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Off-Farm Employment and Agricultural Credit Fungibility Nexus in Rural Ghana

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Abstract: This study examined the impact of off-farm employment on rural household agriculture credit fungibility (CF) using survey data collected from four regions in Ghana; however, the study paid more attention to agriculture credit received from different sources. By employing the endogenous switching regression (ESR) model, we solved the endogenous issue of off-farm employment. The econometrics model result revealed that off-farm employment negatively influences the household's probability of practicing agriculture CF. Our results discovered the importance of off-farm employment on agriculture CF and recommended policy implications capable of alleviating agriculture CF.

Keywords: agriculture credit fungibility; farm investment; endogenous switching regression; rural farm households; Ghana

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1. Introduction

1.1. Background of the Study

The provision of food is likely to be the greatest challenge to humankind in the future due to the rapid growth of the global population; therefore, paying significant attention to key food producers (farmers) is essential. Due to low income and financial constraints, smallholder farmers find it tedious to increase their farm production, household income, and alleviate poverty [1–3]. Smallholder farmers become inefficient if there are insufficient funds for production [4]; however, the provision of agriculture credit to farmers allows smallholder farmers to increase their output and eventually improve their income [5,6].

The impact of credit accessibility on rural residents is uncertain. Some researchers argue that credit is significantly and positively related to agriculture production [7–10]. For example, Dong et al. [10] showed in a study conducted in China that agricultural productivity declines when farmers face credit constraints. Conversely, another group of researchers also suggest that credit, especially microcredit, adds no value to poor rural households; rather, it worsens their welfare, i.e., microcredit does not smooth consumption, alleviate poverty, and increase farm production in poor rural households [11–13]. According to Adams and Von Pischke [11] and Atakora [14], the negative impact of credit on rural households' livelihoods is associated with the misappropriation of funds due to financial literacy. The cause of the inverse relationship between agriculture credit and farm productivity can also be attributed to agriculture CF practices among farmers [15,16].

CF among farmers occurs when credit received for agriculture is used for non-agriculture purposes due to insufficient capital and credit rationing. CF is common in most developing countries where there may be larger family sizes but limited capital to cater to their needs. CF, as discussed previously, has a detrimental effect on agriculture production because credit for agriculture inputs (e.g., seeds or fertilizers), equipment, and land preparation to increase productivity are diverted for other non-agriculture purposes [17,18]. Previous researchers have revealed that substantial amounts of agriculture credit are used for other purposes such as festival celebrations [15,17], purchases for households' needs [19], and repayment of other loan defaults [20]. Based on previous studies, this study assumes that improvements in household income may reduce agriculture CF.

Income from off-farm employment helps increase rural household income [21]. As revealed in previous studies [22–25], off-farm employment appears to greatly help rural dwellers in numerous ways, including income inequality, food security, food expenditures, consumption of durable goods, land use efficiency, and intensity of agricultural production input uses. In this study, off-farm employment and rural development nexus literature is extended and we explore the effect of off-farm work on Ghanaian rural household agriculture CF. By looking at the potential benefit of agriculture credit and off-farm employment and the detrimental impact of CF on rural households' welfare and farm production, it is essential to examine the determinants of agriculture CF.

Of all the studies that examine the nexus between off-farm income and expenditure patterns of rural households, none—to the best of the authors' knowledge—have investigated the effects of off-farm employment on agriculture CF. CF is likely to limit the supply of agriculture products needed for sustainability. To reiterate, CF, has severe adverse effects on farm production and is less examined by researchers. This study fills this gap by using survey data collected from rural Ghana. The main objective of this study is to investigate the impact of off-farm employment agriculture CF. The contributions of this study are threefold. First, this is among the scant studies on agriculture CF; thus, the study expands the sparse literature on the subject and reveals critical policy implications that will enable policymakers to address the relationship between off-farm employment and agriculture CF. Second, we analyzed the heterogeneous effect of off-farm employment of agriculture CF based on gender and credit source status. Finally, using the ESR model, this study considers the potential endogeneity issues associated with off-farm work. The findings of this study will contribute significantly to the existing literature on agricultural credit in developing countries by providing new references for improving credit use efficiency and solving the problems of food and nutrition insecurity.

1.2. A Brief Overview of Agricultural Credit in Developing Countries

The impact of agriculture on developing countries economic growth is tremendous. In 2014, one-third of the global gross domestic product (GDP) was positively affected by agriculture [26], but numerous challenges keep poor farmers (predominately rural dwellers) in developing countries from being productive. For example, inadequate credit facilities, poor environmental policy, marketing, and high incidence of pests and diseases have been identified as some of the challenges faced by farmers in most developing countries [27,28]. The provision of agriculture credit is one of the essential elements to sustain these farmers as they fight against poverty [8,29]. Agriculture credit is a form of credit obtained from formal institutions (e.g., banks) and other informal institutions (e.g., money lenders) for agricultural production purposes [30,31]; thus, it helps farmers to alleviate most of their challenges and improve livelihood and farm productivity. This kind of credit can be in the short or long term, depending on the purpose of the credit used [12,30,32]. Long-term agriculture loans are mostly for the purchase of fixed assets such as lands, agriculture machinery, etc., while short-term loans are for variable inputs purchases such as seeds, fertilizers, etc. The studies of Mukherjee [33] in India, Jia et al. [34] in China, and Shoji et al. [35] in Sri Lanka revealed that the adoption of agricultural technologies and innovations increases if farmers can access agricultural credit. Similar findings were echoed in studies from sub-Saharan Africa [36–39].

While the benefit of agriculture credit is profound and could help farmers boost their production in developing nations, most institutional credits are given to large scale farmers, which leaves small scale farmers handicapped [29,30,40–43]. For instance, Lin et al. [43] showed that formal credit meant for poor rural households to improve their livelihood is often given to well-to-do rural households in China. Stiglitz and Weiss [29] and Yaron's [30] studies revealed that the imperfect rural financial market in most developing countries is influenced by the problems of asymmetric information (moral hazards and adverse selection) due to the high credit rationing and rejection among smallholder farmers by financial institutions. Moreover, the perception that farming is associated with high risks prevents both institutional and non-institutional lenders from supplying loans to farmers.

As discussed above, several interventions have been initiated by governments, policy-makers, and NGOs in many developing countries to improve the rural credit market to support agriculture through the provision of adequate and productive credit. For example, in 2005, to enhance capital accumulation in rural areas, the China Banking Regulatory Commission (CBRC) made the conditions of entry into the rural credit market more flexible for township/village banks, private loan companies, and rural mutual cooperatives. In Nepal, the Nepal Poverty Alleviation Fund helped small farmers and rural poor people access microcredit, assets, services, and training [44]. The government of Ghana paved the way for the increment of microfinance institutions (MFIs) in the 2000s in response to the market failure in the rural credit sector. The MFIs aimed to enhance credit to the rural areas since formal banks have failed to reach them. The story is similar for India, where the national government has launched several programs, including the social banking policy scheme, to improve rural dwellers' access to financial services (e.g., credit). In 2014, the world bank's Bank Group invested $8.3 billion in new commitments to agriculture with the aim of supporting rural farmers in their production to enhance food security and access to markets [26].

Given this background, the question is: do farmers fully utilize agriculture credit for its intended purposes? As discussed above, prior studies have argued that agriculture fungibility exists among farmers due to low household income for catering to the entirety of household expenses. Moreover, households tend to improve their income by engaging in off-farm activities. This study has determined whether off-farm activities, which are likely to enhance household income, can prevent or alleviate rural farm households' agriculture CF.

1.3. Conceptual Analysis

The new economics of labor migration theory indicate that household income is maximized through off-farm employment [45]. This study assumes that a rational peasant with economic interest would seek an off-farm job to increase household income, which may affect agriculture credit usage; therefore, this study tests whether off-farm employment significantly influences agriculture CF.

Off-farm employment may help reduce rural household agriculture CF. This is because off-farm activities, which enhance household income levels, facilitate better access to and use of agriculture credit. Having an additional source of income relaxes financial constraints and smooths household consumption expenditure [46,47], thereby enabling farmers to abolish or curtail agriculture CF. Farmers with access to an additional job may use their off-farm income to solve household financial issues (e.g., cost of unforeseen events, festivals, etc.) and utilize agriculture credit for agriculture purposes compared with those without it [48]. Increasing household income can enable farmers to reduce CF associated with lower potential agriculture production returns. Due to low income and capital, many farmers misappropriate agriculture funds [49]. Therefore, it is assumed that off-farm employment may positively influence household income and consumption, which will cause farmers to reduce agriculture CF.

Moreover, in terms of gender differences, the off-farm employment status of males and females may have a different effect on agriculture credit use behavior. Due to the perception that men are the main financial providers of household expenditures, rural households' expenditures may have a clear division between men and women; thus, from the perspective of gender, agriculture CF alleviation may be more effective among females with off-farm employment. Again, because of asymmetric information, the off-farm work status of formal and informal credit sources may also have different effects on agriculture credit use behavior.

As discussed above, it is obvious that off-farm employment may influence farmers' agriculture credit usage. Therefore, this study proposes three hypotheses about the influences of off-farm employment on rural households' agriculture CF:

H_1. *A rural household with off-farm employment is more likely to reduce agriculture CF.*

H_2. *Compared to males, the impact of females with off-farm employment on agriculture CF reduction is more effective.*

H_3. *Compared to formal sources, farmers who obtained credit from the informally sourced off-farm employment have a more effective impact on agriculture CF.*

2. Materials and Methods

2.1. Data

The data of this study consists of 505 farm households obtained from four regions in Ghana from March to June 2018 following a multi-stage sampling technique. Due to the purpose of the study, only households who were able to obtain credit were selected for the analysis. Four (4) regions, including the Savannah, Bono East, Central, and Eastern regions, were selected in stage one. These regions were selected because farming is predominately high in those regions [50]. In the next stage, we randomly selected a district from each selected region. The districts are: East Gonja, Atebubu Amantin, Ekumfi, and Kwahu Afram Plains in the Savannah, Bono East, Central, and Eastern regions, respectively. In stage three, we randomly chose three (3) communities from each selected district: Yankanjia, Akyenteteyi, and Salaga for East Gonja District; Asempanye, Dobidi Nkwanta, and Atebubu for Atebubu Amantin District; Essarkyir, Otuam, and Kontankore for Ekumfi District; and Tease, Bumpata, and Ahiatroga for Kwahu Afram Plains District.

Information from the Ghana Living Standard Survey 7 (GLSS 7) shows that about 44% of rural residents have access to financial services (GSS, 2019) [51]. We estimated our sample size based on the information by following the estimation method proposed by Kotrlik et al. (2001) [52]; thus, assuming a 95% confidence level and 5% margin of error, the total number of respondents was estimated as follows:

$$n = \frac{S^2(x)(y)}{(E)^2} = \frac{1.96^2(0.44)(0.56)}{0.05^2} = 378 \quad (1)$$

where $n,\ x,\ and\ y$ refer to sample size, the proportion of the population having access to financial services, and the proportion of the population having no access to financial services. S equals the number of standard deviations for a chosen confidence interval level E = the error margin allowed. For fair distribution and the hope that some of the questionnaires will not be submitted, the sample size was increased to 520. Around 30–45 farm households were selected randomly, resulting to 520 farmers. However, after screening the data, 505 farmers were used for the study analysis.

The data collection of rural farm households was conducted using interview schedules and structured questionnaires. This was done after pretesting the questionnaires. We considered well trained enumerators to assist us to do the interview. In this study, farmers who have obtained credit for agriculture purposes were interviewed. Diverse information gathered from the questionnaires for the survey includes: household socioeconomic and demographic characteristics, agriculture credit (credit from formal (e.g., banks, microfinance) and informal (e.g., relatives/friends, money lenders)), credit fungibility (CF), and other various variables that will help achieve the study's aim. We used STATA 14 and SPSS 26 to edit and code our data.

2.2. Analytical Techniques

There are two categories of CF, financial substitution and real expenditure substitution, that have detrimental effects on credit obtained to enhance agricultural productivity [53]. The process where the borrowers consider credit for farming purposes and non-agro credit as integrated funds is known as financial substitution. In contrast, real expenditure substitution occurs when borrowers use credit for agricultural purposes to accomplish alternative objectives; the latter is the concern of this study. Following Saqib et al. [16] and Hussain and Thapa [15], agriculture CF was analyzed as:

$$\mathrm{CF} = \frac{C_f}{\hat{C}_t} \; or \; in \; percentage \; \frac{C_f}{\hat{C}_t} \times 100 \tag{2}$$

where CF represents the share of agriculture credit fungibility. C_f and $\hat{C}_t$ represent the annual amount of credit used for non-agriculture activities and the annual amount of credit obtained from a different source, respectively.

After the deduction of fungible credit, the balance, known as credit margin of farm investment, is specified as follows:

$$C_m = \left(\hat{C}_t - C_f\right) \tag{3}$$

$$C_{mip} = \frac{C_m}{\hat{C}_t} \; or \; in \; percentage \; \frac{C_m}{\hat{C}_t} \times 100 \tag{4}$$

where C_m refers to the annual amount of credit margin of farm investment and C_{mip} is the share of credit margin of farm investment.

2.3. Variable Selection

This study examines the influential factors of agriculture CF; therefore, the dependent variable becomes the share of agriculture credit used for non-agricultural purposes in total credit received by the household (see Equation (1)). Concerning the control variables, many studies have revealed that householder/household, farm, and some social characteristics serve as determinants of agriculture CF. For example, Hussain and Thapa [15] explored the fungibility of smallholders agriculture credit by controlling householder factors (e.g., age, sex, and education level), household characteristics (e.g., household size, household assets), farm characteristics (e.g., farm size, labors) and other social characteristics (e.g., off-farm employment, source of credit). Similarly, the studies of [16,32] also controlled those variables. Based on prior studies, this study will also explore householder and household characteristics (e.g., age, gender, education level, household size, and household members with chronic disease), farm characteristics (e.g., years of farming experience, farm size), and other social characteristics (e.g., non-farm employment) which are considered to influence agriculture CF. The model variables and summary statistics are described in Table 1.

2.4. Empirical Model

This study investigates rural farm households in Ghana's causes of agriculture CF. We analyzed how off-farm employment may influence agriculture CF. Since off-farm employment is self-selected, i.e., a farmer decides to secure an off-farm job or not, it is essential to consider the issue of potential endogeneity associated with it. Using an ordinary least square (OLS) makes the estimated result biased and inconsistent because of the selection bias [54,55]; therefore, econometrics models, including Propensity score matching (PSM), regression adjustment (RA), inverse probability weighted with regression adjustment (IPWRA), and endogenous switching regression (ESR) are appropriate for this study's estimations. Among these models, we selected the ERS model because it takes observed and unobserved factors into account when the issue of endogeneity is being addressed [56,57]. The other remaining models ignore the unobserved factors (e.g., inner motivation and risk traits) associated with the variables of interest [58,59]. Dealing with the unobserved factors prevents inconsistency in our estimation; thus, the ESR model becomes suitable for this study's analysis.

Table 1. Definitions and data description of the variables in the model.

Variables	Definitions and Assignment	Mean	S.D
Agriculture CF proportion	The share of household's agriculture CF	0.42	0.25
Agriculture CF amount (GH¢)	Amount of fungible agriculture credit	600.35	637.17
Margin of farm Investment amount (GH¢)	Amount of agriculture credit on farm investment	826.05	603.11
Margin of farm Investment amount proportion	The share of household's margin of farm investment	0.58	0.25
Credit received (GH¢)	Amount of agriculture credit received	1426.40	1029.73
Off-farm employment	Whether the respondent had any off-farm employment (1 = yes, 0 = otherwise)	0.52	0.50
Gender	Whether the respondent is a male (1 = yes, 0 = otherwise)	0.70	0.46
Marrital Status	Whether the respondent is married (1 = yes; 0 otherwise)	0.63	0.54
Age	Respondent age (numbers)	41.72	12.20
Education	Whether the respondent had high school education (1 = yes; 0 otherwise)	0.43	0.49
Remittances	Whether the respondent has received remittances in past years (1 = yes; 0 otherwise)	0.46	0.49
Household Size	Number of members in the household(number)	4.68	1.97
Credit source	Whether the respondent obtained credit from formal source (1 = yes; 0 otherwise)	0.44	0.47
Loan payback period	Whether the respondents feel that the loan payback period is long (1 = yes; 0 otherwise)	0.33	0.47
Farm size	Respondent farm size (in acres)	3.34	1.87
Social network	Whether the respondent has a link with relatives in the city; 0 otherwise	0.57	0.49

Source: Survey results, 2018. 1 USD = 4.9 Ghana cedis (GH¢). CF = credit fungibility.

The ESR model comes with 3 equations: one treatment selection equation and two separate outcome equations. The outcome equations are separated based on (1) farmers with off-farm work and (2) farmers without off-farm work. The outcome equations are known to be linear, while the treatment equation takes a dummy format; therefore, a probit model can be used to estimate the treatment (off-farm employment) variable. The linear equation, which is predicted by some attributes of the farmer/household and some other characteristics can be expressed as:

$$I_i^* = \gamma'_i Z + \alpha Y_i + \varepsilon_i \tag{5}$$

$$Y_i^* = \beta X_i + \mu_i \quad Y_i = \begin{cases} 1 \text{ if, } Y_i^* > 0 \\ 0 \text{ if, otherwise} \end{cases} \tag{6}$$

where I_i^* is agriculture CF; thus, the share of agriculture CF a year ago. γ'_i and Y_i are the exogeneous (e.g., gender, age, and education) and endogenous (off-farm employment which is equal to one (1) if the farmer has an off-farm job and zero (0) otherwise) variables, respectively. Y_i^* is the probability of off-farm engagement and a latent indicator. α, β, and Z are the vector of parameters to be estimated while μ_i and ε_i denote the random disturbance terms. The variables in X_i are the same as those in γ'_i; however, at least one variable in X_i should be exempted from γ'_i. That variable is called an instrumental variable. A variable that does not correlate with the outcome indicator (agriculture CF) is straightforward because of the treatment indicator (off-farm employment). Following previous studies [24,60], the variable social network (whether the respondent has a link with relatives in the city who can assist him/her in finding a job) was used as an instrument in X_i in Equation (6). This instrument was chosen because it is expected to affect a household member's decision to find off-farm employment (treatment) but does not directly affect the agriculture CF (outcome) status. For example, Fink and Masiye [61] revealed that household members with friends and relatives working in the city are more likely to find off-farm jobs through social networks with household migrants, which may help them increase household income, thereby influencing CF decision when compared to their counterparts with no such advantages. This implies that the instrument can only influence the outcome (CF) through the treatment (off-farm employment). The IV validity can be seen in the Appendix A, i.e., Table A2.

The two aforementioned separate outcome equations follow the expression below. The expressions are divided into regimes [62]:

$$\begin{aligned} &\text{Regime 1 (off-farm employment) } I_{1i} = \gamma_{1i} Z_1 + \varepsilon_{1i}, \text{ if } Y_i = 1 \\ &\text{Regime 2 (non-off-farm employment) } I_{2i} = \gamma_{2i} Z_2 + \varepsilon_{2i}, \text{ if } Y_i = 0 \end{aligned} \tag{7}$$

where agriculture CF for a farmer with off-farm work is represented by I_{1i} and I_{2i} refers to agriculture CF for a farmer without off-farm work. (γ_{1i} and γ_{2i}), (Z_1 and Z_2), and (ε_{1i} and ε_{2i}) are the explanatory variables, vector of parameters to be calculated, and error terms, respectively, for farmers with off-farm employment and those without off-farm employment.

These indicators, μ_i, ε_{1i}, and ε_{2i}, are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\text{cov}(\mu_i, \varepsilon_1, \varepsilon_2) = \begin{bmatrix} \sigma^2_1 & \sigma_{12} & \sigma_{1\mu} \\ \sigma_{12} & \sigma^2_2 & \sigma_{2\mu} \\ \sigma_{1\mu} & \sigma_{2\mu} & \sigma^2_\mu \end{bmatrix} \tag{8}$$

where the disturbance term's (ε_{1i} and ε_{2i} in Equation (7)) variance is represented by σ^2_1 and σ^2_2 and σ^2_μ takes on the variance of the error term, μ_i, in Equation (5). Likewise, σ_{12}, $\sigma_{1\mu}$, and $\sigma_{2\mu}$ are the covariance of ε_{1i} and ε_{2i}, ε_{1i} and μ_i, and ε_{2i} and μ_i, respectively. The model assumes that $\sigma^2_\mu = 1$ because β is can be estimated only up to a scale factor [63,64]. To solve the selection bias issue in the ESR model, an inverse mills ratio (IMR) (λ_1 and λ_2) and the covariance term ($\sigma_{1\mu}$ and $\sigma_{2\mu}$) are calculated. The estimated IMR and covariance term is incorporated in Equation (7). The new Equation (7) is expressed as:

$$\begin{aligned} E(I_{1i} | Y_i = 1) &= \gamma_{1i} Z_1 + \sigma_{1\mu} \lambda_1 \\ E(I_{2i} | Y_i = 1) &= \gamma_{2i} Z_2 + \sigma_{2\mu} \lambda_2 \end{aligned} \tag{9}$$

The best way to prevent inconsistent standard error in this current model is by simultaneously estimating both the selection and outcome equations using a full information maximum likelihood (FIML) method [62,63]. $\rho_1 = \text{corr}(\mu_i, \varepsilon_{1i})$ and $\rho_2 = \text{corr}(\mu_i, \varepsilon_{2i})$ are also calculated when the FIML approach is applied. The moment ρ_1 and ρ_2 become non-zero indicates that a selection bias resulting from unobservable factors exists. As this study has indicated, the treatment effect of off-farm jobs on agriculture CF is of interest; thus, we need to estimate the average treatment effects on the treated (ATT) and average treatment effects on the untreated (ATU). The following steps are considered:

Farmers with off-farm work:

$$E(I_{1i} | Y_i = 1) = \gamma_{1i} Z_1 + \sigma_{1\mu} \lambda_1 \tag{10a}$$

Farmer with off-farm work had they not secured off-farm employment:

$$E(I_{2i} | Y_i = 1) = \gamma_{2i} Z_2 + \sigma_{2\mu} \lambda_1 \tag{10b}$$

Farmer without off-farm work had they secured off-farm employment:

$$E(I_{1i} | Y_i = 0) = \gamma_{1i} Z_1 + \sigma_{1\mu} \lambda_2 \tag{11a}$$

Farmer without off-farm work had they not secured off-farm employment:

$$E(I_{2i}|Y_i = 0) = \gamma_{2i}Z_2 + \sigma_{2\mu}\lambda_2 \tag{11b}$$

The above expressions (the expected outcomes) can be utilized for consistent treatment effect, ATT and ATU, derivation while considering unobserved and observed heterogeneity [65].

$$ATT = E(I_{1i}|Y_i = 1) - E(I_{2i}|Y_i = 1) = \gamma(Z_1 - Z_2) + \lambda_1(\sigma_{1\mu} - \sigma_{2\mu}) \tag{12}$$

$$ATU = E(I_{1i}|Y_i = 0) - E(I_{2i}|Y_i = 0) = \gamma(Z_1 - Z_2) + \lambda_2(\sigma_{1\mu} - \sigma_{2\mu}) \tag{13}$$

3. Results and Discussions

3.1. Descriptive Analysis

The key variables of interest of the study are presented in Table 1. The data depicts the mean agriculture credit received by respondents as GH¢1426.40, with 44% obtaining their credit from a formal source. Only 33% of the farmers believe that the loan payback period is long. While agriculture CF proportion and amount are 0.42 and GH¢600.35, respectively, the credit margin of farm investment proportion and its amount are 0.58 and 826.05, respectively; this indicates that there is CF among rural farm households. Approximately 52% of the heads of households have off-farm employment, 70% of the respondents are males, and 63% of the respondents are married. The average household size is 5 members, and the average head of household is approximately 42 years old. The average farm size is 3.34 acres. Moreover, only 43% of respondents have a high school education or above, while about 46% of respondents received remittances in the last 12 months. Finally, 57% of the sample have a link with relatives in the city.

To reiterate, based on Figure 1 (the heatmap), we established a matrix of Pearson's correlation coefficients for the model variables. The colors are used to represent the values in the correlation matrix; thus, the deeper the color, the bigger the correlation coefficient's absolute value, and vice versa. The map depicts lighter colors in most areas, and none of the correlation coefficients are above 0.46, which suggests that multi-collinearity is not an issue. Off-farm employment and agriculture CF also show a negative correlation. This implies that off-farm employment reduces agriculture CF. Figure 1 does not give a clear understanding of the quantitative connection between the variables because the correlation between the outcome variable and the key variable does not consider unobserved factors; therefore, an econometric model such as IV Tobit becomes suitable for the study's quantitative analysis.

3.2. Difference between Means of Farmers with and without Off-Farm Employment Annual Credit Received, Agriculture CF and Credit Margin of Farm Investment Status

Table 2 also shows the average differences between the annual average amount of credit received from different sources (GH¢1426.4) used for non-farm purposes (GH¢600.3) and farm investments (GH¢826.1) by farmers. The table also reveals the differences between the means of farmers with and without off-farm employment, annual credit received, agriculture CF, and the credit margin of farm investment status; thus, model (1) is for the overall results and model (2) and (3) are for the gender compositions. The average annual credit received is GH¢1305.2 for farmers with an off-farm job and GH¢1552 for those without an off-farm job. The difference is significant at 1%. The reason could be that farmers with an off-farm job may increase their income from their off-farm activity and may not need to borrow [66]; also, the average annual amounts of agriculture CF and credit margin for farm investment are GH¢422.3 and GH¢882.9, respectively, for farmers with an off-farm job, and GH¢784.7 and GH¢767.3, respectively, for those without an off-farm job. The percentage of agriculture CF among farmers without an off-farm job was much greater than those with off-farm jobs. The overall results (model 1) are similar to models (2)–(3), i.e., gender composition results. A female or male with an off-farm job tends to reduce agriculture CF; thus, the descriptive results seem to indicate that off-farm employment may be key to understanding agriculture CF. These findings do not reflect the impact of off-farm jobs on agriculture CF, but to do point to the fact that there is selection bias in the sample; therefore, we employed the IV Tobit estimation model to eliminate observable and unobservable biases in the sample and provide a consistent estimate of the impact.

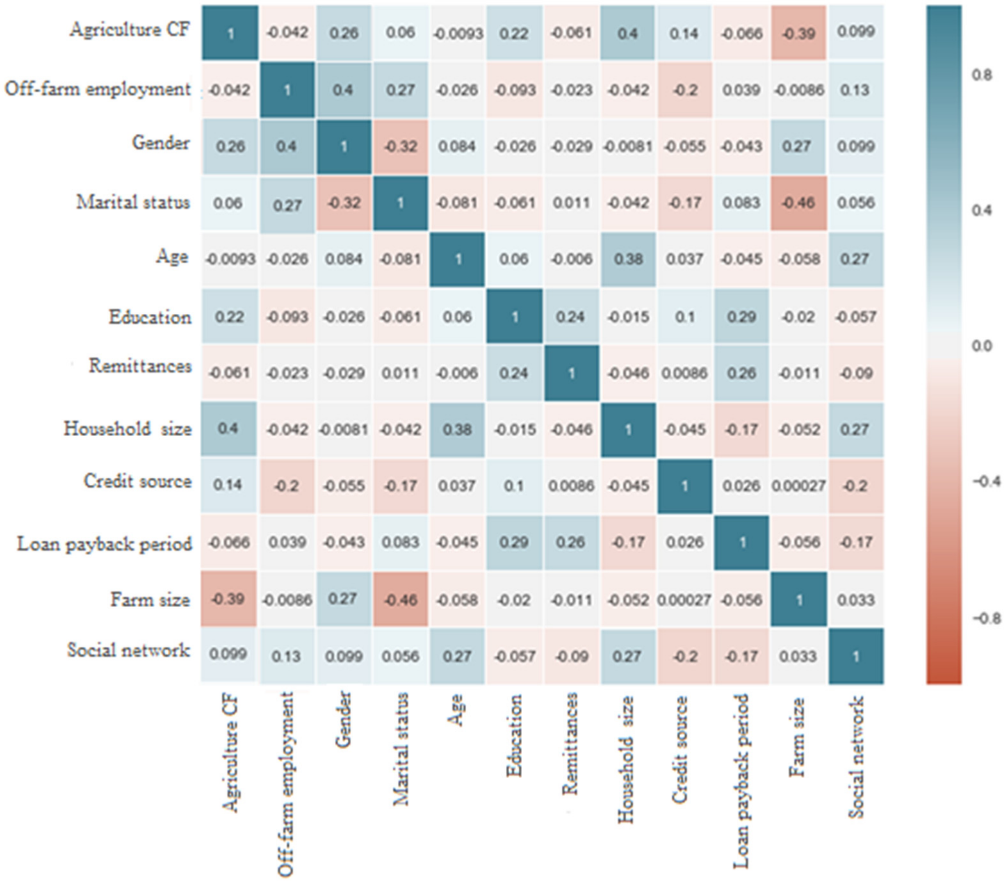

Figure 1. The heatmap for the matrix of Pearson's correlation coefficients.

Table 2. Differences between means of farmers with and without off-farm employment credit fungibility and credit margin of farm investment status.

Variables	Pool Sample	Farmers with Off-Farm Job Model 1			Male Farmers with Off-Farm Job Model 2			Female Farmers with Off-Farm Job Model 3		
	Total	Yes	No	Diff	Yes	No	Diff	Yes	No	Diff
Annual amount of credit received by farmers ($\hat{C}_t$)	1426.4 (1029.7)	1305.2 (968.6)	1552.0 (1076.8)	246.8 ***	1381.8 (983.4)	1452.1 (1055.9)	70.3	1186.1 (955.3)	1469 (1037.5)	282.9 **
Annual amount of credit used for non-farm purpose (C_f)	600.3 (637.1)	422.3 (515.0)	784.7 (697.2)	362.4 ***	473.7 (558.9)	673.3 (668.1)	199.6 ***	357 (446.9)	643.4 (656.2)	286.4 ***
Annual amount of credit margin for farm investment (C_m)	826.1 (603.1)	882.9 (618.4)	767.3 (582.1)	−115.6 ***	908.13 (604.53)	778.79 (598.03)	−129.35 **	829.1 (643.3)	825.5 (596.4)	−3.6
Agriculture CF (%) (CF)	42.10	32.4	50.4		34.3	46.4		30.1	43.8	
Credit margin of farm investment (%) (C_{mip})	57.90	67.6	49.4		65.7	53.6		69.9	56.2	

Source: Survey results, 2018. Note: *** $p < 0.01$, ** $p < 0.05$. Standard errors in parentheses.

3.3. Empirical Results

3.3.1. The Determinants of Off-Farm Employment

The determinants of off-farm employment are presented in Table A1 in the Appendix A. The results reveal that a social network (instrumental variable), education, remittances, and loan payback period positively and significantly influence the likelihood of securing an off-farm job. In contrast, age square has an inverse relationship with off-farm employment.

Gender is positive and significant, implying that male farmers are more likely to participate in off-farm employment. In developing countries like Ghana, male financial responsibilities are higher than those of their female counterparts; therefore, males are more likely to seek off-farm jobs [67]. The study is consistent with the findings of Liu et al. [68]. The age square variable's significant negative effect implies that a U-shaped relationship exists between age and off-farm employment; that is, younger farmers may choose to engage in off-farm jobs, as they get older, their willingness to participate in off-farm jobs is reduced. The positive marginal effect of the social network variable indicates that farmers who have connections with relatives in the city are more likely to secure an off-farm job. This study confirms the study of Ma et al. [24] in China, who reported that farmers having relatives in the city have a higher likelihood of securing an off-farm job than their counterparts without such connections. In addition, the education level of the respondents revealed that an increase in education could increase the chance of obtaining an off-farm job. Education may improve the farmers' understanding of income diversification sources; hence, they will be more likely to take an additional job to improve household income. These findings are in line with Leng et al's [69] study.

Moreover, the remittances variable's positive marginal effect suggests that as farmers receive remittances, they are more likely to engage in off-farm activities. Remittances boost total household income and empower individuals to create businesses [23].

3.3.2. The Impact of Off-Farm Employment on Agriculture Credit Fungibility (CF)

The results of the ESR models are presented in Table A1 in the Appendix A. As expected, the social network's (IV) impact on off-farm employment is statistically significant. Table A1's ρ_1 is significant, implying that off-farm employment is not random; thus, selection bias is an issue. Therefore, the ESR model becomes suitable for the analysis. The Wald tests for joint independence of the equation have a significant sign at the 1% level. This suggests that rejecting the null hypothesis of no correlation between the treatment error μ_i and the outcome errors (ε_{1i} and ε_{2i}) is acceptable.

The outcome variables results are also depicted in Table A1. However, we focused mainly on the treatment effect (Table 3) rather than Table A1 to explain how off-farm work impacts agriculture CF. The results in Table A1 give little understanding of how off-farm employment influences agriculture CF, but the treatment effect result report the specific impact of farm employment on agriculture CF.

Table 3. The impact of off-farm employment on agriculture credit fungibility.

Mean Share of Agriculture CF (ESR)			**Treatment Effect**	***t*-Value**
	Off-Farm Employment	**Non-Off-Farm Employment**		
Off-farm employment	0.3013	0.4825	ATT = −0.1812	−7.94 ***
Non-off-farm employment	0.4118	0.5322	ATU = −0.1204	−3.91 ***
Heterogeneity effects	−0.1105	−0.0497	−0.0608	
Mean Share of Agriculture CF (PSM [a])				
Off-farm employment	0.3148	0.4209	ATT = −0.1061	−11.67 ***

Source: Survey results, 2018. Note: *** $p < 0.01$. [a] Nearest neighbor matching techniques is used.

The ATT is shown in Table 3. As shown in Table 3, the expected share of agriculture CF for farmers who engage in off-farm jobs is 0.3013, and the expected share of agriculture CF for farmers without off-farm jobs who had secured an off-farm job is 0.4825. To reiterate, the expected share of agriculture CF for farmers with no off-farm job if they had secured an off-farm job is 0.4118, and the expected share of agriculture CF for farmers with off-farm work if had they not secured any off-farm work is 0.5322. As revealed in Table 3, the ATT of off-farm work on the share of agriculture CF is −0.1812, suggesting a −0.1812 reduction in the share of agriculture CF for an average farmer who engages in off-farm activities over a farmer that had no off-farm activity. Further, the heterogeneous effect result indicates that farmers who secure off-farm employment reduce agriculture CF practices more than their counterparts without off-farm employment. These findings have similarities with those of prior studies [15,48,70,71] that reported that off-farm employment increases household income, which in turn can be used for non-agriculture activities. More accurately, Ref. [15] argued that higher earnings from non-farming activities might enable farmers to use less or no agriculture credit for non-agricultural purposes such as food, clothing, health, and other daily household needs; thus, agriculture credit will be used for its purposes, which increases production to improve food security.

The study further analyzed the agriculture CF impact of off-farm employment using the PSM approach for robustness check purposes. As shown in the lower part of Table 3, the PSM estimated ATT is −0.1061, indicating that an average farmer who engages in off-farm activities is more likely to reduce the share of agriculture CF by 0.1061 than farmers without off-farm jobs. The two models (ESR and PSM) show that off-farm employment reduces the share of agriculture CF; however, the ATT of the PSM approach is minimal compared with the ESR. The inability of the PSM model to recognize unobserved factors could be the reason for its small ATT estimation.

3.3.3. Additional Analysis

The heterogeneous results of this study are presented in Table 4 for gender status and sources of credit level to gain further insights into the impact of off-farm work on agriculture CF. As previously discussed in the conceptual analysis section, the share of agriculture CF effect of off-farm employment might be different under these two variables. It is vital to heterogeneously analyze the off-farm job and agriculture CF nexus based on the farmers' credit source and gender status.

Table 4. Impact of off-farm employment on agriculture CF by gender status and source of credit.

Variables		**The Share of Agriculture CF Mean**			
		Off-Farm Employment	**Non-Off-Farm Employment**	**ATT_{ESR}**	***t*-Value**
Source of credit	Formal	0.3788 (0.0124)	0.5007 (0.0319)	−0.1219	−12.15 ***
	Informal	0.3021 (0.1120)	0.4819 (0.0455)	−0.1798	−8.81 ***
Gender	Male	0.4570 (0.0662)	0.5144 (0.2491)	−0.0574	−16.13 ***
	Female	0.3429 (1.3821)	0.4703 (0.0574)	−0.1274	−7.41 ***

Source: Survey results, 2018. Note: *** $p < 0.01$, Standard errors in parentheses.

The results show that off-farm employment positively contributes to reducing agriculture CF even with the farmers' credit source and gender status. The ATT values for females and males with off-farm employment are particularly negative; thus, there is evidence that a female and a male with off-farm employment can help reduce agriculture CF (Table 4). A male with an off-farm employment ATT value (−0.0574) is less than that of the female with off-farm employment ATT value (−0.1274), which suggests that a female with off-farm employment has a more significant impact on agriculture CF than a male. In summary, the impact of a female with off-farm employment on agriculture CF is clear. A possible explanation is that most males are recognized as the main providers of households; thus, they have more substantial financial obligations than females and are tempted to practice agriculture CF [72]. Although income from off-farm work may help reduce CF, its impact on males' agriculture CF practices may be small. This provides evidence for H_2.

In regard to the farmers' source of credit level's heterogeneous result, the estimates suggest that off-farm work decreases agriculture CF for farmers who obtained formal and informal credit. However, the ATT value for farmers with off-farm employment who received credit from the informal source (−0.1798) is greater than their counterparts whose sources of credit were from the formal sector (−0.1219). An indication that farmers with off-farm work who receive loans from the informal sector are less likely to misappropriate the loan obtained. Unlike the formal sector, where asymmetric information exists, in the informal sector, it is alleviated due to the acquaintance relationships among Ghanaian rural community dwellers; thus, it may be difficult for the farmer to misuse the loans obtained from their lenders because in times of additional need, the farmer would be denied by the lender [27,73]. This provides evidence for H_3.

Overall, male and female farmers and farmers who received credit from both formal and informal financial institutions all had their agriculture CF reduced due to off-farm jobs; thus, we can conclude that off-farm jobs acquisition help reduce agriculture CF

4. Conclusions

With the help of household survey data from four regions (Savannah, Eastern, Central, and Bono East), this study explored the impact of non-farm employment on agriculture CF. Based on the above analysis, the research mainly draws the following three conclusions:

Off-farm employment of a household exerts a negative and significant impact on agriculture CF. That is, farmers who are engaged in off-farm jobs are less likely to practice agriculture CF.

Compared with males with off-farm employment, the impact of females with off-farm employment on the reduction of agriculture CF is greater.

Compared with the formal sources, the impact of farmers who obtained credit from informally sourced off-farm work on the reduction of agriculture CF is greater.

From the aforementioned results, this study offered several implications. First, the results have revealed that designing policies to promote and generate off-farm employment opportunities for rural households by the government and policymakers is essential because off-farm income could curtail some household expenditure that agriculture credit could be used for if there was no off-farm employment. Second, the profound impact of off-farm employment on agriculture CF reduction for farmers who obtained credit from informal source implies that policies to improve formal credit accessibility is vital. Credit from the informal sector has potential risk; therefore, farmers' ability to secure formal credit must be encouraged. To reiterate, not all farmers may be able to secure informal credit since its accessibility is mostly based on acquaintance relationships. Therefore, to alleviate the problem of CF, policymakers should focus on designing policies that will help households secure a loan from formal financial institutions.

With this study, future researchers can address several limitations. First, the study focused on only four (4) out of (10) regions in Ghana due to credit constraints. Future researchers can consider larger sample sizes, perhaps even the entire nation. Second, self-reporting was used to measure off-farm employment and found that rural households with off-farm work are more likely to reduce CF. Future researchers can formulate more advanced scales to measure off-farm jobs. Finally, future researchers can further explore the dynamic relationship between off-farm employment CF using panel data due to the dynamism in household off-farm employment.

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Appendix A

Table A1. Determinants of off-farm employment and the determinants of the agriculture CF.

Variables	First Stage Selection Equation Off-Farm Employment	Second Stage Agriculture Credit Fungibility Equation Off-Farm Employment	Non-Off-Farm Employment
Gender	0.0343 (0.0129) **	−0.0213 (0.0130)	0.0436 (0.0173) ***
Marital status	−0.0153 (0.0125)	0.0086 (0.0064)	0.0832 (0.0643)
Age	0.0249 (0.0168)	0.0056 (0.0018) **	0.0106 (0.0051) *
Age^2	−0.1204 (0.0437) **	−0.0173 (0.0086) *	−0.0024 (0.0009) **
Education	0.0476 (0.0173) **	0.0278 (0.0191)	0.1644 (0.1207)
Remittances	0.0339 (0.0120) ***	−0.0149 (0.0056) **	−0.0020 (0.0007) **
Household Size	0.0724 (0.0980)	0.0078 (0.0051)	0.0201 (0.0093) ***
Credit source	−0.1047 (0.0788)	−0.0068 (0.0022) ***	1.1028 (0.9139)
Loan payback period	0.0155 (0.0089)	−0.0261 (0.0108) *	−0.9261 (0.7308)
Farm size	−0.0270 (0.0537)	−0.0211 (0.0098) *	−0.0011 (0.0009)
Social Network	0.0165 (0.0029) ***		
Constant	0.1372 (0.1005)	0.2783 (0.0745) ***	1.1654 (1.8317)
σ_1	0.1483 (0.1007)		
σ_2	0.3126 (0.2521)		
ρ_1	0.0125 (0.0039) ***		
ρ_2	−0.0132 (0.0193)		
	LR test of indep. eqns.: chi^2(1) = 6.43 Prob > chi^2 = 0.0007		

Source: Survey results, 2018. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2. Pearson correlation analysis of the selected IV.

Variables	Correlation Coefficient	*p*-Value
Off-farm employment	0.1201 *	0.0525
Share of agriculture CF	0.3886	0.2132

Source: Survey results, 2018. Note: * $p < 0.1$.

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