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Economic Assessment of the Impact of Non-Agricultural Activities on Income from Crop and Livestock Production in Household Farms: The Case of Samarkand Region

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Abstract
This study investigates the impact of non-agricultural activities on the income generated from household farming in rural areas. The research is based on data from a social survey conducted among 1,843 household farms in the villages of Samarkand region. Using a Latent Class (Gaussian) model, household farms engaged in non-agricultural activities related to farming were classified into "green," "yellow," and "red" zones. Furthermore, to identify the relationship between household farm income and influencing variables, an ANOVA (Analysis of Variance) test was applied. To address issues of heterogeneity, multicollinearity, and to ensure robustness of the results, a Variance Inflation Factor (VIF) diagnostic test was conducted. In addition, a Tobit model was employed to economically assess the effect of innovations on income from household farming activities. The findings revealed that the development and/or establishment of non-agricultural activities linked to household farming in rural areas has a statistically significant impact at the 1 percent level (***p<.01). Based on the results, scientifically grounded recommendations have been developed to increase the income of household farms.
Keywords: household farming, crop production, livestock farming, non-agricultural activities, Latent Class (Gaussian) model

1. INTRODUCTION

Nearly 1.5 billion rural inhabitants worldwide rely on household farming for their livelihoods [1]. Income from agricultural and non-agricultural activities plays a vital role in meeting the growing needs of the population, reducing poverty, improving well-being [2], and ensuring food security [3]. Moreover, the development of non-agricultural activities related to agriculture contributes positively to sustainable agricultural growth by creating employment opportunities in rural areas, diversifying risks, and enhancing the resilience of farming systems [4].

The expansion of non-agricultural activities in rural areas such as storage, processing, distribution of agricultural products, agro-services, agro-tourism, and other related enterprises not only meets the needs of rural residents but also addresses the demand of urban populations in regional centers. However, the pace of development across rural economic sectors varies depending on agricultural growth, household income levels, infrastructure development, and the degree of urbanization.

For households with limited land resources, engagement in non-agricultural activities provides opportunities to secure higher income [5], improve family well-being, and, in turn, reduce poverty, hunger, and undernourishment [6]. Thus, increasing employment in rural non-agricultural activities becomes a crucial "driver" of local development. In particular, household participation in specific non-agricultural activities not only raises income and employment but also stimulates agricultural productivity, slows rural-to-urban migration, and enhances rural livelihoods [7].

According to Steven et al. [8], in agrarian economies, addressing low agricultural productivity requires attention to non-agricultural activities as complementary sources of income and resilience. Household income from farming often serves as initial capital for engaging in non-agricultural activities, thereby diversifying income and reinvesting in farming development. At the same time, the expansion of rural non-agricultural enterprises depends on land resources, as it may reduce the area available for cultivation. Nevertheless, research suggests that while such expansion affects landholding size, it does not significantly diminish income from household farming [9].

In household farming, family members involved in crop and livestock production primarily aim to meet their consumption needs and generate additional income. However, as Haggblade et al. [10] note, households with more family members not directly employed in agriculture but engaged in farming activities often rely on non-agricultural income to finance the purchase of consumer goods (both food and non-food). Therefore, strengthening non-agricultural activities—particularly diversified production and service sectors—can play an important role in boosting household farming income [11]. In remote rural areas, income from household farming is also a key source of investment in children's education, in addition to meeting basic consumption needs. Seasonal and permanent labor engagement in farming is common, and such activities significantly contribute to the growth of local economies.

In Uzbekistan, household farms account for 70.1 percent of agricultural production, underscoring their critical role in the national economy. Today, there are over 5 million household farms, which is 1.5 times higher than in 2000. Of the total 3.69 million hectares of land used in agriculture, 13 percent is cultivated by household farms. These farms not only contribute substantially to national food security but also serve as the main source of income for residents of remote rural areas. Compared to other forms of agricultural production, household farms demonstrate higher levels of efficiency and motivation [12]. Ensuring adequate food supply is essential for population growth, development, and healthy living [13]. Therefore, the systematic development of rural non-agricultural activities, especially service sectors supported by government financial mechanisms, remains an urgent task.

The main objective of this research is to analyze the development of non-agricultural activities related to household farming in rural areas and to provide an economic assessment of their impact on household income, thereby generating scientifically grounded conclusions.

2. RESEARCH MATERIALS AND METHODS

2.1. Research Materials

This study is based on data from a social survey conducted in 2025 across 1,843 household farms located in 14 districts of Samarkand region. The majority of household farm members participated in the survey. In cases where household heads had migrated abroad or to other regions for work, other family members were interviewed. The survey was carried out between March and May 2025.

In the region, there are a total of 1,098 neighborhood citizens' assemblies (*mahalla fuqarolar yig'ini*), of which 852 (77.6%) are located in rural districts. Among these, 97 assemblies (11.4%) were selected for the survey. The average distance between the surveyed households and the respective district centers was 10.9 km.

It is well known that a certain share of agricultural products produced in household farms is consumed by family members themselves. However, determining the exact value of these self-consumed products or the income derived from them is subject to uncertainty. To address this, the following approach was applied: respondents were asked, *"If agricultural products had not been produced in your household farm, how much would you have spent to purchase them?"*

Moreover, households located closer to non-agricultural activities related to farming tended to sell a larger share of their produce and generate higher income. This was particularly true for households cultivating vegetables in greenhouses and for those producing goods from high-yield livestock.

Based on this approach, the statistical description of household farm income revealed that the average income amounted to 18.23 million UZS, ranging from a minimum of 3.8 million UZS to a maximum of 42.5 million UZS (see Table 1).

Table 1. Statistical Description of the Variables

Indicators	Mean	Std. Dev.	Min	Max
Income from household farming (income), mln UZS	18.230	6.347	3.8	42.5
Distance to agricultural processing facility (processing), km	8.759	4.352	.6	15.5
Distance to agro-veterinary service (agro_veterinary), km	3.381	2.915	.4	9.6
Distance to fertilizer outlet (fertilizer_service), km	3.138	2.09	.2	4.5
Distance to feed outlet (feed_service), km	2.235	1.816	.2	3.4
Household farm land size (land), sotix*	6.922	3.138	4	12
Distance to district center (district_center), km	11.135	5.283	2	26
Primary occupation of household head (nonfarm), binary	0.543	0.502	0	1
Education level of household head (education), categorical	1.825	0.785	1	3
Gender of household head (male), binary	0.821	0.470	0	1
Age of household head (age), years	47.183	12.924	28	60

The average distance from household farms to non-agricultural activities associated with them, particularly to agricultural processing facilities, is 8.759 kilometers. The development of services related to agricultural product processing and/or storage in rural areas has a significant impact on agricultural production [14]. The average distance to agro-veterinary services is 3.381 kilometers, while mineral fertilizer and mixed-feed outlets are located at an average distance of 0.243 km and 1.146 km, respectively.

In household farming activities, the average crop cultivation area is 6.922 sotix. Among household landowners, 54.3% are primarily engaged in non-agricultural activities. Overall, 82.1% of household landowners are men.

2.2. Research Methodology

In this study, the economic assessment of non-agricultural activities directly affecting income from household farming was conducted by applying the Latent Class (Gaussian) Model [15]. For group formation, the following variables were used to represent non-agricultural activity: distance to agricultural processing facilities, distance to agro-veterinary services, and distance to mineral fertilizer and mixed-feed outlets.

When simultaneously assessing or analyzing the influence of multiple production or service sectors, econometric problems often arise. The Latent Class Model helps prevent such econometric issues by forming groups based on objective rather than subjective influences, thus determining the appropriate scale of variables [16].

For grouping the independent variables—namely, distance to agricultural processing facilities, distance to agro-veterinary services, and distance to mineral fertilizer and mixed-feed outlets—the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) [17,18] were applied. According to these criteria, the optimal number of groups is determined by the smallest values of AIC and BIC, and the variables are classified using the Latent Class Model. The newly formed latent group variable is expressed as a qualitative indicator (see Table 2).

Table 2. AIC and BIC Criterion Results for Grouping Variables Representing the General Characteristics in the Latent Class Model

Variables	AIC	BIC	Entropy
Establishment of Non-Agricultural Activities Serving Household Farms in Rural Areas	26564.58	26606.69	-
	25784.57	25853	0.467
	25554.39	25649.15	0.713
	25564.39	25685.47	0.691

Entropy was applied to determine the optimal number of groups. The entropy statistic measures the amount of uncertainty associated with the values of a random variable or the outcomes of random groupings, and in model analysis it evaluates how distinctly the identified groups differ from one another [19]. The closer the entropy value is to 1, the greater the clarity of group separation, meaning that the variables are more accurately classified within the group representing the general characteristics.

Overall, the Latent Class Analysis (LCA) model used in this study is expressed through the following formula:

$$P[Y_i = y_i | X_i = x_i] = \sum_{c=1}^{K} \gamma_{c_i}(X_i) \prod_{m=1}^{M} \prod_{r_m=1}^{R_m} \rho_{mr_m|c}^{I(y_m=r_m)}$$

In this model:

Y denotes the vector expression of the possible response forms of all respondents;

y represents the response pattern of an individual respondent;

X refers to the vector expression of all variables;

x represents the vector expression of an individual variable;

c denotes the groups;

γ is the probability of belonging to the *c*-th latent group;

r_m ($r_m = 1, 2, 3, \ldots, r_m$) represents the categories of a variable;

m (*m = 1, 2, 3,…, M*) is the indicator of the variable group;

the conditional probability of variable category (r_m) given membership in group (*c*) is expressed relative to the variable group indicator (*m*).

Based on the non-farm activities affecting household production—including the distance to agricultural processing facilities, agro-veterinary services, fertilizer outlets, and feed stores three distinct groups were formed (Figure 1).

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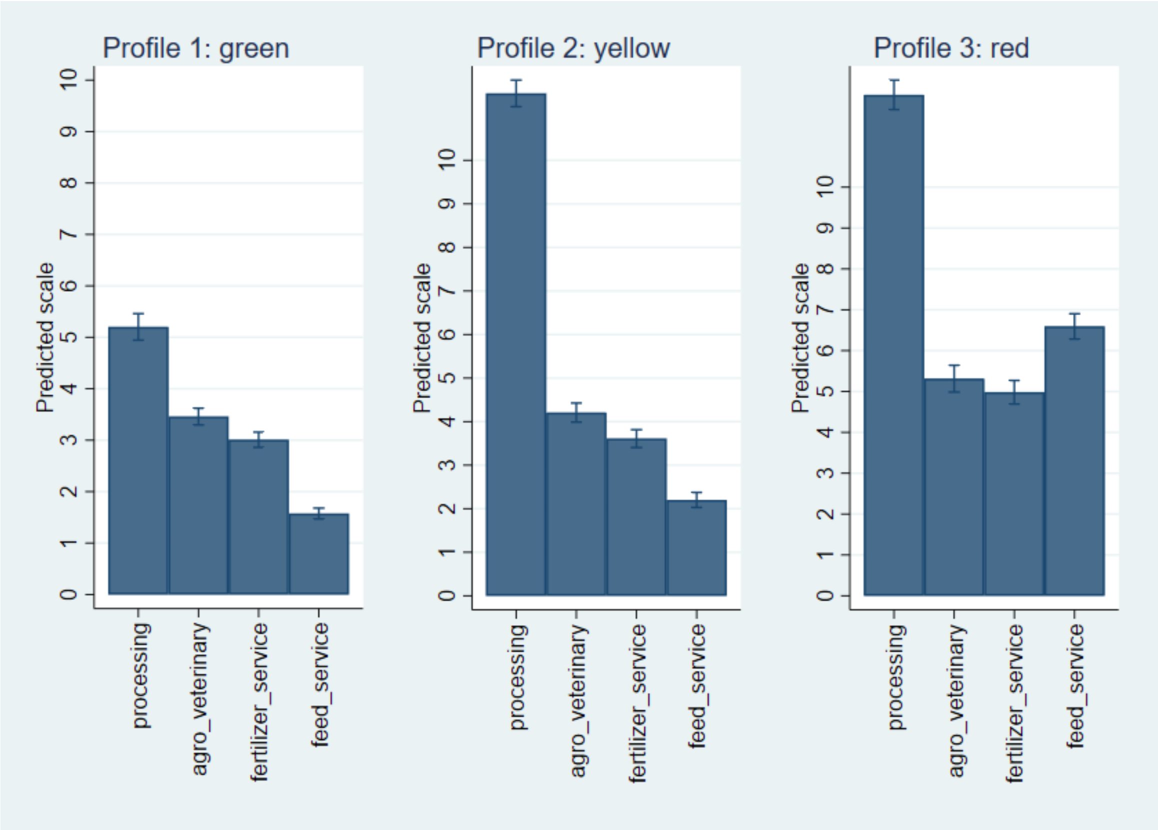

Figure 1. The state of non-farm activities related to household farming in rural areas

Household farms located close to agricultural processing facilities, agro-veterinary services, and mineral fertilizer and feed outlets were classified as "green" areas. These areas indicate well-developed non-farm activities that positively influence income from household farming. Areas with moderately developed non-farm activities were designated as "yellow" areas. In contrast, non-farm activities located far from household farms were classified as "red" areas. Overall, establishing or expanding non-farm activities in "red" areas may positively affect income derived from household farming.

To examine the relationship between income from household farming and the influencing factors, an ANOVA (Analysis of Variance) test was conducted (Table 3). The results show that income from household farming is statistically significantly related (at 1%, $p < 0.05$) to farm land size, distance to the district center, the household head's primary occupation, education level, gender, and age.

Table 3. ANOVA Test Analysis to Examine the Relationship Between Income from Household Farming and Independent Variables

Variables	F
Household farm land size (land)	47.70***
Distance to district center (district_center)	2.65***
Primary occupation of household head (nonfarm)	26.21***
Education level of household head (education)	123.92***
Gender of household head (male)	12.60***
Age of household head (age)	2.27***

**** p<.01, ** p<.05, * p<.1*

However, this effect does not explain whether it leads to an increase or decrease in income, nor does it indicate which independent variables influence other variables. An increase in standard errors among the variables may suggest that some independent variables are statistically insignificant. Consequently, the correlation of predictions among two or more independent variables, or strong relationships between them, can result in multicollinearity. To detect such cases and ensure the robustness of our results, a Variance Inflation Factor (VIF) diagnostic test was conducted (Table 4).

Table 4. Multicollinearity Analysis of the Variables

Variables	VIF	1/VIF
Group of non-farm activities serving household farms (nonfarm_class)	1.67	0.597
Education level of household head (education)	1.58	0.631
Primary occupation of household head (nonfarm)	1.45	0.688
Household farm land size (land)	1.06	0.946
Distance to district center (district_center)	1.26	0.795
Gender of household head (male)	1.10	0.910
Age of household head (age)	1.07	0.937
Mean VIF*	1,31	

*VIF test < 10

A high VIF value indicates that a correlated independent variable is strongly related to other variables in the model. However, according to the VIF test results obtained in this study, the mean VIF is 1.31, indicating no multicollinearity among the independent variables.

The age of household farm owners affects the income derived from household farming [20]. However, we cannot assert that reaching a specific age will necessarily increase or decrease income. In such cases, the age of household farm owners was included as a squared independent variable. Additionally, to evaluate the economic effect of the gender and education level of household farm owners on income, a new variable combining gender and education was constructed.

Since the dependent variable (*Y*) is measured as a quantitative indicator, a Tobit model was used to assess the extent to which independent variables (*X*) influence it, i.e., to analyze factors affecting income from household farming [21]. The Tobit model is particularly useful when the dependent variable is censored or has specific threshold values. The mathematical representation of this model is expressed as follows [22].

$$\rho_i^* = \beta_0 + \sum_{j=1}^{i} \beta_j x_{ij} + \varepsilon_i$$

$$\rho_i = \rho_i^* \quad 0 \le p_i^* \le 1$$

$$\rho_i = 0 \qquad p_i^* < 0$$

$$\rho_i = 1 \qquad p_i^* > 1$$

Where:

ρ_i^* - unobserved (error) variables;

ρ_i – dependent variable;

x_{ij} – independent variable;

β_0 – constant term;

β_j – vector of correlation coefficients;

$\varepsilon_i - \varepsilon_i \sim N(0, \sigma^2)$ normally distributed error term with mean 0 and variance.
Using this method, the economic impact of household farm income and its influencing factors was evaluated based on the analysis results obtained from the STATA-17 software package.

3. RESULTS OF THE ANALYSIS

The analysis results indicate that non-farm activities, particularly service-related sectors, influence income from household farming, including crop and livestock production (Table 5). In rural areas where non-farm activities are well developed classified as "green" areas household farm income is positively affected. However, as the location of the household farm shifts from a "green" area to a "yellow" area, and from a "yellow" area to a "red" area, income from household farming decreases by a coefficient of 0.602, which is statistically significant at the 1% level (***p < 0.01).

Our findings suggest that establishing or developing non-farm activities related to household farming in rural areas has a positive effect on income derived from household farming. In other words, developing non-farm activities in "yellow" and "red" areas is crucial for enhancing household farm income, as indicated by the analysis results.

Table 5. Economic Evaluation of Factors Affecting Income from Household Farming

Influencing Factors	Coef. (St.Err.) p-value
nonfarm_class	-.602 (.192)***
land	1.144 (.045)***
nonfarm	1.563 (.256)***
district_center	-.139 (.028)***
age	.942 (.167)***
age2	-.009 (.002)***
male	1.892 (.749)**
education	3.068 (.384)***
maly_education	-.561 (.41)
Constant	-21.584 (3.962)***
var(e	15.915

Mean dependent var	14.531	SD dependent var	5.458
Pseudo r-squared	0.100	Number of obs	1843
Chi-square	894.093	Prob > chi2	0.000
Akaike crit. (AIC)	8026.130	Bayesian crit. (BIC)	8084.034

**** p<.01, ** p<.05, * p<.1*

An increase of one sotikh in garden plot area raises income from garden activities by 1.114 units, which is statistically significant at the 1% level (*** p<.01). However, garden owners' engagement in non-farm agricultural activities and/or increases in rural population may reduce the effective plot size. In areas close to district centers, this natural reduction in plot area may occur without negatively affecting garden income. Specifically, each additional kilometer from the district center decreases income from garden activities by 0.139 units, a statistically significant effect at the 1% level (*** p<.01). This pattern can be attributed to the presence of organized non-farm agricultural services near district centers and/or the participation of garden owners in non-farm agricultural activities.

Consistent with prior studies, participation in non-farm agricultural activities positively influences income from garden activities. Overall, rural households can utilize income generated from non-farm agricultural activities as an investment to develop crop and livestock production or to adopt innovative practices within their garden plots.

The age of garden owners exhibits a non-linear effect on income: income initially increases with age but declines after a certain point. Both age-related effects are statistically significant at the 1% level (*** $p<.01$), with coefficients of 0.942 (age) and -0.009 (age^2), respectively. Male garden owners are associated with higher income levels compared to female owners.

Although garden owners whose primary occupation is non-farm agriculture may not fully participate in crop production activities, income from their non-farm agricultural involvement contributes positively to overall garden income. Engagement in non-farm agriculture also provides the opportunity to hire additional labor, further enhancing income. Notably, each additional unit of education among garden owners increases income by 3.068 units, statistically significant at the 1% level (*** $p<.01$). While higher education among male garden owners does not achieve statistical significance, it may exert a slight negative influence.

Overall, there are significant opportunities to increase income from garden activities in rural areas. The development and organization of non-farm agricultural services that support garden production are critical. Importantly, shifting from “green” to “yellow” and from “yellow” to “red” areas reduces garden income by 0.602 units.

While the efficiency of garden owners’ use of production resources cannot be conclusively determined, the potential for higher income from garden activities is closely associated with the availability of related non-farm agricultural services. Therefore, policy support is necessary to develop and organize non-farm agricultural activities in remote rural areas located far from district centers.

4. CONCLUSION

This study provides a comprehensive empirical analysis of the impact of non-farm agricultural activities on household farm income in the Samarkand region. By employing a robust methodological framework—including Latent Class (Gaussian) modeling for zoning, ANOVA for variance analysis, and Tobit models to assess innovation effects—the research confirms that the integration of non-agricultural services into rural farming structures has a statistically significant positive impact at the 1 percent level ($p < .01$).

The classification of household farms into "green," "yellow," and "red" zones offers a precise roadmap for regional intervention. These findings underscore the critical importance of targeted rural development policies that enhance access to non-farm services. By strategically supporting the expansion of such services in remote areas, policymakers can stimulate higher income from garden activities, encourage capital investment in crop and livestock production, and accelerate the adoption of innovative agricultural practices.

In conclusion, prioritizing policy interventions in "yellow" and "red" zones, where income growth is currently constrained by structural inefficiencies, is essential to reducing regional disparities. Scientifically grounded recommendations derived from this study suggest that fostering an integrated ecosystem of non-farm activities is not merely an auxiliary strategy but a primary driver for ensuring equitable economic development and enhancing the long-term resilience of rural farming communities.

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