Water level in pond 1=set is a certain meter, 2=No (let ie fluctuate, 3=others (specify)
PID	SP1	SP2	SP3	SP4	SP5	SP6	SP7	SP8	SP9	SP18	SP19

Code for SP2: 1=Aerator, 2=Others (specify), 3=None
Code for SP7 & SP8 & SP12: 1=Only at the start, 2=Only after harvesting, 3=Daily, 4=Weekly, 5=Bi-weekly, 6=Monthly, 7=Others (specify)

SP10	At what time do you feed shrimps in a day? (e.g., 5am, 8am, 1pm, etc.)							
SP11	Do you use feed trays to feed shrimps? 1=Yes, 2=No		SP12	When do you test water quality of your pond? (Use code for SP7 above)				
SP13	What elements of water quality do you test?							
SP14	How do you test these elements of water quality? 1=litmus paper, 2=electric device, 3=taste, 4=look, 5=other(specify)							
SP15	Do you think water quality in your canal has degraded in recent years? 1=No, 2=Somewhat yes, 3=Definitely yes							
SP16	Do you record the following activities? 1=Yes, 2=No	SP17a	Water quality ( )	SP17b	Seed use ( )			
	SP17c	Inputs use ( )	SP17d	Feeding ( )	SP17e	Sales price ( )	SP17f	Sales ( )
SP20	Where do you take water to pond during the crop? 1= From the reservoir, 2= From river/ canal							
SP21	Where do you discharge water if over rain? 1=To river/ canal directly, 2=To the reservoir, 3=No discharging, let high level, 4=Other (record)							
SP22	After harvest, where do you discharge? 1=To river/ canal directly, 2=To the reservoir, treat water then discharge to river/canal, 3=To the reservoir, store and reuse for the next crop, 4= other (record)							
SP23	If disease outbreak, how do you treat water? 1=No treatment, wait to the next crop, 2=Treat water then wait to the next crop, 3=Discharge to river/ canal directly ,4=Chemical treat, then discharge to river/ canal, 5=Other (record)							
SP24	How do you treat the waste from the bottom? 1=Discharge to river/ canal directly, 2=Store in a spare ground or spare pond, no treatment, 3=Process into other uses, 4=Other (record)							

Sp13: 1=pH, 2=DO (dissolved oxygen), 3=COD (chemical oxygen demand), 4=BOD(biochemical oxygen demand), 5=Salinity, 6=SS (suspended solids), 7=Soluble Phosphorus, 8=Total Nitrogen, 9=Others (Specify)

5. Marketing Activity

For Agricultural Plots: (AM)

Plot ID	Production ID (a=1st crop, b=2nd crop, etc.)	Marketing ID (a=1st sales, b=2nd sales, etc.)	CropID	Harvest			Sales				
				MM	Qty	Unit (mVND)	MM	Qty	Unit	Price/unit (mVND)	To whom? 1=Trader, 2=Taken to market, 3=Cooperative, 4=Others (specify)
PID	PRID	MKID	AM1	AM2	AM3	AM4	AM5	AM6	AM7	AM8	AM9

For Shrimp Ponds: (SM)

In case one plot is harvested several times, record each harvest separately.

Plot ID	Production ID (a=1st crop, b=2nd crop, etc.)	Marketing ID (a=1st sales, b=2nd sales, etc.)	Harvest & Sales						
			MM	Qty	Unit	Price/unit (mVND)	To whom? 1=Collector, 2=Processor, 3=Cooperative, 4=Others (specify)	Quality check how: 1=eye check, 2=lab-test, 3=others (specify), 4=none	Points checked: 1=size, 2=color, 3=weight, 4=disease, 5=others (specify), 6=none
PID	PRID	MKID	SM1	SM2	SM3	SM4	SM5	SM6	SM7

PRID: 1=1st crop, 2=2nd crop, etc MKID: 1=1st sales, 2=2nd sales, etc

6. Knowledge about Shrimp Production (KS)

KS1	Have you received any training on good shrimp production? 1=yes, 0=No							
KS1b	Would you like to join a training? 1=yes, 0=No							
KS1c	If KS1b=Yes, how much would you agree to pay for a one-day training (maximum)?							
KS2	Have you ever had your shrimps tested in laboratory? 1=Yes, 2=No							
KS3	If so, who paid for the costs? 1=Buyer, 2=Myself, 3=Others (specify)							
KS4	Do you know which chemicals are prohibited for use? 1=Yes, 2=No							
KS5	If so, pls. list them.							
KS6	Do you know which product (inputs) contain prohibited elements? 1=Yes, 2=No							
KS7	Pls. list elements of water quality that is important							
KS8	How many shrimp buyers do you know?		KS9	How many shrimp seed sellers do you know?				
KS10	How many shrimp input sellers do you know?							
KS11a	Who is the most reliable information source to you on: shrimp cultivating technology? 1=friends, 2=input seller, 3=buyer, 4=extension officer, 5=other(specify)							
KS11b	On input use?		KS11c	On shrimp prices?		KS11d	On treating diseases?	
KS12a	From how many people do you obtain advice on shrimp cultivation (technology, input use, treating disease, etc.)?		KS12b	From how many people do you obtain information about shrimp prices?				
KS13a	To how many people have you taught shrimp cultivation?		KS13b	To how many people did you tell your shrimp prices?				
KS14	How often do you meet with extension officers? 1=every day, 2=once a week, 3=once in two weeks, 4-once a month, 5=twice a year, 6=others (spcify)							
KS15	In order to prepare pond for shrimp crop, which stages are important? 1=Remove the waste in the bottom, 2=wash the pond,3=Dry pond, 4=Filter water, 5=Water treatment in pond by chemicals, bio-products, fertilizers							
KS15a	Which are important stages but you can't do? 1=Remove the waste in the bottom, 2=Wash the pond 2-3 times, 3=Dry pond ,4=Filter water, 5=Water treatment in pond by chemicals, bio-products, fertilizers							
KS15b	If some, why? 1=High cost, 2=Accept the risk, 3=Others (record)							

KS16	Which are important criteria to assure shrimp health and effect to disease out-breaking? 1=pH, 2=Alkalinity, 3=Dissolved oxygen, 4=Salinity ,5=Transparency, 6=Temperature ,7=Harmful gases NH3, H2S, NO2…,8=The bottom quality	
KS16a	Which are important criteria but you can't test? 1=pH, 2=Alkalinity, 3=Dissolved oxygen, 4=Salinity ,5=Transparency, 6=Temperature ,7=Harmful gases NH3, H2S, NO2…,8=The bottom quality	
KS16b	Why don't you test? 1=Expensive equipment, 2=High cost for lab test, 3=Other (record)	
KS17	Do you think it is necessary to prevent disease germ carried by pets, birds, craps, fishes, snails, frogs …. 1=yes, 2=no	
KS17a	If KS17 =yes, what are your measures? 1=No, 2= specify	
KS17b	If KS17A=1 (No), why? 1=More investment, 2=Other (specify)	
KS18	Do you think growing higher density of shrimp take more risks of disease? 1=yes, 2=No, 3=don't know	
KS18a	If KS18=yes, what is the best PLs density in your ponds? (1 PLs/ m2 = 100.000 PLs/ha)	
KS19	Do you think certified/ uncertified seeds effect to the ability of shrimp diseased? 1=Yes, 2=No, 3=I don't know	
KS19a	If KS19=yes, what kind of seed do you buy? 1=Certified seeds, 2=Uncertified seeds, 3=Both	
KS19b	If KS19A= "uncertified seeds" or "both", why do you use uncertified seeds while you know certified seeds are better? 1=High price, 2=Lack of certified seed, 3=The lack of belief in certifications, 4=Binding relationship (contract, patron-client ties, loans), 5=Others (record)	
KS20	Do you think the visible quality of seeds is important for purchasing? (color, size, similarity, reflex, signs of diseases…) 1=yes, 2=no, 3= don't know	
KS20a	If KS20=yes, do you usually check and buy the seeds with all of good visible quality above? 1=Yes, 2=No, 3=Yes but not all	
KS20b	If KS20A=no or not all, why? 1= High price, 2=Lack of the seed, 3=Binding relationships (contract, patron-client ties, loans), 4=Others (record)	
KS21	How long to transport the seeds from its shop to the pond?	
KS21a	Are there any equipment to keep suitable temperature and oxygen supplement during the transportation? 1=yes, 2=No, 3=Only 1	
KS22	Do you think industrial feed from certified factory is better and help to prevent risk of disease? 1=Yes, 2=No, 3=I don't know	
KS22a	If KS22=yes, do you use another feed beside certified industrial feed? 1= yes, 2=No	
KS22b	If KS22A=yes, why? 1=High price, 2=Lack of the certified feed, 3=The lack of belief in certifications or labeling, 4=Binding relationship (contract, patron-client ties, loans), 5=Other (specify)	
KS23	Do you know the effect of bio-products in intensive shrimp farming? 1=I don't know, 2=Improve and stabilize the water environment in pond, 3=Improve the bottom of pond, 4= Other (specify)	
KS23a	How often do you use bio-product? 1=periodically, 2= sometimes, 3=No use, 4=Other(record)	

7. Labor (LL)

LL1	Did you hire permanent laborers between Jan.-Dec. 2016? 1=Yes, 2=No				
LL2	If yes, how many of them?		LL 3	If yes, how much did you pay them in total for 2016? (tVND)	
LL4	Did you hire casual laborers between Jan.-Dec. 2016? 1=Yes, 2=No				
LL5	If yes, what activities did they do? 1=planting crops, 2=harvesting crops, 3= feeding shrimps, 4=harvesting shrimps, 5=others (specify)				
LL6	If yes, how much did you pay them in total for 2016? (tVND)				
LL7	How many of your household members are mainly engaged in cultivating shrimps in your ponds, including you?				

8. Savings, Remittance, Earning, Expenditure (FQ)

FQ1	Were you engaged in non-farm activities between Jan.-Dec.2016? 1=Yes, 2=No					
FQ2	If yes, what type? 1=trading, 2=hired worker, 3=transportation biz, 4=mechanics, 5=construction, 6=other (specify)					
FQ3	If yes, how much did you earn per month and for how many months?				tVND/m	months
FQ1b	Were you engaged in non-farm activities between Jan.-Jul.2017? 1=Yes, 2=No					
FQ2b	If yes, what type? 1=trading, 2=hired worker, 3=transportation biz, 4=mechanics, 5=construction, 6=other (specify)					
FQ3b	If yes, how much did you earn per month and for how many months?				VND/m	months
FQ4	Did you save regularly between Jan.-Dec.2016? 1= Yes, 2=Yes but not regularly, 3=None at all					
FQ5	If yes (1or2), how much did you save per month on average?				tVND	
FQ4b	Did you save regularly between Jan.-Jul.2017? 1= Yes, 2=Yes but not regularly, 3=None at all					
FQ5b	If yes (1or2), how much did you save per month on average?				tVND	
FQ6	Did you send money to your family members or relatives regularly between Jan.-Dec.2016? 1= Yes, 2= Yes, but not regularly, 3= No					
FQ6b	Did you send money to your family members or relatives regularly between Jan.-Jul.2017? 1= Yes, 2= Yes, but not regularly, 3= No					
FQ7	If yes (1or2), how much did you send in total in 2016?				tVND	
FQ7b	If yes (1or2), how much did you send in total in 2017?				tVND	
FQ8	Did you receive remittance from someone between Jan.-Dec. 2016? 1= Yes, 2= Yes, but not regularly, 3= No					
FQ9	If yes (1or2), how much did you receive in total in 2016?				tVND	
FQ8b	Did you receive remittance from someone between Jan.-Jul. 2017? 1= Yes, 2= Yes, but not regularly, 3= No					
FQ9b	If yes (1or2), how much did you receive in total in 2017?				tVND	
FQ10	About how much is the total monthly earning in your household between Jan.-Dec. 2016?				tVND	
	In 2016, about how much did your household spend on:					
	FQ11	food purchase per month?	tVND	FQ14	housing per month?	tVND
	FQ12	education per year?	tVND	FQ15	medical fees per year?	tVND

	FQ13	utility (electricity, water, gas, communication, etc.) per month?	tVND	FQ16	entertainment (travel, buying clothes, furniture, etc.) per year?	tVND
FQ10b	About how much is the total monthly earning in your household between Jan.-Jul. 2017?					
	In 2017, about how much did your household spend on:					
	FQ11b	food purchase per month?	tVND	FQ14b	housing per month?	tVND
	FQ12b	education per year?	tVND	FQ15b	medical fees per year?	tVND
	FQ13b	utility (electricity, water, gas, communication, etc.) per month?	tVND	FQ16b	entertainment (travel, buying clothes, furniture, etc.) per year?	tVND

9. Social Network (SN)

SN1	From whom (only shrimp farmer) do you obtain advice on shrimp cultivation? (same village)	a)	b)	c)
SN2	To whom (only shrimp farmer) do you advise on shrimp cultivation?	a)	b)	c)
SN3	Do you have any advisers who are shrimp farmers and live in another village? 1= Yes, 2= No			
SN3a	If yes, what is the village name?	a)	b)	c)
SN3b	If yes, what is the advisor name?	a)	b)	c)
SN4	Are you an adviser for a shrimp farmer who lives in another village? 1= Yes, 2= No			
SN4a	If yes, what is the village name?	a)	b)	c)
SN4b	If yes, what is the farmer's name?	a)	b)	c)
SN5	Do you have any friends who are shrimp farmers and live in same village? 1= Yes, 2= No			
	If yes, what's his/her name?	a)	b)	c)
SN6	Do you have any friends who are shrimp farmers and live in another village? 1= Yes, 2= No			
SN6a	If yes, what is the village name?	a)	b)	c)
SN6b	If yes, what is the farmer's name?	a)	b)	c)

10. Water Test (WT)

WT1	Do you use any pH test kit? 1= Yes, 2= No			
WT2	Since when have you been using the pH test kit? (MMYY)			
WTSN1	From Jan. 2017 to July 2017, who inform you of pH test kit?	a)	b)	c)
WTSN2	From Jan. 2017 to July 2017, whom did you inform of pH test kit?	a)	b)	c)
WT3	Do you use any NO3 test kit? 1= Yes, 2= No			
WT4	Since when have you been using the NO3 test kit? (MMYY)			
WTSN3	From Jan. 2017 to July 2017, who inform you of NO3 test kit?	a)	b)	c)
WTSN4	From Jan. 2017 to July 2017, whom did you inform of NO3 test kit?	a)	b)	c)
WT5	Do you use any NH3/NH4 test kit? 1= Yes, 2= No			
WT6	Since when have you been using the NH3/NH4 test kit?(MMYY)			
WTSN5	From Jan. 2017 to July 2017, who inform you of NH3/NH4 test kit?	a)	b)	c)
WTSN6	From Jan. 2017 to July 2017, whom did you inform of NH3/NH4 test kit?	a)	b)	c)

11. Knowledge Test (KT)

11-1. Prohibited elements

Q1	If imported shrimp contains some prohibited elements, EU, Japan, and the U.S., the major importers of Vietnamese shrimp, reject shrimp imports because the substance is harmful to the human. Do you know which chemicals are prohibited for use? (O/X)	
	1. Chloramphenicol	
	2. Enrofloxacin	
	3. Ciprofloxacin	
	99. I don't know	

Q2	Choose prohibited elements among substances.	
	1. Sorbitol	
	3. Methionine	
	4. Ciprofloxacin	
	5. Lysine	
	6. Insorbitol	
	7. Enrofloxacin	
	8. Chloramphenicol	
	9. Bacillus licheniformis	
	10. Bacillus megaterium	
	11. Bacillus subtilis	
	12. Pediococcus acidilactici	
	13. Sodium selenite	
	14. Vitamin E	
	99. I don't know	

11-2. Water Quality

Q1	Is the most suitable transparency when you measure transparency of your shrimp pond?	Answer the number (single-select)
	1. 20cm	
	2. 50cm	
	3. 30-40cm	
	4. 50-60cm	
	5. 1m20cm	
	99. I don't know	

Q2	What is the reason of 10cm transparency? (O/X)	1=Yes, 2= No
	Phytoplankton grows up considerably such that the water color becomes dark. In the water, too much organic substances exist. The bottom of the pond is dirty due to the feed surplus.	
	The water is clear since too few phytoplankton exists in the water. The pond environment has poor nutrition. The use of chemistries decreases the number of phytoplankton. The water is polluted by the alum.	
	99. I don't know	

Q3	What kind of problems may happen if transparency is 10cm?	1= Yes, 2= No	Q4	What kind of problems may happen if transparency is 50cm?	1= Yes, 2= No
	1. Oxygen is not enough in the early morning			1. Shrimps suffer stress and their ability of finding food is degraded	
	2. The pH increases and fluctuates during the day			2. The algae in the bottom of the pond grow considerably	
	3. Natural feed for tiny shrimps is not enough			3. Shrimps are more sensitive to diseases	
	4. Shrimps grow up slowly			4. The NH3 concentration rises up	
	5. Shrimps become weak and more sensitive to diseases			99. I don't know	
	99. I don't know				

Q5	What is the solution to 10cm transparency?	Multi-select	Q6	What is the solution to 50cm transparency?	Multi-select
	1. Always maintain the high-water level (above 1.4 m)			1. Manage the amount of feed every day	
	2. Use the new water source with adequate number of phytoplankton			2. Use the bio products periodically	
	3. Use organic fertilizers			3. Use the new water source with adequate number of phytoplankton	
	4. Use inorganic fertilizers			4. Use organic fertilizers	
	5. Use the bio products periodically			5. Always maintain the high-water level (above 1.4 m)	
	99. I don't know			99. I don't know	

12. Games

"In this part, we would like you to play some simple games. Please think about each case carefully and make your decision. The results will be used to determine how much your payment will be in the end. That is, one of the games will be picked randomly at the end and you will be rewarded according to your choice"

A. Risk Preference Game

"Suppose that you are to choose either Project A or Project B. For Project A, you are certain to receive the payment as in the table. For Project B, a half of the time, you will receive 200 VND, but the other half of the time, you will receive 0 VND. For each RG, please select which Project you prefer."

	Project A You obtain for sure:	**Project B** 50% chance of obtaining:	50% chance of obtaining	**A or B?**
RG1	1mVND	2mVND	0 VND	
RG2	1.2mVND	2mVND	0 VND	
RG3	1.4mVND	2mVND	0 VND	
RG4	1.6mVND	2mVND	0 VND	
RG5	1.8mVND	2mVND	0 VND	
RG6	2mVND	2mVND	0 VND	

<DECIDING REWARD AFTER SELECTION>

Now, flip a coin once and decide which game to be played.
Head = Risk preference, Tail = Time preference

If Risk preference, flip a coin once and decide whether it would be Project A (Head) or B (Tail).
If Project A, hold 6 cards (#1-6) to the respondent and let him pick one.
-> His reward is decided. (e.g., If #4 picked, it is 1.6mVND)
If Project B, flip a coin again to decide 2mVND (Head) or 0VND (Tail).
-> His reward id decided.

If Time preference, flip a coin once and decide whether it would be Option A (Head) or B (Tail).
If Option A, it is 2mVND.
-> His reward id decided.
If Option B, hold 10 cards (#1-10) to the respondent and let him pick one.
-> His reward id decided. (e.g., If #4 picked, it is 2.8mVND)

B. Time Preference Game

B1: Suppose that you will receive a payment. Which option do you prefer?

	Option A Today	Option B 3 months later	A or B?
TP1	2mVND	2.2mVND	
TP2	2mVND	2.4mVND	
TP3	2mVND	2.6mVND	
TP4	2mVND	2.8mVND	
TP5	2mVND	3mVND	
TP6	2mVND	3.2mVND	
TP7	2mVND	3.4mVND	
TP8	2mVND	3.6mVND	
TP9	2mVND	3.8mVND	
TP10	2mVND	4mVND	

B2: What about the next case?

	Option A 3 months later	Option B 6 months later	A or B?
TP11	2mVND	2.2mVND	
TP12	2mVND	2.4mVND	
TP13	2mVND	2.6mVND	
TP14	2mVND	2.8mVND	
TP15	2mVND	3mVND	
TP16	2mVND	3.2mVND	
TP17	2mVND	3.4mVND	
TP18	2mVND	3.6mVND	
TP19	2mVND	3.8mVND	
TP20	2mVND	4mVND	

13. Dictator Game

1. This game is played in pairs. Each pair consists of a Player 1 and a Player 2 household. I will give 280,000 VND to each of you who are Player 1. You (player 1) decide how much you want to keep and how much you want to send to Player 2. You can send between 0 and 70,000 VND to each Player 2.
2. Any money sent to Player 2 will be doubled. Player 2 will receive any money player 2 will receive any money you sent multiplied by two. For example, here are the 70,000 VND. Imagine that you choose to send 10,000 VND to Player 2. Then, Player 2 will receive 20,000 VND (10,000 VND multiplied by 2).
3. We'll give you the amount of money as much as you keep the amount. For example, imagine that you keep 10,000 VND of game 1, 10,000 VND of game 2, 10,000 VND of game 3, and 10,000 VND of game 4. Then, you will receive 40,000 VND (10,000VND+10,000VND+10,000VND+10,000VND).

<table>
<tr><td></td><td colspan="5">Anonymous-Random: I'll randomly choose Player2 and give you 70,000VND. May be it's someone who you don't know. I won't never tell Player 2 your name and how much you send to him/her.</td></tr>
<tr><td>DG1</td><td colspan="3">How much you want to send to Player2?</td><td colspan="2">VND</td></tr>
<tr><td></td><td colspan="5">Revealed-Random: I'll randomly choose Player2 and give you 70,000VND. May be it's someone who you don't know. But, I'll tell Player 2 your name and how much you send to him/her.</td></tr>
<tr><td>DG2</td><td colspan="3">How much you want to send to Player2?</td><td colspan="2">VND</td></tr>
<tr><td></td><td colspan="5">Anonymous-Chosen: Please select player 2 from the list below. I'll give you 70,000VND. I won't never tell Player 2 your name and how much you send to him/her.</td></tr>
<tr><td>DG3.1</td><td>Please select player 2. What is the player 2's name?</td><td></td><td>DG3.2</td><td>How much you want to send to Player2?</td><td>VND</td></tr>
<tr><td></td><td colspan="5">Revealed-Chosen: Please select player 2 from the list below. I'll give you 70,000VND. I'll tell Player 2 your name and how much you send to him/her.</td></tr>
<tr><td>DG4.1</td><td>Please select player 2. What is the player 2's name?</td><td></td><td>DG4.2</td><td>How much you want to send to Player2?</td><td>VND</td></tr>
</table>

Appendix 2. The BMPs Book

NUÔI TÔM THÂM CANH

December 2016

<u>NỘI DUNG QUAN TRỌNG</u>

I. Tên hóa chất, kháng sinh

- Chloramphenicol, Enrofloxacin and Ciprofloxacin là các kháng sinh cấm sử dụng
- Oxytetracycline: 100ppb

II. Độ trong: Độ trong của thích hợp nhất là 30-40 cm

III. pH: pH rất quan trọng trong ao nuôi, pH thích hợp từ **7,5 - 8,5**

IV. Các loại khi độc: NH_3, NO^{2-}

- NH_3 dưới 0,1 mg/lít
- NO^{2-} dưới 0,01 mg/lít

DARD's logo

Mục tiêu của dự án này là để tìm các cách thức hữu hiệu giúp các hộ nuôi tôm ở Cà Mau áp dụng những phương pháp nuôi trồng tiên tiến để tạo ra các sản phẩm tôm có chất lượng cao cho xuất khẩu.

CONTACT US

Aya Suzuki, Ph.D
Associate professor
Department of International Studies, Graduate School of Frontier Sciences, University of Tokyo
Email: ayaszk@k.u-tokyo.ac.jp

Vu Hoang Nam, Ph.D

Associate Professor

Director of International Affairs, Foreign Trade University

Tel: 84.4.32595168 (ext. 256) | Fax: 84.4.37755118

Email: namvh@ftu.edu.vn

Mr. Hùng

Mr. Phu

I. Danh Mục Hóa Chất, Kháng Sinh Hạn Chế Sử Dụng Trong Sản Xuất Kinh Doanh Thủy Sản

-Nếu tôm nhập khẩu có chứa chất cấm, các thị trường nhập khẩu tôm của Việt Nam như Châu Âu , Nhật Bản, Mỹ trả về vì tôm Việt Nam gây nguy hiểm cho người sử dụng.

Tên hóa chất, kháng sinh	Dư lượng tối đa
Chloramphenicol	kháng sinh cấm sử dụng
Enrofloxacin	kháng sinh cấm sử dụng
Ciprofloxacin	kháng sinh cấm sử dụng
Oxytetracycline	100ppb

II. pH

Quản lý giá trị pH rất quan trọng trong ao nuôi, pH thích hợp từ 7,5 - 8,5 và dao động trong ngày không quá 0,5 đơn vị pH. Kiểm tra pH 2 lần/ngày (sáng, chiều)

III. Độ trong: Độ trong của thích hợp nhất là 30-40 cm

1. Trưởng hợp độ trong thấp dưới 20cm:

-Nguyên nhân: Tảo phát triển đáng kể làm cho màu nước trở lên sậm. Trong nước có nhiều chất hữu cơ lơ lửng. Đáy của ao bẩn do dư thừa thức ăn.

-Tác hại: Thiếu oxy vào buổi sáng sớm. pH tăng và dao động trong ngày, tăng khí độc NH_3. Tôm phát triển chậm, Tôm đề kháng yếu và dễ nhiễm bệnh.

- Cách khắc phục: Luôn duy trì mực nước cao (trên 1.4 m), quản lý tốt lượng thức ăn hàng ngày, và sử dụng chế phẩm sinh học định kỳ.

2. Trường hợp độ trong cao trên 40 cm:

-Nguyên nhân: Vuông ít tảo, nước trong. Môi trường nước vuông nuôi nghèo dinh dưỡng/ Do sử dụng hóa chất làm mất tảo. Vuông bị nhiễm phèn tiềm tàng.

-Tác hại: Tôm nuôi bị căng thẳng (stress), giảm khả năng bắt mồi, Tảo đáy phát triển nhiều, tôm dễ nhiễm bệnh. Thiếu lượng thức ăn tự nhiên ở giai đoạn tôm còn nhỏ.

- Cách khắc phục: Bón phân vô cơ hoặc phân hữu cơ để gây màu nước cho vuông. Trường hợp khó gây màu nước nên sử dụng nguồn nước mới có mật độ tảo phù hợp.

IV.Các loại khí độc: NH_3, NO^{2-}

Do có nhiều xác tảo chết, thức ăn dư thừa và phân tôm, …. tồn đọng ở đáy vuông làm phát sinh các khí độc như: Amoniac (NH_3), Nitrite(NO^{2-})… Các loại khí độc này đều gây dộc cho tôm, tùy theo mức độ nặng, nhẹ còn phụ thuộc vào nồng đô của các khí độc và pH trong vuông cao hay thấp. Mức giới hạn nồng độ của các khí độc trong vuông nuôi: NH_3 dưới 0,1 mg/lít. NO^{2-} dưới 0,01 mg/lít.

- Cách phòng và khắc phục:

+Nên cân đối lượng thức ăn hàng ngày cho tôm, tránh tình trạng thức ăn dư thừa tồn đọng trong vuông.

+ Máy quat nước đặt đúng vị trí và đúng qui cách để khi vận hành sẽ gom được chất thải vào vị trí giữa vuông.

+ Dùng vôi để lắng tụ các chất cặn bã xuống đáy vuông.

+ Định kỳ sử dụng chế phẩm sinh học chiết xuất từ cây Yucca để hấp thu bớt lượng khí độc trong vuông.

+ Quản lý tốt pH trong vuông (ở ngưỡng thích hợp).

+ Không để tảo trong vuông phát triển quá nhiều.

THÁNG MỘT

pH**: pH rất quan trọng trong ao nuôi, pH thích hợp từ **7,5 - 8,5

	Ao 1			Ao 3			Ao 3			Số ao đã thu hoạch tôm
Ngày	Sáng	Chiều	Trung bình cộng	Sáng	Chiều	Trung bình cộng	Sáng	Chiều	Trung bình cộng	
1/1										
2/1										
3/1										
4/1										
5/1										
6/1										
7/1										
8/1										
9/1										
10/1										
11/1										
12/1										
13/1										
14/1										
15/1										
16/1										
17/1										
18/1										
19/1										
20/1										
21/1										
22/1										
23/1										
24/1										
25/1										
26/1										
27/1										
28/1										
29/1										
30/1										
31/1										
Trung bình hàng tháng										