

Patterns and Characteristics of Households Income Diversification: The Case of Thai Rural Households

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Received 6 May 2022, Received in revised form 21 October 2022,

Accepted 13 November 2022, Available online 8 January 2024

Abstract

To mitigate the socio-economic problems arising from income disparity, a comprehensive view and insights into rural households' behaviors and environment are crucial. This study employs cluster analysis to develop an empirical taxonomy of households' occupations in Thai rural areas and gain insights into households' income diversification and occupation patterns, as well as contributing factors. Results of the study indicate that, among the five groups, the extent of the income diversification is rather low as the households concentrate on one main production activity to produce household income. There is no evidence of the income generated through value-added products. The limitation of the household's ability to diversify their income sources is due to household size and composition.

Keywords: Cluster Analysis, Income Diversification, Rural Households

JEL Classifications: J24, R2, Q12, O53

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1. Introduction

Urban-rural income disparity gives rise to many socio-economic problems and poses potential risks of inefficient economic development, as experienced by many countries such as China, India, Indonesia, Thailand, and Vietnam. Many studies investigate factors influencing the income disparity and provide policy references to mitigate the problem. For instance, even though urbanization greatly contributes to the growth of a country's economy, Hong and Zhang (2020) showed that the urbanization rate can cause an increase in regional inequality. Industrial structure upgrades can then play a crucial role in reducing the gap.

In addition, an unbalanced financial structure can cause rural residents to be excluded from the formal financial system due to a lack of credit information, leading to an unbalanced economic and social structure. Improving financial quality and inclusivity will thus help bridge the urban-rural income gap (Ji et al., 2021; He & Du, 2021). To tackle these problems, Sibirian (2020) suggested that a government implement policies at both national and subnational levels in sustainable ways to promote income diversification. The author also postulates that fiscal decentralization is more effective and efficient compared to a centralized system, as regional heads usually have better insights about the social context, the behavior, the needs, and the limitations of the households under their responsibility.

An effective fiscal decentralization policy, with the purpose of encouraging the income diversification nevertheless requires a comprehensive view and insights into the occupation patterns and the drivers of the diversification of incomes of rural households. These understandings are crucial in the design and implementation of government policies aimed at the sustainable allocation of natural resources, the stimulation of the rural economy, and the mitigation of the rural-urban disparity.

However, while there have been many studies on the behavioral heterogeneity in rural and farm households (Makhura et al., 1998; Bidogeza et al., 2009; Pacini et al., 2014; Kuivanen et al., 2016), the investigation of income diversification strategies in the existing literature is rather limited (Weltin et al., 2017), as most studies use regressions (e.g., a Probit model and a Tobit model) to study the main determinants driving households' decision towards income diversification (Démurger, et al., 2010; Anderzén, et al., 2020; Le & Le, 2020; Khan et al., 2020).

In general, rural households are likely to achieve income diversification through farm and off-farm activities rather than through intensification and specialization in order to reduce market risks, income variability, and income insufficiency. Theoretically, households allocate their labor between the activities to maximize their utility over consumption and leisure, subjected to time and budget constraints. Such an income diversification strategy has been shown to alleviate poverty and vulnerability, as households possess more options to generate income and increase liquid assets in the form of cash (Reardon et al., 2000; Block & Webb, 2001; Canagarajah et al., 2001; De Janvry & Sadoulet, 2001). With the income earned, households can acquire basic goods and services while allocating a portion of their income to savings, which in turn allows for the financing of productive investments in human and business capital for future business growth.

However, the ability of the rural households to diversify their incomes depends on many socio-economic factors (e.g., average education level, age, and gender of the household head)

and the accessibility to infrastructure. In the existing literature, the results with regard to the effects of socio-economic factors on households' income diversification are rather mixed across regions. For instance, Démurger et al. (2010) showed that, for a township in northern China, the average education level of household members is not a statistically significant determinant of income diversification, as only low-paid jobs are offered to the rural households. De Brauw et al. (2002), and Micevska and Rahut (2008), on the other hand, showed that higher education can increase the likelihood for households to participate in local wage employment in China and the Himalayas, respectively.

The age of the household head can also affect households' decisions towards the strategy. On one hand, experienced household heads are likely to diversify their income portfolio as they understand the risks of relying on a single income source (Micevska & Rahut, 2008; Olale, Henson & Cranfield, 2013). On the other, it is also possible that older household heads might be less likely to diversify their income-generating activities as they are not willing to move away from their farming-based comfort zone (Dercon & Krishnan, 1996; Senadza, 2014; Anderzén et al., 2020). In a few cases, the age of the household head shows no statistically significant impact (Démurger, et al., 2010; Memon et al., 2020).

In addition, the significance of the gender of the household head towards income diversification is found to be context specific. For instance, Senadza (2014) showed that a female head in Ghana is more likely to implement the strategy while Schwarze and Zeller (2005) revealed that, in Indonesia, the gender of the household head does not statistically increase the households' likelihood to diversify income sources.

To fill these gaps in the existing literature, the main objective of this study is to provide additional empirical evidence on rural income diversification and its determinants in the context of Thailand, where fiscal decentralization policies have been implemented for a few decades through the Million Baht Village Fund Program. More specifically, we employ cluster analysis to comprehensively develop an empirical taxonomy of households' occupations in Thai rural areas using the Townsend Thai Monthly Survey¹. By performing cluster analysis, we can statistically differentiate income diversification strategies among rural households without any predefined assumptions, minimizing the loss of information from the data. The insights into different income diversification decisions based on households' occupation patterns and demographics allow us to better profile target groups for the appropriate implementation of rural development policies. These will in turn improve households' production activities and eventually maintain sustainable income growth in rural areas. This study also departs from others in the existing literature in that the differences in occupation patterns within a region are taken into consideration when examining socio-economic factors contributing to an income diversification decision.

The paper is organized as follows: Section II introduces the Townsend Thai Monthly Survey and research methodologies. Section III presents key empirical findings and a discussion. Section IV concludes the study and makes policy recommendations.

¹ The focuses of other studies using this data set are mostly on institutional assessments (Kaboski & Townsend, 2005; Boonperm et al., 2012), households' participation (Chandoevvit & Ashkul, 2008), and the overall impacts of the Million Baht Village Fund Program on consumption expenditure, investment, and income levels (Chandoevvit & Ashkul, 2008; Kaboski & Townsend, 2012).

2. Data, Methodology and Variables

2.1 The Townsend Thai Monthly Survey

To pursue our research objective, we use household demographic and financial accounting panel data compiled and constructed from the Townsend Thai Monthly Survey². The survey was initiated in August 1998 in a subset of villages from the original sampling frame. In total, there are 16 villages, four villages in each of the four provinces, resulting in 720 households surveyed. The data collected includes household composition, economic activities carried out by the household, financial services used by households, etc.

While the household composition and other demographic data needed for this study are directly extracted from the survey, the household financial information is retrieved from Household Financial Accounting: Aggregate Data³. The database was developed under the Thai Household Financial Accounting Data for Economic and Social Research Project, with the intention to construct household financial accounts and statements from the Townsend Thai Monthly Data. The specific period we select for this study is 2012, the latest year for which the household financial accounting data are available. After taking out missing values and outliers, we have a sample of 510 households.

² The Townsend Thai Monthly Survey is a part of the Townsend Thai Data, the database developed under the Townsend Thai Project initiated by Professor Robert M. Townsend under the supervision of the Thai Family Research Project (TFRP). The project has been financially supported by many institutions, such as the National Institute of Child Health and Human Development (NICHD) and the National Science Foundation (NSF) by the US government, the Bill & Melinda Gates Foundation for the Consortium on Financial Systems & Poverty at the University of Chicago, the Ford Foundation, the John Templeton Foundation for the Enterprise Initiative. Organizations that support the use of Townsend Thai Data include the National Opinion Research Center at the University of Chicago, the National Bureau of Economic Research at the Massachusetts Institute of Technology, the Andrew W. Mellon Foundation, and the University of the Thai Chamber of Commerce (UTCC). Researchers can request data from RIPED <http://riped.utcc.ac.th/data-reques/> or Dataverse <http://dataverse.harvard.edu/>

³ This set of information is usually detailed and complex. Because the data is stored at the transaction level. Calculating the economic numbers such as the cost of production, consumption, property, debt, and wealth of a particular household often requires gathering information from a variety of data categories. For example, income calculations require data from household asset classes. agricultural assets, land type, cultivation, etc. The dataset is useful for validating the value of variable data according to accounting principles. It also makes the use of data convenient for further analysis or research.

2.2 Methodology

To develop an empirical taxonomy of household occupation patterns in Thai rural areas, we perform a k-means cluster analysis for classifying households into occupation pattern groups according to their amounts of income from each income source. The method has the advantage that it is an explorative statistical method which requires no predefined assumptions (Christoffer & Josep Maria Puigvert, 2006). It allows for a more understandable description of observations with minimal loss of information (Hair et al., 2010). In addition, the k-mean clustering is more appropriate, compared to the hierarchical clustering technique, since the number of households in the sample is over 200. As a proximity measure, the Euclidean distance is employed for measuring within-cluster and between-cluster variances.

We calculate, compare, and analyze different cluster solutions of household occupation patterns according to the number of households in each cluster and the households' characteristics. Consequently, we decide for a five-cluster solution based on face validity and that fits with theory (Hair et al., 2010)⁴.

To examine the differences in the characteristics of the households across clusters, we first conduct the one sample Kolmogorov-Smirnov test on all the passive cluster variables. The normality test results show that all the variables are non-normal, requiring the use of medians and the nonparametric Kruskal-Wallis H test results for the interpretation of whether there are statistically significant differences between two or more household occupation clusters on the passive cluster variables.

2.3 Variables

As the household occupation pattern is of key interest in this study, the percentage revenue contributions from six household production activities, namely cultivation, livestocking, fish and shrimp farming, household businesses, labor, and other production activities, are used as the active cluster variables.

To analyze the characteristics of the resulting clusters, we include a number of household's demographic data, including the number of members, age, gender, and education, as the passive cluster variables. In addition, we further examine the revenues and profits of the production activities to gain insights into the relationship between the occupation pattern and the household's specialization derived from the production profits. See Table 1 for the descriptions of the active and passive cluster variables.

In addition to the above-mentioned household characteristics, we also calculate the Herfindahl-Hirschman index (HHI) in order to examine a potential variation in the extent of the households' income diversification among the five pre-processed clusters. In agriculture, while one dimensional income diversification indices in the context of rural areas have been the estimation of non-farm income's share of total household income (Block & Webb, 2001; Davis et al., 2010; Lanjouw et al., 2001), Zhao and Barry (2013) argued that two-dimensional

⁴We also perform the k-means analyses using 3, 4, and 6 as the number of clusters. The results from these analyses are unsatisfactory, whereas the number of households in some clusters is relatively lower or the mean square errors are relatively higher, compared to the case in which 5 is used as the number of clusters. Moreover, the sum of the percentages of revenue contributions from the top two or three production activities accounts for more than 85% when the number of clusters is 5, reflecting better the reality of the households' occupation choices in the Thai rural areas.

measures that contain both the number of areas of activities and their relative volumes of turnover, such as the Herfindahl-Hirschman index (HHI), the Berry index, and the entropy measure of diversification (Mishra et al., 2010; McNamara & Weiss, 2000) are more superior to one-dimensional indices for reflecting rural diversification.

The general form of two-dimensional income diversification indices, developed by Hannah and Kay (1997) can be expressed as:

$$D = \left[\sum_{j=1}^n s_j^\alpha \right]^{1/(1-\alpha)} \quad \text{for } \alpha \geq 0 \text{ and } \alpha \neq 1$$

Where D is the diversification index, s_j is the share of the j^{th} income source, and n is the number of income sources. α represents the diversification parameter that determines the weight of the number of income sources versus the evenness in the distribution of income shares. The higher the α value, the greater the emphasis on the distribution of income shares. The upper limit value of the index of any α value is the number of income sources, and the lowest limit is one. The lower value occurs when a given household has only one source of income, the upper value occurs only if the shares are equal across all sources of income.

Specifically, when $\alpha = 2$, the index becomes $1/\sum_{j=1}^n s_j^2$ or the inverse of the Herfindahl-Hirschman index. For a rural household, the smaller the HHI, the greater the number of diversified income sources. In this study, the HHI of a household range from 0 to 1, whereas 0 refers to pure diversification and 1 represents the situation of a single concentrated income source.

3. Results and Discussion

3.1 Sample Characteristics

The descriptive statistics for the sample of 510 households are shown in Table 2. On average, the households in the sample derive 44.1% of their incomes from cultivation, followed by 30.1% from labor, and 11.5% from household business, revealing the top three main alternatives for occupations and income sources. The average numbers of males and females in the households are at a similar level of approximately 2 per household, while the average number of household members is about 4.

The average age of the household's head is 60.4, around the formal retirement age in Thailand, while the average length of the school year of the household's head is 5, indicating the reliance on elders with a low level of formal education to lead a household. The average education level, on average, is 6 years of school, the lowest education level in the household, on average, is 3 years of school; and the longest school year, on average, is 9. The first and the latter, however, may be underestimated due to the relocation of younger members in the households.

With regard to the profits obtained from production activities, the households in the sample generate roughly a 26% profit margin, on average, considering all income sources.

Cultivation, labor, and household businesses generate profit margins of 43.8%, 28.0%, and 14.5% on average, respectively, in line with the income contribution results mentioned above. The variations of the incomes and profits for these occupation groups, though, are quite high, indicating a varying ability of the households in the sample to generate income and profits.

3.2 Cluster description

The cluster analysis results in five different occupation pattern clusters, which are statistically significant from each other with regard to occupation choices, as shown in Table 3.

Cluster 1: The majority of the households in the sample are in this cluster (73.5%). The households in this group earn over 50% of their total incomes from productions on average from cultivation and about 40% from providing labor in both agricultural and non-agricultural sectors. The occupation pattern reflects well the nature of cultivation activities, which are normally seasonal.

Cluster 2: The households in this cluster (31 households, 6.1%) choose livestocking as their main production activity and earn 64.2% of their total incomes from production on average, while cultivation is another main income source (26.7%). The combination of the two main production activities chosen by the households in this cluster reflects the supplementary effect, whereas the outputs from cultivation can be normally used as animal feed while organic fertilizers used for cultivation can be made from animals manure.

Cluster 3: This is the smallest cluster, with only 13 households (2.5%). The households in this cluster earn about two-thirds of their total incomes from productions, on average from fish and shrimp farming. The rest is from cultivation (14.5%) and labor (11.6%).

Cluster 4: The main portion of the total income for the households in this cluster (64 households, 12.5%) derives from their household businesses (74.6% on average), such as rice mills, trading, and shops, supplemented by the incomes from labor (13.9%) and cultivation (8.5%).

Cluster 5: The most important source of income for the households in this group is the proceeds earned from the production activities (73.3%) not included in other clusters, while cultivation incomes account for 17.6% of the total incomes. This is the second- smallest cluster with only 27 households (5.3%).

3.3 Cluster comparison and characteristics

Key insights emerge from the cluster analysis. Firstly, the majority of the households in the sample derive their main incomes from cultivation and labor, with the weighted average revenue contributions of 44.13% and 31.54%, respectively, as shown in Table 3. The top two occupation categories are followed by household business, which accounted for only 11.52% of the total, while the rest is shared among livestocking, fish and shrimp farming, and other production activities. Considering all the households in the sample, the results indicate a low level of diversification of occupations and thus the sources of income. With the limited occupation and income diversification, the households in the sample may be vulnerable to external shocks or stressors which reduce their well-being and the growth of the rural economy in the long run.

One of the limiting factors for diversification is household size and composition. As presented in Table 4, except for Cluster 5, the number of adults as productive workforces is significantly and positively related to the likelihood of households engaging in a variety of occupations. For Cluster 5, on the other hand, with the presence of elders and one adult available to work, the households are likely to focus mainly on other production activities, such as crafting, rather than other physically demanding occupations. Similar findings are found by Dercon and Krishnan (1996) in Ethiopia, Tanzania et al. (2008) in India; Démurger, et al. (2010) in China; and Anderzén, et al. (2020) in Mexico.

A higher education level is also found to increase the likelihood of households engaging in local wage employment, as observed in Clusters 1, 3, and 4, with the highest average education level in households, in line with the results found by De Brauw et al. (2002) and Micevska and Rahut (2008). Nonetheless, the gender of the household's head does not significantly influence the households' decisions towards income diversification and occupation patterns, showing no evidence of gender bias among rural households in Thailand.

Secondly, there is a clear division of labor among the households in the sample in terms of the level of commercial orientation. Specifically, the majority of the households, except for Cluster 4, focus on generating production surplus to sell in markets and earn only minimal incomes in the household business category, showing no evidence of the income generated through value-added agricultural products. Limited access to advanced production technologies such as rice mills and a lack of vocational training in tradespeople discourage these households from adding value to their agricultural products and, in turn, pursue local wage employment as their alternative occupation instead. In addition, small household size in rural areas is another crucial constraint that causes a household to not be able to manage both upstream and downstream in production. These factors have also been shown to have a negative relationship with the degree of households participation in the output market by Martey et al. (2012), Muriithi and Matz (2015), Fredriksson et al. (2017), and Abdullah et al. (2019).

Thirdly, the median total revenues earned by the households in Clusters 2, 3, and 4 are statistically higher than those earned by the households in Clusters 1 and 5. Such a finding implies that the majority of the households (about 78.8%) in the sample earn relatively lower incomes than the rest. In other words, the households which choose cultivation and labor as the production activities earn relatively lower total incomes from production than those that choose livestocking, fish and shrimp farming, and household business as the production activities. With regard to profitability, the result indicates that the production activities chosen by the households in cluster 5 generate a relatively higher profit, a potential reason being that such activities require no investment but rather skills. The comparison results of the profit contribution from each occupation group among clusters indicate that the specialization of a household in their main chosen production activities is positively related to the profitability level generated from each production activity group.

Lastly, as shown in Table 4, the median HHI for all the households in the sample is as high as 0.77, and the median HHI in each cluster ranges from 0.53 - 0.86, whereas the HHI of Cluster 1 (0.86) is statistically higher than that of other clusters. Borrowing from the application of HHI for measuring the level of market concentration, a HHI value above 0.25 indicates a strong concentration. Figures 1 and 2, and the results shown in Table 4, all point in the same direction that the households in the sample are poor with regard to income diversification,

which may be due to an ineffective use of funds obtained from the Million Baht Village Fund Program and may give rise to the income disparity and other socio-economic problems in the areas.

4. Conclusion

In the current study, we examine the empirical taxonomy of occupation patterns of the Thai rural households and the contributing factors toward income diversification, with the aim of providing additional insights to the existing related literature, although the results are inconclusive, and the methodology is limited to traditional regression analysis.

Using the k-mean clustering analysis and cluster comparison tests on the sample of 510 households from the Townsend Thai Monthly Survey, we are able to cluster the households into five groups based on their choices of income-generating activities. We found that the extent of the income diversification for all the clusters is rather low, with most of them having one main income source from a specialized production activity and another source of income from local wage employment. Key limiting factors for income diversification include household size and composition; small households are less likely to diversify their incomes through new occupations, and younger members with a higher education level are more likely to relocate or engage in local wage employment rather than in other physically demanding production activities. The ability to extract profit from their choices of occupations, though, has a rather high potential due to their knowledge base as a key intangible resource.

Policy Recommendations

The findings in this study reveal that the degree of income diversification in the households of interest remains low. Hence, the problem of poverty and vulnerability to economic shocks among households persists and dampens the mitigation of the rural-urban disparity in the country. The results are in line with the impact assessments of the Million Baht Village Fund program, which found that the benefits in the forms of increased consumption and income growth were short-lived, despite the increase in overall credit and the creation of a multiplier effect (Kaboski & Townsend, 2005; Chandoevmit & Ashkul, 2008; Boonperm et al., 2012; Kaboski & Townsend, 2012).

To improve the effectiveness of such policy, occupation and income diversification must be one of the main objectives, and appropriate support in the forms of capacity building, technical assistance, and improved market access are needed. Given the findings that the majority of the Thai rural households earn relatively low incomes, there should also be motivation and reward schemes designed in the policy to motivate and educate members of the households to be willing to capitalize on traditional knowledge and innovate to increase the value of agricultural products. Moreover, the network effect within the village can be another crucial determinant that influences the households' decision to diversify, especially when there is a limitation in household size and composition, as observed in Thai rural households. A strong engagement in diversification at the village level can then increase the likelihood of households participating in any diversification activities.

Appendix

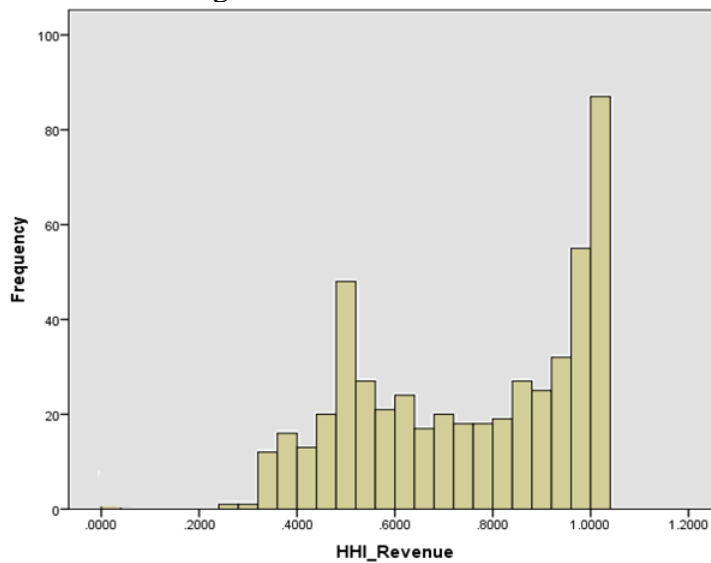
Table 1: Passive and Active Cluster Variables

Measurement	Description
<i>Active cluster variables</i>	
% of total revenues from cultivation	Revenues from rice, corn, orchard, and rotating crop cultivation
% of total revenues from livestocking	Revenues from livestock capital gain and livestock produce
% of total revenues from fish and shrimp farming	Revenues from fish and shrimp farming
% of total revenues from household business	Revenues from household businesses, e.g., rice mills, trading, and shops
% of total revenues from labor	Revenues from labor jobs, e.g., construction worker, factory worker, mechanic, administrative worker, and governmental officials
% of total revenues from other production activities	Revenues from other activities, e.g., crafting
<i>Passive cluster variables</i>	
<i>Demographics</i>	
Number of males	Number of males in household
Number of females	Number of females in household
Number of elders	Number of elders in household (> 60)
Number of adults	Number of adults in household (19 - 60)
Total member number	Number of household members who sleep in for at least 15 days per month
Age of household's head	Age of household's head
Gender of household's head	Male; Female
Education of household's head	Length of school year of household's head
Average education level in household	Average length of school year of all household members
Lowest education level in household	Lowest length of school year of all household members
Highest education level in household	Highest length of school year of all household members
<i>Revenues and Profits</i>	
Total revenues from production	Annual total revenues from all production activities
Profit margin from production	% profit from all production activities
Profit contribution from cultivation	% of total profits from production
Profit contribution from livestocking	% of total profits from production
Profit contribution from fish and shrimp farming	% of total profits from production

Measurement	Description
Profit contribution from household business	% of total profits from production
Profit contribution from labor	% of total profits from production
Profit contribution from other production activities	% of total profits from production

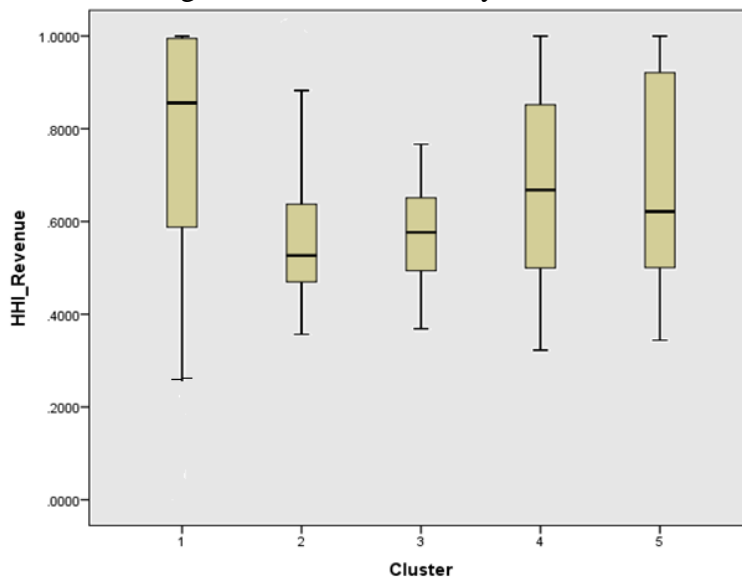
Source: The household composition and other demographic data are directly extracted from the survey. The household financial information is retrieved from the Household Financial Accounting: Aggregate Data, developed under the Thai Household Financial Accounting Data for Economic and Social Research Project.

Figure 1: Distribution of HHI



Source: Authors' calculations

Figure 2: HHI Box Plot by Cluster



Source: Authors' calculations

Table 2: Descriptive Statistics (N = 510)

Measurement	Mean	Median	Std. Dev.	Skewness	Kurtosis	Minimum	Maximum	25 th	50 th	75 th
<i>Active cluster variables</i>										
% of total revenues from cultivation	44.1%	37.3%	40.3%	0.21	-1.63	0.0%	100.0%	0.7%	37.3%	89.3%
% of total revenues from livestocking	4.7%	0.0%	16.2%	4.04	16.29	0.0%	100.0%	0.0%	0.0%	0.2%
% of total revenues from fish and shrimp farming	1.9%	0.0%	11.0%	6.27	39.37	0.0%	86.6%	0.0%	0.0%	0.0%
% of total revenues from household business	11.5%	0.0%	25.9%	2.28	3.92	0.0%	100.0%	0.0%	0.0%	0.7%
% of total revenues from labor	30.1%	11.0%	36.7%	0.91	-0.76	0.0%	100.0%	0.0%	11.0%	56.5%
% of total revenues from other production activities	5.9%	0.0%	17.6%	3.95	15.76	0.0%	100.0%	0.0%	0.0%	1.6%
<i>Passive cluster variables</i>										
Number of males	1.8	2.0	1.1	0.65	0.53	0	6	1	2	2
Number of females	2.0	2.0	1.2	1.08	1.57	0	7	1	2	3
Number of elders	0.7	0.0	0.8	0.67	-0.90	0	3	0	0	1
Number of adults	2.4	2.0	1.4	0.41	0.53	0	8	2	2	3
Number of kids	0.3	0.0	0.5	1.77	2.28	0	2	0	0	0
Total member number	3.8	4.0	1.8	0.68	0.77	1	11	2	4	5
Age of household's head	60.4	60.0	15.3	-1.07	3.43	0	95	52	60	72
Education of household's head	5	4	3	4.54	1.70	0	16	4	4	4
Average education level in household	6	5	2	1.11	2.60	0	16	4	5	7
Lowest education level in household	3	4	2	6.89	1.56	0	16	2	4	4
Highest education level in household	9	9	4	-0.96	0.15	0	16	4	9	12
Total revenues from production	712,229	188,573	4,222,404	456.26	20.83	12,568	93,279,574	59,696	188,573	576,979
Profit margin from production	25.9%	77.5%	897.3%	492.63	-22.05	-20022.9%	100.0%	60.3%	77.5%	89.2%
Profit contribution from cultivation	43.8%	31.3%	51.0%	1.32	13.46	-252.9%	477.6%	0.3%	31.3%	89.8%
Profit contribution from livestocking	4.5%	0.0%	30.7%	-2.64	66.38	-377.6%	267.5%	-0.1%	0.0%	0.0%
Profit contribution from fish and shrimp farming	1.6%	0.0%	9.3%	6.46	43.13	-4.5%	80.5%	0.0%	0.0%	0.0%
Profit contribution from household business	14.5%	0.0%	112.6%	21.24	469.31	0.0%	2499.5%	0.0%	0.0%	0.8%
Profit contribution from labor	28.0%	14.7%	114.2%	-19.01	405.82	-2402.9%	104.2%	0.0%	14.7%	64.9%
Profit contribution from other production activities	6.2%	0.0%	26.7%	5.31	60.11	-139.9%	352.9%	-0.1%	0.0%	1.7%

Source: The household composition and other demographic data are directly extracted from the survey. The household financial information is retrieved from the Household Financial Accounting: Aggregate Data, developed under the Thai Household Financial Accounting Data for Economic and Social Research Project

Table 3: Cluster Results and Description

% revenue contribution	Clusters					F-stat	Weighted average
	1	2	3	4	5		
Cultivation	54.60%	26.70%	14.54%	8.46%	17.63%	30.8***	44.13%
Livestocking	0.95%	64.16%	0.00%	0.30%	1.19%	849.9***	4.70%
Fish and shrimp farming	0.13%	0.01%	67.26%	0.96%	0.00%	1612.5***	1.93%
Household business	2.24%	3.71%	6.48%	74.61%	2.12%	722.8***	11.52%
Labor	39.32%	4.70%	11.56%	13.87%	5.75%	15.9***	31.54%
Other production activities	2.76%	0.72%	0.15%	1.79%	73.32%	599.3***	6.18%
N	375	31	13	64	27		
% of households	73.5%	6.1%	2.5%	12.5%	5.3%		
Description	Households that earn incomes mainly from cultivation and labor	Households that earn incomes mainly from livestocking and cultivation	Households that earn incomes mainly from fish and shrimp farming, cultivation, and labor	Households that earn incomes mainly from household businesses and labor	Households that earn incomes mainly from other production activities and cultivation		

Notes: N = 510; ANOVA F-statistics: ***p<0.01, **p<0.05, *p<0.1.

Source: Authors' calculations

Table 4: Cluster Comparison: Demographics, Revenue and Profits

Variable	Clusters					Max	Kruskal-Wallis Pearson χ^2
	1	2	3	4	5		
Demographics							
Number of males	2	2	2	2	1	1,2,3,4	18.8***
Number of females	2	2	3	2	1	3	12.3**
Number of elders	0	0	1	0	1	5	8.0*
Number of adults	2	3	4	2	1	3	33.9***
Total member number	4	4	5	4	2	3	22.9***
Age of household's head	61	53	56	58	73	5	20.7***
Gender of household's head							
Male (N = 315)	61.8%	58.6%	50.0%	62.9%	51.9%		1.8
Female (N = 195)	38.2%	41.4%	50.0%	37.1%	48.1%		
Education of household's head	4	4	4	4	4		7.5
Average education level in household	5	5.7	6.7	6.1	4	1,2,3,4	29.1***
Lowest education level in household	4	4	4	4	4		2.7
Highest education level in household	9	9	12	12	4	1,2,3,4	39.7***
Revenues and Profits							
Total revenues from production	140,000	984,432	2,027,460	687,693	36,870	2,3,4	116.4***
Profit from production	77.5%	85.2%	41.0%	49.0%	94.3%	5	104.3***
Profit contribution from cultivation	57.5%	22.3%	22.5%	1.9%	2.9%	1	56.1***
Profit contribution from livestocking	0.0%	69.6%	0.0%	0.0%	0.0%	2	78.6***
Profit contribution from fish and shrimp farming	0.0%	0.0%	55.5%	0.0%	0.0%	3	213.8***
Profit contribution from household business	0.0%	0.0%	0.0%	63.1%	0.0%	4	268.6***
Profit contribution from labor	25.6%	0.0%	8.0%	15.9%	0.0%	1	42.2***
Profit contribution from other production activities	0.0%	0.0%	0.0%	0.0%	80.9%	5	80.3***
Herfindahl-Hirschman index (HHI)	0.86	0.53	0.58	0.67	0.62	1	45.0***

Notes: N = 510, Pearson's χ^2 test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The median HHI for the whole sample (N = 510) is 0.77.

Source: The household composition and other demographic data are directly extracted from the survey. The household financial information is retrieved from the Household Financial Accounting: Aggregate Data, developed under the Thai Household Financial Accounting Data for Economic and Social Research Project.

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