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Received: 14 February 2022 | Revised: 11 November 2022 | Accepted: 17 November 2022

DOI: 10.1002/agr.21792

RESEARCH ARTICLE

Agribusiness An International Journal WILEY

Welfare implications of participating in agri-value chains among vegetable farmers in Northern Ghana

Wanglin Ma[1] | **Awal Abdul-Rahaman**[2] | **Gazali Issahaku**[3]

[1]Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand

[2]Department of Agribusinessm, Faculty of Agriculture, Food and Consumer Sciences, University for Development Studies, TL, Tamale, Ghana

[3]Department of Food Security and Climate Change, Faculty of Agriculture, Food and Consumer Sciences, University for Development Studies, TL, Tamale, Ghana

Correspondence

Wanglin Ma, Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand.

Email: Wanglin.Ma@lincoln.ac.nz

Abstract

This study investigates the welfare implications of agri-value chain participation utilizing data collected from 423 smallholder vegetable farmers in northern Ghana. The endogenous switching regression (ESR) model estimates the determinants of agri-value chain participation and their associated impacts on farmers' welfare, measured by household income and consumption expenditure. The ESR model accounts for selectivity bias associated with observed and unobserved factors. We find that agri-value chain participation improves vegetable farmers' welfare. Participation significantly increases household income and consumption expenditure by about 22% and 40%, respectively. Our results also reveal that agri-value chain participation is significantly determined by education, household size, mobile phone ownership, irrigation, farm size, farmer group membership, and extension visits. Variables such as education, access to irrigation, farm size, access to credit, farmer group membership, and extension are the significant determinants of farmers' welfare [EconLit Citations: D24, Q12, Q18].

KEYWORDS

agri-value chain, ESR model, Ghana, selectivity bias, vegetable farmers, welfare

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1 | INTRODUCTION

Agri-value chain encompasses a series of related activities required to bring an agricultural commodity or service through different stages such as input supply, production, processing, marketing, and sales to consumption (Aboah et al., 2021; Kafle et al., 2022; Muflikh et al., 2021; van Dijk et al., 2022; Zhang et al., 2019). The chain constitutes various actors, including input suppliers, producers, processors, marketers, consumers, and service providers. High-quality agricultural commodities are targeted at each stage of the agri-value chain. Over the past decades, developing and emerging countries have continuously experienced rapid growth and structural transformation of agri-value chains. Many past studies have attributed this transformation to increased consumer demand for high-value and processed food products, quality, safety, and convenience, which is typically linked to rising incomes and urbanization (Awafo & Owusu, 2022; Bellemare et al., 2022; Kafle et al., 2022; Reardon et al., 2009).

While this transformation is widely acknowledged in past studies as an opportunity for smallholder farmers' integration into agri-value chains, several production and marketing constraints continue to impede their inclusion in these chains due to market imperfections (Aboah et al., 2021; Meemken & Bellemare, 2020; Muflikh et al., 2021; Rao & Qaim, 2011). These constraints including, for example, high transaction costs associated with accessing both input and output markets, inadequate access to inputs and improved technologies, extension advisory and financial services, and weak bargaining power, jointly result in low crop yields, poor quality, low output prices, and insufficient profits (Reardon et al., 2009; van Dijk et al., 2022). To improve smallholder farmers' production and marketing performance, governments, nongovernmental organizations (NGOs), and agribusiness firms have continuously made efforts at creating an enabling environment for resource-poor farmers to transition from subsistence to market-oriented farming through investments in agriculture and rural transformation (Abdul-Rahaman & Abdulai, 2020; Humphrey & Navas-Alemán, 2010; Rabbi et al., 2019). These agricultural investments are rolled out using agri-value chain approaches in the form of development interventions to resolve these multiple constraints in the smallholder agricultural sector.

Agri-value chain approach has been increasingly promoted as a key component of agricultural and rural transformation in developing and emerging countries. Apart from ensuring value creation and effective market linkages, the agri-value chain approach improves access to inputs and certain essential services related to improved technologies, finance, and extension and facilitates smallholder inclusion in agrifood markets (Rao & Qaim, 2011). Stakeholders in the agri-value chains largely focus on strengthening the bargaining power of smallholder farmers through farmer group formation and establishing efficient farmer-buyer linkages to ensure sustainable and equitable outcomes. Modern retailers and agribusiness firms serving high-value markets often purchase produce, especially fresh fruits and vegetables, from smallholder farmers through oral or written contractual arrangements and other forms of vertical coordination mechanisms to ensure a regular supply of high-quality products (Bellemare & Bloem, 2018; Meemken & Bellemare, 2020; Ogutu et al., 2020).

Many existing studies have investigated the benefits of smallholder farmers' participation in agri-value chains in developing and emerging countries. They found that agri-value chain participation increases farm income (Montalbano & Nenci, 2022; Ogutu et al., 2020), improves farm production efficiency (Rao et al., 2012), reduces rural poverty (Ogutu et al., 2020), and ensures food and nutrition security (Debela et al., 2022). Other studies also found positive impacts of agri-value chain participation on employment inclusiveness and job quality among rural youth and migrants (Beltrán-Esteve et al., 2017; Fabry et al., 2022) and land redistribution and asset holding (Henderson & Isaac, 2017; Michelson, 2013). Agri-value chains' contribution to household income is very relevant from a development policy perspective. However, household income does not adequately reflect farmers' basic needs (e.g., food, education, and shelter), although it has been widely used as an important welfare indicator (Ma & Wang, 2020; Ogutu et al., 2020; Tambo & Mockshell, 2018). This study extends the welfare analysis of agri-value chains beyond just household income to include its contribution to household consumption expenditure among smallholder farmers.

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This study contributes to the literature by examining the welfare implications of agri-value chain participation among vegetable farmers. It is implemented using data from a survey of 423 vegetable farmers growing diverse crops in northern Ghana. The data comprise 191 agri-value chain participants and 232 nonparticipants. We attempt to achieve three major objectives. First, the study examines the drivers of agri-value chain participation among smallholder farmers. Second, we investigate the factors influencing farmers' welfare, measured by household income per capita and consumption expenditure per capita. It is important to mention that although some previous studies have used crop yield as a welfare measure (Awotide et al., 2016; Kumar et al., 2018; Ma & Abdulai, 2016; Zhang et al., 2021), the present study did not consider it because farmers in our sample cultivate different types of vegetables (e.g., cabbage, okro, onion, Chilli/hot pepper, garden eggs, tomatoes, lettuce, amaranthus (Aleefu), and carrot). This makes vegetable yield incomparable among farmers. Third, we evaluate the impact of agri-value chain participation on household income and consumption expenditure among vegetable farmers. Note that participation in agri-value chains is not random but rather farmers' self-selection. The self-selection decisions and their associated outcomes could be influenced by unobserved factors (e.g., farmers' innate abilities and motivations), resulting in selectivity bias issues during estimation. Failure to account for this bias could lead to biased and inconsistent agri-value chain impact estimates. To address the selectivity bias issues in nonrandomized studies like the present one, some past studies have used propensity score matching (PSM) (Jia et al., 2022; Lu et al., 2021; Wordofa et al., 2021) or inverse probability weighted regression adjustment (IPWRA) methods (Danso-Abbeam & Baiyegunhi, 2018; Nikam et al., 2022; Zheng & Ma, 2021). However, these methods account for the selectivity bias issue due to only observed factors, ignoring the effects of unobservable factors. Therefore, we address this issue by employing an endogenous switching regression model, accounting for the selectivity bias issue stemming from observed and unobserved factors.

In this study, agri-value chain participants refer to farmers who obtained some support from vegetable development interventions, that is, Northern Ghana Integrated Development Project (NGIDP) implemented by Urban Agriculture Network (URBANET) (Seville et al., 2011). Under these agri-value chain interventions, farmers have participated in a number of activities, such as improved agronomic practices, business expansion strategies, value chain thinking and quality compliance measures, input provision, and linkages with modern retailers and agribusiness companies. These farmers are expected to comply with the quality requirements spelt out in their sales agreements. Non-participants produce vegetables with their resources and target the local markets or home consumption (Seville et al., 2011). Their engagement with buyers is mainly through spot market transactions and does not involve prior agreements on quality and pricing.

This study focuses on vegetable farmers because of the important role it plays in enhancing incomes and food and nutrition security among farm households in Ghana. Vegetables are important sources of minerals, vitamins, and dietary fiber, and as such, play a critical role in the fight against hidden hunger in Ghana (GEPA, 2022). They are mostly grown in urban and peri-urban areas on a small-scale basis under irrigated and rainfed conditions. Moreover, vegetables as part of horticultural crops are major sources of employment for smallholder farmers in northern Ghana. It is important to point out that since the establishment of the Ghana Export Promotion Authority, the production and export of horticultural crops including vegetables have received a lot of attention as part of the nontraditional export in Ghana, which is notably one of the important foreign exchange earning sectors that augments the traditional export sector (GEPA, 2021).

The policy value of the current study is very relevant for the development of the vegetable value chain, poverty reduction, and overall rural economic transformation in northern Ghana. The recent dynamics within Ghana's vegetable landscape show a picture of a robust sector that can generate urban and peri-urban growth, through job creation and contribute significantly to the economic development of the country. The performance of the horticultural sector in the 2021 Ghana Export Promotion Authority Report suggests that government support should be given to the sector (GEPA, 2021). The study's findings can inform robust policies to enhance the efficiency of the vegetable value chain through the provision of basic infrastructure (e.g., irrigation) and services (e.g., access to credit, extension, and education), improve farmers' welfare through increased productivity and farm

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incomes, as well as contributing to the achievements of the United Nations' Sustainable Development Goals in alleviating poverty (Goal 1), combating hunger (Goal 2), and promoting responsible consumption and production (Goal 12).

The remainder of this article proceeds as follows. Section 2 describes the conceptual framework followed by the econometric approach in Section 3. Section 4 describes the data and summary statistics, whilst Section 5 presents the results and discussion. Conclusions and recommendations are presented in the final section.

2 | CONCEPTUAL FRAMEWORK

2.1 | Nexus between agri-value chain participation and farmers' welfare

Participation in agri-value chains can influence household income and consumption expenditure by affecting farm economic performance (e.g., production costs, yields, sales prices, and net farm income). Figure 1 depicts a simple framework of potential influencing pathways. The pathway reveals that agri-value chain participation affects production costs and yields by influencing vegetable farmers' production behaviors. For example, agri-value chain participants receive production inputs (e.g., fertilizers, pesticides, and improved seeds) and

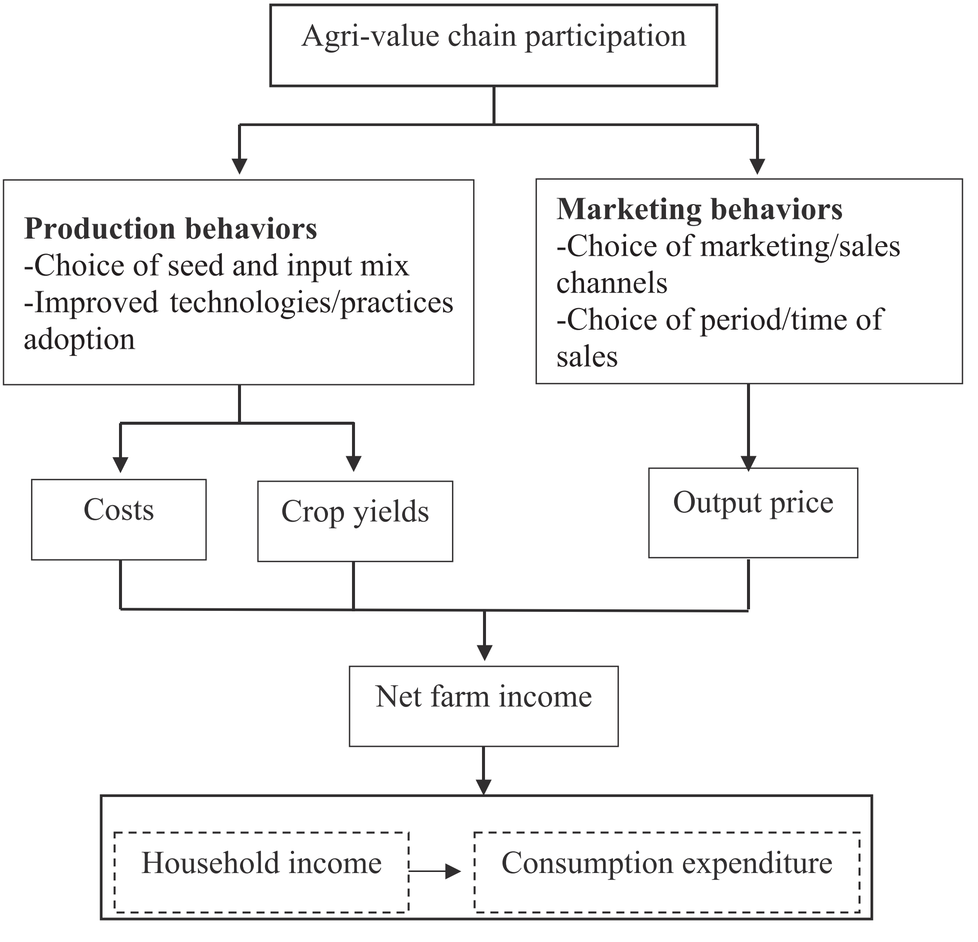

FIGURE 1 Agri-value chain participation and welfare nexus.

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special training on how to use input mix efficiently, lowering their production costs but increasing vegetable yields (Society & Wallace, 2017). Relative to non-participants, agri-value chain participants are also more likely to adopt sustainable agricultural practices due to production contract interventions, improving vegetable yields further.

The second pathway suggests that agri-value chain participation affects output price by influencing vegetable farmers' marketing behaviors. The contractual arrangements between agri-value chain participants and buyers reduce the uncertainties and risks of vegetable prices in the spot markets (Poku et al., 2018), enabling agri-value chain participants to sell vegetables with stable marketing channels timely. Therefore, agri-value chain participants could receive a relatively higher price than non-participants who sell in spot markets.

The above analysis clearly indicates that agri-value chain participation helps increase net farm income by increasing vegetable yields and sales prices but reducing production costs. Previous studies have revealed that agri-value chain participation increases farm income (Briones, 2015; Rao et al., 2012; Zhang et al., 2019). Investigating the tobacco industry in the Philippines, Briones (2015) found that smallholder farmers' participation in high-value chains through contract farming increased net farm income. A higher farm income can directly influence household income and consumption expenditure, it also affects consumption expenditure by determining household income. Nevertheless, farm income only captures a partial picture of household welfare. Therefore, in this study, we make further efforts to empirically examine how agri-value chain participation impacts household income and consumption expenditure to improve our understanding of the welfare implications of agri-value chain participation.

3 | ECONOMETRIC APPROACH

3.1 | Farmers' participation in agri-value chains

Agri-value chain participation decision is considered binary, where farmers decide whether to participate or not based on a set of observable factors. This binary participation decision is modeled in a random utility framework (Ma & Zheng, 2022; Yang et al., 2022). In this context, farmers' decisions are mainly based on a comparison of the expected utilities (V_{Pi} and V_{Ni}) obtained from agri-value chain participation and nonparticipation, respectively. Let the difference in the expected utility be represented by V^*, a farmer i will participate in agri-value chains if $V^* = V_{Pi} - V_{Ni} > 0$. However, the utility difference (V^*) is unobservable, but can be specified as a function of observable factors in a latent variable framework as follows:

$$V_i^* = \varphi X_i + \omega_i, \text{ with } V_i = \begin{cases} 1 & \text{if } V_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where V_i^* is a binary decision indicator, which equals one if farmer i participates in agri-value chains, and zero otherwise; φ denotes a vector of unknown parameters to be estimated; X_i represents a vector of observable factors. These include age, education, gender, household size, mobile phone ownership, irrigation, farm size, access to credit, farmer group membership, extension visits, distance to available farm plots and location variables, drawn from existing literature (e.g., Abdul-Rahaman & Abdulai, 2020; Awafo & Owusu, 2022; Kafle et al., 2022; Ogutu et al., 2020; Rao & Qaim, 2011; Tray et al., 2021; Zhang et al., 2019). ω_i is the error term. A farmer's probability of participating in agri-value chain is specified as follows:

$$\Pr(V_i = 1) = \Pr(V_i^* > 0) = \Pr(\omega_i > -\varphi X_i) = 1 - F(-\varphi X_i), \tag{2}$$

where F represents the cumulative distribution function for ω_i.

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3.2 | Welfare effects of agri-value chain participation

This study examines the welfare implications of agri-value chain participation among smallholder vegetable farmers in northern Ghana, using welfare measures such as household income and consumption expenditure (Addison et al., 2022; Ahimbisibwe et al., 2020; Mishra et al., 2022; Zegeye et al., 2022). Given that these outcome variables are linear functions of observable factors along with the agri-value chain participation dummy, we specify the linear equation as follows:

$$Y_i = \delta Z_i + \vartheta V_i + \mu_i \tag{3}$$

where Y_i denotes the outcome variables; Z_i represents a vector of observable factors that influence the outcome variables; V_i is the binary indicator variable for agri-value chain participation; δ and ϑ denote vectors of unknown parameters to be estimated; μ_i is the error term.

In Equation (3), the impact of agri-value chain participation (V_i) on the outcomes is captured by the coefficient ϑ, an assumption that the agri-value chain participation is exogenously determined. However, this method might lead to biased and inconsistent impact estimates, especially using the ordinary least square (OLS) estimation method. This is because farmers' participation in agri-value chains is not randomly assigned but involves self-selection. In this case, unobserved factors (e.g., farmers' skills, motivation, and risk preference) influencing the welfare outcomes may also be correlated with the agri-value chain participation dummy (V_i), which can result in selectivity bias (Abdul-Rahaman et al., 2021; Lin et al., 2022; Yang et al., 2022). In such a case, the error terms in the selection equation and the outcome equation, that is, ω_i and μ_i, may be correlated [$(corr(\omega_i, \mu_i) \neq 0)$]. As discussed earlier, the PSM and IPWRA methods can account for the selectivity bias due to only observable factors. A model that accounts for selectivity bias from observable and unobservable factors is the endogenous switching regression (ESR), a method employed in this study and described in the next section.

3.3 | Endogenous switching regression (ESR) method

The ESR method is a two-stage procedure involving the estimation of the determinants of farmers' decisions to participate in agri-value chains in the first stage and the determinants of welfare outcomes in the second stage (Lin et al., 2022; Liu et al., 2021; Lokshin & Sajaia, 2004; Zheng, Ma & Li, 2021). As mentioned earlier, this method addresses selectivity bias associated with observable and unobservable factors to generate unbiased and consistent parameter estimates. The model is specified below as two regimes of equations for participants and non-participants of agri-value chains with a criterion function V_i determining which regime a vegetable farmer faces.

$$\text{Regime 1}: Y_P = \delta_P Z_i + \mu_P \ \text{if} \ V_i = 1 \tag{4a}$$

$$\text{Regime 2}: Y_N = \delta_N Z_i + \mu_N \ \text{if} \ V_i = 0 \tag{4b}$$

where Y_P and Y_N are the welfare outcome variable (household income or consumption expenditure) for agri-value chain participants (Regime 1) and nonparticipants (Regime 2), respectively; Z_i is a vector of observable factors determining the outcome variables; δ_P and δ_N are unknown parameters to be estimated; μ_P and μ_N are error terms. Within the ESR framework, the error terms in Equations (1), (4a), and (4b) are assumed to have a trivariate normal distribution with mean zero and a non-singular covariance matrix expressed as

$$\text{cov}(\mu_P, \mu_N, \omega_i) = \begin{bmatrix} \sigma_P^2 & \sigma_{PN} & \sigma_{P\omega} \\ \sigma_{PN} & \sigma_N^2 & \sigma_{N\omega} \\ \sigma_{P\omega} & \sigma_{N\omega} & \sigma_\omega^2 \end{bmatrix} \tag{5}$$

where σ_P^2 = var(μ_P), σ_N^2 = var(μ_N), σ_{PN} = cov(μ_P, μ_N), $\sigma_{P\omega}$ = cov(μ_P, ω), and $\sigma_{N\omega}$ = cov(μ_N, ω). Following Greene (2012), we assume that $\sigma_\omega^2 = 1$, as φ in the selection equation is estimable only up to a scale factor.

It is required that the ESR model is properly identified since the set of factors in X_i and Z_i overlap during estimation. In doing so, at least one variable called an instrument in X_i will not be featured in Z_i. The identification involves including one or more valid instruments in the selection equation before estimation. The employed instrument should be highly significant in the selection equation but not the outcome equation. Distance from the farmer's home to available plots for vegetable production has been identified as the instrument. We argue that longer distances from a farmer's home to available plots for vegetable production discourage farmers from participating in the vegetable agri-value chain. However, we are unable to establish its direct influence on welfare outcomes. An instrument validity test based on correlation coefficient analysis reveals that the distance from a farmer's home to available vegetable plots is significantly and negatively associated with agri-value chain participation but is not associated with welfare outcomes, confirming the validity of the employed IV.

Moreover, in estimating the determinants of agri-value chain participation, variables such as farmer group membership, access to credit, and extension visit are potentially endogenous. Produce buyers engage farmers in the form of groups to ensure efficient and cost-effective agribusiness transactions. This means that a farmer can join a farmer group to participate in agri-value chains, which makes both decisions jointly determined. Similarly, a farmer can make a joint decision of participating in agri-value chains to facilitate his/her access to credit. Finally, farmers who receive extension visits can obtain information from extension officers on available and functional agri-value chains in the area, which might influence their participation decision. We address this potential endogeneity issue of the control variables using a control function approach (Wooldridge, 2015) and the appropriate instruments to ensure consistent estimation of the model. Specifically, the instruments used are distance to the group's meeting venue for the farmer group membership variable, distance to credit source for access to credit variable, and distance from the farm to the extension office for the extension visit variable. The first stage regression results of the control function approach and the endogeneity test results are not reported here due to space limitation but are available upon request. The residual terms predicted after the first stage regression are then included in the selection equation to help mitigate endogeneity issues.

The ESR model specified so far accounts for observed systematic differences between agri-value chain participants and non-participants. However, to account for unobserved factors, inverse mills ratios for agri-value chain participants (λ_{Pi}) and non-participants (λ_{Ni}) are computed together with the corresponding covariance terms $\sigma_{P\omega}$ and $\sigma_{N\omega}$ and included in Equations (4a) and (4b) after estimating the selection Equation (1) as follows:

$$Y_P = \delta_P Z_i + \sigma_{P\omega}\lambda_{Pi} + \mu_P \quad \text{if} \quad V_i = 1 \tag{6a}$$

$$Y_N = \delta_N Z_i + \sigma_{N\omega}\lambda_{Ni} + \mu_N \quad \text{if} \quad V_i = 0 \tag{6b}$$

In Equations (6a) and (6b), the inverse mills ratios λ_{Pi} and λ_{Ni}, evaluated at φX_i, are used to account for selectivity bias arising from unobserved factors in a two-step procedure, which generates heteroskedastic standard errors (Greene, 2012; Wooldridge, 2002). In line with Lokshin and Sajaia (2004), a more appropriate way to estimate the ESR model is using the full information maximum likelihood (FIML) method, which estimates the selection and outcome equations jointly and generates correlation coefficients $\rho_{P\omega}$ and $\rho_{N\omega}$ associated with the error terms in the selection and outcome equations. The significance of $\rho_{P\omega}$ or $\rho_{N\omega}$ would confirm the presentence of selection bias issues (Liu et al., 2021; Lokshin & Sajaia, 2004).

3.4 | Estimating the average treatment effects of agri-value chain participation

Apart from estimating the effects of observed factors on the welfare outcomes—household income and consumption expenditure—in the agri-value chain participation and nonparticipation regimes, the ESR model

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can be used to further evaluate the net effect of agri-value chain participation on the welfare outcomes. Here, we compare the expected welfare outcomes from agri-value chain participants to the expected welfare outcomes of the counterfactual case that they did not participate in agri-value chains to derive the average treatment effects on the treated (ATT). Specifically, the expected welfare outcomes of vegetable farmers with participation (observed) and vegetable farmers without participation (counterfactual), respectively, are expressed as:

$$E\left[Y_{Pi} \mid V = 1\right] = \delta_P Z_i + \sigma_{P\omega}\lambda_{Pi} \tag{7a}$$

$$E\left[Y_{Ni} \mid V = 1\right] = \delta_N Z_i + \sigma_{N\omega}\lambda_{Pi} \tag{7b}$$

Finally, the ATT associated with agri-value chain participation is computed as the difference between Equations (7a) and (7b), expressed as follows:

$$ATT = E\left[Y_{Pi}|V = 1\right] - E\left[Y_{Ni}|V = 1\right] = Z_i(\delta_P - \delta_N) + \lambda_{Pi}(\sigma_{P\omega} - \sigma_{N\omega}) \tag{8}$$

4 | DATA AND SUMMARY STATISTICS

The study uses data from a survey of smallholder vegetable farmers between September and November 2019, covering districts namely Tolon, Sagnarigu, Savelugu, Kumbungu, and Tamale metropolis in northern Ghana. We used a multistage sampling procedure in drawing up our sample for the study by purposively selecting the districts based on accessibility to these areas, suitable agroecology, and the intensity of vegetable production and randomly selecting the communities and rural households. A total of 423 vegetable farmers were sampled in proportion to the farmer population in each district to ensure precision. The sample is composed of 191 vegetable farmers who participated in agri-value chains and 232 non-participants. The farmers were interviewed using a structured questionnaire. The data were collected on the farm and household characteristics, agri-value chain activities, access to credit and extension services, asset ownership, and production and marketing activities.

The variables employed for the analysis in this study and their respective descriptive statistics are presented in Table 1. The sample constitutes 45% agri-value chain participants and 55% non-participants. About 63% of the sample is male, with an average age of 39 years. In addition, a vegetable farmer has about 3.4 years of formal education and cultivates an average of 1.04 hectares of land.

Table 2 shows the descriptive statistics concerning the variables, with their corresponding statistical t-tests of mean differences between agri-value chain participants and non-participants. We observe significant mean differences for some of the variables. Table 2 shows that, on average, agri-value chain participants are older and cultivate larger farm sizes. In addition, a higher proportion of agri-value chain participants mostly own mobile phones, have access to credit, and cultivate vegetables under irrigation than nonparticipants.

A significant difference also exists between participants and nonparticipants concerning farmer group membership and the number of extension visits. Farmer group members and those with a relatively higher number of extension visits are more likely to participate in agri-value chains. Participants have higher household consumption expenditures than non-participants. This suggests improved welfare associated with agri-value chain participation in northern Ghana. However, both categories are similar in terms of variables such as education, gender, and household income, although slightly higher for participants. These mean differences cannot be interpreted as impacts since confounding factors and selectivity bias issues are not considered in the analysis. The next section presents and discusses the results obtained using econometric analysis that accounts for other confounding factors and selectivity bias issues.

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TABLE 1 Variable definitions and summary statistics

Variables	Definitions	Mean (Std. Dev.)
Dependent variables		
Household income	Annual household income per capita (GH¢)	133.90 (128.21)
Consumption expenditure	Annual household consumption expenditure per capita (GH¢)	112.96 (144.65)
Agri-value chain participation	1 if household participates in a formal vegetable value chain, 0 otherwise	0.45 (0.49)
Independent variables		
Age	Age of respondent (years)	39.32 (10.94)
Education	Education of respondent (years)	3.37 (4.76)
Gender	1 if farmer is male, 0 otherwise	0.63 (0.48)
Household size	Size of the household	10.49 (7.09)
Mobile phone	1 if farmer owns a mobile phone, 0 otherwise	0.71 (0.45)
Irrigation	1 if farmer cultivates vegetables under irrigation, 0 otherwise	0.52 (0.50)
Farm size	Size of farm (hectares)	1.04 (1.08)
Access to credit	1 if farmer has access to enough credit and not liquidity constraint, 0 otherwise	0.45 (0.50)
Farmer group	1 if farmer belongs to a vegetable farmer group, 0 otherwise	0.32 (0.46)
Extension visit	Number of extension visits to a farmer in the last 12 months	1.58 (4.36)
Tolon	1 if a farmer is located in Tolon district, 0 otherwise	0.30 (0.46)
Tamale	1 if farmer is located in Tamale metropolis, 0 otherwise	0.11 (0.32)
Kumbungu	1 if farmer is located in Kumbungu district, 0 otherwise	0.25 (0.43)
Savelugu	1 if farmer is located in Savelugu Municipal, 0 otherwise	0.29 (0.45)
Sagnarigu	1 if farmer is located in Sagnarigu Municipal, 0 otherwise	0.02 (0.13)
Distance to available plots	Distance from home to available vegetable plots (km)	1.80 (3.41)

Note: GH¢ is Ghanaian currency (US$1 = GH¢ 5.70 as at December, 2019).
Abbreviation: Std. Dev., standard deviation.

5 | RESULTS AND DISCUSSIONS

5.1 | Determinants of participation in agri-value chains

This section discusses the results of the determinants of smallholder farmers' participation in agri-value chains. These are obtained from the first stage (probit) estimation of the ESR model. Column 2 of Tables 3 and 4 presents the estimation results. The insignificant coefficients of the FGM residual, credit residual, and extension residual suggest the potential endogeneity issues of the control variables representing farmer group membership, access to credit, and extension visit have been sufficiently addressed (Wooldridge, 2015). As observed, the variables in column 2 of both tables have the same name and exhibit statistically similar effects on the probability of agri-value chain participation. Given this, we interpret the results as normal probit coefficients.

Age exerts a positive and significant effect on agri-value chain participation, suggesting that an older farmer is more likely to participate in agri-value chains, probably because of long experience. Farmers with better formal

TABLE 2 Differences in characteristics of farmers by agri-value chain participation

Variable	Participants		Nonparticipants		Difference (*t*-stat.)
	Mean	Std. Dev.	Mean	Std. Dev.	
Age	41.34	10.55	37.67	10.99	3.475***
Education	3.62	5.34	3.17	4.22	−0.968
Gender	0.67	0.47	0.61	0.48	1.236
Household size	13.72	8.74	7.83	3.66	9.318***
Mobile phone	0.87	0.33	0.58	0.49	6.884***
Irrigation	0.75	0.43	0.32	0.47	9.624***
Farm size	1.20	1.13	0.91	1.02	2.800***
Access to credit	0.55	0.30	0.41	0.45	−4.940***
Farmer group	0.51	0.50	0.17	0.37	7.958***
Extension visit	3.00	6.11	0.41	0.97	6.355***
Tolon	0.57	0.49	0.09	0.29	12.235***
Tamale	0.12	0.33	0.11	0.32	0.429
Kumbungu	0.12	0.32	0.37	0.48	−6.349***
Savelugu	0.14	0.35	0.41	0.49	−6.266***
Sagnarigu	0.02	0.01	0.02	0.01	−0.278
Distance to available plots	0.53	2.54	2.84	3.68	−7.348***
Household income	140.11	143.74	128.79	113.92	0.903
Consumption expenditure	138.73	135.40	91.73	148.81	3.366***
Sample size	191		232		

Abbreviation: Std. Dev., standard deviation.

***Represents significance at the 1% level.

education are more likely to participate in agri-value chains. These findings are consistent with previous studies (Abdul-Rahaman & Abdulai, 2020; Rao & Qaim, 2011). Farmers with better education can make informed decisions and efficient adjustments to improved production technologies and market requirements. We also find that the likelihood of agri-value chain participation is higher for farmers with larger household sizes, as indicated by its positive and significant coefficient. Mobile phone ownership and irrigation play important roles in determining farmers' decisions to participate in agri-value chains. In particular, farmers who own mobile phones and those who cultivate vegetables under irrigation are more likely to participate in agri-value chains. Mobile phone ownership enables farmers to access information related to production and marketing (Fischer & Qaim, 2014; Hoang, 2020; Zheng & Ma, 2021).

Farm size exhibits a positive and significant effect on agri-value chain participation, indicating that cultivating relatively larger farm sizes increases the likelihood of participation. Previous studies have recorded similar results (Rao & Qaim, 2011). Farmers with larger farm sizes benefit from fixed transaction costs associated with market and information search. Farmer group membership and the number of extension visits also tend to positively and significantly influence agri-value chain participation. In particular, the likelihood of agri-value chain participation increases for farmers belonging to vegetable farmer groups. Similarly, farmers with more extension visits are more likely to participate in the agri-value chain. It is intuitive to note that access to extension services facilitates farmers'

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information acquisition on available and functional agri-value chains and their associated dynamics (Nikam et al., 2022). This study also reveals significant location-fixed effects on agri-value chain participation. Specifically, relative to Sagnarigu Municipal (reference district), farmers who cultivate vegetables in Tamale, Kumbungu, and Savelugu are more likely to participate in agri-value chains. The coefficient of the instrument is negative and significant, implying that an increase in distance to available plots for vegetable production significantly reduces farmers' likelihood of agri-value chain participation.

5.2 | Determinants of household income

This section examines the determinants of household income for agri-value chain participating and nonparticipating vegetable farmers. This forms the second stage of FIML estimation of the ESR model, and the results are reported in the fourth and sixth columns of Table 3. The correlation coefficient ($\rho_{\mu 1}$) (lower part of Table 3) is negative and significant for the participants' household income equation, suggesting the presence of selectivity bias associated with unobservable factors. The presence of the unobservable selectivity bias justifies the use of the ESR model in the estimations. In addition, the likelihood ratio test of joint independence of the agri-value chain participation equation and household income equation reveals that both equations are dependent.

Regarding the determinants of household income, we find that education significantly increases household income for agri-value chain participants relative to non-participants at the 5% level. Better-educated farmers can easily access information on production and marketing, available agri-value chain opportunities, and make informed decisions such as adopting improved production technologies and agri-value chain participation, all of which contribute to higher incomes (Rao & Qaim, 2011). Household size positively and significantly impacts household income for agri-value chain participants and non-participants, suggesting that farmers with larger household sizes earn higher household incomes. A larger household size ensures the availability of family labor for agricultural activities (Ma & Abdulai, 2016). The results also reveal positive and significant effects of irrigation at the 1% level. This implies that vegetable cultivation under irrigation significantly increases household income for agri-value chain participants and non-participants. Irrigation facilities ensure the availability of water for the crops all year round, which increases productivity and product quality (Li et al., 2020).

Access to credit, farmer group membership, and extension visits also play important roles in increasing household income. In particular, access to credit positively and significantly affects household income for agri-value chain participants but is positive and insignificant for non-participants. This is consistent with the findings by Ma and Abdulai (2016). Access to credit facilitates farmers' acquisition of production inputs and the ability to pay for labor expenses for increased productivity, and ultimately household income. In addition, household income increases significantly for agri-value chain participants with group membership. Members of farmer groups benefit from access to improved production technologies, marketing information, and reduced transaction costs (Fischer & Qaim, 2014). Extension visits affect household income positively and significantly for both agri-value chain participants and non-participants at least at the 5% level. This finding implies that vegetable farmers with a higher number of extension visits obtain higher household incomes. This is in line with intuition because agricultural extension builds farmers' capacities through information provision and exposure to improved production technologies, increasing farm yields and, in turn, household income (Nikam et al., 2022).

5.3 | Determinants of consumption expenditure

The determinants of consumption expenditure for agri-value chain participants and non-participants are examined in this section, estimates of which are reported in the fourth and sixth columns of Table 4. Similarly, the results

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TABLE 3 Determinants of agri-value chain participation and determinants of household income

Variables	Selection		Household income (participants)		Household income (nonparticipants)	
	Coefficient	Std. err	Coefficient	Std. err	Coefficient	Std. err
Constant	−7.933***	1.050	5.473***	0.420	5.617***	0.999
Age	0.028**	0.010	0. 002	0.004	−0.001	0.007
Education	0.046**	0.024	0.021**	0.09	−0.109	0.018
Gender	−0.509**	0.233	0.198**	0.099	0.532***	0.156
Household size	0.092***	0.027	0.050***	0.005	0.071***	0.021
Mobile phone	0.958***	0.270	0.224	0.142	−0.027	0.156
Irrigation	0.427*	0.233	0.216***	0.014	0.127***	0.014
Farm size	0.174***	0.041	0.092**	0.039	0.184**	0.072
Access to credit	0.191	0.261	0.400**	0.164	0.083	0.165
Farmer group	1.422***	0.263	0.150***	0.020	−0.126	0.186
Extension visit	0.408***	0.091	0.041***	0.007	0.036**	0.015
Tolon	−0.725	0.700	−0.791***	0.295	−1.183	0.990
Tamale	1.382***	0.614	−0.627**	0.273	−1.277	0.972
Kumbungu	1.990**	0.631	−1.595***	0.282	−1.979**	0.972
Savelugu	1.288*	0.687	0.188	0.289	−0.181	0.991
Distance to available plots	−0.156***	0.036				
FGM residual	0.213	0.184				
Credit residual	0.171	0.280				
Ext. residual	1.379	1.512				
ln σ_1			0.558***	0.025		
$\rho_{\mu 1}$			−0.301***	0.108		
ln σ_2					0.934***	0.043
$\rho_{\mu 2}$					0.238	0.170
Log-likelihood: −584.71						
LR test of indep. eqns.: $\chi^2(1)$: 4.68**						
Observations	423		191		232	

Note: The dependent variable is the log of household income.
*Significance at 10%,
**Significance at 5%, and
***Significance at 1% levels, respectively.

reveal the presence of selectivity bias associated with unobservable factors, as indicated by the negative and significant correlation coefficient ($\rho_{\mu 1}$) for the participant's specification, which also confirms the appropriateness of estimating the ESR model. The likelihood ratio test of joint independence shows that the agri-value chain participation and the consumption expenditure equations are dependent.

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TABLE 4 Determinants of agri-value chain participation and determinants of consumption expenditure

Variables	Selection		Consumption expenditure (participants)		Consumption expenditure (nonparticipants)	
	Coefficient	Std. err	Coefficient	Std. err	Coefficient	Std. err
Constant	−7.552***	1.128	5.928***	0.576	4.148***	0.664
Age	0.023**	0.010	0. 004	0.006	0.005	0.005
Education	0.041**	0.023	0.074***	0.012	0.005	0.012
Gender	−0.628**	0.234	−0.020	0.128	0.135	0.108
Household size	0.114***	0.026	0.049***	0.007	0.128***	0.014
Mobile phone	0.975***	0.245	−0.133	0.201	0.045	0.114
Irrigation	0.426*	0.233	0.055***	0.017	0.072***	0.021
Farm size	0.170***	0.041	0.035**	0.013	0.028***	0.010
Access to credit	0.179	0.260	0.349***	0.088	0.112	0.113
Farmer group	1.291***	0.247	0.669***	0.140	0.235*	0.141
Extension visit	0.416***	0.087	0.007	0.009	0.067	0.057
Tolon	−0.852	0.678	−0.721*	0.383	1.144*	0.661
Tamale	1.551**	0.607	−0.769**	0.358	1.112	0.652
Kumbungu	2.028***	0.628	−0.296	0.395	0.937	0.664
Savelugu	1.284*	0.673	−0.753**	0.380	−0.117	0.726
Distance to available plots	−0.151***	0.034				
FGM residual	0.209	0.178				
Credit residual	0.154	0.267				
Ext. residual	1.041	1.289				
ln σ_1			0.723***	0.039		
$\rho_{\mu 1}$			−0.321***	0.027		
ln σ_2					0.657***	0.045
$\rho_{\mu 2}$					0.691*	0.415
Log-likelihood: −538.82						
LR test of indep. eqns.: $\chi^2(1)$: 5.01**						
Observations	423		191		232	

Note: The dependent variable is the log of consumption expenditure.
*Significance at 10%,
**Significance at 5%, and
***Significance at 1% levels, respectively.

Education positively affects household consumption expenditure but is only significant for the participant category at the 1% level. The finding suggests that agri-value chain participants with better education obtain higher consumption expenditure than their nonparticipant counterparts, indicating higher welfare. This is consistent with Ahimbisibwe et al. (2020) for Uganda but in contrast with the findings by Rabbi et al. (2019) for Nigeria. Variables

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such as household size, irrigation, and farm size have positive and significant effects on consumption expenditure at the 1% level. Larger household sizes increase household consumption expenditure for participants and non-participants. Household members can supply labor services and engage in off-farm work, and the proceeds generated could contribute to the consumption pool of the households. Some past studies find contrasting results in the household size variable (Ahimbisibwe et al., 2020; Rabbi et al., 2019). Vegetable farmers cultivating under irrigation obtain higher consumption expenditure for participants and non-participants. This is possible through irrigation's role in increasing farm productivity and incomes (Amfo et al., 2021; Li et al., 2020). In addition, cultivating vegetables on larger farm sizes increases household consumption expenditure for agri-value chain participants and non-participants. Other factors that positively and significantly affect household consumption expenditure for agri-value chain participants include access to credit and farmer group membership. Credit obtained by farmers is normally utilized to purchase production inputs, as well as undertake other farm expansion activities for increased productivity, whilst group membership facilitates farmers' access to improved technologies, capacity building, access to credit, and reduces transaction costs associated with marketing and sales of farm produce (Abdul-Rahaman et al., 2021; Ma & Abdulai, 2016).

5.4 | Average treatment effects of agri-value chain participation

The results of average treatment effects on the treated (ATT), which measure the potential impacts of agri-value chain participation on farmers' welfare—household income and consumption expenditure—are presented in Table 5. Note that the selectivity bias due to observable and unobservable factors is considered in estimating the ATTs. The results show that participation in agri-value chains significantly increases farmers' welfare. Specifically, vegetable farmers who participated in agri-value chains gained 22% more household income per capita, compared to a situation if these farmers did not participate. Similarly, agri-value chain participation can significantly increase household consumption expenditure per capita by about 40%, compared to a situation if these farmers did not participate. These findings are in line with previous studies in developing countries that smallholder farmers observe significant benefits from agri-value chain participation in the form of increased welfare (Abdul-Rahaman & Abdulai, 2020; Maertens & Vande Velde, 2017; Mishra et al., 2018).

5.5 | Robustness checks

In this section, the consistency of the results has been examined through robustness checks. We employ other impact assessment methods—PSM and IPWRA—to derive the average treatment effects of agri-value chain participation on household income and consumption expenditure. Table 6 reports the estimation results. Consistent

TABLE 5 Impacts on household income and consumption expenditure: ESR model estimates

	Mean outcomes				
Outcomes	Participants	Nonparticipants	ATT	*t*-value	Change (%)
Household income	4.526 (0.792)	3.703 (0.861)	0.823	37.673***	22.22
Consumption expenditure	4.541 (0.611)	3.249 (1.291)	1.292	21.492***	39.76

Note: The dependent variables are the logs of outcome variables. ATT calculation is based on logs of the outcome predictions.

Abbreviations: ATT, average treatment effects on the treated; ESR, endogenous switching regression.

***Represents significance at the 1% level.

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TABLE 6 Impacts on household income and consumption expenditure: PSM and IPWRA estimates for robustness check

Outcomes	ATT (PSM)	ATT (IPWRA)
Household income	0.372 (0.112)***	0.256 (0.105)**
Consumption expenditure	1.176 (0.107)***	1.212 (0.114)***

Note: The dependent variables are the logs of outcome variables. ATT calculation is based on logs of the outcome predictions.

Abbreviations: ATT, average treatment effects on the treated; IPWRA, inverse probability weighted regression adjustment; PSM, propensity score matching.

**Significance at 5%,

***Significance at 1% levels, respectively.

with the ESR model estimation findings, the PSM and IPWRA results reveal significant and positive welfare impacts associated with agri-value chain participation. Specifically, the ATT results from the PSM and IPWRA estimations of household income are 0.372 and 0.256, respectively, and 1.176 and 1.212 for household consumption expenditure. As observed, the ATT estimates from the PSM and IPWRA models appear lower for both household income and consumption expenditure than the ones obtained from the ESR model estimation. This can be attributed to the inability of these models to account for unobservable selectivity bias in the estimations, unlike the ESR model which accounts for selectivity bias due to both observed and unobserved factors (Liu et al., 2021; Lokshin & Sajaia, 2004; Zheng & Ma, 2021).

6 | CONCLUSIONS AND POLICY RECOMMENDATIONS

The rapid transformation of agri-value chains linked to rising incomes, urbanization, and changes in consumer preferences for food quality and safety has considerable implications for smallholder farmers' livelihoods and rural economic development in developing countries. In this study, we examined the impact of agri-value chain participation on the welfare of smallholder vegetable farmers, measured by household income and consumption expenditure. The data used for this study came from a survey of 423 vegetable farmers in some selected districts in northern Ghana. The ESR model was employed in the empirical estimations to account for observable and unobservable selectivity bias that arises from the nonrandom assignment of agri-value chain participation.

The results reveal the presence of positive selectivity bias. After accounting for it, we find that agri-value chain participation improves welfare among vegetable farmers in northern Ghana. Vegetable farmers who participated in the agri-value chain earned significantly higher household income and consumption expenditure than farmers who did not participate. Farmers with better education, cultivating vegetables on relatively larger farms under irrigation benefit from improved household welfare. Similarly, farmer group membership and extension services also significantly improve farmers' welfare. The findings also reveal that farmers' level of education, household size, farm size, irrigation, farmer group membership, and extension visits are the important determinants of agri-value chain participation.

The findings suggest the use of the agri-value chain programs supported by the government, donor agencies, NGOs, and the private sector help improve the welfare indicators of rural vegetable farmers in northern Ghana. Therefore, there is a need to help improve vegetable farmers' understanding of engaging in agri-value chains. This can be achieved through training farmers by collaborating with farmer-based organizations. The findings that access to irrigation improves agri-value chain participation and farmer welfare significantly highlight the importance of investing in irrigation facilities for the availability of water for the crops all year round, which, in turn, contribute to increased farm productivity and improved household welfare. Developing programs that help facilitate effective

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and sustainable agribusiness relationships through contractual arrangements between vegetable farmers and buyers can help address market constraints, reduce transaction costs, and enhance welfare gains among smallholder vegetable farmers.

In this study, we considered agri-value chain activities as a package when defining the agri-value chain participation variable. However, different activities, such as production services and marketing services provided in the agri-value chains, may have differential impacts on farmer welfare. This is not investigated in the present study. However, we believe this would be another interesting area for further research.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support from the Seed Fund Projects within the Faculty of Agribusiness and Commerce, Lincoln University, New Zealand. Open access publishing facilitated by Lincoln University, as part of the Wiley - Lincoln University agreement via the Council of Australian University Librarians.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Awal Abdul-Rahaman upon request.

ORCID

Wanglin Ma http://orcid.org/0000-0001-7847-8459
Awal Abdul-Rahaman http://orcid.org/0000-0002-7356-6326
Gazali Issahaku http://orcid.org/0000-0002-3471-7347

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AUTHOR BIOGRAPHIES

Wanglin Ma is an Associate Professor at the Department of Global Value Chains and Trade at Lincoln University, New Zealand. He specializes in Applied Economics, with a focus on Agricultural Economics and Development Economics. His research outputs have covered a wide range of topics, such as sustainability and economies of agrifood systems, food production and marketing, farmer organization, agribusiness, rural development, rural-to-urban migration, climate change, and adaptation, land transfer, agricultural technology adoption, information technology adoption, welfare and well-being, productivity and efficiency, income growth, farmer subjective well-being, and rural energy transition.

Awal Abdul-Rahaman is a Senior Lecturer, Researcher, and Agribusiness and Value Chain Development expert in the Department of Agribusiness at the University for Development Studies, Tamale, Ghana. He obtained his PhD in Agricultural Economics from the University of Kiel, Germany. His research focuses on agribusiness and value chain development, smallholder agricultural productivity growth, food and nutrition security, and project impact assessments. He has written extensively on agricultural development in developing countries. Dr. Abdul-Rahaman has also led and managed development interventions in several districts and communities in Ghana. He has coordinated and led development efforts aimed at improving farming systems, increasing input supply to smallholder farmers, improving agricultural yields, and promoting smallholder market access. He has substantial expertise in participatory appraisal processes, baseline surveys, project monitoring, and evaluation and impact assessment.

Gazali Issahaku holds a PhD in Agricultural Economics from the University of Kiel, Germany. He is a Senior Lecturer in the Department of Food Security and Climate Change of the University for Development Studies with over eight years' experience in teaching, skills development and research. He served as a Post-Doctoral Researcher with the Centre for Development Research (ZEF) at the University of Bonn, and a member of the Scientific Group of the UN Food Systems Summit. His research focuses on climate-smart agricultural technology adoption and impacts on welfare and other policy outcomes, including food and nutrition security, sustainable land management and environmental efficiency. Dr. Issahaku has worked on different projects, which sought to enhance water and energy security, as well as the provision of ecosystem services and conservation agriculture. He is currently the socio-economist in the UDS team on the SUSTIN-AFRICA project.

How to cite this article: Ma, W., Abdul-Rahaman, A., & Issahaku, G. (2022). Welfare implications of participating in agri-value chains among vegetable farmers in Northern Ghana. *Agribusiness*, 1–19. https://doi.org/10.1002/agr.21792

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