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Water Pollution Spillovers or Peer Effects?

Determinants of Disease Outbreak in Shrimp Farming in Vietnam

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Abstract

Disease outbreak is a major issue in aquaculture sector that may lead to a significant economic loss. While the source of disease is difficult to trace, understanding how it occurs is important in mitigating the problem. One important factor that has not received sufficient attention is the presence of spillover among fish farmers who are connected by waterways. In this paper, we examine the presence of spillover among shrimp farmers in Southern Vietnam based on the primary data. In particular, we quantify the effects of water pollution spillover of disease outbreak in one farm to another farm and the peer effects of farming practices among the neighbors. We solve the reflection problem posed by Manski (1993) by employing a method developed by Bramoullé et al. (2009) in social network analyses. Our findings indicate that neighbors' farming practices indeed positively affect a farmer's practices and the disease outbreak in neighbors' ponds affects the disease outbreak in a farmer's pond, even after controlling for contextual peer effects and correlated effects. The magnitude of negative effects from neighbors' ponds on disease outbreak may offset the positive effects from farmers' good farming practices, suggesting the importance of considering neighboring farmers as a group in addressing the issue of disease control.

Keywords

peer effect
shrimp farming
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JEL Classification

O12
Q10
Q56
D62

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1. Motivation

The rise in aquaculture production in the past two decades has increasingly received attention, particularly in Asia (Day and Ahmed, 2005; Bush et al., .2019; ADB, 2021). The volume of fish production due to aquaculture exceeds that of capture fishing in 2018 and the share of fish in the total animal protein consumed is higher than that of beef in the world as of 2013 (FAO, 2018 & 2020). As most fish producers in Asia are smallholders who convert their farmland of less than 1 hectare to ponds to raise fish or shrimp (Hall, 2004), development of this sector contributes to poverty reduction both by providing income opportunities for the poor and providing higher nutrition opportunities for self-consumption (Filipski and Belton, 2018). The success of the sector has been praised as “Blue Revolution” and the case of Bangladesh is well documented in the literature (Murshed-e-Jahan et al., 2010; Rashid and Zhang, 2019). The sector is also important for its impacts on the surrounding natural environment, including preserving coastal area marine biodiversity, wild fish depletion due to its demand for fish feed, and salinization and ground subsidence of farmland in the neighborhood (Páez-Osuna, 2001; Cao et al., 2015; Klinger and Naylor, 2012; Suzuki, 2021).

One persistent issue in the sector is the frequent occurrence of disease outbreak. As Lafferty et al. (2015) puts it: “Aquaculture’s history is one of victories over diseases followed by new challenges (p476).” Various diseases exist, and while the cause of the disease is difficult to trace, poor water management, high stocking density, and monoculture are highly associated with the outbreak (Leung and Tran, 2000; Lafferty et al., 2015; Suzuki and Nam, 2018). The risk of disease is magnified by the intensification of fish farming methods that have been adopted by farmers to meet the ever-increasing global demand. Raising fish in high density tends to pollute the pond water more often due to the left-over feed and waste from fish, causing stress for the fish (Klinger and Naylor, 2012). Guidelines have been published at various levels, such as International Principles for Responsible Fish Farming and Better Management Practices (BMP hereafter). While these are available, farmers behave differently in terms of adopting these practices, and studies have been conducted to understand the determinants of BMP adoptions (Suzuki & Nam, 2018; Lee et al., 2019).

One important factor that has not received sufficient attention in the study of disease occurrence is the potential negative spillover effects among farmers. Spillovers may occur through two channels. First is by water pollution spillover of pathogens from one pond to another. Farmers are connected via canals and if the farmer's neighbor pollutes the water and discharges it to the canals, the farmer's pond may also be affected. Second is by spillover of farming practices among neighbors known as peer effects. Neighbors tend to adopt similar practices, and the importance of peer effects in technology adoption has been examined in many of recent literature (Bandiera and Rasul, 2006; Conley & Udry, 2010; Aida, 2018; Beaman et al., 2021). These two types of spillovers are inherently related, and both effects may be working at the same time. Understanding the presence of and the mechanism of spillovers is important in considering how to reduce the occurrence of disease outbreak among small-scale fish farmers in developing countries. While the presence of externalities in aquaculture sector is well acknowledged (Asche et al., 2022), to our best knowledge, spillover among farmers on disease outbreak has not been examined rigorously in the fish farming contexts despite its apparent possibility.

This paper aims to examine whether the spillover among farmers is important for the disease occurrence, both through the water pollution spillover of disease and the peer effects on adoption of farming practices, taking the shrimp farming sector in Southern Vietnam as a case study. The shrimp sector in Vietnam has been rapidly intensifying farming methods over the past decades to meet the global demand, and the disease outbreak has been a major concern. In order to reduce the risk of disease, some farmers are reported to use antibiotics, which are prohibited internationally (Thi Kim Chi et al., 2017; Lee et al., 2019). The shipment rejection at the ports of importing countries harms the export volume and country reputation (Jouanjean et al., 2015). Thus, it is of critical importance to understand how we can mitigate the occurrence of disease outbreak. We collected primary data from about 650 shrimp farmers. Additionally, locations of each farmer's pond were georeferenced, and these coordinates allow the distance of every farmer's pond to every other pond to be measured. Using this information, we examined whether the probability of disease outbreak is affected by neighbors' characteristics, farming practices, and outcomes.

To model the nature of possible water pollution spatial spillover, we use spatial econometric methods. While spatial econometric methods are appropriate to model geographical spillovers, a difficulty in identifying the causal effect lies in solving the reflection problem raised by Manski (1993). That is, because an individual's outcome tends to be simultaneously determined with his/her neighbors' outcomes and characteristics, and an individual also tends to choose his/her own group, decomposing these will be necessary to identify the presence of spillovers. These effects are named as "endogenous peer effect," "exogenous contextual peer effect," and "correlated effects"

(Manski, 1993). Advancement in social network studies provides several solutions to this problem (Lin, 2010; Lee, 2010; Bramoullé et al., 2020), and we rely on the IV methods developed by Bramoullé et al. (2009), which uses the variables of higher order of peers to instrument one's peer's variables to identify the causal effect.

Based on spatial autoregressive models using the pond-level data and controlling for farmer and village fixed effects, we find that spatial clustering of disease outbreak indeed exists. The higher the probability of disease outbreak around a farmer, the higher the likelihood that his own pond has disease outbreak. This was consistent in all models. Further, we find that greater shrimp farming knowledge, better recording practices, and better equipment used are associated with lower likelihood of disease outbreak on the farmer's own pond. These effects can be decomposed into direct effects from farmers themselves and indirect effects from neighbors, and both of these effects were statistically significant.

While spatial regression provides comprehensive relationship between all farmers in our sample, we still face endogeneity problem. Bramoullé's method utilizes the characteristics of higher-order peers who are not connected to the original farmer as valid instrumental variables to control for the outcomes of farmers' peers. We examine two outcomes, i.e., farmers' farming practices and probability of disease outbreak in each pond. In farming practice models based on OLS and IV regressions, we find that the neighbors' farming practices are indeed endogenous and that even after controlling for this endogeneity, neighbors' good practices on recording, water quality check, and using better equipment affect the farmer's own good farming practices. In disease outbreak models, we use pond-level data and control for farmer fixed effects and canal fixed effects and rely on probit and instrumental variable probit estimations. While the exogeneity test on neighbors' disease outbreak is not rejected, we find that the neighbors' disease outbreak is positive and statistically significant in all models, confirming the strong presence of water pollution spillovers across ponds. In fact, the magnitudes of positive effects of water pollution spillovers from neighbors are larger than the magnitude of negative effects of own (good) farming practices, indicating that your good behavior may be offset by the neighbors' outcomes. Our results suggest the strong interdependence among farmers in rural Vietnam in terms of the choice of adopting good farming practices and experience of disease outbreak. It is important to consider neighboring farmers as a group in addressing the issue of disease control.

Our paper contributes to literature in three aspects. Firstly, we quantified the existence of spatial spillovers among shrimp farmers. While spatial spillovers are examined in agricultural context, such as on the use of fertilizer and pesticides (e.g. Paudel and Crago, 2021; Wang et al., 2023), to our best knowledge, ours is the first to rigorously examine water pollution spillovers of disease and farming methods for aquaculture sector. Spillovers are apparent in aquaculture sector where farmers are connected via waterways. Acknowledging the presence of spillover and the mechanism of effects is important as it affects farmers' incentives to adopt better practices and also provides information on effective policies to reduce disease outbreak. Secondly, we confirmed pure effects of water pollution spillovers on disease outbreak and the peer effects on adopting good farming practices, which are free from the neighbors' contextual peer effects and correlated effects by solving Manski's reflection problem using

Bramoulle's methods. While these methods are also used in other empirical studies, notably Lim et al. (2021) and Wang et al. (2023), ours is different as we examined two outcomes (disease and practice) together and provided evidence that both peer effects are at work. We find that controlling for contextual peer effects, neighbors' farming practices are important determinant for farmers practices, and the disease outbreak in neighboring ponds positively affect the disease outbreak in farmers' own pond. This shed light on further understanding of the mechanism of spillovers among farmers. Thirdly, we find that farming practices and farming knowledge are important determinants for reducing the likelihood of disease outbreak. These results point to the importance of disseminating knowledge related to shrimp farming and promoting farmers to keep faming records to tackle the problem of disease outbreak.

Next section describes the study setting, mechanism of spillovers, and data collection. Section 3 details our estimation methods while Section 4 provides our results. Then a conclusion follows.

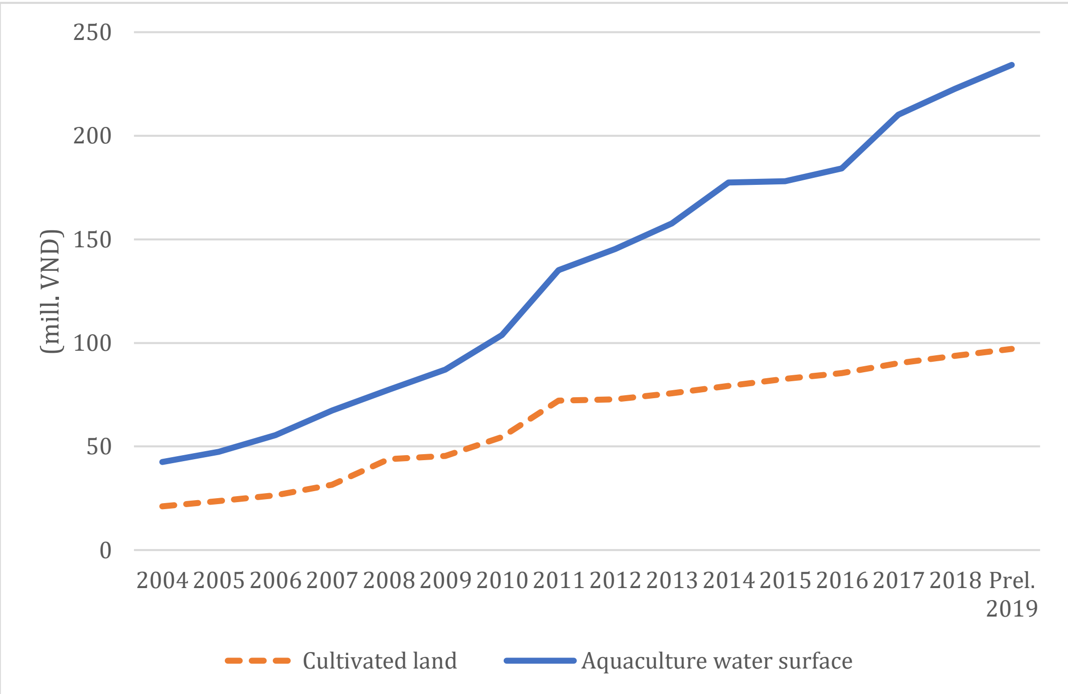
2. Context

2.1 Shrimp Sector in Southern Vietnam

Aquaculture sector in Vietnam has continued to grow over the past two decades. In export value, it grew by 475% between 2000 and 2019 (General Statistical Office of Vietnam). The shrimp sector contributed 40.4% of the total seafood exports in 2018, which is the largest proportion in the sector (VASEP, 2018). Even under the COVID-19, Vietnam managed to increase production of shrimp in 2020 when most of other exporting countries reduced production, benefitting from the success in containing the pandemic in 2020 and the diversity of export markets that the country had been exporting to (FAO, 2021 - globefish).

Our field is one district in Ca Mau Province, Vietnam, which is located in the southmost tip of the country. The Mekong Delta is the center of shrimp farming in Vietnam, and Ca Mau province produces the largest share of farmed shrimp in Vietnam (22% in 2018, General Statistics Office of Vietnam, 2020). In 2000, the government issued a decree to allow conversion of rice fields to fishponds and this benefitted many farmers in this province who were previously suffering from the low rice yields in this area due to the high salinity in the water (Tran et al., 2013). Since then the aquaculture production proliferated, continuously increasing the return to per acre land (Figure 1).

Figure 1. Change in the Gross Output of Product Per Hectare Land Area



Source) General Statistical Office of Vietnam (2021)

According to farmers interviewed, shrimp farming is three times more profitable than rice production and some literature even reports it is 10 times more profitable than rice (Belton and Little, 2008). However, it accompanies high risks, and one study reports that the average occurrence of disease is 3 times per crop (Phong et al., 2021). Common types of disease are Acute Hepatopancreatic Necrosis Disease (AHPND), formerly called Early Mortality Syndrome (EMS), and White Spot Syndrome (WSS). Some diseases are fatal, and farmers may lose all the shrimp harvest. As the source of disease is often not detectable, farmers are cautious and hesitate to let strangers come near their ponds for the fear of disease outbreak.

As this area is estuary of the Mekong river, the land is flat and many small canals exist. People use these canals daily to transport goods. While there are two main shrimp crop seasons, the first between January and April and the second between September and December, some farmers stock three or even four times per year. Shrimp farming can take different forms. At one end, we have the extensive farming method, in which farmers raise shrimp in naturally formed ponds without any use of inputs. At the other end, we have the super-intensive farming method, which requires a lot of inputs and use of equipment, such as aerators, plastic cover, and pumps to take out wastes from the pond. Normally these methods are categorized based on the shrimp density stocked in ponds. Extensive farming takes 2-5 shrimp seed/m^2, improved extensive (4-8 pieces/m^2), semi-intensive (9-15 pieces/m^2), intensive (70-150 pieces/m^2), and recently emerging super-intensive (250+pieces/m^3) production systems (Joffre et al., 2018; Nguyen et al., 2019). Vannamei and black tiger are two common types of shrimp produced. Vannamei are often produced in intensive method while black tigers are more common for extensive farming.

In our study, we focus on farmers who employ intensive and super-intensive methods as they use inputs and water quality matter more for their production. Due to the farming environment required by the higher density of shrimp, the risk of disease outbreak is higher in intensive farming than in extensive shrimp farming and hence, intensive/super-intensive farmers' practice matter greatly to the occurrence of disease or water contamination.

2.2 Mechanism of Spillover

Shrimp disease has been a major challenge for this industry since its initiation. Various types of disease exist, and some are fatal as it may kill all the shrimp within a day. Khiem et al. (2020) cites that a report published by the Asian Development Bank and the Network of Aquaculture Centres in Asia Pacific that almost 80% of all shrimp ponds face disease. The causes for disease are various and largely not very well known. Intensification of shrimp farming in recent years increased the density of shrimps stocked as well as inputs used. High density gives shrimp more stress, and more inputs means water becoming more effluent as not all feeds are eaten by shrimp. Shrimp wastes and uneaten feed pollutes water and if water quality is not managed well, it affects the health of shrimp, leading to a disease outbreak.

One mechanism of spillover is via waterways, which is a classic environmental externality problem. Freshwater pollution in rivers has been examined well in association to human health and sanitation (Graff Zivian and Neidell, 2013; Garg et al., 2018), but rarely so in relation to fish farming outcomes. While the negative effects of discharging polluted water directly to the canal without any treatment are well-known to farmers, it is also true that water discharges are not monitored. Water quality is not observed without the use of special equipment, so it is practically difficult to regulate water discharges in these villages. Water pollution may be due to disease pathogens that existed in shrimp ponds or excessive amount of nutrition and wastes that water holds from poor water quality management.[1]

Another mechanism of spillover works through the peer effects on the adoption of farming practices. Social connections have been shown to affect the tendency of technology adoption (Bandiera and Rasul, 2006; Beaman et al., 2021; Case, 1992; Conley and Udry, 2010; Feder, Just and Zimmerman, 1982; Foster and Rosenzweig, 1995). It may be that in a certain place farmers tend to follow similar practices, which may be causing a higher likelihood of disease occurrence. In our paper, we focus on geographical neighbors and examine whether neighbors' practices affect the farmer's practices. While recent development of digital technologies provides opportunities for farmers to interact with farmers who are located far away and obtain farming information (e.g. Lee and Suzuki, 2020), in our study site, such social information exchange has not been very active. Thus, we focus on geographical neighbors in our analysis.

2.3 Data Collection

We conducted a census survey of intensive and super-intensive shrimp farmers in 35 villages in all the 9 communes in the Phu Tan District, Ca Mau Province, Vietnam in 2019.

[1] While the direction of river flow matters in many settings as downstream residents tend to suffer more from pollution (e.g. Lipscomb and Mobarak 2017), in our target area, most of the land is near the sea-level, and seawater backflow into rivers. In fact, this is why the area is well-suited for shrimp farming. Thus, we do not consider the direction of river flow in our analysis.

We selected these 35 villages randomly out of 65 villages in the district where shrimp farmers are located and picked all the farmers in these villages based on the list of shrimp farmers provided by the Ministry of Rural and Agricultural Development in Ca Mau Province. However, because the list was outdated when we went to the field (e.g. some farmers had stopped farming shrimp), we first interviewed village leaders and made an updated list of shrimp farmers in these villages. We had to exclude some areas in these villages as they were not reachable by road[2]. In total, we had 701 shrimp farmers in the list. We contacted each shrimp farmer and conducted face-to-face interviews. Some of them were not willing to cooperate with our survey, and finally we interviewed 633 farmers, which is 90% of the target number. In the estimations, we had to drop several more farmers due to missing variables. Note that by restricting the number of villages within a commune, we are not able to examine the effects of farmers in non-surveyed villages. We explain some implications of this on our result in the following.

We restricted the sample to this group of shrimp farmers who conduct intensive and super-intensive farming as these farming methods require high usage of agricultural inputs. In other farming methods, such as extensive farming and semi-extensive farming, shrimp are grown naturally without industrial feeds or inputs. Thus, the risk of spillover from these farming methods is minimum, and we expect that the behavior of farmers with these extensive methods must be different from our target farmers. In terms of land area, our sample farmers are located within an area of about 20km x 20km. We hired enumerators who are fluent in local dialects and conducted in-person interviews. The

[2] By excluding those observations unreachable by road, our sample may be more accessible by road. However, we believe that this won't cause a serious to our results as pathogen spillover in shrimp farming is more likely to be carried through water and not by road.

survey was pre-approved by the Ethics Review Committee at the University of Tokyo as well as the local government. We collected information on socio-economic characteristics of the household heads, the details of their shrimp production, practices and sales, consumption and expenditure details, social network, and GIS information on the main shrimp ponds.

3. Empirical Framework

To examine the effects of water pollution spillover among farmers, we use spatial econometric methods. A key aspect of these models that aids in studying spillovers is that possible interactions between spatial units are summarized with a $N \times N$ spatial weights matrix, W. In our paper, we use a row normalized symmetric weights matrix in which for non-neighbors, $w_{ij}=0$, while for neighbors we use the inverse distance in which $w_{ij} = 1/d_{ij}$ where d_{ij} is the distance between farmers i and j[3]. Symmetric matrices fit our case as our target area is very low in altitude, and there is no definite direction in how water flows. We also varied the definition of neighborhood using a circular area around the farmer i with 200 meters radius, 500m radius, and 1km radius.

We start with a very general spatial autoregressive model with spatial autoregressive errors (SARAR) that nests some popular models, such as the spatial Durbin Model, spatial lag, spatial error and aspatial model like OLS.

[3] Another popular option is the contiguity spatial weights based on administrative units, but the inverse distance weights fit our purpose better as the nature of the spillover of our concern is based on the proximity between farmers or ponds rather than based on specific administrative units.

$$y_i = \rho W y_j + X_i'\beta + \delta W X_j' + \lambda M u + \varepsilon \quad (1)$$

where y_i is a dummy variable on whether the pond had a disease outbreak in the past 1 year. In the context of shrimp farming, disease outbreak refers to the sudden and widespread occurrence of a contagious infection among the cultivated shrimp. This can include specific diseases such as the White Spot Syndrome Virus (WSVV), Early Mortality Syndrome (EMS) or others. These outbreaks can result from various factors such as poor water quality, inadequate sanitation, overcrowding, environmental stressors, or introduction of pathogens. X_i includes socio-economic characteristics of farmer i, where y_j is the outcome for farmer j, X_j are the socio-economic characteristics of farmer j where $i \neq j$.

The SARAR model allows for changes in an outcome variable in a given area to have effects on contemporaneous outcomes in other areas (via the autoregressive spatial lag of the dependent variable, if $\rho \neq 0$). It also allows changes in independent variables to affect not only own-area outcomes but also outcomes in neighboring area (i.e. if $\delta \neq 0$). The $\lambda M u$ term allows for spatial autocorrelation, where errors for a given area correlate (λ) with a weighted average of errors from surrounding areas. Equation (1) nests a spatial Durbin model (SDM) if $\lambda = 0$, a spatial autoregressive model (SAR, aka spatial lag model) where only the dependent variable is spatially lagged if $\lambda = \delta = 0$, a spatial error model where only the errors are spatially lagged (if $\rho = \delta = 0$), and the most restrictive of all, which is an aspatial model with no spatial lags (if $\rho = \delta = \lambda = 0$). A feature of these models, other than the spatial error model, is that the spatial lags imply that there are spillovers.

We estimate these models by maximum likelihood estimation methods as it is known to produce consistent estimations in spatial regression models while the least squares estimations lead to inconsistency (Le Sage and Pace, 2008). Additionally, we confirmed that our results hold with the GS2SLS (Generalized Spatial Two Stage Least Squares).

Equation (1) allows for a general-to-specific model selection strategy which appears to be more robust than the reverse simple-to-general selection strategy, especially if they are any anomalies in the Data Generating Process (Mur and Angulo, 2009). Therefore, it is common in the spatial econometrics literature to start with an OLS model and to use the residuals from that model to test against spatial alternatives. Moran's I test is widely used to detect spatial autocorrelation and can be expressed as:

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{2}$$

where n is the number of farmers, w_{ij} is the spatial weight between farmers, and z_i is the deviation of the outcome x from its mean, i.e., $z_i = x_i - \bar{x}$. A feature of Moran's I is that the alternative hypothesis does not specify the process generating the autocorrelated disturbances.

In addition to the global Moran's I, we also examine the local tendency of geographical spillovers in our sample using two different measures, the Gi* statistic by Getis and Ord (1992) and the local Moran's I statistic by Anselin (1995). The raw form of the Gi* is given as:

$$G_i^* (d) = \frac{\sum_{j=1}^{n} w_{ij}(d) x_j}{\sum_{j=1}^{n} x_j}, j \; may \; equal \; to \; i \tag{3}$$

where *w* is symmetric one or zero spatial weighting matrix which has one if the distance between points *i* and *j* are below a specific bandwidth *d* and zero otherwise and *x* is any variable of interest. It is the ratio of the sum of neighborhoods to the sum of all observations and essentially shows whether *x* in the area around *i* tends to be larger than a typical neighborhood. The local Moran's I is a similar concept that shows the local spatial association and is defined as:

$$I_i = z_i \sum_{j=1}^{n} w_{ij} z_j \tag{4}$$

where z is variable of interests in deviations from the mean and w is the spatial weighting matrix. Thus, it shows the size of local covariation around an observation *i* while the Gi* statistic shows the local sum. They are both considered useful in analyzing the importance of spatial associations.

The analysis of decomposing the endogenous peer effects in this study relies on instrumental variable regressions. While spatial regressions are a well-structured method to model geographical spillovers, it also has a concern that it does not show causal relationships as the reflection problem raised by Manski (1993) is not solved (Gibbons and Overman, 2012; Fafchamps, 2015). That is, an outcome of a person *i* may be affected by an outcome of a person *j* due to a) the influence that the outcome of person *j* has on the outcome of person *i* (i.e., "endogenous peer effect"), b) the influence that the characteristics of person *j* has on the outcome of person *i* (i.e., "exogenous contextual peer effect"), or c) because they face similar environmental or institutional conditions (i.e., "correlated effect"). It is often difficult to distinguish endogenous peer effect and exogenous contextual peer effect because person *i*'s action tends to affect person *j*'s action and vice versa. In recent years, identification methods of these effects have been advanced particularly by economists working to identify the effects of social network.[4] We apply the result of Bramoullé et al. (2009) to our setting, which established that under a case where the correlated effect is not an issue, the simultaneity of endogenous peer effects and exogenous contextual effects can be identified using the higher order spatial lag as an instrument for the endogenous peer effects. If farmers *i* and *j* are connected, farmers *j* and *k* are connected, but farmers *i* and *k* are not connected ("intransitive triad" by Bramoullé et al. (2009), then farmer *k*'s characteristics can be used to identify farmer *j*'s effect on farmer *i* as farmers *i* and *k* are not connected. In our case, we defined $d_{ij}=0$ in the spatial weighting matrix for a pair of farmers who are more than some threshold distance apart. We report the case of 500 m radius in the following result section and also present results for 200m radius and 1km radius for robustness checks in the appendix. It is safe to assume that correlated effects are not important in our case because our study area is small and farmers live in homogenous villages with little movement in or out of the villages. Unlike social network groups, where people self-select into a certain group, which makes correlated effects important, our farmers have been living in these villages for many years, and in that sense self-selection into a group is not an issue. To be prudent, however, we also include village fixed effects, farmer fixed effects, and canal fixed effects in our models to control for the remaining correlated effects. We estimate:

$$y_i = X_i'\beta + \rho W\hat{y}_j + WX_j'\gamma + e_i \tag{5}$$

where $\hat{y}_j$ is the predicted value of y_j using the instrument W^2x_k in the first stage regression. We examine determinants of farming practices and disease outbreak and whether peer effects are at work using these models. We constructed farming practice

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[4] For recent review, refer to Fafchamps (2015) and Bramoullé et al. (2020).

indexes, particularly on recording, water quality check, and use of equipment, based on the survey data and use farmer-level data as our data on practices are taken at farmer-level. We use pond-level data to examine the determinants of disease outbreak. As farming practice also affects disease outbreak, we use farming practice variable as an independent variable in the disease determinant models. To correct for the potential endogeneity of farming practice, we additionally include another instrumental variable, i.e., whether the parents are shrimp farmers or not, in these models. Parents' status as shrimp farmers is likely to affect the farming practices of farmers, but not the occurrence of disease outbreak on a farmer's pond directly. The first stage results are provided in the appendix.

We note a point of caution in our study. While we have census data of intensive and super intensive shrimp farmers in selected villages from all the 9 communes in the district, we do not have information from all villages in each commune. Admittedly this is the limitation of our study, but the implication of our sampling design is that our estimation results below are likely to be underestimation of the effects which one would have observed with the full information for three reasons. Firstly, as we picked villages randomly, the likelihood of disease outbreak in the non-surveyed villages is expected to be similar with the villages we have information of. Secondly, because the relation between farmers is computed based on the distance measured using GPS locations, even with the missing information in between two farmers in different villages, the distance between farmers remains true. We are not altering the relationships between surveyed farmers. Thirdly, as we have full information within villages, the majority of our farmers are not affected by missing information of neighboring villages.

4. Results

Before presenting the regression results, we examine the characteristics of farmers. Table 1 provides summary statistics for those farmers who did not have any disease outbreak in the production season in 2018/2019 and those farmers who had some cases. Most farmers tend to be male with average years of 47 years old. Farmers tend to have ponds which are about 0.32 to 0.36 hectares and on average they have 1.6 ponds per farmer. Only 6 to 7 % of the farmers are engaged in non-farm activities. Among the characteristics, only the shrimp farming knowledge index was significantly different between the two group. Farmers who had no outbreak had higher knowledge. In other words, small farms or less education do not seem to matter for having disease outbreaks.

However, there are stark differences in terms of practice indexes and financial performances. The practice indexes of recording and equipment are higher for the farmers who did not have any disease outbreak. Recording practices involve the systematic documentation and tracking of various aspects of shrimp farming operations, which includes keeping records of data such as water quality parameters, seed and input usage, feeding schedules, sales price and sales volume. Equipment practices on the other hand entail the use, maintenance and management of infrastructure used in shrimp farming operations, this includes usage of aerator, pump, feeding tray and water circulation system. Revenues, the difference between revenue and the input costs (seed + feed, which consists of about 70-80% of the total costs), and the success rate (a ratio of quantity of harvest to input) are all higher for the group without any disease outbreak. These indicate the importance of good farming practices as well as significance of experiencing disease on the financial outcomes.

Table 1. Summary Statistics

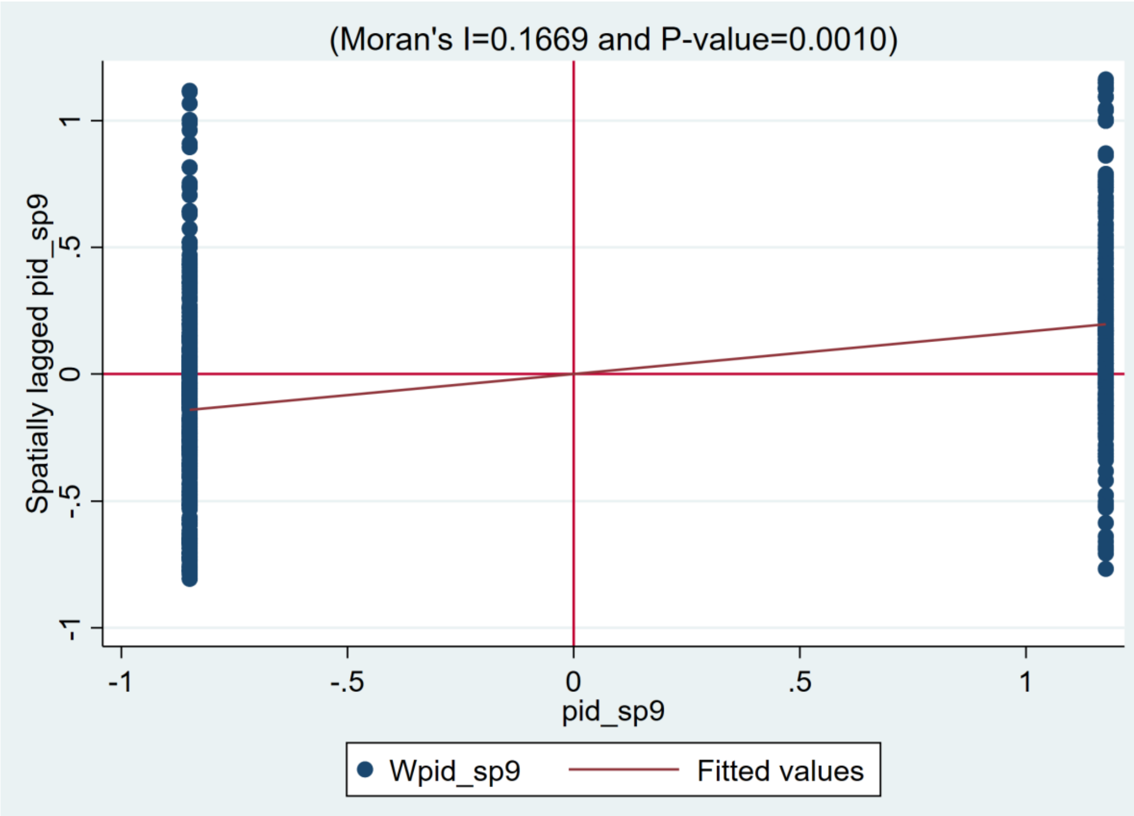
	No disease outbreak (316) (1)	Had disease outbreak (301) (2)	p-value (3)
% disease outbreak	0	88.8	0.000***
		(0.21)	
=1 if male	0.946	0.928	0.326
	(0.23)	(0.26)	
Age	47.1	46.9	0.841
	(11.57)	(11.38)	
Shrimp farming experience (years)	7.42	7.80	0.282
	(4.12)	(4.64)	
Education completed (years)	8.91	9.13	0.387
	(3.40)	(2.92)	
Shrimp farming knowledge (18 max, 0 min)	11.18	10.34	0.000***
	(2.50)	(2.33)	
=1 if belong to a shrimp cooperative	0.04	0.04	0.904
	(0.19)	(0.20)	
Total pond size (ha)	0.32	0.36	0.106
	(0.28)	(0.32)	
Average shrimp density (pieces/ha)	2,472,025	2,506,400	0.857
	(2,423,417)	(2,306,043)	
# ponds used	1.63	1.53	0.242
	(1.12)	(0.96)	
# buyers farmer knows	6.67	7.17	0.195
	(4.89)	(4.59)	
=1 if engaged in non-farm activities	0.06	0.07	0.514
	(0.23)	(0.26)	
Frequency of farmer meeting (5 max, 0 min)	2.93	3.05	0.216
	(1.28)	(1.25)	
Trust in village (4 max, 1 min)	2.79	2.79	0.966
	(1.10)	(1.01)	
Practice: recording (1 max, 0 min)	0.46	0.31	0.000***
	(0.32)	(0.33)	
Practice: water check (1 max, 0 min)	0.68	0.65	0.083
	(0.26)	(0.25)	
Practice: equipment (1 max, 0 min)	0.89	0.84	0.000***
	(0.14)	(0.17)	
Revenue/ha (mVND)	4893	2420	0.000***
	(5935)	(4805)	
Revenue–Cost/ha (mVND)	2556	903.8	0.000***
	(3684)	(3164)	
Qty harvested/input/ha (kg/pcs)	0.017	0.008	0.000***
	(0.01)	(0.01)	

Note) Standard deviation in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.1 Results of Testing for Spatial Autocorrelation Effects

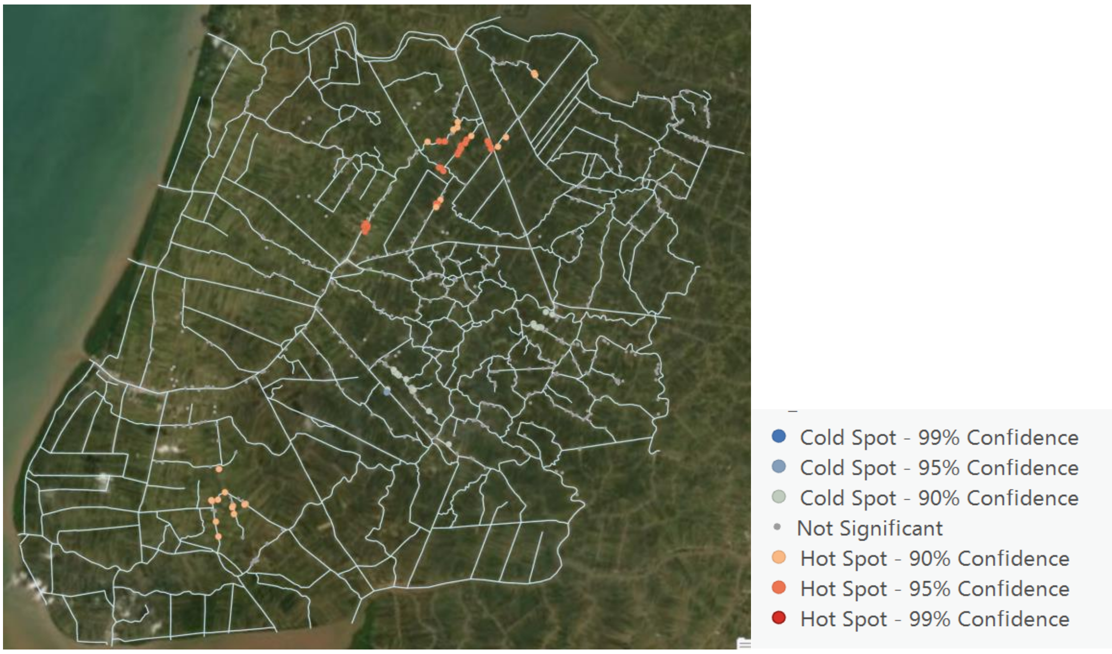
In Figure 2, we first plot the global Moran's I with the percentage of disease outbreak as the horizontal axis and the spatial lag of the same variable on the vertical axis. The Moran's I is calculated as 0.1669, which is statistically significant at 1% level, suggesting that there is a positive spatial autocorrelation in our data.

Figure 2. Moran's I plot (Global Moran's I)



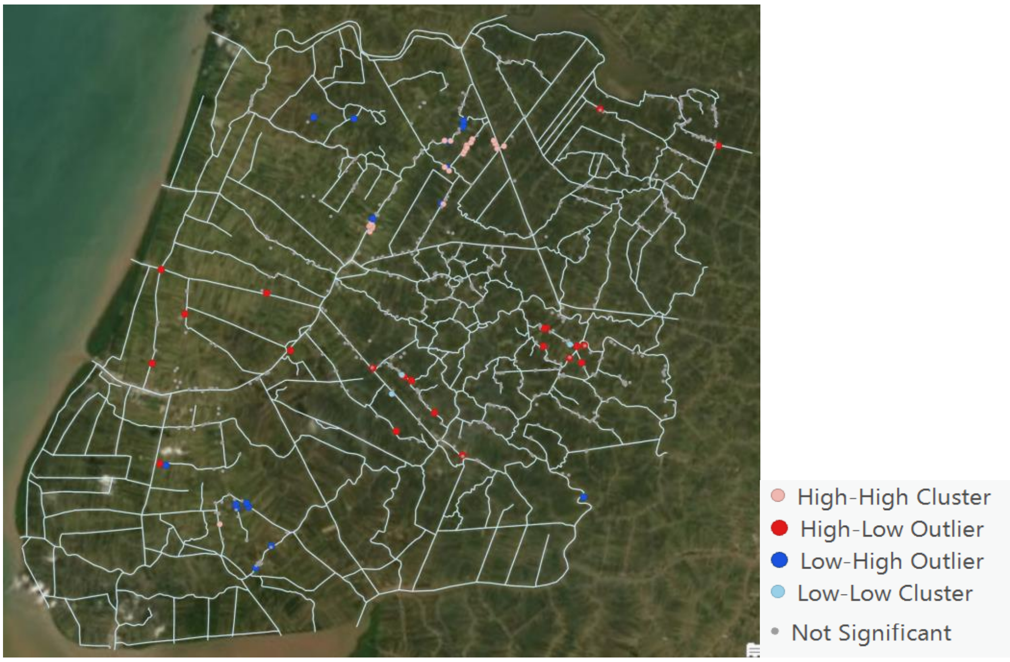
Given the statistical significance of the global Moran's I, we also examine the local tendency of geographical spillovers in our sample using two different measures, the Gi* statistic by Getis and Ord (1992) and the local Moran's I statistic by Anselin (1995). Figures 3a and 3b show the results of optimized hot spot analyses based on Gi* statistics and optimized outlier analyses based on Local Moran's I statistics using ArcPro. Both show that there exist several "hot spots" and "clusters" in which disease outbreaks occurred, indicating the possibility of spatial spillovers across farmers in some areas.

Figure 3a: Optimized Hot Spot Analyses (based on Getis-Ord GI* stat)



Note) Lines indicate waterways, dots are shrimp ponds where cold/hot spots were detected.

Figure 3b: Optimized Outlier Analysis (Based on Local Moran's I stat)



Note) Lines indicate waterways, dots are shrimp ponds where clusters and outliers were detected.

4.2 Regression Results

Table 2 presents the spatial regression results, Columns (1) and (2) for SAR and (3) and (4) for SDM. While the size of pond is positively related to the probability of disease outbreak, farmer's own shrimp farming knowledge is an important factor to reduce it in all models. Larger ponds may experience more disease outbreak most likely because farmers who conduct super-intensive shrimp farming tend to have smaller ponds and tend to provide more care during farming. Own farming practices of recording and equipment are negative and statistically significant in columns (2) and (4), indicating that better practices reduce the probability of disease. For spatial lags, which show the effects from neighbors, we find that the coefficients of lagged disease rates are positive and statistically significant at 1 % level across models, suggesting a strong water pollution spatial spillover of disease outbreak. It is also worth noting that other spatial variables are all insignificant, suggesting that SAR are more preferred to SDM in our case. The spatial terms are jointly statistically significant in all models. We also run 2GSLS estimations with the same models and confirm similar results.

Table 2. Estimates from Spatial Autoregressive Regression Models and Spatial Durbin Models on Disease Outbreak (MLE, pond-level)

	=1 if there was a disease outbreak in the pond			
	SAR1	SAR2	SDM1	SDM2
	(1)	(2)	(3)	(4)
Own Characteristics				
Size of pond (ha)	0.278***	0.215**	0.240**	0.200*
	(2.646)	(2.050)	(2.215)	(1.856)
Years used for cultivation	0.003	0.001	0.002	-0.001
	(0.643)	(0.288)	(0.257)	(0.188)
Average density (pieces)	0.000	0.000	0.000	0.000
	(0.931)	(0.139)	(0.964)	(0.312)
Shrimp farming knowledge	-0.032***	-0.023***	-0.028***	-0.018*
	(4.238)	(2.911)	(2.891)	(1.737)
Practice: recording		-0.188***		-0.205***
		(3.358)		(3.024)
Practice: water check		0.068		0.118
		(0.950)		(1.286)
Practice: equipment		-0.322**		-0.362**
		(2.280)		(2.328)
Constant	0.589***	0.829***	0.773*	0.720*
	(5.553)	(5.825)	(1.893)	(1.778)
Spatial lags				
=1 if disease outbreak	0.453***	0.449***	0.435***	0.441***
	(8.574)	(8.475)	(8.039)	(8.172)
Size of pond (ha)			0.322	0.318
			(0.830)	(0.828)
Years used for cultivation			0.006	0.009
			(0.404)	(0.623)
Average density (pieces)			0.000	0.000
			(0.337)	(0.214)
Shrimp farming knowledge			-0.003	-0.014
			(0.148)	(0.657)
Practice: recording			-0.241	0.063
			(1.556)	(0.345)
Practice: water check			-0.003	-0.167
			(0.021)	(0.849)
Practice: equipment			-0.21	0.211
			(0.489)	(0.459)
Observations	773	773	773	773
Pseudo R2	0.089	0.109	0.096	0.112
Wald Chi2 for main regression	147.6***	167.6***	152.8***	172.6***
Wald Chi2 for spatial terms	73.5***	71.8***	76.5***	75.0***

Note) Robust T-statistics in parentheses. Village FE and Farmer FE are used in all models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Row-normalized spatial weights based on inverse distance are used.

Table 3. Marginal Effects of Spatial Autoregressive Regression Models

	=1 if there was a disease outbreak in the pond					
	SAR1			SAR2		
	Direct (1)	Indirect (2)	Total (3)	Direct (4)	Indirect (5)	Total (6)
Size of pond (ha)	0.287***	0.220**	0.507***	0.222**	0.168*	0.390**
	(0.108)	(0.095)	(0.198)	(0.108)	(0.089)	(0.194)
Years used for cultivation	0.003	0.002	0.006	0.001	0.001	0.002
	(0.005)	(0.004)	(0.009)	(0.005)	(0.004)	(0.009)
Average density (pieces)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Shrimp farming knowledge	-0.033***	-0.025***	-0.058***	-0.024***	-0.018***	-0.042***
	(0.008)	(0.008)	(0.014)	(0.008)	(0.007)	(0.015)
Practice: recording				-0.194***	-0.147***	-0.342***
				(0.058)	(0.053)	(0.106)
Practice: water check				0.070	0.053	0.123
				(0.073)	(0.057)	(0.130)
Practice: equipment				-0.333**	-0.252**	-0.585**
				(0.146)	(0.122)	(0.262)

Note) Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

In Table 3, we present the marginal effects of these spatial regressions, separating the effects into direct effects, indirect effects via neighbors, and total effects, which are the sum of the former two. We report the SAR models based on the results of Table 2. We find that pond size affects the likelihood of disease both directly and indirectly. Increasing a farmer's own shrimp farming knowledge by 1 unit (out of the maximum of 18) reduces the probability of having the disease by 2.4 to 3.3% while the same increase for neighboring ponds reduces the disease by 1.8 to 2.5%. Having a perfect score for farmer's own recording practice index reduces the probability of disease outbreak by 19.4%, and the same effect from neighbors reduces the probability of disease by 14.7%, totaling the reduction of 34.2% if all the farmers had the perfect score for the recording. Having a full score for farmer's own equipment reduces the disease by 33% and the indirect effects from neighboring ponds reduces it by 25.2%.

As the spatial regression models do not control for endogeneity of peer effects, in Tables 4 and 5, we use OLS and IV estimation, using the higher order peer's characteristics as IVs to estimate the determinants of farming practices and disease outbreaks. For Table 4, we report the results for each farming practice. Based on endogeneity tests at the bottom of the table, we reject the null hypotheses that the farming practice of neighbors is exogenous in Columns (2) and (4), suggesting the use of IV models, while we cannot reject it for Column (6).

Table 4: Estimated Effects of Own and Neighbors' Characteristics on Farming Practices (Farmer level, 500m radius)

	Recording		Water		Equipment	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Own Characteristics						
=1 if male	0.011	0.048	-0.099***	-0.092***	-0.040**	-0.037**
	(0.199)	(0.728)	(3.151)	(2.938)	(2.263)	(2.114)
Age	0.002*	0.002*	0.003***	0.003***	0.000	0.000
	(1.913)	(1.683)	(2.84)	(3.097)	(0.696)	(0.875)
Shrimp farming experience	-0.002	-0.002	-0.001	-0.001	0.000	0.000
	(0.698)	(0.431)	(0.684)	(0.341)	(0.338)	(0.212)
Education completed	0.012*	0.01	0.009**	0.010**	0.005**	0.005***
	(1.951)	(1.622)	(2.084)	(2.321)	(2.692)	(2.775)
Shrimp farming knowledge	0.045***	0.046***	0.027***	0.028***	0.012***	0.013***
	(5.095)	(5.016)	(4.782)	(4.78)	(4.131)	(4.235)
=1 if belong to a shrimp cooperative	0.037	0.045	0.106**	0.104*	0.067***	0.069***
	(0.688)	(0.937)	(2.057)	(1.806)	(3.073)	(3.173)
Total pond size (ha)	-0.039	-0.075**	0.017	-0.014	-0.015	-0.002
	(1.146)	(2.066)	(0.719)	(0.496)	(0.979)	(0.076)
Ave shrimp density (pcs)	0.000	0.000	0.000***	0.000***	0.000***	0.000***
	(0.079)	(0.202)	(4.362)	(4.292)	(6.516)	(6.583)
# buyers farmer knows	-0.003	0.000	0.002	0.004	0	0.001
	(0.996)	(0.119)	(0.702)	(1.43)	(0.378)	(0.591)
=1 if engaged in non-farm activities	-0.015	0.041	-0.022	-0.025	-0.074**	-0.071**
	(0.279)	(0.707)	(0.605)	(-0.778)	(-2.366)	(2.270)
Frequency of farmer meeting	-0.043**	-0.041**	-0.016	-0.023	0.021*	0.029**
	(2.285)	(2.113)	(0.929)	(-1.488)	(1.807)	(2.135)
Trust in village	-0.050	-0.082**	-0.004	0.011	-0.012	0.001
	(1.182)	(1.994)	(0.258)	(0.679)	(-0.765)	(0.03)

Endogenous Peer Effects (W*Y)						
Practice: recording [a)]	0.267***	0.903***				
	(4.009)	(6.594)				
Practice: water check [a)]			0.237***	0.925***		
			(2.917)	(5.064)		
Practice: equipment [a)]					0.239***	0.546**
					(3.198)	(1.962)
Contextual Peer Effects (W*X)						
=1 if male	-0.085	-0.083	0.003	0.079	-0.042	-0.054**
	(1.219)	(1.143)	(0.049)	(1.213)	(1.527)	(2.056)
Age	0.000	-0.002*	-0.003**	-0.004***	0.000	-0.001
	(0.295)	(1.700)	(2.142)	(3.510)	(0.108)	(0.844)
Shrimp farming experience	-0.002	0.003	0.002	0.002	0.000	0.000
	(0.388)	(0.524)	(0.536)	(0.619)	(0.197)	(0.181)
Education completed	0.000	-0.008	-0.004	-0.010*	0.004	0.000
	(0.03)	(1.122)	(0.793)	(1.877)	(1.300)	(0.098)
Shrimp farming knowledge	-0.011	-0.040***	-0.009*	-0.027***	-0.008*	-0.013**
	(1.081)	(3.134)	(2.004)	(2.983)	(1.856)	(2.044)
=1 if belong to a shrimp cooperative	-0.04	-0.006	-0.059	-0.077	-0.013	-0.029
	(0.660)	(0.157)	(1.140)	(1.119)	(0.541)	(0.970)
Total pond size (ha)	0.132**	0.143**	0.071*	0.006	-0.024	-0.034
	(2.144)	(2.065)	(1.77)	(0.123)	(0.866)	(1.289)
Ave shrimp density (pcs)	0.000	0.000	0.000	-0.000***	0.000	0.000
	(1.450)	(0.048)	(1.427)	(2.905)	(1.150)	(1.574)
# buyers farmer knows	-0.009	-0.003	-0.005*	-0.006	-0.003	-0.004
	(1.659)	(0.549)	(1.699)	(1.439)	(1.059)	(1.454)
=1 if engaged in non-farm activities	-0.132**	-0.076	0.01	0.018	-0.009	0.039
	(2.087)	(1.140)	(0.161)	(0.414)	(0.274)	(0.65)
Frequency of farmer meeting	0.018	0.04	0.021	0.021*	-0.028**	-0.038**
	(0.882)	(1.641)	(1.405)	(1.677)	(2.101)	(2.504)
Trust in village	0.064	0.080**	0.027	-0.013	0.023	0.004
	(1.641)	(1.986)	(1.197)	(0.652)	(1.403)	(0.184)
Constant	0.058	0.018	0.159	0.087	0.536***	0.448***
	(0.313)	(0.122)	(1.249)	(0.797)	(7.656)	(4.067)
Observations	603	603	603	603	603	603
Adj. R2	0.191	0.034	0.21	0.045	0.262	0.226
AIC	285.947	.	-44.421	.	-690.73	.
Wald Chi2 for the model		1117.98***		2942.4***		500.47***
F stat for endogeneity test		18.54***		10.22***		1.092

Note) Absolute values of cluster-robust T-statistics at commune levels in parentheses. Village FE included in all models. * p < 0.1, ** p < 0.05, *** p < 0.01. a) instrumented with the higher order peers' characteristics in IV models. Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 500m radius are used.

We find that neighboring farmers' practices are statistically significant across all the models, indicating strong endogenous peer effects in shaping farming practices. It implies that disregarding the characteristics of the neighbors, neighbors' practices indeed influences a farmer's practices. This result is in line with previous studies in other contexts which show peer effects matter (e.g. Conley and Udry, 2010; Dupas, 2014; Wang et al., 2023). The magnitude is quite large, as in the range of 90% in IV models for recording and water quality check, while it is lower for equipment use at about 24% for OLS model. Note again that peer effects indicate the effects from all the neighboring farmers summed up. Apart from peer effects, own education, shrimp knowledge, belonging to a shrimp cooperative, and higher shrimp density lead to better farming practices. The first stage regression results for IV models are presented in Appendix Table 1, and the robustness check using different definitions for spatial weights (200m radius and 1km radius) are also presented in Appendix Tables 3 and 4, which show similar results.

Table 5 shows the results for disease outbreak using Probit and IV Probit as the dependent variables are discrete. In Columns (2) and (4), farmer and canal fixed effects are also included in addition to village fixed effects. We cannot reject the exogeneity of peer neighbor's likelihood of disease outbreak on the farmer's own likelihood of disease outbreak in Columns (3) and (4). Thus, our preferred models are Probit models. Disregarding this, in all models the endogenous peer effects of neighboring ponds' disease are consistently positive and statistically significant. This suggests that indeed there is a water pollution spillover of disease outbreak from neighboring ponds. In Manski's term, this is the endogenous peer effect, which is free from the contextual peer effect and correlated effects. While other contextual peer effects are insignificant, own characteristics of higher shrimp farming knowledge and better farming practices reduces the likelihood of disease outbreak in the pond. Observing the marginal effects, the magnitude of the effects from peer's disease outbreak is larger than the effects from farmer's own practices, indicating the importance of controlling for the disease in neighboring ponds. The first stage regression results for IV models are presented in Appendix Table 2, and the robustness check using different definitions for spatial weights (200m radius and 1km radius) are also presented in Appendix Tables 5 and 6, which show similar results. Taken together, we find the strong evidence on endogenous peer effects, which are free from contextual peer effects and correlated effects, of neighboring farmers' farming practice as well as neighboring ponds' disease outbreak.

Table 5: Estimated Effects of Own and Neighbors' Characteristics on Disease Outbreak (pond level, 500m radius)

	=1 if there was a disease outbreak in the pond			
	Probit		IVProbit	
	(1)	(2)	(3)	(4)
Own Characteristics				
Size of pond (ha)	0.688**	0.713**	0.485	0.492
	(2.007)	(2.001)	(0.988)	(1.041)
Years used for cultivation	-0.002	0.000	0.006	0.004
	(0.103)	(0.016)	(0.292)	(0.192)
Average density (pieces)	0.000	0.000	0.000	0.000
	(0.044)	(0.016)	(0.271)	(0.326)
Shrimp farming knowledge	-0.059**	-0.058**	-0.031	-0.028
	(2.197)	(2.136)	(0.442)	(0.428)
Average practice$^{a)}$	-0.795**	-0.762**	0.068	-0.1
	(2.395)	(2.260)	(0.035)	(0.050)
Endogenous Peer Effects (W*Y)				
=1 if disease outbreak$^{b)}$	1.267***	1.200***	2.812***	2.858***
	(7.779)	(7.246)	(5.369)	(5.784)
Contextual Peer Effects (W*X)				
Size of pond (ha)	-0.255	-0.327	-1.513*	-1.458**
	(0.526)	(0.685)	(1.938)	(2.153)
Years used for cultivation	0.002	0.007	-0.032	-0.035
	(0.114)	(0.324)	(1.276)	(1.380)
Average density (pieces)	0.000	0.000	0.000	0.000
	(0.483)	(0.574)	(1.399)	(1.483)
Shrimp farming knowledge	-0.029	-0.022	-0.005	-0.008
	(1.293)	(0.938)	(0.192)	(0.389)
Farmer FE	No	Yes	No	Yes
Canal FE	No	Yes	No	Yes

Marginal Effects of:

Own average practice	-0.263**	-0.250**	0.017	-0.025
Peers' disease outbreak	0.419***	0.394***	0.702***	0.713***
Observations	773	773	749	749
Pseudo R2	0.1425	0.1486		
AIC	925.5	923.11	761.57	723.16
Wald Chi2 for main model	115.01***	117.06***	303.35***	363.52***
Test of endogeneity (F stat)			3.27	3.7
(P value)			0.1951	0.157

Note) Absolute values of cluster-robust T-statistics at Farmer levels in parentheses. Village FE included in all models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. a) is the average of practice indexes on recording, water quality check, and equipment and it is instrumented with whether the parents were shrimp farmers or not and b) is instrumented with higher order peers' characteristics in Columns (3) and (4). Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 500m radius are used.

5. Conclusion

This paper examined empirically whether spillover effects are important for disease outbreak taking a case of shrimp sector in Vietnam based on primary data of about 620 farmers. We find that disease outbreak tends to be clustered in some areas, and this was both due to the peer effects of farming practices among farmers in proximity as well as the water pollution spillover of disease or polluted water between farmers. We used the Bramoullé's method (2009) to solve the reflection problem posed by Manski (1993) in our identification.

We contribute to shedding light on the mechanism of disease outbreak, which is a major challenge in aquaculture sector. Based on our findings, when governments or international organizations offer technical training, it is important to consider farmers in close proximity as a group and target them together rather than individually selecting farmers. Increasing farmers' shrimp farming knowledge also should be emphasized in trainings as we find that it has significant effect in reducing the occurrence of disease outbreak. Another possibly effective pathway to reduce the effects of spillover is to internalize the spillover by such means as publicizing where the disease occurred to farmers. This may promote collaborative activities among farmers to mitigate the problem together. [5]

Our findings provide implications for further research. While individual farm-level actions are essential for disease prevention and management in shrimp farming, communal management could also play a vital role in enhancing the effectiveness and sustainability of these practices. For example, shrimp farmers in Sri Lanka voluntarily set rules on the timing of water intake and release, and this co-management system has worked successfully for them (Galappathti and Berkes, 2015). However, in a society where social capital is well developed, communal management may need to be supplemented with locally developed rules and sanctions (Bowles and Gintis, 2002). This approach has been used in the context of irrigation and water user's group for rice farmers in the Philippines and Sri Lanka (Pretty and Ward, 2001). Norwegian experience from the salmon aquaculture teaches the importance of the involvement of public authority in addition to private regulation to manage common pool resources (Osmundsen, 2021). While we did not consider temporal aspects in our study given the data limitation, with more frequent data collection, studying spatio-temporal aspects of disease transmission will provide more implications on how to manage the spillovers and merits attention for future research.

Our study also confirmed the importance of farming specific knowledge, which

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[5] This is akin to the 'walk of shame' in Community-Led Total Sanitation (CLTS). CLTS is a program being widely implemented in more than 60 countries throughout Asia, Africa, Latin America, the Pacific and the Middle East to address the sanitation burden. CLTS aims to create demand for sanitation by facilitating graphic, shame-inducing community discussions of the negative health consequences of existing sanitation practices, rather than through the more traditional approach of providing sanitation hardware or subsidies (Cameron et al., 2019)

had higher effects than formal education in reducing the disease outbreak. The rapid spread of information and communication technologies (ICTs) in developing countries offers opportunities to provide more timely and low-cost information services to farmers. Several studies have shown that the usage of mobile phones improves agricultural outcomes and improve farmer's welfare (e.g. Jensen, 2007; Aker, 2015). By providing affordable access to technical information to shrimp farmers especially those in remote areas, mobile phone applications could harness farmers' adoption of good shrimp farming practices.

Another topic that is worth exploring is why some farmers drop shrimp farming over time while others remain and its consequences. Anecdotal evidence from our field suggests the presence of high risks of disease outbreak and increase in the production costs led many farmers to exit the sector. Our study showed the interdependence of farmers within geographical areas, and this entry and exit behavior of farmers likely affect the dynamics of local communities. As this may well affect how spillovers can or should be managed, it is also important to examine their dynamic behaviors.

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Appendix

App Table 1: First stage regression results for IV Models in Table 4

	Recording (1)	Water (2)	Equipment (3)
Instruments			
W^2xMale	-0.195	-0.122	0.016
	(1.13)	1.00)	(0.20)
W^2xAge	-0.003	-0.001	0.001
	(0.81)	(0.39)	(0.31)
W^2xExperience	-0.001	0.015	0.011^{**}
	(0.06)	(1.56)	(2.07)
W^2xEducation	0.013	0.002	-0.002
	(0.92)	(0.26)	(0.25)
W^2xShrimp farming knowledge	0.013	-0.009	0.001
	(0.92)	(1.05)	(0.13)
W^2xBelong to a shrimp cooperative	-0.020	0.247	0.099
	(0.1)	(1.63)	(1.58)
W^2xTotal pond size (ha)	0.485^{***}	0.047	-0.083
	(3.43)	(0.40)	(1.35)
W^2xAve shrimp density	0.000	0.000	0.000
	(1.6)	(0.94)	(0.48)
W^2x# buyers farmers know	-0.026^{***}	0.001	-0.007
	(3.15)	(0.24)	(1.13)
W^2xEngaged in non-farm activities	-0.243	-0.146	-0.093
	(1.29)	(1.17)	(1.26)
W^2xFreq. farmer mtg	0.062^{**}	-0.031	-0.027
	(2.08)	(1.53)	(1.37)
W^2xTrust in village	0.010	0.088^{***}	0.006
	(0.30)	(2.81)	(0.32)
Other Xs			
Male	-0.044	0.000	-0.009
	(1.35)	(0.01)	(0.55)
Age	0.001	-0.001	-0.001
	(0.77)	(1.44)	(1.13)
Experience	-0.002	-0.001	0.000
	(0.87)	(0.4)	(0.30)
Education	0.004	-0.002	-0.001
	(1.25)	(0.74)	(0.37)
Shrimp farming knowledge	0.001	-0.002	-0.002
	(0.27)	(0.73)	(0.94)
Belong to a shrimp cooperative	0.011	-0.006	-0.016
	(0.21)	(0.39)	(1.19)
Total pond size (ha)	0.041^{*}	0.040^{**}	-0.046^{***}
	(1.65)	(2.33)	(3.16)
Ave shrimp density	0.000	0.000	0.000
	(0.55)	(0.25)	(0.51)
# buyers farmers know	-0.004^{*}	-0.003^{***}	-0.001
	(1.84)	(2.74)	(0.68)
Engaged in non-farm activities	-0.071^{*}	0.010	-0.005
	(1.88)	(0.35)	(0.29)
Freq. farmer mtg	-0.006	0.006	-0.029^{***}
	(0.41)	(0.79)	(3.43)
Trust in village	0.053^{**}	-0.027^{**}	-0.037^{***}
	(2.00)	(2.25)	(4.14)

WxMale	0.057	-0.045	0.045
	(1.29)	(0.75)	(1.22)
WxAge	0.004***	0.003*	0.002
	(2.64)	(1.87)	(1.59)
WxExperience	-0.005	-0.005	-0.004
	(1.38)	(1.31)	(1.53)
WxEducation	0.014*	0.009**	0.011***
	(1.86)	(2.05)	(3.68)
WxShrimp farming knowledge	0.041***	0.029***	0.015***
	(5.37)	(4.19)	(3.25)
WxBelong to a shrimp cooperative	-0.042	-0.096	-0.013
	(0.33)	(0.77)	(0.27)
WxTotal pond size (ha)	-0.121**	0.098***	0.054**
	(2.31)	(2.92)	(2.35)
WxAve shrimp density	0.000	0.000***	0.000***
	(0.56)	(2.90)	(6.14)
Wx# buyers farmers know	-0.002	0.000	0.005**
	(0.32)	(0.03)	(2.11)
WxEngaged in non-farm activities	-0.044	0.026	-0.122**
	(0.57)	(0.88)	(2.48)
WxFreq. farmer mtg	-0.062**	0.014	0.042***
	(2.55)	(1.16)	(3.62)
WxTrust in village	-0.048	0.018	0.059***
	(1.60)	(0.66)	(3.58)
Constant	0.021	0.123*	0.295***
	(0.16)	(1.68)	(4.56)
Observation	603	603	603
Adj. R2	0.404	0.623	0.843
F-stat	413.88***	135709.7***	2711.4***

Note) Absolute values of cluster-robust T-statistics at commune levels in parentheses. Village FE included in all models. Column (1) is the first stage results for Column (2) in Table 4, Columns (2) is the first stage results for Column (4) in Table 4, and Column (3) is first stage results for Column (6) in Table 4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 500m radius are used.

App Table 2: First stage regression results for IVProbit Models Table 5

	Average practice		WxDisease outbreak	
	(1)	(2)	(3)	(4)
Instruments				
=1 if parents shrimp farmers	-0.039**	-0.037**	-0.007	-0.005
	(2.393)	(2.311)	(0.197)	(0.137)
W^2xSize of pond	-0.033	-0.005	0.092	-0.077
	(0.244)	(0.036)	(0.339)	(0.318)
W^2xYears used for cultivation	0.006	0.006	0.014	0.019
	(1.06)	(1.03)	(1.178)	(1.532)
W^2xAverage shrimp density	-0.000*	-0.000*	0.000*	0
	(1.784)	(1.779)	(1.663)	(1.61)
W^2xShrimp farming knowledge	0.000	0.000	-0.023**	-0.021**
	(0.114)	(0.066)	(2.185)	(2.053)
Other Xs				
Size of pond (ha)	-0.106***	-0.098**	0.074	0.052
	(2.691)	(2.489)	(0.884)	(0.677)
Years used for cultivation	-0.007***	-0.007***	-0.002	-0.001
	(3.067)	(3.142)	(0.467)	(0.215)
Average shrimp density	0.000***	0.000***	0	0
	(4.139)	(4.103)	(1.375)	(1.327)
Shrimp farming knowledge	0.026***	0.025***	-0.019**	-0.015**
	(7.565)	(7.111)	(2.509)	(2.091)
WxSize of pond	-0.044	-0.025	0.695***	0.649***
	(0.559)	(0.325)	(4.215)	(3.927)
WxYears used for cultivation	0.007*	0.007*	0.009	0.011
	(1.845)	(1.675)	(1.103)	(1.216)
WxAverage shrimp density	0.000	0.000	0.000	0.000
	(1.614)	(1.498)	(0.48)	(0.536)
WxShrimp farming knowledge	0.000	-0.001	0.000	0.005
	(0.024)	(0.190)	(0.045)	(0.583)
Constant	0.389***	0.432***	0.291***	0.296***
	(8.653)	(8.749)	(2.971)	(2.892)

Note) Absolute values of cluster-robust T-statistics at Farmer levels in parentheses. Village FE included in all models and Farmer FE and Canal FE included in Columns (2) and (4). Columns (1) and (3) are first stage results for Column (3) in Table 5 while Columns (2) and (4) are first stage results for Column (4) in Table 5. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 500m radius are used.

App Table 3: Estimated Effects of Own and Neighbors' Characteristics on Farming Practices s (Farmer level, 200m radius)

	Recording		Water		Equipment	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Own Characteristics						
=1 if male	0.000	0.037	-0.100***	-0.099***	-0.040**	-0.044**
	(0.002)	(0.544)	(3.153)	(3.150)	(2.214)	(2.455)
Age	0.002*	0.002	0.003**	0.004***	0.000	0.001
	(1.775)	(1.561)	(2.655)	(3.072)	-0.808	(0.945)
Shrimp farming experience	-0.005	-0.004	-0.001	-0.001	0.000	-0.001
	(1.334)	(1.276)	(0.685)	(0.554)	(0.346)	(0.536)
Education completed	0.011*	0.011*	0.008*	0.010**	0.005***	0.006***
	(1.753)	(1.815)	(1.89)	(2.141)	(2.792)	(3.024)
Shrimp farming knowledge	0.047***	0.048***	0.026***	0.027***	0.012***	0.013***
	(5.421)	(5.562)	(4.451)	(4.503)	(4.202)	(4.194)
=1 if belong to a shrimp cooperative	0.029	0.015	0.098**	0.095**	0.072***	0.073***
	(0.456)	(0.277)	(2.363)	(2.177)	(2.944)	(3.107)
Total pond size (ha)	-0.034	-0.048	0.017	-0.004	-0.022	-0.013
	(0.944)	(1.201)	(0.699)	(0.133)	(1.444)	(0.805)
Ave shrimp density (pcs)	0.000	0.000	0.000***	0.000***	0.000***	0.000***
	(0.435)	(0.202)	(4.403)	(4.242)	(6.256)	(6.262)
# buyers farmer knows	-0.005	-0.001	0.002	0.003	0.000	0.001
	(1.259)	(0.399)	(0.659)	(0.952)	(0.278)	(0.573)
=1 if engaged in non-farm activities	-0.004	0.029	-0.006	0.008	-0.072**	-0.075**
	(0.065)	(0.575)	(0.162)	(0.245)	(2.242)	(2.376)
Frequency of farmer meeting	-0.032	-0.029	-0.002	-0.005	0.002	0.008
	(1.612)	(1.518)	(0.129)	(0.411)	(0.323)	(0.937)
Trust in village	-0.010	-0.022	0.015	0.021	0.003	0.01
	(0.308)	(0.708)	(0.806)	(1.167)	(0.197)	(0.642)
Endogenous Peer Effects						
Practice: recording [a)]	0.163***	0.585***				
	(2.855)	(3.339)				
Practice: water check [a)]			0.113	0.636***		
			(1.279)	(2.901)		
Practice: equipment [a)]					0.114*	0.455**
					(1.728)	(2.035)
Contextual Peer Effects						
=1 if male	-0.098*	-0.088*	0.021	0.06	-0.007	-0.016
	(1.758)	(1.651)	(0.39)	(0.806)	(0.275)	(0.626)
Age	0.002	0.001	-0.003***	-0.004***	0.000	-0.001
	(0.911)	(0.715)	(2.730)	(3.958)	(0.239)	(0.900)
Shrimp farming experience	-0.001	-0.001	0.002	0.002	0.000	0.000
	(0.238)	(0.329)	(0.515)	(0.511)	(0.039)	(0.061)
Education completed	0.008	0.003	-0.002	-0.005	0.002	-0.002
	(1.612)	(0.657)	(0.473)	(1.154)	(1.116)	(0.655)
Shrimp farming knowledge	-0.012	-0.030***	-0.003	-0.014**	-0.006	-0.014**
	(1.423)	(2.823)	(0.903)	(2.221)	(1.463)	(2.202)

=1 if belong to a shrimp cooperative	-0.053	-0.014	-0.025	-0.049	-0.012	-0.023
	(0.624)	(0.225)	(0.834)	(0.992)	(0.468)	(0.760)
Total pond size (ha)	0.112	0.100	0.101*	0.055	-0.014	-0.015
	(1.477)	(1.394)	(1.915)	(0.874)	(0.561)	(0.534)
Ave shrimp density (pcs)	0.000	0.000	0.000	-0.000*	0.000	0.000
	(1.622)	(0.802)	(0.125)	(1.796)	(0.478)	(1.471)
# buyers farmer knows	-0.008*	-0.006	-0.004*	-0.006*	-0.001	-0.001
	(1.917)	(1.229)	(2.012)	(1.734)	(0.386)	(0.696)
=1 if engaged in non-farm activities	-0.173**	-0.106*	-0.093	-0.090*	-0.019	0.014
	(2.200)	(1.823)	(1.496)	(1.871)	(0.504)	(0.314)
Frequency of farmer meeting	0.005	0.022	0.012	0.01	-0.009	-0.018
	(0.284)	(1.091)	(1.010)	(0.979)	(0.886)	(1.639)
Trust in village	0.033	0.032	0.012	-0.015	0.01	-0.004
	(1.078)	(1.132)	(0.699)	(0.789)	(0.649)	(0.217)
Constant	-0.025	-0.121	0.106	0.053	0.577***	0.520***
	(0.130)	(0.624)	(1.000)	(0.524)	(8.09)	(6.608)
Observations	603	603	603	603	603	603
Adj. R2	0.173	0.091	0.198	0.082	0.227	0.174
AIC	299.147	.	-35.147	.	-662.71	.
Wald Chi2 for the model		2248.08		5477.704		837.632
F stat for endogeneity test		5.3127**		5.6207**		1.9539

Note) Absolute values of cluster-robust T-statistics at commune levels in parentheses. Village FE included in all models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. a) instrumented with the higher order peers' characteristics in IV models. Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 200m radius are used.

App Table 4: Estimated Effects of Own and Neighbors' Characteristics on Farming Practices (Farmer level, 1km radius)

	Recording		Water		Equipment	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Own Characteristics						
=1 if male	0.019	0.045	-0.084***	-0.052*	-0.035*	-0.031*
	(0.342)	(0.769)	(2.765)	(1.904)	(1.950)	(1.777)
Age	0.002*	0.002*	0.003**	0.003***	0.000	0.000
	(1.955)	(1.729)	(2.676)	(2.844)	(0.737)	(0.836)
Shrimp farming experience	-0.001	-0.001	-0.001	0.000	0.000	0.000
	(0.388)	(0.158)	(0.326)	(0.048)	(0.388)	(0.168)
Education completed	0.014**	0.012**	0.009*	0.010**	0.004**	0.004**
	(2.223)	(1.995)	(1.953)	(2.043)	(2.456)	(2.345)
Shrimp farming knowledge	0.040***	0.040***	0.025***	0.027***	0.012***	0.013***
	(4.404)	(4.452)	(4.279)	(4.414)	(4.17)	(4.607)
=1 if belong to a shrimp cooperative	0.006	-0.005	0.103**	0.108*	0.064**	0.064**
	(0.115)	(0.095)	(2.265)	(1.864)	(2.354)	(2.194)
Total pond size (ha)	-0.054	-0.067**	0.015	-0.005	-0.016	-0.005
	(1.660)	(1.983)	(0.582)	(0.199)	(1.013)	(0.281)
Ave shrimp density (pcs)	0.000	0.000	0.000***	0.000***	0.000***	0.000***
	(0.036)	(0.209)	(4.307)	(4.111)	(6.466)	(6.884)
# buyers farmer knows	-0.001	0.000	0.002	0.004	0.001	0.002
	(0.285)	(0.091)	(0.834)	(1.401)	(0.879)	(1.079)
=1 if engaged in non-farm activities	-0.01	0.013	-0.013	-0.009	-0.062*	-0.052
	(0.203)	(0.246)	(0.355)	(0.297)	(1.881)	(1.539)
Frequency of farmer meeting	-0.048**	-0.053***	-0.017	-0.017	0.029**	0.041**
	(2.472)	(2.769)	(0.903)	(1.297)	(2.454)	(2.292)
Trust in village	-0.089	-0.105**	-0.024	0.002	-0.007	0.008
	(1.621)	(2.137)	(0.889)	(0.100)	(0.397)	(0.361)
Endogenous Peer Effects						
Practice: recording [a)]	0.335***	0.730***				
	(3.671)	(4.989)				
Practice: water check [a)]			0.283**	1.151***		
			(2.546)	(7.368)		
Practice: equipment [a)]					0.310***	0.731**
					(3.355)	(2.036)
Contextual Peer Effects						
=1 if male	-0.183**	-0.115	-0.067	0.104	-0.018	-0.011
	(2.108)	(1.390)	(0.709)	(1.136)	(0.460)	(0.322)
Age	0.000	-0.001	-0.002	-0.004**	0.000	0.000
	(0.140)	(0.785)	(1.178)	(2.122)	(0.323)	(0.375)
Shrimp farming experience	-0.004	-0.003	0.000	-0.002	0.000	0.001
	(0.639)	(0.460)	(0.046)	(0.575)	(0.039)	(0.225)
Education completed	0.001	-0.007	0.003	-0.004	0.006	0.000
	(0.158)	(0.784)	(0.446)	(0.635)	(1.506)	(0.031)
Shrimp farming knowledge	-0.007	-0.032**	-0.005	-0.026***	-0.005	-0.010*
	(0.603)	(2.294)	(0.774)	(2.958)	(0.978)	(1.666)

=1 if belong to a shrimp cooperative	-0.011	0.038	-0.096	-0.135*	-0.017	-0.044
	(0.102)	(0.411)	(1.391)	(1.842)	(0.381)	(0.935)
Total pond size (ha)	0.157*	0.145**	0.104**	0.043	-0.015	-0.029
	(1.849)	(2.021)	(2.092)	(0.731)	(0.408)	(0.702)
Ave shrimp density (pcs)	-0.000*	0.000	0.000	-0.000***	0.000	0.000
	(1.706)	(0.873)	(0.871)	(2.705)	(0.693)	(1.558)
# buyers farmer knows	-0.012*	-0.006	-0.007*	-0.007*	-0.004	-0.005*
	(1.816)	(0.874)	(2.010)	(1.660)	(1.159)	(1.653)
=1 if engaged in non-farm activities	-0.158	-0.092	-0.006	0.002	-0.032	0.029
	(1.663)	(1.200)	(0.088)	(0.048)	(0.809)	(0.544)
Frequency of farmer meeting	0.023	0.044*	0.023	0.019	-0.036**	-0.048**
	(1.015)	(1.751)	(1.277)	(1.368)	(2.480)	(2.438)
Trust in village	0.103*	0.115**	0.044	-0.014	0.018	-0.004
	(1.872)	(2.276)	(1.304)	(0.487)	(0.903)	(0.153)
Constant	0.138	0.122	0.076	-0.13	0.397***	0.242*
	(0.605)	(0.614)	(0.497)	(1.063)	(4.30)	(1.691)
Observations	603	603	603	603	603	603
Adj. R2	0.173	0.091	0.198	0.082	0.227	0.174
AIC	299.147	.	-35.147	.	-662.71	.
Wald Chi2 for the model		2248.08		5477.704		837.632
F stat for endogeneity test		5.3127**		5.6207**		1.9539

Note) Absolute values of cluster-robust T-statistics at commune levels in parentheses. Village FE included in all models. * p < 0.1, ** p < 0.05, *** p < 0.01. a) instrumented with the higher order peers' characteristics in IV models. Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 1km radius are used.

App Table 5: Estimated Effects of Own and Neighbors' Characteristics on Disease Outbreak (pond level, 200m radius)

	=1 if there was a disease outbreak in the pond			
	Probit		IV Probit	
	(1)	(2)	(3)	(4)
Own Characteristics				
Size of pond (ha)	0.714**	0.740**	1.044***	0.970**
	(2.006)	(1.987)	(3.004)	(2.492)
Years used for cultivation	0.001	0.002	0.01	0.014
	(0.034)	(0.14)	(0.517)	(0.747)
Average density (pieces)	0.000	0.000	0.000	0.000
	(0.339)	(0.301)	(1.086)	(1.224)
Shrimp farming knowledge	-0.071***	-0.068**	-0.158***	-0.148***
	(2.630)	(2.493)	(3.136)	(3.278)
Average practice[a)]	-0.788**	-0.762**	2.089	2.414
	(2.382)	(2.259)	(0.93)	(1.062)
Endogenous Peer Effects (W*Y)				
=1 if disease outbreak[b)]	1.111***	1.049***	-0.287	-0.646
	(7.514)	(6.963)	(0.202)	(0.400)
Contextual Peer Effects (W*X)				
Size of pond (ha)	-0.015	-0.004	0.844	0.839
	(0.032)	(0.010)	(1.039)	(1.047)
Years used for cultivation	-0.004	0	-0.004	0.006
	(0.192)	(0.002)	(0.128)	(0.19)
Average density (pieces)	-0.000*	-0.000*	0.000	0.000
	(1.756)	(1.820)	(0.759)	(0.509)
Shrimp farming knowledge	-0.016	-0.012	-0.008	0.004
	(0.857)	(0.630)	(0.401)	(0.174)
Farmer FE	No	Yes	No	Yes
Canal FE	No	Yes	No	Yes
Marginal Effects of:				
Own average practice	-0.263**	-0.252**	0.748	0.837
Peers' disease outbreak	0.371***	0.347***	-0.103	-0.224
Observations	773	773	749	749
Pseudo R2	0.1345	0.1428		
AIC	933.879	929.137	886.05	849.304
Wald Chi2 for main model	110.73***	115.50***	47.50***	72.17***
Test of endogeneity (F stat)			1.98	2.12
(P value)			0.3717	0.3462

Note) Absolute values of cluster-robust T-statistics at Farmer levels in parentheses. Village FE included in all models. * p < 0.1, ** p < 0.05, *** p < 0.01. a) is the average of practice indexes on recording, water quality check, and equipment and it is instrumented with whether the parents were shrimp farmers or not and b) instrumented with higher order peers' characteristics in Columns (3) and (4). Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 200m radius are used.

App Table 6: Estimated Effects of Own and Neighbors' Characteristics on Disease Outbreak (pond level, 1km radius)

	=1 if there was a disease outbreak in the pond			
	Probit		IV Probit	
	(1)	(2)	(3)	(4)
Own Characteristics				
Size of pond (ha)	0.638*	0.673*	0.746*	0.792*
	(1.849)	(1.883)	(1.879)	(1.952)
Years used for cultivation	-0.006	-0.006	-0.004	-0.002
	(0.342)	(0.324)	(0.159)	(0.094)
Average density (pieces)	0.000	0.000	0.000	0.000
	(0.677)	(0.710)	(0.863)	(0.916)
Shrimp farming knowledge	-0.049*	-0.050*	-0.068	-0.073
	(1.684)	(1.698)	(1.369)	(1.451)
Average practice[a)]	-0.730**	-0.728**	0.126	0.281
	(2.212)	(2.172)	(0.066)	(0.145)
Endogenous Peer Effects (W*Y)				
=1 if disease outbreak[b)]	1.510***	1.445***	1.946**	1.839
	(7.898)	(7.379)	(1.964)	(1.48)
Contextual Peer Effects (W*X)				
Size of pond (ha)	-0.222	-0.238	-0.433	-0.373
	(0.409)	(0.444)	(0.499)	(0.424)
Years used for cultivation	0.012	0.017	0.002	0.003
	(0.497)	(0.701)	(0.066)	(0.099)
Average density (pieces)	0.000	0.000	0.000	0.000
	(0.715)	(0.644)	(0.613)	0.527)
Shrimp farming knowledge	-0.035	-0.028	-0.024	-0.022
	(0.982)	(0.763)	(0.430)	(0.433)
Farmer FE	No	Yes	No	Yes
Canal FE	No	Yes	No	Yes
Marginal Effects of:				
Own average practice	-0.238**	-0.237**	0.039	0.088
Peers' disease outbreak	0.493***	0.470***	0.604***	0.576**
Observations	773	773	749	749
Pseudo R2	0.152	0.156		
AIC	915.25	915.02	529.21	492.98
Wald Chi2 for main model	119.57***	120.38***	78.24***	85.53***
Test of endogeneity (F stat)			0.36	0.41
(P value)			0.837	0.815

Note) Absolute values of cluster-robust T-statistics at Farmer levels in parentheses. Village FE included in all models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. a) is the average of practice indexes on recording, water quality check, and equipment and it is instrumented with whether the parents were shrimp farmers or not and b) instrumented with higher order peers' characteristics in Columns (3) and (4). Row-normalized spatial weights based on inverse distance between farmer's main ponds with neighbors within 1km radius are used.