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**Online Communities of Practises as Agricultural Information Platforms: A Case Study
of Indonesian Shrimp Farmers during the COVID-19 Pandemic***

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Abstract

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Amidst the challenges of the COVID-19 pandemic, this study examines the potential of Online Communities of Practises (OCoPs) for providing agricultural extension services. Using a unique dataset of 1,574 shrimp farmers, including members of one of Indonesia's largest public OCoP Facebook groups, we found that despite the pandemic, Indonesian farmers continue to rely primarily on their neighbours for farming information, utilising OCoPs only as a complementary resource. This reliance may stem from the fragmented and codified nature of information shared by OCoP members, making it challenging to access specific and useful farming information, particularly on shrimp disease, and difficult to revalidate practices in the field. Consequently, farmers prefer to observe their neighbours' practices and replicate their farming success, given similar ecological prerequisites. To compensate for these shortcomings, it is recommended that context-specific and timely information from conventional extension services be integrated into OCoPs.

Keywords: Online communities of practises; agricultural extension service; farmer-to-farmer extension; social learning; shrimp farming

JEL Codes: D80; O33; Q1

1. Introduction

Providing relevant agricultural information to farmers enhances their technology adoption, market access and resource efficiency. Traditionally, agricultural extension agents have been responsible for the dissemination of technologies and practices to farmers (Anderson and Feder 2004). Deemed as “public goods,” governments are assumed to be the primary providers of extension services (Umali-Deininger 1996). However, traditional extension services face several challenges, including limited face-to-face interactions with farmers due to geographical barriers and local government's fiscal constraints (Fabregas, Kremer, and Schilbach 2019), generic advice that lacks technical and contextual specificity (Steinke et al. 2021), and a

shortage of qualified extension officials, thus making services less accessible to many smallholder farmers in developing countries (Cole and Sharma 2017; Fabregas, Kremer, and Schilbach 2019). According to USAID (2021), the ratio of government extension agents to farmers in most countries is in excess of 1:5,000, which is significantly lower than the World Bank's recommended ratio of 1:500. This suggests that limited availability of extension agents might possibly hinder the widespread adoption of new agricultural technologies and practices. During the pandemic, the challenges faced by extension agents in providing face-to-face services to farmers were particularly pronounced (Alvi et al. 2021). This necessitates innovative approaches to improve the current agricultural extension delivery, both in terms of complementing and substituting the conventional extension services.

Since the late 1990s, farmer-to-farmer extension (F2FE) has been regarded as an alternative approach to public agricultural extension services (Takahashi, Muraoka, and Otsuka 2020). Many smallholder farmers in developing countries heavily rely on their peers for agricultural information (Bandiera and Rasul 2006; Conley and Udry 2010; Liverpool-Tasie and Winter-Nelson 2012; Magnan et al. 2015). F2FE has been recognised as an effective means of disseminating new practises to a larger number of farmers through peer networks, providing timely, accessible, and context-specific agricultural information (Fisher et al. 2018). There were also efforts to combine the strength of social learning under F2FE with public extension services, such as the training and visit (T&V) approach that relied on contact or model farmers, and farmer field schools (FFSs) (Waddington et al. 2014). At the same time, the rapid proliferation of mobile phones in developing countries since the 2000s has enabled farmers to communicate and share information with their peers, thus overcoming physical barriers (Aker 2011). The number of studies investigating the effects of mobile phones on agricultural markets has grown, with a particular emphasis on how mobile phones contribute to the reduction of information asymmetry (Aker and Mbiti 2010; Nakasone, Torero, and Minten 2014). The

earlier studies by Jensen (2007) and Aker and Mbiti (2010) showed that the introduction of mobile phones narrows price dispersions across the markets in India and Niger, respectively. Even during the pandemic, the utilisation of these information and communications technologies (ICT) is likely to be effective in getting the information that farmers need.

Combining the benefits of F2FE and digital technologies, online communities of practises (OCoPs) have emerged as platforms that facilitate information sharing among peers, offering several distinct advantages compared to public extension services and F2FE. First, once a user shares information with their online community, other members can access it at no additional cost (Rayna 2008). Second, these platforms allow for simultaneous access by multiple users, which encourages the provision of information without rivalry (Lee and Suzuki 2020). Third, public groups of OCoPs have a non-exclusive feature that allows anyone interested to become a member, unlike closed groups that require specific qualifications or membership fees. Extensive research has explored the benefits of OCoPs in a range of professions, including health professionals, researchers, police officers, entrepreneurs, legal professionals, educators, and librarians, and has demonstrated their value to novice workers seeking guidance from experienced peers (Carroll and Mallon 2021; Hafeez et al. 2019; Hajisoteriou, Karousiou, and Angelides 2018; Hurtubise et al. 2019). Given these special features, OCoPs have the potential to serve as a low-cost platform for agricultural producers to exchange specialised information whenever and wherever they need it, especially for those with limited access to public extension services or F2FE. Nevertheless, there is still a lack of knowledge about the contribution of OCoPs as a platform to complement or substitute traditional methods of disseminating information to farmers. Concerns have been raised regarding the dependence of F2FE on family or neighbourhood networks. This reliance can pose challenges for farmers with limited connections to their peers, as they may struggle to access the valuable information and resources shared within these networks. In addition, farmers may be reluctant to share

information or practises that require a significant amount of time to transmit unless they have strong connections, which can further exacerbate the knowledge gap among farmers (Takahashi, Muraoka, and Otsuka 2020). It remains unclear how farmers perceive various information channels and whether they distinguish between them when obtaining agricultural information.

To address these gaps, this study employs farm-level data, collected through household surveys in 2021 during the COVID-19 pandemic, to examine whether OCoPs developed and managed by farmers can supplement or, to some extent, replace public agricultural extension services and F2FE. Thus, we empirically investigated the association between the use of conventional extension services and three outcomes related to OCoPs, namely: (1) OCoP usage; (2) selection of OCoPs as the most reliable information source; and (3) information sharing and enquiry within OCoPs. To identify these associations, we focused on one of the largest Indonesian OCoPs related to shrimp production on Facebook—the Indonesian Vannamei Shrimp Community or *Komunitas Udang Vaname Indonesia* (henceforth, KUVI).

In this study, we identified key patterns among KUVI members. Those who relied on neighbours or extension workers tended to use KUVI more frequently, but they didn't consider it their primary information source. Interestingly, the COVID-19 pandemic didn't significantly increase the use of OCoPs. Additionally, farmers who actively shared information in OCoPs were less likely to rely on face-to-face interactions (F2FE) for information. These findings indicate that Indonesian farmers still heavily depend on neighbours for information, using KUVI as a secondary resource. This reliance on neighbours persists due to the fragmented nature of information within KUVI. For instance, only 6% of members sought information on critical topics like shrimp diseases within the platform. To address these limitations of OCoPs,

we propose that more context-specific, precise, and timely information from conventional extension services should flow into OCoP platforms.

Our study makes two important contributions to the literature on OCoPs and their potential to support agricultural development in developing countries. First, OCoPs have been studied primarily in work environments in developed societies and there has been limited research on their potential in rural farming community settings. Our study focuses on OCoP application in rural farming communities where they have received less attention. This contributes to a deeper understanding of the potential of OCoPs to support information and knowledge acquisition in areas where access to formal institutionalised learning and extension services coverage is limited. Second, our study offers a novel approach to examining the characteristics of information transmitted via virtual means in F2FE. The use of ICT, Facebook groups in the agricultural extension being the most notable, is primarily driven by officials or used as an external intervention. In contrast, our study examines the world's largest shrimp aquaculture OCoP which is established and managed by farmers. As the Internet's reach extends to remote areas, barriers to joining Facebook groups have significantly decreased, making them an inclusive platform for users irrespective of locations. This is especially important in sparsely populated areas where finding peers is a challenge (Townsend et al. 2013). In addition, these groups become invaluable during periods of restricted human mobility due to factors such as epidemics or disasters. As this phenomenon is widespread, occurring not only in agriculture in developing countries but also in various industrial sectors worldwide, our research provides valuable insights for policymakers and practitioners interested in effectively utilizing ICT for industrial and agricultural development.

2. Data

In this study, we collected data through telephone and face-to-face surveys of 1,574 shrimp farmers, comprising 243 KUVI members and 1,331 non-members (see Appendix 1). Our survey solicited information on respondents' socio-economic and farm characteristics, as well as their information acquisition behaviour. We chose to focus on shrimp farmers because they are sensitive to timely and precise information regarding ways to prevent shrimp diseases and are more proactive in seeking out sources of information (Lee, Suzuki, and Nam 2019). Accordingly, shrimp farmers worldwide have voluntarily formed OCoPs and actively share information about shrimp cultivation (Lee and Suzuki 2020). Among the OCoPs created by shrimp farmers, to the best of our knowledge, KUVI, created on September 19, 2018, is currently the world's largest shrimp aquaculture OCoP with approximately 120,100 members (as of August 2024). The group's membership list is publicly accessible, allowing anyone to view it. Upon reviewing the list, we observed that it encompasses not only shrimp farmers but also sellers, traders, researchers, and other stakeholders associated with shrimp farming. Additionally, we noted the participation of multiple individuals from the same household within the group. Although the specific count of members excluding these individuals remains elusive, it is reasonable to surmise that the total number would experience a substantial reduction if the group was confined solely to household heads actively engaged in shrimp farming activities.

As shown in Appendix 2, the data from January to December 2020 were collected using the following steps. First, we scraped the KUVI members list with a self-made web crawler and sent invitations to 24,129 KUVI members who signed up in 2019 or earlier, using Facebook Messenger. Out of these members, 230 shrimp farmers (0.95%) agreed to a telephone interview, with an average age of 33.3 years. This raised concerns about potential bias in the

sample selection, which could skew it towards younger age groups, and potentially lead to an over-representation of younger respondents. To examine the actual age of KUVI users, we initially attempted to estimate the average age using the information available on their Facebook profiles. However, due to insufficient data—since most members did not disclose their age—we employed a deep learning-based convolutional neural network (CNN) model (see Appendix 3 for the Python code). This model, trained on approximately 23,000 photos from Kaggle.com, was used to analyse members' photos and accurately predict their average age. We then applied sampling weights to adjust the age distribution of respondents to more accurately reflect the average age of the entire KUVI population. Based on this analysis, we found that the estimated average age of the broader KUVI member population is 39.63 years, making our respondents' average age 6.6 years younger than the estimated average for the total KUVI population.

In an effort to develop the regional economy through the fishery sectors, the government established the *Minapolitan* area under Minister of Maritime Affairs and Fisheries Regulation No 38 of 2014 (MMF, 2014). Following this, East Java designated Gresik and Lamongan as centers for vannamei shrimp development (Lestari et al., 2019). Therefore, to complement the small sample obtained from the KUVI Facebook group, we conducted face-to-face interviews with 1,344 shrimp farmers in East Java, Indonesia. The farmers were recruited from 89 villages in Lamongan, home to approximately 27,788 farmers (District of Lamongan, 2021), and 19 villages in Gresik, with around 8,282 farmers (East Java Province, 2021). Due to the COVID-19 constraints, survey sites were selected based on the 2014 policy, accessibility, and convenience. The survey results will be used to address the selection bias from the low response rate for the telephone survey. Because of the high concentration of respondents in East Java for the face-to-face interviews and the smaller, nationally distributed sample for the telephone

survey, we analyse the full sample and the subsample (excluding the face-to-face data) separately to better represent these distinct sample populations.

Using data from 243 KUVI members, we visualise their residential locations in Figure 1. As shown in the figure, most KUVI members reside in Java, followed by Sumatra, Sulawesi, and Kalimantan, with relatively few members residing in the Maluku Islands and Western New Guinea. Although the distribution of the KUVI members in Figure 1 may be biased due to the large numbers of farmers surveyed face-to-face in East Java who may also be KUVI members, the results are consistent with FAO statistics on the distribution of shrimp farmers in Indonesia (FAO 2022).

Figure 2 illustrates the frequency of access, information sharing, and inquiries by KUVI members, distinguishing between two groups: extensive and intensive shrimp-farming groups. Extensive shrimp farmers⁶ cultivate shrimp in a low-density and relatively natural environment, which requires less investment and inputs. Due to the low-density environment, the risk of disease outbreak is lower in extensive farming compared to intensive shrimp farming methods such as semi-, super-, and intensive shrimp farming (Rubel et al. 2019). Note that in this study, the term “intensive shrimp farming” includes semi-intensive and super-intensive methods for ease of comparison with “extensive shrimp farming.” Considering the characteristics of shrimp-farming methods, the extensive and intensive shrimp-farming groups have different demands for timely information. Therefore, we divided the study sample into these two groups. However, Figure 2 shows that contrary to our expectations, in 2020, extensive shrimp farmers

⁶ Shrimp stocking densities vary: extensive farms (1-3 PL/m²), semi-intensive farms (10-30 PL/m²), intensive farms (0-300 PL/m²), and super-intensive farms (300-750 PL/m²).

accessed KUVI and exchanged information with other KUVI members as often as farmers in the intensive shrimp-farming group did. This may be because the extensive shrimp farmers who participated in KUVI also planned to convert to intensive shrimp farming. Overall, approximately 75% of the KUVI members in the extensive group accessed the group at least once a week, but only 33% shared information, and 40% made inquiries.

Figure 3 shows the types of information shared and inquired about by the KUVI members. Although the eight administrators of KUVI allow anyone to view posts in the group and become a member without their approval, they pre-censor all posts and only allow posts that follow the group's rules: 1. Be kind and courteous; 2. No hate speech or bullying; and 3. No advertising or spam. As a result, advertisements and political posts are rarely seen in the group. As depicted in Figure 3, extensive shrimp farmers primarily share information about shrimp price, input use, shrimp cultivation technology, and shrimp disease, in that order. In contrast, intensive farmers most frequently share information on input use, accounting for 40.48% of their posts. This is because intensive shrimp farming generally requires a large variety and quantity of inputs, whereas extensive shrimp farmers tend to use fewer inputs (Rubel et al. 2019). Despite the critical importance of disease prevention for optimising profits and ensuring sustainability, topics of shrimp disease generate the lowest number of posts for both groups. Firstly, posts about shrimp farming techniques and input use often incorporate information about shrimp treatments or disease prevention methods. Secondly, effective disease prevention necessitates a combination of robust scientific evidence and consideration of local conditions, such as weather patterns and precipitation. However, the group's information exchange appears to be fragmented and predominantly lacks specificity, which might lead farmers to seek alternative primary sources for comprehensive and targeted information on shrimp diseases.

Table 1 outlines the respondents' socioeconomic characteristics. On average, the household heads were 47.3 years old; 96% of the respondents were male, 94% were Javanese, 100% were Muslim, and the average years of education was 10.2 years. Columns (2) and (3) show that KUVI members were on average 16.5 years younger than non-members, had 0.39 fewer family members, and were less likely to be Javanese, Muslim, or married. Conversely, KUVI members had 2.7 more years of education than non-members, and a higher percentage of KUVI members were literate and owned smartphones. Although all these differences are statistically significant, when we exclude the extensive shrimp farmers from the dataset for the reasons mentioned above, only the age difference remains statistically significant, with KUVI members being 8.7 years younger than the non-members. In other words, farmers using intensive farming methods do not differ significantly based on their KUVI membership status. Furthermore, the table highlights the respondents' shrimp farm characteristics. Column (3) shows that 99% of non-KUVI members conduct extensive farming. KUVI members, however, employ a wider variety of methods with 53% engaged in extensive farming, 24% in semi-intensive, 23% in intensive, and 4% in super-intensive methods. Columns (2) and (3) indicate that the percentage of extensive shrimp farmers among the KUVI members is 46% lower than that among non-members, and KUVI members have seven years fewer shrimp farming experience, suggesting that relatively newer farmers are more likely to join KUVI. It is also evident that KUVI members incur higher production costs, have greater sales volume, and achieve higher sales revenues than non-KUVI members, indicating they engage in significantly different types of shrimp farming. However, when we exclude farmers engaged in extensive farming (Columns (4), (5), and (4)-(5)), the differences between KUVI members and non-KUVI members diminish, with the share of semi-intensive farming, years of shrimp farming, and other costs being the only variables that remain statistically significant.

Tables 2 shows the types of information sources on shrimp cultivation and the correlation between these sources, respectively. As shown in Table 2, 80% of respondents reported obtaining information from farmers living in the same village, 20% from family members, 9% from extension officers, and 5% from KUVI. When excluding extensive farms, the differences in agricultural information sources between KUVI members and non-members become minimal. The correlation matrix in Appendix 4 denotes that the correlation between using KUVI and acquiring information from other sources is less than 0.45, suggesting weak correlation. Notably, the correlation between using KUVI and obtaining information from farmers living in the same village is negative in the total sample (-0.08), but positive when excluding extensive farms (0.03) or non-KUVI members (0.12). Conversely, the correlation between using KUVI and obtaining information from family members is positive in the total sample (0.06), but negative in the subsample excluding non-KUVI members (-0.02).

Table 3 depicts farmers' responses regarding their most trusted information sources, reflecting the same order as in Table 2. This implies that most shrimp farmers in Indonesia tend to rely more on informal sources, such as family members or neighbouring farmers, rather than formal sources like extension officers. Even among KUVI members, only 9.9% of the full sample and 11.3% for the subsample excluding extensive farms selected KUVI as the most reliable source, ranking it 4th among all agricultural information sources in both sample. This indicates that KUVI is less trusted and less popular among Indonesian shrimp farmers compared to other sources, despite being the largest shrimp farming OCoP in Indonesia in 2020.

The low percentage of KUVI members choosing KUVI as the most reliable information source may be related to the quality of information shared through the platform. To explore this, we asked KUVI members about their satisfaction and dissatisfaction with their KUVI experience, as shown in Table 4. The percentages of KUVI members satisfied with information related to inputs, prices, and diseases were 71%, 59%, and 77%, respectively. Among them, the percentage of extensive shrimp farmers satisfied with price-related information was 13% higher than that of farmers in the intensive shrimp-farming group, a difference statistically significant at the 5% level. Regarding dissatisfaction, 13% of respondents cited inaccurate information, and 15% believed the information was not suitable for their region. The high percentage of members selecting “none” to the dissatisfaction question (72%) may reflect the fact that most KUVI members belong to the community with low expectations. Additionally, the percentage of intensive shrimp farmers who found the information obtained from KUVI inaccurate for their region was 13% higher than that of extensive shrimp farmers, which is statistically significant at the 5% level. This suggests that intensive shrimp farmers are more sensitive to the quality of information than extensive shrimp farmers. It is also notable that a significant number of farmers indicated that the information obtained from KUVI is not suitable for their region.”

3. Empirical Strategies

This study explores the association between farmers' use of public extension services or F2FE and their use of OCoPs. To achieve this, we used the dataset mentioned in Section 2 and empirically addressed the following research questions (RQs): (1) How does the utilisation of conventional extension services relate to the use of OCoPs? (2) Is there a link between the utilisation of conventional extension services and farmers' preference for selecting OCoPs as their primary and reliable information source? Furthermore, our study aims to determine

potential information spillovers from these services to KUVI. Subsequently, we addressed the following RQ: (3) Do farmers who utilise F2FE or public extension services actively contribute information to KUVI?

Since the study participants included KUVI members who did not use KUVI in 2020, we distinguished between KUVI members and KUVI users and created separate variables for each group. As shown in Appendix 2, we asked all respondents if they used KUVI in 2020 to create a dummy variable for KUVI users, identifying 65 KUVI members and eight non-KUVI members who used the platform.

We employed the linear probability model, logistic regression, and ordered logistic regression to answer the research questions mentioned above. The regression was performed using the following equation:

$$Y_{ijk} = \alpha + \beta X'_{ijk} + \gamma F2FE'_{ijk} + \delta EW_{ijk} + Mobil_{jk} + \eta_k + u_{ijk} \quad (1)$$

Where the subscript i denotes an individual, j denotes a province, and k denotes a geographical unit. Y is a binary variable equal to 1 if the respondent is using KUVI or answers that they trust KUVI the most among the sources of information, and 0 otherwise, in the analyses of RQ (1) and (2). In the analysis of RQ (3), Y represents a categorical variable indicating how often the respondent shares information or enquiries and is equal to 0 for never, 1 for more than once a year but less than once a month, 2 for more than once a month but less than once a week, and 3 for more than once a week. X' accounts for characteristics of the main farmer⁶, household, and the shrimp farm. To address potential selection bias related to respondent age, we applied an age-weighting based on the population's average age of 39.63, as detailed in Section 2.

⁶ In this study, a household member who makes decisions on shrimp farming and sales is defined as the main farmer.

F2FE' refers to the sources of information a farmer uses for shrimp farming, including neighbouring farmers and family members. The variable could be endogenous due to its possible correlation with unobservable variables, such as the respondent's abilities or willingness to work hard in 2020, which are in error terms. The binary variable *EW* is equal to 1 if the respondent receives information on shrimp farming from an extension worker, and 0 otherwise. Due to the COVID-19, Indonesians spent more time at home and avoided going out in 2020 (Pramana et al. 2021). Consequently, farmers had less face-to-face contact with people outside their family members, potentially making it more difficult to obtain information from extension officers or neighbouring farmers (see Appendix 5). To capture the effect of COVID-19 restrictions, we added a variable, *Mobil*, indicating the change in the number of hours the farmers in each province *j* spent at home in 2020 compared to pre-pandemic times.⁷ This variable was constructed using Google's COVID-19 Community Mobility Reports. η captures the unobserved heterogeneity across regions, and u is an error term.

Regarding the results related to RQ (1), a positive coefficient γ (δ) suggests a complementary relationship between *F2FE* (public extension services) and *KUVI*. This indicates that farmers utilise both sources of information to enhance productivity and/or profits, although the primary source of information remains unclear. Conversely, if the associations are negative, it suggests that *KUVI* may be substituting for *F2FE* (public extension services), implying that users may shift from those services to *KUVI*, or that individuals without access to extension services may rely on *KUVI* instead. In relation to RQ (2), a positive association between the use of *F2FE* or public extension services and choosing *KUVI* as the most reliable source of agricultural information indicates that farmers may consider *KUVI* as their primary information source. Conversely, a negative value indicates that users of *F2FE* or public

⁷ The baseline day is the median value from the five-week period Jan 3–Feb 6, 2020.

extension services do not consider KUVI the most reliable source. This implies that KUVI's information is not superior enough to fully substitute F2FE or public extension services. For RQ (3), a positive coefficient γ (δ) suggests an active transfer of information between KUVI and F2FE or public extension services, while a negative coefficient γ (δ) indicates a less active transfer of information between these services and KUVI.

To address the binary endogenous regressor $F2FE'$, we also employed a two-stage least squares (2SLS) method. The first-stage regression can be expressed as follows:

$$F2FE'_{ijk} = \alpha + \beta X'_{ijk} + \theta IV'_{ijk} + Mobil_{jk} + \eta_k + u_{ijk}, \quad (2)$$

where IV' represents instrumental variables, which include dummy variables that take the value of 1 if: (1) the respondent initially learnt about shrimp farming from their family; (2) the respondent initially learnt about shrimp farming from their neighbouring farmers; or (3) the respondent participated in a collective activity using the same canal as the respondent in 2020. IV' is deemed valid since it is considered to be correlated with the endogenous variable $Corr(IV', F2FE') \neq 0$ and meets the condition of being uncorrelated with the unobserved variables $Corr(IV', u) = 0$.

To further address endogeneity concerns, we emphasise that our analysis primarily identifies associations of the variables rather than asserting causality between them, as establishing strict causal relationships with IVs in this context can be challenging. We also acknowledge that farmers' choice of information source (which is Y), may influence their choice of F2FE, but we argue that this influence is mediated through their reliance on F2FE for information rather than directly affecting the outcome variables Y .

In Appendix 6, the first stage regression results confirm our expectation that the first IV positively affects F2FE through family members, while the second and third IVs positively affect F2FE through neighbours. The F-tests of excluded instruments, with p-values of 0.00 across all models, indicate joint significance, supporting the relevance of our IVs. However, some Sanderson and Windmeijer (SW) F-statistics, such as 6.78 in the Appendix, fall below the conventional threshold of 10, indicating that the instruments may not be sufficiently strong. The linear combination two-stage least square (LC 2SLS) method, which is used to compute robust 95% confidence intervals, further highlights this potential weakness and emphasises the need for caution in interpreting the results.

4. Results

This study uses the data mentioned in Section 2 and empirically investigates whether OCoPs can complement or serve as substitute for conventional agricultural extension services. To improve estimation precision, we cluster standard errors at the village level and include dummy variables for regions and shrimp-farming methods. As mentioned in Section 3, we employed 2SLS in Tables 5–8; however, the results of the Hausman test for endogeneity indicate that all models using the instrumental variables in these tables fail to reject the null hypothesis that the regressors are exogenous. Accordingly, the variables for information sources are unlikely to be endogenous, suggesting that ordinary least squares, ordered logit, or marginal effects from the logit model may have more explanatory power. Tables 5 and 6 employ integrated information on shrimp cultivation as one of the dependent variables. To further understand the relationship between the use of conventional information sources and the choice of OCoPs as the most reliable source, the models in Appendix 7 divide the variables by information types, such as input usage, shrimp farm prices, and treatment of shrimp diseases.

Columns (1)–(6) of Table 5 show that the variables representing whether farmers obtain information from family, neighbouring farmers, or extension officers are not statistically significantly correlated with the use of KUVI or OCoPs. Thus, no evidence of substitution or complementarity is found when all sample farmers are considered. Contrary to general expectations, the correlation between the use of KUVI and age is not statistically significant in any columns. Additionally, we find no association between increased time spent at home due to the COVID-19 pandemic and increased use of the OCoPs.

Regarding the reliability of KUVI or any OCoP as presented in Columns (7), (8), and (10)–(11), our findings indicate that those who obtain information from neighbouring farmers or family members are less likely to choose KUVI or any OCoP as their most reliable source of information. Overall, the results for these two dependent variables are almost identical, providing no evidence suggesting that KUVI information is superior enough to substitute information from conventional routes.

In addition to examining the determinants of KUVI and any OCoP use for the full sample, this study also attempts to identify these determinants by excluding data from face-to-face interviews, as shown in Table 6. This adjustment is made for the reasons discussed in Section 2. The result showing no association between increased time spent at home due to the COVID-19 pandemic and the use of OCoPs remains consistent. Columns (1) and (2) show that farmers who obtain information from other farmers residing in the same village are 12–13% more likely to use KUVI than those who do not. Column (3) shows that farmers who get information from extension officers are 16% more likely to use KUVI than those who do not. Therefore, among

KUVI members, we found a complementary relationship between KUVI use and the use of conventional extension sources.

Moreover, Columns (7)–(12) indicate that farmers who obtain information from neighbouring farmers or family members are less likely to choose KUVI or any OCoP as their most reliable information source compared to those who do not. These results are consistent with those from the full sample, confirming that KUVI information is not sufficiently superior to replace other conventional information sources. Furthermore, when combined with the earlier discussion on disease-related information, the negative correlation suggests that Indonesian shrimp farmers use KUVI and any OCoP as complements to conventional information sources, rather than as primary sources.

To explore RQ (1) from a different angle, we examine the correlations between the use of OCoPs and F2FEs, reclassified into three categories in Table 7: (1) “OCoP users”, or farmers who used KUVI or any OCoP in 2020 (Columns (1), (2), (7), and (8)); (2) “F2FE users”, or farmers who obtained information from family members or neighbouring farmers (Columns (3), (4), (9), and (10)); and (3) “OCoPs and F2FEs users”, or farmers who used both OCoPs and F2FEs (Columns (5), (6), (11), and (12)). For the full-sample model, we observe that smaller shrimp farm sizes are associated with a higher probability of using OCoPs or both OCoPs and F2FEs together. Conversely, larger shrimp farm sizes correlate with a higher probability of using F2FEs. These relationships are statistically significant at the 1%, 5%, and 10% levels, except for Column (5). A similar trend is observed in the models using the subsample (excluding data from face-to-face interviews), although only the result in Column (9) is statistically significant at the 10% level. This relationship between pond size and the use of OCoPs and F2FEs may be attributed to intensive farmers, who typically operate smaller

pond sizes and require more sophisticated information on shrimp farming. In both the full sample and subsample models, the disease variable indicates that as the number of shrimp disease outbreaks on a farm increases, the farmers' probability of using OCoPs decreases by 1–4%, which is statistically significant at the 5% or 10% level. In contrast, the shrimp disease and F2FEs variables are positively correlated, though only statistically significant at the 5% level in Column (3). Models with the F2FE variable as the dependent variable show that the probability of extension service users relying solely on F2FEs decreases by 19–45%, depending on the full sample and subsample. Additionally, Columns (6) and (12) indicate that the probability of extension service users utilizing both OCoP and F2FEs together increases by 8–14%.

Finally, to examine the characteristics of those who frequently share information and post inquiries in KUVI (RQ (3)), we exclude non-KUVI members from the models in Table 8, as we did in Table 6. The dependent variables are categorical, as mentioned in Section 3, with values of 0 for never, 1 for more than once a year but less than once a month, 2 for more than once a month but less than once a week, and 3 for more than once a week. We then employ ordered logit models, as shown in Columns (1) and (6). The results of the Brant test in Table 8 confirm that the parallel regression assumption has not been violated. Additionally, although IV-2SLS is employed, the results of the Hausman test for endogeneity show that all models with instrumental variables in Table 8 fail to reject the null hypothesis that the regressors are exogenous.

The dependent variables and sources of information, such as neighbouring farmers, family members, and extension officers, show statistically significant and negative correlations. These results suggest that KUVI members who obtain information from family members, farmers in

the same village, or extension officers are less likely to share or inquire about shrimp farming with other KUVI members compared to those who do not rely on these sources. In other words, they are more likely to merely view the information posted on KUVI. This finding further supports our interpretation of the previous results that KUVI does not substitute information from traditional sources but rather provides complementary information.

5. Conclusion and Discussion

This study used a unique dataset to test whether OCoPs can substitute conventional extension services, such as government extension and F2FE services. To address potential sampling bias due to the low response rate among KUVI members, we applied age-based weighting and supplemented our data collection with face-to-face interviews in selected regions. We found that Indonesian shrimp farmers still primarily relied on information from family and neighbours for accurate and timely information, particularly about shrimp disease, rather than on KUVI, even during the COVID-19 pandemic. This may be attributed to several factors.

First, while KUVI members express satisfaction with information on inputs and shrimp diseases shared on the platform, they report that KUVI becomes less reliable when more specific information is needed. This shortcoming is evident when KUVI information proves inadequate in preventing disease outbreaks. This discrepancy arises because the information shared on the platform is generic, and when members seek more precise and detailed insights, they often encounter fragmented explanation. As the information in KUVI is codified and typically provided by more experienced peers, it is not easily generalized or fully understood by less technical, more traditional farmers, even if they faced similar problems. Consequently, the challenge lies in locating accurate and timely information that aligns with their specific

farming practises. Our findings align with several studies that highlight OCoPs' struggles with fragmented information and concerns about its reliability (e.g., Hafeez et al., 2019; Hajisoteriou et al., 2018; Hurtubise et al., 2019; Lee & Suzuki, 2020; Rayna, 2008).

Secondly, farmers tend to trust information from local networks, such as neighbors or family members, more than information from broader online platforms like KUVI. This is because KUVI includes members from diverse socioeconomic backgrounds with varying levels of expertise and experience in shrimp farming. This diversity leads to different motives for joining, sharing, or inquiring within the group, resulting in a wide range of information and activities related to shrimp farming, which makes it difficult to easily find relevant information and revalidate practices in the field. Because of this, farmers generally prefer to observe their neighbors' practices visually and wait to see their success in the cultivation. Once a neighbour achieves success, others are more likely to imitate, as the similar natural and ecological conditions in the area provide a better opportunity for similar results. This behaviour aligns with social learning processes, where farmers observe others' successes in similar environments and adjust their actions accordingly (Foster and Rosenzweig 1995; Bandiera and Rasul 2006; Beaman et al. 2021; Conley and Udry 2010).

The study further found that during the pandemic, KUVI members who obtained information from conventional extension services, such as family members or fellow farmers in their village, were less likely to share information or inquire about shrimp farming with other KUVI members compared to those who did not. This indicates that these farmers primarily browsed KUVI rather than actively participating in information exchange. This reluctance may stem from the perception that certain farming information or techniques are private goods, meant to be shared only with trusted individuals like family members and neighbours who are more likely to reciprocate support in the future (Ostrom 2010). Moreover, the lack of personal

connection and familiarity with other KUVI members might contribute to distrust in the platform, making farmers hesitant to share farm information they deem valuable (Wiseman et al. 2019).

Lastly, technical barriers may also play a significant role. Slow internet speeds, particularly in rural areas, present a major challenge for farmers to use OCoPs. Indonesia's mobile internet download speed is well below the global average, ranking 98th globally at 23.98 Mbps, which is half the global average of 47.82 Mbps (Ookla 2023). This issue is even more pronounced in rural areas (Townsend et al. 2013), where our observations were concentrated. As a result, users may struggle to view and upload data to OCoP platforms using mobile phones due to persistent connectivity challenges.

Our study concludes that while OCoPs may not fully match the effectiveness of F2FEs in providing tailored information to local farmers, they show potential in narrowing price dispersions across markets. Farmers in our study utilise OCoPs to stay updated on market trends, including market prices and input information. This type of information tends to be straightforward and more generalizable compared to disease treatment, which is often more specific. This finding corroborates previous studies on the impact of mobile phones on farming information dissemination (Aker and Mbiti 2010; Jensen 2007). While this study focuses on shrimp farming, challenges in accessing market information and technical support are common among smallholders across various agricultural sectors (Alvi et al. 2021; Cole and Sharma 2017; Fabregas, Kremer, and Schilbach 2019; Lee, Suzuki, and Nam 2019; Steinke et al. 2021).

Our results highlight the interplay between online and conventional information sources in agriculture, suggesting ways to leverage OCoPs to enhance market efficiencies for smallholders. Potential approaches include creating knowledge aggregation binders and involving extension agents or experts to review and verify the shared information, as noted by

Lee and Suzuki (2020). Additionally, the problem of slow internet speeds, common in many developing countries, underlines the urgent need for infrastructure development to improve mobile and fixed broadband speeds, which is essential for realizing the full potential of OCoP platforms in low- and middle-income countries.

Given that these surveys were not conducted nationally, some selection bias may remain, and these findings should be interpreted with caution when making broader generalisations. Future research should use panel data to address these bias concerns, to provide more robust and a nuanced understanding of OCoPs' impact on farmers' bargaining power, market participation and technology adoption during the pandemic, as well as their wider implications.

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Table 1. Summary Statistics

		Total	Full sample			Subsample excluding extensive farms		
			KUVI member	Non-KUVI mem.		KUVI member	Non-KUVI mem.	
		(1)	(2)	(3)	(2)-(3)	(4)	(5)	(4)-(5)
<i>Socioeconomic characteristics of the respondents</i>								
Age	Years	47.28	33.3	49.83	-16.53***	33.02	41.71	-8.69***
		(12.61)	(9.33)	(11.40)	[0.77]	(9.88)	(11.73)	[2.63]

Gender	1=Male	0.96 (0.19)	0.97 (0.71)	0.96 (0.19)	0.01 [0.01]	0.97 (0.18)	1.00 (0.00)	-0.03 [0.04]
Ethnicity	1=Javanese	0.94 (0.24)	0.63 (0.48)	0.99 (0.08)	-0.36*** [0.01]	0.63 (0.48)	0.82 (0.39)	-0.19 [0.12]
Religion	1=Muslim	1.00 (0.07)	0.98 (0.16)	1.00 (0.03)	-0.02*** [0.00]	0.96 (0.20)	1.00 (0.00)	-0.04 [0.05]
Schooling	Years	10.21 (3.59)	12.5 (2.63)	9.79 (3.58)	2.71*** [0.24]	12.42 (2.88)	12.76 (2.49)	-0.35 [0.74]
Literacy	1=Proficient	0.96 (0.20)	0.99 (0.11)	0.95 (0.21)	0.03** [0.01]	0.99 (0.09)	1.00 (0.00)	-0.01 [0.02]
Marriage	1=Married	0.85 (0.36)	0.62 (0.49)	0.89 (0.31)	-0.28*** [0.02]	0.57 (0.50)	0.76 (0.44)	-0.20 [0.13]
Household size	Number	3.55 (1.55)	3.22 (1.71)	3.61 (1.51)	-0.39*** [0.11]	3.12 (1.65)	2.65 (1.06)	0.47 [0.41]
Mobile phone	1=I have	0.82 (0.38)	0.98 (0.16)	0.79 (0.10)	0.18*** [0.03]	0.97 (0.18)	0.94 (0.24)	0.02 [0.05]
Smart phone	1=I have	0.73 (0.44)	0.95 (0.22)	0.69 (0.46)	0.26*** [0.03]	0.95 (0.22)	0.94 (0.24)	0.01 [0.06]
Annual household spending	Million IDR	32.04 (21.45)	49.15 (34.65)	28.92 (16.20)	20.23*** [1.41]	39.03 (18.52)	39.03 (18.52)	7.52 [7.34]
Characteristics of the respondents' shrimp farms								
Extensive	1=Yes	0.92 (0.28)	0.53 (0.50)	0.99 (0.11)	-0.46*** [0.02]	-	-	-
Semi-intensive	1=Yes	0.05 (0.21)	0.24 (0.43)	0.01 (0.10)	0.23*** [0.01]	0.46 (0.50)	0.71 (0.47)	-0.25* [0.13]
Intensive	1=Yes	0.04 (0.19)	0.23 (0.42)	0.00 (0.06)	0.23*** [0.01]	0.46 (0.50)	0.29 (0.47)	0.17 [0.13]
Super-intensive	1=Yes	0.01 (0.08)	0.04 (0.19)	0.00 (0.00)	0.04*** [0.01]	0.08 (0.27)	0.00 (0.00)	0.08 [0.07]
Years of shrimp farming	Years	14.54 (8.23)	8.00 (7.32)	15.73 (7.82)	-7.73*** [0.54]	6.80 (6.65)	13 (11.91)	-6.20*** [1.95]
Total shrimp pond size	ha	1.28 (2.61)	2.16 (5.60)	1.11 (1.48)	1.05*** [0.18]	2.02 (7.44)	1.05 (0.79)	0.97 [1.81]
Annual seed cost	Million IDR	10.66 (40.51)	42.26 (92.14)	4.89 (13.42)	37.37*** [2.66]	53.43 (93.17)	40.86 (77.37)	12.57 [23.74]
Annual feed cost	Million IDR	32.46 (236.02)	177.57 (547.6)	5.97 (82.82)	171.60*** [15.90]	320.5 (762.54)	268.03 (698.67)	52.47 [196.17]
Annual permanent worker cost	Million IDR	4.25 (41.35)	22.98 (101.2)	0.83 (9.13)	22.15*** [2.83]	41.85 (143.17)	20.66 (45.65)	21.19 [35.09]
Annual temporary worker cost	Million IDR	1.78 (5.90)	2.99 (7.16)	1.56 (5.62)	1.43*** [0.41]	4.22 (9.09)	4.65 (8.65)	-0.42 [2.35]
Annual other costs	Million IDR	4.16 (27.64)	10.56 (37.74)	2.99 (25.21)	7.58*** [1.92]	17.06 (49.92)	48.75 (144.55)	-31.69* [17.92]
Annual shrimp sales volume	kg	1,860.97 (9733.22)	9,319.46 (22403.73)	499.27 (2949.05)	8,820.19*** [641.75]	15,412.66 (29826.83)	10,675.18 (23755.7)	4,737.49 [7573.93]
Annual shrimp sales revenue	Million IDR	112.24 (629.13)	584.54 (1460.77)	26.01 (177.93)	558.53*** [41.58]	990.28 (629.13)	612.29 (1460.77)	377.99 [177.93]
N		1,574	243	1,331	1,574	115	17	132

Notes: Annual household spending is the sum of 'food purchase per year, housing per year, education per year, medical fees per year, utility per year, and entertainment per year. Standard deviations are reported in brackets. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Types of agricultural information sources used by the respondents

	Total	Full sample			Subsample excluding extensive farms		
		KUVI member	Non-KUVI mem.		KUVI Member	Non-KUVI mem.	
	(1)	(2)	(3)	(2)-(3)	(4)	(5)	(4)-(5)
Extension officer	0.09 (0.28)	0.19 (0.40)	0.07 (0.26)	0.12*** [0.02]	0.28 (0.45)	0.41 (0.51)	-0.13 [0.12]
KUVI	0.05 (0.21)	0.28 (0.45)	0.01 (0.08)	0.27*** [0.01]	0.23 (0.43)	0.00 (0.00)	0.23** [0.10]
Other OCoPs	0.02 (0.12)	0.03 (0.18)	0.01 (0.11)	0.02** [0.01]	0.02 (0.13)	0.06 (0.24)	-0.04 [0.04]
Farmers living in the same village	0.80 (0.40)	0.59 (0.49)	0.83 (0.37)	-0.24*** [0.03]	0.61 (0.49)	0.53 (0.51)	0.08 [0.13]
Farmers living in other villages	0.09 (0.29)	0.14 (0.35)	0.08 (0.28)	0.06*** [0.02]	0.15 (0.36)	0.18 (0.39)	-0.03 [0.09]
Family (parents, siblings, etc.)	0.20 (0.40)	0.35 (0.48)	0.17 (0.38)	0.17*** [0.03]	0.26 (0.44)	0.12 (0.33)	0.14 [0.11]
Local feed/input seller	0.02 (0.12)	0.04 (0.20)	0.01 (0.10)	0.03*** [0.01]	0.08 (0.27)	0.00 (0.00)	0.08 [0.07]
Collector/middleman	0.03 (0.16)	0.05 (0.22)	0.02 (0.15)	0.03** [0.01]	0.05 (0.22)	0.18 (0.39)	-0.12* [0.07]
Cooperative	0.01 (0.07)	0.01 (0.11)	0.00 (0.06)	0.01* [0.00]	0.01 (0.09)	0.00 (0.00)	0.01 [0.02]
Others	0.04 (0.19)	0.11 (0.31)	0.02 (0.16)	0.08*** [0.01]	0.14 (0.35)	0.00 (0.00)	0.14 [0.08]
<i>N</i>	1,574	243	1,331	1,574	115	17	132

Notes: Standard deviations are reported in brackets. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Types of agricultural information respondents rely on most

	Total	Full sample		Subsample excluding extensive farms	
		KUVI member	Non-KUVI mem.	KUVI member	Non-KUVI mem.
Extension officer	108 6.86%	35 14.4%	73 5.48%	20 17.39%	6 35.29%
KUVI	33 2.10%	24 9.88%	9 0.68%	13 11.30%	0 0.00%
Farmers living in the same village	1,174 74.59%	111 45.68%	1,063 79.86%	55 47.83%	10 58.82%
Farmers living in other villages	41 2.60%	4 1.65%	37 2.78%	1 0.87%	0 0.00%
Family (parents, siblings, etc.)	193 12.26%	52 21.40%	141 10.59%	18 15.65%	1 5.88%
Others	25 1.59%	17 7.00%	8 0.60%	8 6.96%	0 0.00%
<i>N</i>	1,574	243	1,331	115	17

Table 4. Satisfaction and dissatisfaction points with KUVI

	Total	Extensive	Intensive	(2)-(3)
	(1)	(2)	(3)	
<i>Satisfaction</i>				

Input info.	0.71	0.75	0.66	0.09
	(0.46)	(0.43)	(0.48)	[0.06]
Shrimp pricing info.	0.59	0.66	0.52	0.13**
	(0.49)	(0.48)	(0.50)	[0.06]
Shrimp disease info.	0.77	0.78	0.75	0.03
	(0.42)	(0.42)	(0.44)	[0.05]
Dissatisfaction				
None	0.72	0.77	0.65	0.07
	(0.41)	(0.4)	(0.41)	[0.05]
Inaccurate info.	0.13	0.07	0.20	-0.13***
	(0.34)	(0.26)	(0.40)	[0.04]
Info. obtained from KUVI is not suitable for my region	0.15	0.16	0.15	0.01
	(0.36)	(0.36)	(0.36)	[0.05]
<i>N</i>	243	128	115	243

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Usage and trust on OCoPs (full sample)

	1=Using KUVI			1=Using any OCoP			The most reliable info. (1=KUVI)			The most reliable info. (1=any OCoP)		
	Logit MFX	OLS	IV2SLS	Logit MFX	OLS	IV2SLS	Logit MFX	OLS	IV2SLS	Logit MFX	OLS	IV2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age weight	0.13	0.02	0.05	0.15	0.03	0.05	0.16**	-0.10	0.09	0.17***	0.09	0.08
	(0.09)	(0.10)	(0.11)	(0.13)	(0.13)	(0.14)	(0.06)	(0.07)	(0.07)	(0.06)	(0.08)	(0.08)
Age weight ²	-0.04	0.02	0.01	-0.04	0.03	0.02	-0.05**	-0.02	-0.02	-0.05**	-0.01	-0.01
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)
1=info. from family	0.004	0.02	-0.07	0.01	0.02	-0.03	-0.02**	0.04**	-0.03	-0.02**	-0.05**	-0.02
	(0.01)	(0.03)	(0.11)	(0.02)	(0.03)	(0.13)	(0.01)	(0.02)	(0.07)	(0.01)	(0.02)	(0.07)
1=info. from farmers living in the same village	0.004	0.02	-0.13	-0.01	-0.01	-0.17	-0.04**	0.05**	-0.00	-0.06**	0.06***	-0.02
	(0.01)	(0.03)	(0.12)	(0.02)	(0.03)	(0.12)	(0.02)	(0.02)	(0.09)	(0.03)	(0.02)	(0.08)
1=info. from extension officers	0.02	0.04	-0.01	0.01	0.02	-0.03	0.0001	0.01	0.02	-0.01	-0.003	0.01
	(0.02)	(0.03)	(0.06)	(0.02)	(0.03)	(0.06)	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.04)
Log duration of time spent at home	-0.03	-0.10	-0.09	-0.01	-0.03	-0.01	-0.01	-0.02	-0.03	-0.004	-0.02	-0.02
	(0.03)	(0.12)	(0.12)	(0.04)	(0.12)	(0.13)	(0.03)	(0.07)	(0.07)	(0.03)	(0.07)	(0.07)
<i>N</i>	1,541	1,543	1,543	1,541	1,543	1,543	1,541	1,543	1,543	1,541	1,543	1,543
Weak (Cragg-Donald Wald F statistic)			8.70			8.70			8.70			8.70
Over (p-value)			0.40			0.95			0.11			0.10
Endo (p-value)			0.55			0.27			0.41			0.64
Adjusted R-squared		0.16	0.11		0.15	0.10		0.07	0.05		0.07	0.06

Notes: In addition to the variables in the table above, the models are controlled by variables of main farmer's schooling, annual household spending, number of household members, a dummy for a member of a cooperative, total shrimp pond size, number of shrimp disease cases between 2016 and 2019, annual shrimp farm income, regional and shrimp farming type dummies, and intercept. Standard errors in parentheses are clustered for 175 villages. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Usage and trust on OCoPs (excluding data from the face-to-face interview)

	1=Using KUVI			1=Using any OCoP			The most reliable info. (1=KUVI)			The most reliable info. (1=any OCoP)		
	Logit MFX	OLS	IV2SLS	Logit MFX	OLS	IV2SLS	Logit MFX	OLS	IV2SLS	Logit MFX	OLS	IV2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age weight	-0.26	-0.03	-0.39	-0.51	-0.30	-0.68	0.17	0.06	0.11	0.17	0.09	0.08
	(0.66)	(0.69)	(0.67)	(0.66)	(0.71)	(0.70)	(0.36)	(0.35)	(0.36)	(0.35)	(0.35)	(0.37)
Age weight ²	0.13	0.05	0.17	0.25	0.18	0.31	-0.06	-0.02	-0.03	-0.05	-0.02	-0.02
	(0.25)	(0.26)	(0.25)	(0.24)	(0.27)	(0.26)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
1= info. from family	-0.07	-0.05	0.21	-0.12*	-0.11	0.17	-0.07*	-0.11**	-0.14	-0.10***	-0.13***	-0.13
	(0.06)	(0.07)	(0.20)	(0.06)	(0.08)	(0.19)	(0.04)	(0.05)	(0.11)	(0.03)	(0.05)	(0.12)
1= info. from farmers living in the same village	0.12*	0.13*	0.36	0.06	0.06	0.26	-0.19***	-0.20***	-0.22	-0.22***	-0.21***	-0.26
	(0.07)	(0.07)	(0.23)	(0.07)	(0.08)	(0.23)	(0.05)	(0.05)	(0.16)	(0.05)	(0.05)	(0.16)
1= info. from extension officers	0.09	0.10	0.16*	0.05	0.06	0.12	0.004	-0.02	-0.02	-0.02	-0.03	-0.04
	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)	(0.04)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
Log duration of time spent at home	-0.12	-0.06	-0.07	-0.05	-0.004	-0.01	-0.04	-0.01	-0.01	-0.01	-0.01	-0.003
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.10)	(0.08)	(0.08)	(0.10)	(0.07)	(0.07)
N	217	219	219	217	219	219	217	219	219	217	219	219
Weak (Cragg-Donald Wald F statistic)			3.72			3.72			3.72			3.72
Over (p-value)			0.37			0.40			0.97			0.99
Endo (p-value)			0.20			0.20			0.95			0.94
Adjusted R-squared		0.08	-0.01		0.10	0.01		0.13	0.13		0.13	0.12

Notes: In addition to the variables in the table above, the models are controlled by variables of the main farmer's schooling, annual household spending, number of household members, a dummy for a member of a cooperative, total shrimp pond size, number of shrimp disease cases between 2016 and 2019, annual shrimp farm income, regional and shrimp farming type dummies, and intercept. Standard errors in parentheses are clustered for 158 villages. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Who uses OCoPs, F2FEs, or OCoPs and F2FEs together?

	Full sample						Subsample excluding data from the face-to-face interview					
	1=Using OCoPs		1=Using F2FEs		1=Using OCoPs & F2FEs		1=Using OCoPs		1=Using F2FEs		1=Using OCoPs & F2FEs	
	Logit MFX	OLS	Logit MFX	OLS	Logit MFX	OLS	Logit MFX	OLS	Logit MFX	OLS	Logit MFX	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age weight	0.16	0.03	0.15	0.02	0.17	0.05	-0.82	-0.60	1.02**	0.36	-0.50	-0.82
	(0.13)	(0.13)	(0.10)	(0.09)	(0.11)	(0.09)	(0.57)	(0.66)	(0.49)	(0.33)	(0.51)	(0.53)
Age weight ²	-0.04	0.03	-0.05	-0.02	-0.05	-0.01	0.35	0.27	-0.38**	-0.14	0.19	0.31
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.21)	(0.25)	(0.19)	(0.13)	(0.19)	(0.20)
Schooling	0.004	-0.01	-0.001	0.002	0.01	-0.0003	0.19	0.004	-0.002	0.001	0.08	0.01

	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.16)	(0.04)	(0.05)	(0.02)	(0.09)	(0.03)
Schooling ²	0.0001	0.0004	0.00004	0.00002	0.00001	0.0001	-0.01	0.002	-0.001	0.0002	-0.002	0.001
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.01)	(0.002)	(0.002)	(0.001)	(0.004)	(0.001)
ln_total shrimp pond size	-0.01*	-0.02**	0.02**	0.01**	-0.005	-0.01**	-0.001	-0.01	0.04*	0.01	0.001	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Shrimp disease (0-4)	-0.01*	-0.01	0.01*	0.001	-0.01	-0.01*	0.04*	-0.04**	-0.01	0.02	-0.04**	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
1=info. from extension officers	0.01	0.02	-0.45**	-0.25**	0.01	0.08**	0.03	0.05	-0.32**	-0.19**	0.04	-0.14**
	(0.02)	(0.03)	(0.09)	(0.05)	(0.02)	(0.03)	(0.07)	(0.07)	(0.07)	(0.04)	(0.06)	(0.06)
Log duration of time spent at home	-0.02	-0.03	0.07	0.08	0.02	0.06	-0.01	0.01	0.10	0.06	0.10	0.07
	(0.04)	(0.12)	(0.06)	(0.08)	(0.03)	(0.09)	(0.12)	(0.12)	(0.10)	(0.08)	(0.12)	(0.09)
N	1,541	1,543	1,541	1,543	1,541	1,543	222	224	222	224	217	224
Adjusted R-squared	.	0.15	.	0.69	.	0.17	.	0.12	.	0.72	.	0.28

Notes: In addition to the variables in the table above, the models are controlled by variables of annual household spending, number of household members, a dummy for a member of a cooperative, annual shrimp farm income, regional and shrimp farming type dummies, and intercept. Standard errors in parentheses are clustered for 175 villages (Columns (1)-(6)) and 158 villages (Columns (7)-(12)). *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Who frequently shares and enquires about shrimp farming information with other KUVI members?

	How often did you share info. on KUVI in 2022?					How often did you enquire for info. in KUVI in 2022?				
	Ologit	OLS	OLS	IV2SLS	IV2SLS	Ologit	OLS	OLS	IV2SLS	IV2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Age weight	5.11	0.30	0.43	0.56	0.81	0.59	0.32	0.36	0.98	1.17
	(5.44)	(1.60)	(1.64)	(1.60)	(1.65)	(3.91)	(1.47)	(1.48)	(1.47)	(1.47)
Age weight ²	-2.81	-0.42	-0.46	-0.50	-0.60	-0.78	-0.34	-0.36	-0.55	-0.63
	(2.27)	(0.59)	(0.60)	(0.59)	(0.60)	(1.52)	(0.54)	(0.55)	(0.54)	(0.54)
1=info. from family	-0.69	-0.22	-0.22	-0.46	-0.53	1.01**	0.40***	0.39***	-0.99**	-1.04**
	(0.43)	(0.17)	(0.17)	(0.46)	(0.46)	(0.41)	(0.15)	(0.15)	(0.46)	(0.48)
1=info. from farmers living in the same village	-0.81**	0.37**	-0.35**	-0.36	-0.46	-0.72*	-0.37**	-0.35**	-0.43	-0.46
	(0.36)	(0.15)	(0.15)	(0.56)	(0.55)	(0.39)	(0.15)	(0.15)	(0.62)	(0.61)
1=info. from extension officers	-0.20	-0.07	-0.07	-0.08	-0.11	-0.18	-0.13	-0.12	-0.18	-0.19
	(0.41)	(0.17)	(0.18)	(0.20)	(0.20)	(0.46)	(0.18)	(0.19)	(0.20)	(0.21)
Log duration of time spent at home	0.80	0.36**	0.21	0.35**	0.21	0.53	0.21	0.20	0.20	0.17
	(0.52)	(0.18)	(0.25)	(0.17)	(0.24)	(0.50)	(0.20)	(0.25)	(0.20)	(0.28)
N	227	227	227	227	227	227	227	227	227	227
Regional dummies	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Brant test (p-value)	0.01					0.56				
Weak (Cragg-Donald Wald F statistic)				3.90	3.75				3.90	3.75
Over (p-value)				0.12	0.09				0.04	0.04
Endo (p-value)				0.92	0.82				0.52	0.51
Adjusted R-squared		0.08	0.06	0.07	0.05		0.12	0.10	0.05	0.03

Notes: In addition to the variables in the table above, the models are controlled by variables of main farmer's schooling, annual household spending, number of household members, a dummy for a member of a cooperative, total shrimp pond size, number of shrimp disease cases between 2016 and 2019, annual shrimp farm income, shrimp farming type dummies, and intercept. Standard errors in parentheses are clustered for 158 villages. *** p<0.01, ** p<0.05, * p<0.1.

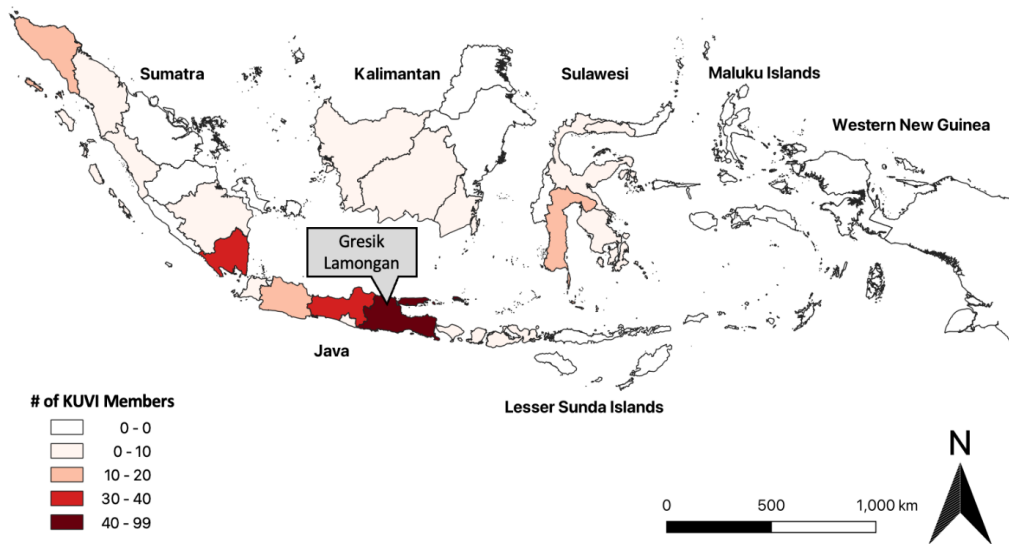


Fig. 1. Map of KUVI members' residences

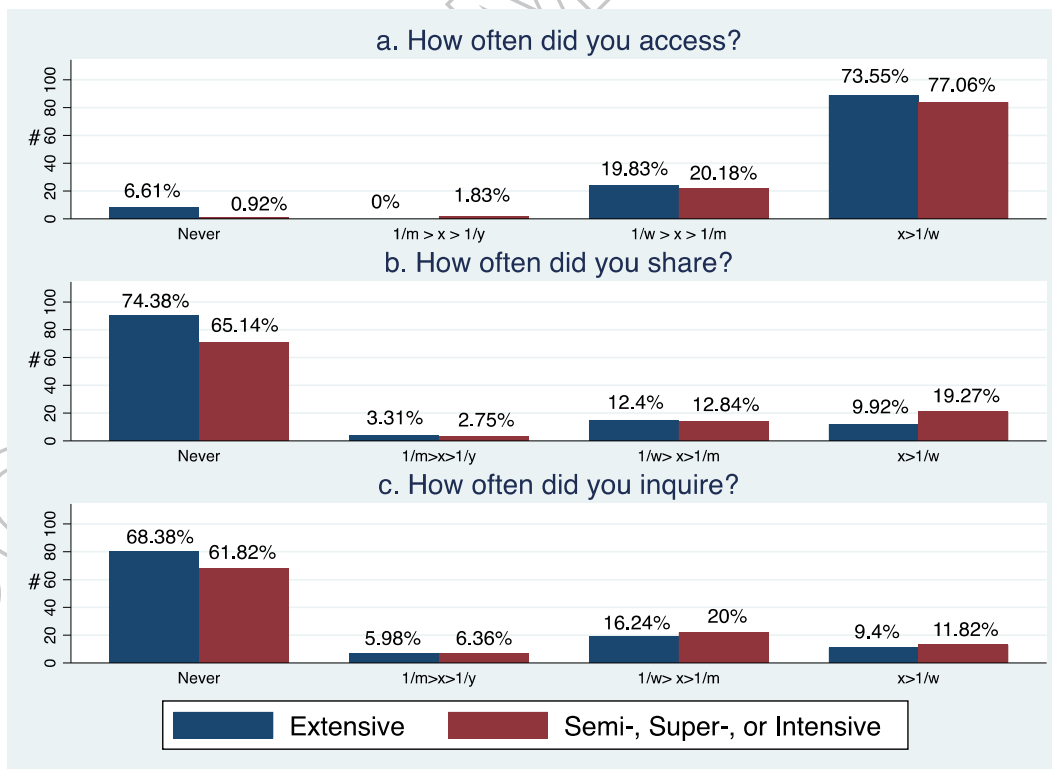


Fig. 2. Frequency of access, information sharing, and enquiries by KUVI members

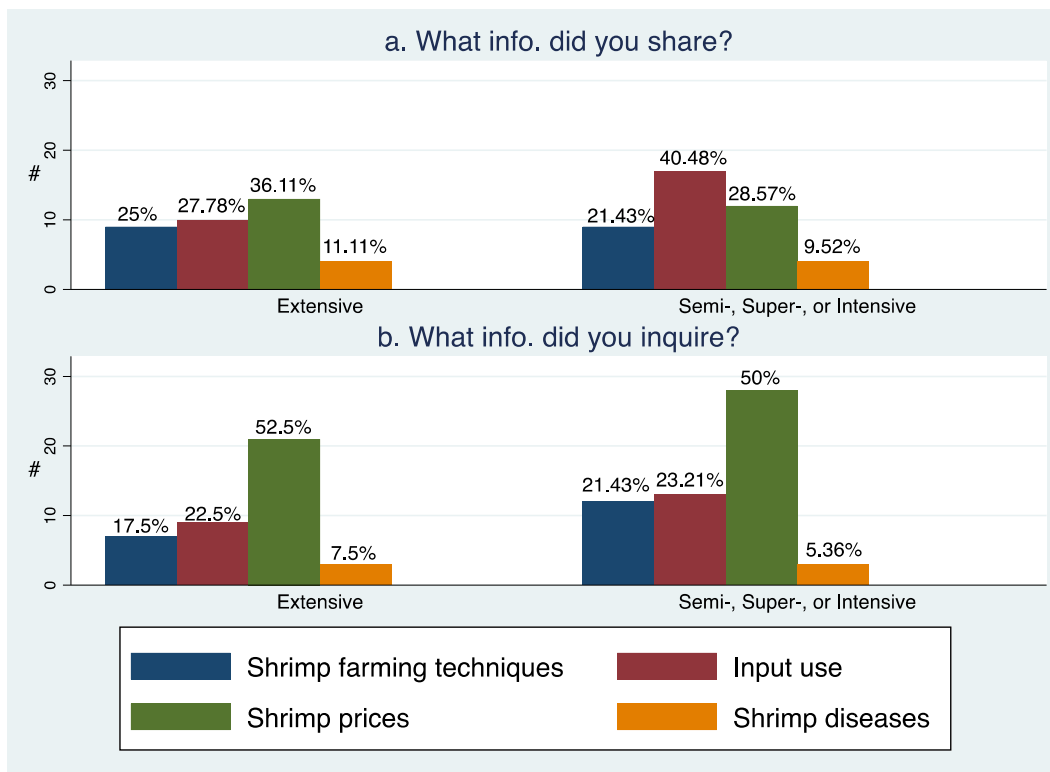


Fig. 3. Types of information shared and enquired by KUVI members

Appendix 1. KUVI on Facebook



Komunitas Udang Vaname Indonesia

+ Invite

Discussion Reels People Media Files

Write something...

Reel Photo/video Poll

Featured

Most Relevant

Kenapa udang vanamei di tambak tidak asin rasanya padahal Kita piara Airnya Asin sama kyk ikan di laut airnya asin tapi rasa ikannya tidak Asin inilah kuasa Allah

See Translation



67 17 comments 1 share

Like Comment Share

About

Selamat Datang di Grup #KomunitasUdangVanameIndonesia... See more

- Public: Anyone can see who's in the group and what they post.
- Visible: Anyone can find this group.

Batam, Riau, Indonesia · Banda Aceh, Indonesia · Makassar · Brebes, Jawa Tengah, Indonesia... See more

Learn more

Topics in this group

- #tambakudang: Pinned by admin · 156 posts
- #tambak: Pinned by admin · 116 posts
- #udang: Pinned by admin · 96 posts

See all

Recent media



Source: KUVI (2020)

Appendix 2. Distribution of respondents

a) Distribution of respondents according to survey method and KUVI membership

			1,574 Respondents			
		Telephonic interview (230 Respondents)			Face-to-face survey (1,344 Respondents)	
		KUVI members (230 Respondents)	Non-KUVI members (0 Respondents)	KUVI members (13 Respondents)	Non-KUVI members (1,331 Respondents)	

b) Distribution of respondents according to the use of KUVI

			1,574 Respondents			
		KUVI members (243 Respondents)			Non-KUVI members (1,331 Respondents)	
		KUVI users (65 Respondents)	Non-KUVI users (178 Respondents)	KUVI users (8 Respondents)	Non-KUVI users (1,323 Respondents)	

Appendix 3. Building and deploying a CNN model for age prediction from images

```

##### 2nd #####
# This code is designed to use a pre-trained model to predict the
ages of individuals
# in images within a specified folder and calculate the average
predicted age for all the images.

import os
import cv2
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import load_model

# 1. Load the model
model = load_model('age_prediction_model.h5')

# 2. Preprocessing function for new images
def preprocess_image(image_path):
    img = cv2.imread(image_path)
    if img is None:
        raise ValueError(f"Image at path '{image_path}' could not be
loaded. Please check the file path.")
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (64, 64)) # Resize to match the model's
input size
    img = img.astype('float32') / 255.0 # Normalize the image
    img = np.expand_dims(img, axis=0) # Add a batch dimension
    return img

# 3. Age prediction function
def predict_age(image_path):
    img = preprocess_image(image_path)
    predicted_age = model.predict(img)
    return predicted_age[0][0] # Return the predicted age

# 4. Calculate the average age for all images in a folder
def predict_average_age(folder_path):
    total_age = 0
    count = 0

    for filename in os.listdir(folder_path):
        if filename.endswith(('.jpg', '.jpeg', '.png')): # Select
only image files
            image_path = os.path.join(folder_path, filename)
            try:
                predicted_age = predict_age(image_path)
                total_age += predicted_age
                count += 1
                print(f'{filename}: Predicted Age:
{predicted_age:.2f} years')
            except Exception as e:
                print(f"Could not process {filename}: {e}")

    if count > 0:
        average_age = total_age / count
        print(f'Average Predicted Age for all images:
{average_age:.2f} years')
    else:
        print('No images to process.')

# 5. Perform predictions
folder_path = '/path/to/your/project/directory/' # Path to the
folder containing images for prediction
predict_average_age(folder_path)

```

```

##### 1st #####
# This code aims to build, train, and evaluate a Convolutional
Neural Network (CNN) model to predict
# the age of individuals based on facial images.

import os
import numpy as np
import cv2
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPool2D, Flatten,
Dense, Dropout
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# 1. Load and preprocess data
def load_data(dataset_path):
    images = []
    ages = []

    for filename in os.listdir(dataset_path):
        if filename.endswith(".jpg"): # If the file extension
            age = int(filename.split("_")[0]) # Extract age from
            the filename
            img_path = os.path.join(dataset_path, filename)
            img = cv2.imread(img_path)
            img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
            img = cv2.resize(img, (64, 64)) # Resize image to
            (64x64)
            images.append(img)
            ages.append(age)

    images = np.array(images, dtype=np.float32) / 255.0 # Normalize
    ages = np.array(ages, dtype=np.int64)

    return images, ages

# Load data using the actual path
folder_name = '/path/to/your/data/UTKFace'
images, ages = load_data(folder_name)

# Split dataset into training, validation, and test sets
x_train, x_test, y_train, y_test = train_test_split(images, ages,
                                                    test_size=0.2, random_state=42)
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train,
                                                  test_size=0.2, random_state=42)

# 2. Build CNN model
def build_age_prediction_model(input_shape):
    model = Sequential([
        Conv2D(32, (3, 3), padding='same', activation='relu',
              input_shape=input_shape),
        MaxPool2D(pool_size=(2, 2)),
        Dropout(0.25),

        Conv2D(64, (3, 3), padding='same', activation='relu'),
        MaxPool2D(pool_size=(2, 2)),
        Dropout(0.25),

        Conv2D(128, (3, 3), padding='same', activation='relu'),
        MaxPool2D(pool_size=(2, 2)),
        Dropout(0.25),

        Flatten(),
        Dense(256, activation='relu'),
        Dropout(0.5),

        Dense(1, activation='linear') # Output layer for age
    ]) # prediction (regression problem)

    model.compile(optimizer=Adam(), loss='mean_squared_error',
                  metrics=['mae'])
    return model

input_shape = (64, 64, 3) # Input image size
model = build_age_prediction_model(input_shape)

# Print model summary
model.summary()

# 3. Data Augmentation
datagen = ImageDataGenerator(
    rotation_range=10,
    zoom_range=0.1,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True
)

# 4. Train the model
batch_size = 32
epochs = 50

history = model.fit(
    datagen.flow(x_train, y_train, batch_size=batch_size),
    validation_data=(x_val, y_val),
    epochs=epochs,
    batch_size=batch_size,
    verbose=1
)

# 5. Evaluate the model
loss, mae = model.evaluate(x_test, y_test)
print(f'Test MAE (Mean Absolute Error): {mae:.2f} years')

# 6. Save the model
model.save('age_prediction_model.h5')

```

Appendix 4. Correlation between agricultural information sources

a) Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) KUVI	1.000									
(2) Extension officer	0.108** *	1.000								
(3) Other OCoPs	0.045*	-0.021	1.000							
(4) Farmers living in the same village	-0.079** *	-0.241** *	-0.079** *	1.000						
(5) Farmers living in other villages	0.154** *	0.007	0.103** *	0.032	1.000					
(6) Family (parents, siblings, etc.)	0.059** *	-0.023	0.067** *	-0.514** *	0.226** *	1.000				
(7) Local feed/input seller	0.070** *	0.016	-0.015	-0.040	0.031	-0.011	1.000			
(8) Collector/middleman	0.169** *	-0.023	0.045*	0.043*	0.167** *	0.038	0.142** *	1.000		
(9) Cooperative	0.026	0.009	-0.009	0.036	-0.023	-0.036	-0.009	-0.012	1.000	
(10) Others	0.081** *	0.079** *	0.303** *	-0.050** *	0.029	-0.032	0.030	-0.032	0.362** *	1.000

*** p<0.01, ** p<0.05, * p<0.1

b) Subsample excluding extensive farms

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) KUVI	1.000									
(2) Extension officer	0.042	1.000								
(3) Other OCoPs	-0.077	0.013	1.000							
(4) Farmers living in the same village	0.032	-0.316** *	-0.082	1.000						
(5) Farmers living in other villages	0.257** *	0.051	-0.064	0.303** *	1.000					
(6) Family (parents, siblings, etc.)	0.108	-0.134	-0.086	-0.114	0.303** *	1.000				
(7) Local feed/input seller	0.086	-0.043	-0.041	-0.085	0.137	-0.013	1.000			
(8) Collector/middleman	0.161*	-0.043	-0.041	0.099	0.556** *	0.268** *	0.285** *	1.000		
(9) Cooperative	-0.044	-0.057	-0.013	0.072	-0.037	-0.049	-0.024	-0.024	1.000	
(10) Others	-0.016	0.217** *	0.099	-0.122	-0.027	-0.102	0.084	-0.100	0.235** *	1.000

*** p<0.01, ** p<0.05, * p<0.1

c) Subsample excluding non-KUVI members

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) KUVI	1.000									
(2) Extension officer	0.094	1.000								
(3) Other OCoPs	0.041	-0.032	1.000							
(4) Farmers living in the same village	0.118*	-0.103*	-0.082	1.000						
(5) Farmers living in other villages	0.309** *	0.073	0.059	0.286** *	1.000					

(6) Family (parents, siblings, etc.)	-0.022	-0.093	-0.037	-0.295** *	0.106*	1.000				
(7) Local feed/input seller	0.011	0.003	-0.038	-0.081	0.096	-0.063	1.000			
(8) Collector/middleman	0.284** *	-0.015	0.064	0.112*	0.510** *	0.154* *	0.240** *	1.000		
(9) Cooperative	0.014	0.040	-0.021	0.093	-0.045	-0.081	-0.023	-0.025	1.000	
(10) Others	0.025	0.235** *	0.309** *	-0.147** *	-0.024	-0.140* *	0.062	-0.079	0.323** *	1.000

*** p<0.01, ** p<0.05, * p<0.1

Appendix 5. Obtaining agricultural information during the COVID-19 pandemic

a) Has it become difficult to contact extension officers after COVID-19?					
		KUVI members		KUVI members w/o extensive	
		Yes	No	Yes	No
Yes, very difficult	#	82	518	31	7
	%	33.74	38.92	26.96	41.18
Yes, a little difficult	#	61	348	26	6
	%	25.10	26.15	22.61	35.29
Same	#	78	394	49	3
	%	32.10	29.60	42.61	17.65
No, more frequently	#	22	71	9	1
	%	9.05	5.33	7.83	5.88
<i>N</i>		243	1331	115	17

b) Has it become difficult to contact the farmers in the same village after COVID-19?					
		KUVI user		KUVI user w/o extensive	
		Yes	No	Yes	No
Yes, very difficult	#	3	92	2	0
	%	1.34	7.89	1.89	0.00
Yes, a little difficult	#	24	361	15	5
	%	10.71	30.96	14.15	31.25
Same	#	170	519	80	10
	%	75.89	44.51	75.47	62.50
No, more frequently	#	27	194	9	1
	%	12.05	16.64	8.49	6.25
<i>N</i>		224	1166	106	16

Appendix 6. The results of the first-stage regression

a) Table 6									
	1= Using KUVI		1= Using OCoPs		The most reliable info. (1=KUVI)		The most reliable info. (1=OCoPs)		
	1= info. from family	1= info. from farmers living in the same village	1= info. from family	1= info. from farmers living in the same village	1= info. from family	1= info. from farmers living in the same village	1= info. from family	1= info. from farmers living in the same village	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	

		the same village		the same village		the same village		the same village
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1= <i>i</i> initially learned about shrimp farming from their family	0.25***	0.11	0.25***	0.11	0.25***	0.11	0.25***	0.11
1= <i>i</i> initially learned about shrimp farming from their neighboring farmers	-0.20**	0.36***	-0.20**	0.36***	-0.20**	0.36***	-0.20**	0.36***
1= <i>i</i> engaged in a collective activity using the same canal	-0.10	0.06	-0.10	0.06	-0.10	0.06	-0.10	0.06
<i>N</i>	227	227	227	227	227	227	227	227
Regional FE	NO	NO	YES	YES	NO	NO	YES	YES
Shrimp farming Type FE	YES	YES	YES	YES	YES	YES	YES	YES
Weak (SW F Statistic)	14.10	5.82	13.81	5.30	14.10	5.82	13.81	5.30
Under id (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F test of excluded instruments (p-value)	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01
LC 2SLS with 95% confidence interval	-2.54, 0.41	-1.32, 1.01	-4.41, 1.09	-4.97, 0.12	-4.32, 0.15	-4.32, 0.01	-2.57, 0.10	-1.98, 0.89

Notes: The models are controlled by variables of the main farmer's age, squared age, schooling, squared schooling, shrimp pond size, shrimp disease, duration of time spent at home, annual household spending, number of household members, a dummy for a member of a cooperative, shrimp farm income, and intercept. Standard errors in parentheses are clustered for 158 villages. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 7. Trust on OCoPs according to information type

a) Full sample									
	The most reliable info. on input usage (1=KUVI)			The most reliable info. on shrimp farmgate prices (1=KUVI)			The most reliable info. on treating shrimp diseases (1=KUVI)		
	Logit Mfx	OLS	IV2SLS	MFx	OLS	IV2SLS	MFx	OLS	IV2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1=info. from family	-0.01*	-0.02	-0.02	-0.01*	-0.03*	-0.01	-0.01	-0.02	0.04
	(0.01)	(0.01)	(0.05)	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.07)
1=info. from farmers living in the same village	-0.01	-0.01	-0.00	-0.02*	-0.04**	-0.04	-0.01	-0.02	0.07
	(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.09)
1=info. from extension officers	0.001	-0.001	0.003	0.001	-0.001	-0.002	0.01	0.02	0.05
	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.04)
Log duration of time spent at home	-0.02	-0.08	-0.08	-0.03	-0.06	-0.06	-0.01	-0.01	-0.02
	(0.02)	(0.09)	(0.09)	(0.02)	(0.07)	(0.06)	(0.02)	(0.07)	(0.08)
<i>N</i>	1,483	1,543	1,543	1,541	1,543	1,543	1,541	1,543	1,543
Regional FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Shrimp farming Type FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Weak (Cragg-Donald Wald F statistic)			8.70			8.70			8.70
Over (p-value)			0.50			0.15			0.56
Endo (p-value)			0.88			0.63			0.46
Adjusted R-squared	.	0.05	0.04	.	0.09	0.08	.	0.10	0.04

Notes: In addition to the variables in the table above, the models are controlled by variables of annual household spending, number of household members, a dummy for a member of a cooperative, shrimp farm income, and intercept. Standard errors in parentheses are clustered for 175 villages. *** p<0.01, ** p<0.05, * p<0.1.

c) Subsample excluding non-KUVI members			
	The most reliable info. on input usage (1=KUVI)	The most reliable info. on shrimp farmgate prices (1=KUVI)	The most reliable info. on treating shrimp diseases (1=KUVI)

	MFX	OLS	IV2SLS	MFX	OLS	IV2SLS	MFX	OLS	IV2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1=info. from family	0.09** *	-0.10**	-0.13	-0.08**	-0.10**	-0.14	-0.10**	-0.13**	-0.12
	(0.03)	(0.05)	(0.12)	(0.04)	(0.05)	(0.09)	(0.04)	(0.05)	(0.12)
1=info. from farmers living in the same village	-0.04	-0.05	-0.01	-0.10**	-0.11**	-0.04	-0.07	-0.08	-0.04
	(0.04)	(0.05)	(0.14)	(0.05)	(0.05)	(0.14)	(0.05)	(0.05)	(0.17)
1=info. from extension officers	0.01	-0.01	-0.01	0.002	0.01	0.02	0.04	0.04	0.05
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.07)
Log duration of time spent at home	-0.07	-0.08	-0.08	-0.13	-0.08	-0.10	-0.04	-0.01	-0.02
	(0.08)	(0.09)	(0.09)	(0.10)	(0.07)	(0.07)	(0.12)	(0.08)	(0.08)
N	214	227	227	225	227	227	225	227	227
Regional FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Shrimp farming Type FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Weak (Cragg-Donald Wald F statistic)			3.75			3.75			3.75
Over (p-value)			0.94			0.78			0.64
Endo (p-value)			0.89			0.77			0.97
Adjusted R-squared	.	0.01	-0.01	.	0.08	0.06	.	0.04	0.03

Notes: In addition to the variables in the table above, the models are controlled by variables of annual household spending, number of household members, a dummy for a member of a cooperative, shrimp farm income, and intercept. Standard errors in parentheses are clustered for 158 villages. *** p<0.01, ** p<0.05, * p<0.1.

d) Subsample excluding non-KUVI members									
	The most reliable info. on input usage (1=Any OCoP)			The most reliable info. on shrimp farmgate prices (1=Any OCoP)			The most reliable info. on treating shrimp diseases (1=Any OCoP)		
	MFX	OLS	IV2SLS	MFX	OLS	IV2SLS	MFX	OLS	IV2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1=info. from family	0.11***	-0.12**	-0.12	-0.09**	-0.12**	-0.15*	-0.11**	-0.15***	-0.11
	(0.03)	(0.05)	(0.12)	(0.04)	(0.05)	(0.09)	(0.04)	(0.05)	(0.13)
1=info. from farmers living in the same village	-0.05	-0.07	-0.04	-0.10**	-0.12**	-0.07	-0.11**	-0.13**	-0.08
	(0.05)	(0.05)	(0.14)	(0.05)	(0.05)	(0.13)	(0.05)	(0.05)	(0.17)
1=info. from extension officers	-0.01	-0.02	-0.02	-0.001	-0.004	0.004	-0.00004	-0.003	0.01
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)	(0.07)
Log duration of time spent at home	-0.07	-0.07	-0.08	-0.15	-0.08	-0.09	-0.04	0.002	-0.001
	(0.08)	(0.09)	(0.08)	(0.09)	(0.07)	(0.07)	(0.11)	(0.08)	(0.08)
N	214	227	227	225	227	227	225	227	227
Regional FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Shrimp farming Type FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Weak (Cragg-Donald Wald F statistic)			3.75			3.75			3.75
Over (p-value)			0.96			0.71			0.66
Endo (p-value)			0.99			0.82			0.92
Adjusted R-squared	.	0.03	0.02	.	0.12	0.10	.	0.07	0.06

Notes: In addition to the variables in the table above, the models are controlled by variables of annual household spending, number of household members, a dummy for a member of a cooperative, shrimp farm income, and intercept. Standard errors in parentheses are clustered for 175 villages. *** p<0.01, ** p<0.05, * p<0.1.