Received: 17 April 2022 | Revised: 25 November 2022 | Accepted: 3 December 2022

DOI: 10.1002/agr.21793

RESEARCH ARTICLE

Agribusiness An International Journal WILEY

Agrifood system participation and production efficiency among smallholder vegetable farmers in Northern Ghana

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Abstract

Formalized marketing arrangements between smallholder farmers and produce buyers are gradually replacing spot market transactions in developing countries due to the rapid structural transformation of agrifood systems. This study examines the impact of agrifood system participation on the total value of vegetable production and technical efficiency (TE), using a sample of 423 vegetable farmers from Northern Ghana. We employ propensity score matching and W. Greene's selection bias-corrected stochastic production frontier methods to correct for observable and unobservable selection bias issues, respectively. We further use a meta-frontier model to derive technology gap ratios (TGRs) and meta-TE for agrifood system participants and nonparticipants. The results reveal that agrifood system participants are about 50% more productive than nonparticipants. In addition, participants have higher meta-TE (58% vs. 55%) and TGR (98% vs. 94%) than nonparticipants. Variables such as farmer group membership, extension visits, mobile phone ownership, irrigation and road access are the notable correlates of smallholder farmers' participation in agrifood systems. The

Abbreviations: BFGS, broyden-fletcher-goldfarb-shanno; BHHH, berndt-hall-hall-hausman; MF, metafrontier; MOAP, market oriented agriculture program; MTE, metafrontier technical efficiency; NGIDP, northern ghana integrated development project; SPF, stochastic production frontier; URBANET, urban agriculture network; TE, technical efficiency; TGR, technology gap ratio.

total value of vegetable production is significantly influenced by fertilizer, agrochemicals, seeds, irrigation, soil fertility, and location-fixed effects. [EconLit Citations: D24, Q12, Q18]

KEYWORDS

agrifood systems, metafrontier, Northern Ghana, stochastic production frontier, technical efficiency, vegetable production

1 | INTRODUCTION

Traditionally, transactions in agrifood systems involving smallholder farmers and buyers were executed via spot markets, characterized by less attention to market requirements, unrestricted competition among market agents, and operating via price mechanism (Poulton & Lyne, 2009; Reardon et al., 2009). In recent decades, the agrifood systems have been undergoing rapid structural transformation linked to several factors, such as rising incomes of the urban middle class and changes in consumer preferences for food quality and convenience (Montalbano & Nenci, 2022; Qaim, 2017; Zhang et al., 2019). Such a transformation presents an opportunity for ensuring inclusive smallholder innovation and agrifood system development, as well as achieving broader social and development outcomes, such as increased incomes and improved food and nutrition security (Bellemare & Bloem, 2018; Kilelu et al., 2017). However, lack of access to production inputs and essential services such as finance, technology, extension, and knowledge about product quality control and certification are the notable constraints limiting smallholder farmers' integration into and benefits from high-value agrifood markets at the local, regional, and global levels in developing and emerging economies (Widadie et al., 2021).

Governments, donors, and development agencies in developing countries continue to feature agrifood system transformation as a key agricultural development policy initiative in their governance agenda, aimed at ensuring poverty reduction, rural economic transformation, and food security (Abdul-Rahaman & Abdulai, 2020; Arouna et al., 2021; Rao et al., 2012; Schoneveld, 2022). Development agencies and other stakeholders continue to implement agricultural development interventions using the agrifood system approach, which ensures the inclusion of smallholder farmers and other resource-poor actors in agrifood markets to achieve sustainable and equitable outcomes, as documented in the new institutional economics literature (Nuthalapati et al., 2020). Such approaches normally involve the establishment and strengthening of horizontal (e.g., farmer group formation) and vertical (e.g., contracting) coordination mechanisms between smallholder farmers and produce buyers or agribusiness firms for the execution of market transactions (Devaux et al., 2018; Markelova et al., 2009; Ragasa et al., 2018). Smallholder farmers benefit from these facilitative arrangements because agrifood system participation is typically associated with better access to inputs and market information, improved production technologies, and higher and more stable prices (Andersson et al., 2015; Kafle et al., 2022; Ogutu et al., 2020).

This study aims to assess the effects of agrifood system participation on the total value of vegetable production and technical efficiency (TE) among smallholder farmers, using cross-sectional data from a survey of 423 smallholder vegetable farmers in Northern Ghana. We make three contributions to the empirical literature. First, we examine the drivers of smallholder farmers' participation in agrifood systems. Second, our study estimates the impacts of agrifood system participation on the value of vegetable production and TE. In doing so, we employ a multistep approach involving the propensity score matching method and W. Greene's (2010) sample selection stochastic production frontier (SPF) model to, respectively, address both observable and unobservable selection bias issues that might arise from farmers' self-selection into agrifood systems (Bravo-Ureta et al., 2012). Third, we use the metafrontier (MF) model to derive technology gap ratios (TGRs) and meta-TE scores, and then meaningfully compare agrifood system participants and nonparticipants.

Many recent studies have repeatedly shown that improved livelihood outcomes are associated with agrifood system participation by smallholder farming households in developing and emerging countries (Ma & Abdulai, 2016; Maertens & Vande Velde, 2017; Meemken & Bellemare, 2020; Montalbano & Nenci, 2022; Ogutu et al., 2020; Rao & Qaim, 2011; Zhang et al., 2019). For example, some studies have revealed positive impacts of agrifood system participation on household income and poverty reduction (Meemken & Bellemare, 2020; Ogutu et al., 2020; Rao & Qaim, 2011), farm yields and profits (Abdul-Rahaman & Abdulai, 2020; Ma & Abdulai, 2016; Maertens & Vande Velde, 2017), and subjective well-being (Dedehouanou et al., 2013). Other recent studies have also observed benefits in the form of improved food and nutrition security and household asset holdings (Bellemare & Novak, 2017; Michelson, 2013).

The structural transformation of the agrifood systems has considerable implications on smallholder farm production and efficiency, because it facilitates smallholder farmers' access to production inputs and market-related information, as well as affects their production technology choices. Yet, the production and efficiency effects of agrifood system participation among smallholder farmers have been given less attention in the literature. To the best of our knowledge, only the study by Rao et al. (2012) assesses the effects of agrifood system participation on farm production and efficiency among vegetable farmers in the East African context where supermarkets are rapidly expanding. Their study combines the MF method with the propensity score matching approach to estimate the impacts of participation in supermarket channels on vegetable farm output and production efficiency. However, relying on the propensity score matching method is not enough as this approach can only address observable selection bias but ignores the potential existence of unobservable selection bias.

Ghana is an interesting case for the present study because vegetable production forms an integral part of the agricultural systems, and is mostly done in the urban and periurban areas. In Ghana, smallholder farmers mostly dominate the vegetable sector, and benefits associated with its production are observed mostly in the form of increased incomes and improved food and nutrition security. Vegetable production and marketing, therefore, play an important role in providing income and employment for a significant proportion of smallholder farmers and traders in Ghana.

In the context of this study, agrifood system participants are the direct beneficiary farmers of ongoing vegetable development projects in Northern Ghana (Abdul-Rahaman & Abdulai, 2020; Wuepper & Sauer, 2016). One example of these projects is the Northern Ghana Integrated Development Project (NGIDP) implemented by Urban Agriculture Network in collaboration with Action Aid Ghana and Tree Aid. It is a 4-year (2019–2023) project funded by the European Union. The beneficiary farmers have undergone capacity building in the areas of improved vegetable production techniques, business development, and marketing, and have received input support for production under the projects. They have also been linked to produce buyers to supply quality vegetables under the projects. In this formalized agrifood system, high-quality vegetables are paramount to produce buyers, and participating farmers whose products do not meet the required quality are rejected. On the other hand, nonparticipants are those farmers who produce vegetables using their own resources and supply them to buyers in the traditional markets (Birthal et al., 2017). Such farmers are not normally held to strict quality, pricing, and packaging requirements. Other agrifood systems interventions implemented by the Ghanaian government, donor agencies, and the private sector include the Ghana Private–Public Partnership Food Industry Development program, and the Market Oriented Agriculture Program. These interventions aim to improve farm value and product quality for both domestic and European markets. This study is very relevant for policy formulation, especially in smallholder farm output growth, poverty reduction, and overall economic transformation in developing countries.

The rest of this paper is presented as follows. In Section 2, we present the conceptual framework followed by the empirical methods in Section 3. Section 4 describes the data, variables, and descriptive statistics, whilst Section 5 presents and discusses the results. Section 6 contains the conclusions and policy implications based on the findings of the study.

2 | CONCEPTUAL FRAMEWORK

2.1 | Farmers' decisions to participate in agrifood systems

Smallholder vegetable farmers self-decide whether or not to participate in agrifood systems. Their participation decisions can be viewed as a binary choice and modeled in a random utility framework (Abdul-Rahaman et al., 2021; Asfaw et al., 2012). In this case, we assume that farmers are risk-neutral and decide whether or not to participate in agrifood systems based on the comparison between the expected benefits (A_{Pi}) from participation and that (A_{Ni}) from nonparticipation. Intuitively, a benefit-maximizing farmer will decide to participate in agrifood systems only if the benefit derived from participation is greater than the benefit from nonparticipation, that is, $A_i^* = A_{Pi} - A_{Ni} > 0$, with A_i^* denoting the benefit difference. A_i^* cannot be observed directly because it is subjective. Instead, it can be expressed as a function of observable farm and household-level characteristics in a latent variable framework as follows:

$$A_i^* = \beta Z_i + \varepsilon_i, \quad \text{with} \quad A_i = \begin{cases} 1 & \text{if } A_i^* > 0, \\ 0 & \text{otherwise}, \end{cases} \tag{1}$$

where A_i is the binary participation indicator assigned a value of one if farmer i participates in agrifood systems, and zero otherwise; β is a vector of parameters to be estimated; Z_i is a vector of farm and household-level characteristics that influence agrifood system participation; ε_i is the error term with zero mean and variance $\sigma^2 = 1(\varepsilon_i \sim N[0, 1])$. The following specification represents the probability of a farmer participating in agrifood systems:

$$\Pr(A_i = 1) = \Pr(A_i^* > 0) = \Pr(\varepsilon_i > -\beta Z_i) = 1 - F(-\beta Z_i) \tag{2}$$

where F is the cumulative distribution function for ε_i.

2.2 | Impact assessment and selection bias correction

As mentioned earlier, participation in the agrifood systems has considerable implications on farm production and TE among smallholder farmers (Rao et al., 2012). Our study explores this empirical evidence. In doing so, we correct for both observable and unobservable selection biases arising from the nonrandom assignment of agrifood system participation. This study employs an SPF model to estimate farm production and TE (Huang et al., 2014). Here, we assume that farmers either participate in the agrifood systems or not in their vegetable production businesses. The SPF model specification is presented as follows:

$$Y_{ij} = f(X_i, A_i) + v_{ij} - u_{ij}, \tag{3}$$

where Y_{ij} represents the production of the ith farmer, measured by the total value of vegetable production; X_i is a vector of farm inputs and other factors; A_i is a binary variable representing vegetable farmers' decisions on agrifood system participation; v_{ij} is the two-sided error term, and u_{ij} denotes the one-sided error term that captures TE. Subscript j represents A_P for agrifood system participants ($j = 1$), and A_N for nonparticipants ($j = 0$).

Note that farmers self-select into agrifood system participation rather than random assignment. Observable farm and household-level characteristics (e.g., age, gender, education, and farm size) and unobservable attributes (e.g., farmer skills, motivation, and risk preference) might affect both the participation decisions and the outcomes, such as farm production and TE, leading to selection bias. For example, unobserved selection bias might occur when the error term (ε_i) in the selection equation (Equation 1) is correlated with the noise term (v_i) in the conventional SPF model (Equation 3) (Abdul-Rahaman et al., 2021; Bravo-Ureta et al., 2012; W. Greene, 2010). It is important to correct for selection bias in the empirical estimations to obtain unbiased and consistent impact estimates. Following Bravo-Ureta et al. (2012) and Abdul-Rahaman et al. (2021), we employ the PSM and W. Greene's (2010) selection bias-corrected SPF methods to correct for biases associated with observable and unobservable farmer attributes, respectively.

Using the PSM method, we fit a probit model to generate propensity scores that are used to construct a suitable comparable sample comprising both agrifood system participants (treated group) and nonparticipants (control group) based on observed characteristics (Shahidur et al., 2010). The matched sample mitigates the observed selection bias. W. Greene's (2010) selection bias-corrected SPF method, which corrects for the biases from unobservable farmer attributes, is specified as follows:

$$\begin{aligned} \text{Sample selection:}\quad & A_i = 1[\beta' Z_i + \varepsilon_i > 0], \quad \varepsilon_i \sim N[0, 1], \\ \text{SPF:}\quad & Y_i = \gamma' X_i + \mu_i, \\ & (Y_i, X_i) \text{ is observed only when } A_i = 1, \\ \text{Error term structure:}\quad & \mu_i = v_i - u_i, \\ & u_i = |\sigma_u U_i| = \sigma_u |U_i|, \quad \text{where } U_i \sim N[0, 1], \\ & v_i = \sigma_v V_i, \quad \text{where } V_i \sim N[0, 1], \\ & (\varepsilon_i, v_i) \sim N_2\left[(0, 1), \left(1, \rho\sigma_v, \sigma_v^2\right)\right], \end{aligned} \tag{4}$$

where A_i is a binary participation indicator equal to 1 for agrifood system participants and 0 for nonparticipants; Z is a vector of explanatory variables; ε_i is the error term; Y_i is the total value of vegetable production of farmer i; X is a vector of conventional inputs and other factors used in the SPF model, and μ is the composite error term. β and γ denote unknown parameters to be estimated. The error structure corresponds to that in the SPF model. ρ refers to the selectivity-correction term, which is calculated after estimating the treatment specification (i.e., Equation 1) and included in the production function to address unobserved selection bias. The significant ρ would indicate the presence of selection bias arising from the unobserved factors (Asmare et al., 2022; Feng et al., 2022; Ma et al., 2018).

3 | EMPIRICAL METHODS

3.1 | Empirical model specification and estimation procedure

Correcting for observable and unobservable selection bias in estimating the impact of agrifood system participation on smallholder farm production and TE remains important to obtain unbiased and consistent estimates (Bravo-Ureta et al., 2012; Ma et al., 2018). The process begins with fitting a probit model to generate propensity scores, which represent the probability of agrifood system participation. We use the propensity scores to match agrifood system participants with nonparticipants based on similar observable time-invariant factors. This is done to correct selection bias associated with observable farm and household-level attributes. The literature has documented several propensity score matching criteria, such as nearest-neighbor matching, radius matching, spline matching, Mahalanobis matching, kernel matching, and stratified and interval matching (Caliendo & Kopeinig, 2008; Cameron & Trivedi, 2005; Shahidur et al., 2010).

In line with common practice, the nearest-neighbor and kernel-matching criteria have been implemented in this study to ascertain which one would generate a better-matched sample. This study employed a maximum of five matches per participant and a calliper of 0.005 for the nearest-neighbor matching, resulting in 404 matched samples (191 participants and 213 nonparticipants). In addition, we used a bandwidth of 0.025 for the kernel-matching criterion. Next, we conducted a balancing test and compared the means of agrifood system participants and nonparticipants for the explanatory variables. The results reveal that the nearest-neighbor matching produced a better-matched sample relative to the kernel-matching criterion. Therefore, the nearest-neighbor matching was used for the present analysis. Using a trimming procedure, we established a common support region, defined by an area of positive density within A = 1 and 0 distributions, and propensity scores range of 0.017–0.999 (Smith & Todd, 2005). The matching results revealed that very few observations (dropped from analysis) are outside the common support region, suggesting that the agrifood system nonparticipants form an acceptable counterfactual for the participants (see Figure A1 in the Appendix A).

The next step is to estimate W. Greene's (2010) selection bias-corrected SPF, a method that corrects for selection bias arising from unobservable farmer attributes. We carry out such estimation by first modeling farmers' decisions to participate in agrifood systems, which is specified as a function of explanatory variables (Z_{ij}) as

$$A_i = \beta_0 + \sum_{j=1}^{17} \beta_j Z_{ij} + \varepsilon_i, \tag{5}$$

where A_i denotes a binary participation indicator equal to one for agrifood system participants and zero for nonparticipants; β_j is a vector of unknown parameters to be estimated; and ε_i is an error term. The explanatory variables in Z_{ij} include age, education, gender, household size, mobile phone ownership, irrigation, total farm size, access to credit, distance to market, distance to the main road, road access, farmer group membership, extension visits, and location (district) dummies. These variables are selected mainly drawing upon the existing studies on agrifood systems (Abdul-Rahaman & Abdulai, 2020; Kafle et al., 2022; Ma et al., 2018; Montalbano & Nenci, 2022; Rao et al., 2012; Tray et al., 2021; Zhang et al., 2019).

In estimating W. Greene's (2010) selection bias-corrected SPF model, we conducted a likelihood ratio (LR) test to compare the translog model with the Cobb–Douglas model. The test results suggest that the Cobb–Douglas model is preferred for estimating the production function. The Cobb–Douglas model is specified as follows:

$$\ln(Y_i) = \gamma_0 + \sum_{j=0}^{5} \gamma_j \ln(X_{ji}) + \sum_{k=0}^{6} \delta_k D_{ki} + v_i - u_i, \quad \text{if } A_i = 1, \tag{6}$$

where Y_i is the value of farm production of farmer i; X_{ji} is the quantity of the jth input (land, quantity of seed, quantity of fertilizer, quantity of active ingredients in chemicals, and amount of labor); D represents dummy variables (soil fertility, irrigation, and location-fixed factors); γ and δ are vectors of unknown parameters to be estimated; v and u represent the elements of the composed error term, μ.

The model parameters are estimated using the Broyden–Fletcher–Goldfarb–Shanno method. In addition, the Berndt–Hall–Hall–Hausman estimator is used to estimate the asymptotic standard errors for the parameter estimators (see W. Greene, 2010). Note that we first run the model for agrifood system participants (i.e., $A_P = 1, A_N = 0$), and then repeat the estimation for nonparticipants, in which case the participation variable is reversed in the selection equation (i.e., $A_P = 0, A_N = 1$) (W. Greene, 2010). Several previous studies have implemented the selection bias-corrected SPF model (Abdul-Rahaman et al., 2021; Asmare et al., 2022; Bravo-Ureta et al., 2021; Ma et al., 2018; Zheng et al., 2021). For example, using the selection bias-corrected SPF model, Ma et al. (2018) estimated the impact of membership in agricultural cooperatives on the output and TE of apple farmers in China. They pointed out that the efficiency levels of both members and nonmembers of cooperatives would be underestimated if one does not appropriately address the selectivity bias issues.

It is important to mention that the TE scores derived from the conventional and selection bias-corrected SPFs, which represent the group-specific TE estimates, $\text{TE}_{ij} = E[e^{-u_{ij}}, j = 1, 0]$, cannot be used to directly compare agrifood system participants and nonparticipants to ascertain the technological differences between them. We interpret the TE scores relative to each group's own production frontier (Villano et al., 2015). Following the approach by Huang et al. (2014), we estimate an MF model, which envelopes both the participant and nonparticipant group production frontiers to determine the technological differences between these groups. In order words, the MF analysis determines the gap between the MF and each group frontier, referred to as the meta-TGR. The production frontier for each group of agrifood system participants and nonparticipants is expressed as

$$Y_{ij} = f^{j}(X_{ij}, \gamma_j)e^{v_{ij}-u_{ij}}, \tag{7}$$

where Y_{ij}, X_{ij}, γ_j, v_{ij}, and u_{ij} are as defined earlier. v_{ij} and u_{ij} are assumed to be uncorrelated, and u_{ij} follows a truncated-normal distribution (Huang et al., 2014). The TE scores obtained from the production frontier model for each farmer and participation group are expressed as

$$TE_i^j = \frac{Y_{ij}}{f^{j}(X_{ij}, \gamma_j)e^{v_{ij}}} = e^{-u_{ij}}, \tag{8}$$

Let $f^M(X_{ij}, \gamma_j)$ be the common MF that envelopes the participant and nonparticipant group frontiers. This is specified with respect to the group frontier as follows:

$$f^{j}(X_{ij}, \gamma_j) = f^{M}(X_{ij}, \gamma_j)e^{-u_{ij}^{M}}, \qquad \forall i, j, \tag{9}$$

where $u_{ij}^M \geq 0$. Thus, $f^M(X_{ij}, \gamma_j) \geq f^j(X_{ij}, \gamma_j)$. The meta-TGR, which is defined as the ratio of the group frontier to the MF, is expressed as

$$TGR = \frac{f^{j}(X_{ij}, \gamma_j)}{f^{M}(X_{ij}, \gamma_j)} = e^{-u_{ij}^{M}} \leq 1. \tag{10}$$

The TE relative to the metafrontier technical efficiency (MTE) $f^M(X_{ij}, \gamma_j)$ is estimated using Equation (11):

$$MTE = \frac{Y_{ij}}{f^{M}(X_{ij}, \gamma_j)e^{v_{ij}}} = TGR_{ij} \times TE_{ij} \times e^{v_{ij}}. \tag{11}$$

3.2 | Control function approach estimates

As outlined earlier, smallholder vegetable farmers' decisions to participate in agrifood systems are likely to be influenced by several factors. However, three control variables, including farmer group membership, access to credit, and extension visits, are potentially endogenous, which should be addressed to ensure consistent model estimations. The concept of farmer group is very important in agrifood systems in developing countries. Produce buyers or agribusiness companies normally engage smallholder farmers as a group rather than as individuals to ensure bulk procurement of products and minimize costs associated with having to mobilize produce from individual farmers. Smallholder farmer participation in farmer groups can also ensure guaranteed markets for their produce (Ochieng et al., 2017). Therefore, farmers can join farmer groups to participate in agrifood systems, which makes both decisions jointly determined. Similarly, access to credit plays an important role in smallholder agricultural development (Kumar et al., 2020). Smallholder farmers' participation in agrifood systems can enable them to access credit through linkages to financial institutions and agribusiness companies by NGOs and the government. Hence, farmers' decisions to participate in agrifood systems, and also to access credit may be jointly determined. In the same vein, farmers' participation in the agrifood system can be influenced by extension agents through their visits to their farms (Emmanuel et al., 2016). As mentioned previously, it is important to account for these potential endogeneities to ensure that the model is consistently estimated.

This study employs the control function approach to address these potential endogeneity problems (Wooldridge, 2015). In a two-stage procedure, we first model separately farmer group membership, access to credit, and extension visits (potential endogenous variables) as a function of observable factors in the agrifood system participation model plus valid instrument(s). The instruments should significantly influence the endogenous variables but not the agrifood system participation. Distance to the group's meeting venue is used as an instrument for the farmer group membership variable. We argue that farmers who would have to travel a longer distance for group meetings are less likely to join farmer groups. Regarding access to credit, the variable representing the distance to the credit source is used as an instrument. The farther away the credit institution to a farmer's home/community, the less likely such farmers would access credit. Similarly, distance from the farm to the extension office is employed as an instrument for the extension visits variable. Here, the hypothesis is that farms at locations very far from extension offices might not receive extension services. However, these instruments do not directly influence agrifood system participation. In the second stage, we model the agrifood system participation decision as a function of the explanatory variables, including the observed potential endogenous variables and their respective residuals predicted after the first stage estimation (Wooldridge, 2015).

In the context of this study, we assume the absence of potential endogeneity of control variables, such as farm size, mobile phone ownership, and irrigation in the model. First, farmers in the study localities do not rent the land, but rather make use of what is available in the community to cultivate their vegetables. Second, the relationship between mobile phone ownership and use is assumed to influence information diversity and access among farm households in Ghana, where new mobile phone use is now common with 44.90 million cellular mobile connections in Ghana at the start of 2022.[1] Thus, ownership here is closely linked to use by at least, some or all members of a household. Third, in the study area, vegetable production under irrigation is a matter of access to land with proximity to the location of water source, rather than the decision to use the water. We statistically tested the potential endogenous issues of farm size, mobile phone ownership and irrigation using the seemingly unrelated probit model (Baum, 2009) and conditional mixed process model (David, 2011), but we did not find endogeneity issues.

4 | DATA, VARIABLES, AND DESCRIPTIVE STATISTICS

4.1 | Data

The data used for this study were collected from a farm household survey in Northern Ghana from September to November 2019. Using a multistage sampling procedure, the districts such as Tamale metropolis, Savelugu, Tolon, Sagnarigu, and Kumbungu districts were first purposively selected based on the intensiveness of vegetable production around these areas. Second, about 2–3 communities were randomly selected from each district. Finally, 423 farm households, cultivating diverse vegetable crops, were sampled in proportion to the farmer population in the study area. The sample comprises 191 agrifood system participants and 232 nonparticipants, which were interviewed using a structured questionnaire for information on farm and household characteristics, agrifood system dynamics, and production and marketing.

In this study, agrifood system participation is measured as a dummy variable. It is equal to one if a vegetable farmer has participated in agrifood systems, and zero otherwise. As discussed previously, agrifood system participants are farmers participating in ongoing vegetable development projects such as NGIDP in Northern Ghana, and nonparticipants are those producing vegetables based on their experiences and selling them at the traditional spot markets. The NGIDP is implemented in selected districts across Northern Ghana. In all, 15 districts are being targeted by the NGIDP project, including the five districts considered in this study. The list of vegetable-producing households was compiled in each targeted community where the project was implemented. We assumed that each household has an equal opportunity of participating in the project so long as they cultivate the crops

[1] https://datareportal.com/reports/digital-2022-ghana

considered by the project. Thus, the selected households in this study were randomly chosen from each community. However, not all households were participants, as some farm households never benefitted from any training or services provided by the project. Such farm households are referred to as nonparticipants in the agrifood system. Examples of vegetables produced by farmers include okro, chili/hot pepper, amaranthus/spinach (aleefu), onion, garden eggs, tomatoes, lettuce, cabbage, and carrot.

Following the examples of Solís et al. (2007), Bravo-Ureta et al. (2012), Rao et al. (2012), and Issahaku and Abdulai (2020) for mixed-crop farming situations, the outcome variable used in the production function is the total value of vegetable production, referring to the values of all vegetables produced by the farmers on various plots in a season. Ghanaian farmers usually grow various vegetables to diversify household income and mitigate production uncertainties and risks induced by fluctuating market conditions and weather shocks.

4.2 | Choice of control variables

We draw upon the literature on agrifood value chain to select the control variables included in the matching Equation (5) (e.g., Abdul-Rahaman & Abdulai, 2020; Aker et al., 2016; Mojo et al., 2017; Montalbano & Nenci, 2022; Tray et al., 2021; Widadie et al., 2021; Zanello et al., 2014; Zhang et al., 2022). Specifically, age and education are considered important measures of human capital, which influence farmers' ability to perceive, interpret, and respond to new events (Schultz, 2006). Older and better-educated farmers have more experience and skills to respond to the demands and requirements of other players in agrifood systems. Thus, we include age and education variables and expect they affect the likelihood of agrifood system participation decisions positively. Women in Northern Ghana have lower opportunities, capacities, and motivation than men, to effectively participate in agrifood systems, which is attributed to their engagement in household activities and unpaid care work in addition to their farming activities (Meinzen-dick & Zwarteveen, 1998). We include a gender variable and expect that females are more likely to participate in agrifood systems than males.

To a great extent, lager household size indicates more labor endowments, motivating farming households to participate in agrifood systems and benefit from agricultural production. Larger farm sizes lower average fixed costs associated with agrifood system participation decisions (Abdul-Rahaman & Abdulai, 2020; Fischer & Qaim, 2012), and therefore, we included a farm size variable and expect that it increases the probability of participating in agrifood systems. Vegetable production and marketing require investments in inputs and labor. Resource-constrained farmers require sufficient financial capital to undertake these activities. We included a dummy variable representing access to credit to ascertain the liquidity status of the farmers, and expect that access to credit is positively correlated with agrifood system participation.

Farmers form groups for effective engagement with buyers and other stakeholders in the supply chains (Abdul-Rahaman & Abdulai, 2018), and extension visits help improve farmers' understanding of the benefits associated with agrifood systems. Therefore, we include farmer group and extension visit variables in our model and expect they are positively associated with agrifood system participation. Mobile phone ownership facilitates the acquisition of information on input and output prices, which could serve as a guide for farmers to negotiate better prices with input dealers and output buyers. It enables farmers to cut down costs associated with the search for buyers, as well as setting up and negotiating transactions (Aker et al., 2016; Zanello et al., 2014). Mobile phone ownership tends to promote efficient communication amongst value chain actors (Fischer & Qaim, 2012). Thus, we include a mobile phone ownership variable and expect it is positively correlated with agrifood system participation.

District-level variables featured in the matching equation are distance to markets, distance to main road, road access, irrigation facility, and district/location dummies. We expect a positive influence of distance to market and distance to main road on agrifood system participation. Motorable roads lower transaction costs of both produce and inputs (Dercon et al., 2009). Vegetable cultivation under a community irrigation facility enhances farm productivity. Therefore, road access and irrigation facility, which are considered proxies for quality of infrastructure, are also included as control variables and expected to influence agrifood system participation positively. Finally, we include a set of district/location dummies to account for possible spatial effects, neighborhood effects, infrastructural differences of the sample districts, as well as differences in environmental and biophysical factors, without assigning any prior signs.

4.3 | Descriptive statistics

Table 1 presents the variables used in the empirical estimations and respective summary statistics. As shown, 45% of the vegetable farmers participate in the agrifood system whilst 55% of them participate in the traditional chains. This suggests that the majority of them do not still have the opportunity to be integrated into such formalized agrifood systems in Northern Ghana. On average, a vegetable farmer is 39 years old, with 3 years of formal education, cultivating about an acre of land and generating a total value of GH¢ 1227.65 (roughly 200 USD).

Table 2 presents the mean differences in characteristics of vegetable farmers by agrifood system participation status for both the unmatched and matched samples. We observe significant differences between agrifood system participants and nonparticipants with respect to most of the variables in the unmatched sample. In particular, the agrifood system participants appear older, better educated, and mostly access credit, relative to nonparticipants. They also constitute a higher proportion that uses irrigation facilities in vegetable production. Moreover, agrifood system participants cultivate more land, apply higher quantities of inputs, and generate higher revenue from vegetable production than nonparticipants. On the other hand, except for a location dummy (i.e., Sagnarigu), no significant differences in variable means between participants and nonparticipants have been recorded in the matched sample, which suggests fulfillment in the balancing condition in the PSM method.

5 | RESULTS AND DISCUSSIONS

5.1 | Drivers of agrifood system participation decisions

This section examines the drivers of agrifood system participation among smallholder vegetable farmers. The variable coefficients and marginal effects are presented in Table 3. As revealed by the χ^2 test [LR χ^2(20), (Prob > χ^2 = 0.000)], the estimated parameters are jointly significant at the 1% level. The coefficients of residuals associated with extension visits, access to credit, and farmer group membership are not statistically significant, implying that these variables are not endogenously determined in smallholder farmers' agrifood system participation decisions. Table 3 reveals that demographic and social-economic factors affect vegetable farmers' decisions to participate in the agrifood system. For example, gender exerts a negative and significant marginal effect on agrifood system participation at the 5% level, indicating that male vegetable farmers are about 21.4% less likely to participate in agrifood systems. Agrifood system participation is also positively and significantly determined by mobile phone ownership. This suggests that farmers who own mobile phones have about a 42.7% higher probability of participating in agrifood systems. This finding is in line with intuition, as mobile phones promote effective communication between suppliers and produce buyers and serve as a medium for receiving production and marketing information (Abdul-Rahaman & Abdulai, 2020; Fischer & Qaim, 2012).

Irrigation also plays an important role in vegetable agrifood system participation. Smallholder farmers who cultivate vegetables under irrigation are about 6.9% more likely to participate in agrifood systems. Irrigation enhances crop output due to the regular water supply to crops all year round (Li et al., 2020; Rao et al., 2012). In addition, farmers with relatively larger farm sizes have about a 2.6% higher probability of participating in the agrifood system. The road access variable has a positive and significant marginal effect on agrifood system participation. In particular, vegetable farmers whose farms are located around motorable roads are more likely to

TABLE 1 Variable definitions and summary statistics

Variables	Definitions	Mean (SD)
Dependent variables		
TVP	The total value of vegetable production (GH¢)	1227.65 (1543.10)
AFP	1 if a farmer participates in a vegetable agrifood system, 0 otherwise	0.45 (0.49)
Control 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)
Total farm size	Total size of farm cultivated by a household	5.24 (4.79)
Access to credit	1 if a farmer has access to enough credit and is not credit-constrained, 0 otherwise	0.45 (0.40)
Farmer group	1 if farmer belongs to a vegetable farmer group, 0 otherwise	0.32 (0.46)
Extension visits	Number of extension visits to a farmer in the last 12 months	1.58 (4.36)
Mobile phone	1 if a farmer owns a mobile phone, 0 otherwise	0.71 (0.45)
Distance to market	Distance to vegetable market (km)	6.54 (5.85)
Distance to main road	Distance to community's main road	2.38 (4.64)
Road access	1 if road to community is accessible, 0 otherwise	0.52 (0.49)
Irrigation	1 if a farmer cultivates vegetables under irrigation, 0 otherwise	0.52 (0.50)
Tolon	1 if 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)
Input variables in the SPF model		
Land	Total land size devoted to vegetable production	1.04 (1.08)
Seed	Total amount of seed planted (kg/acre)	4.85 (26.98)
Fertilizer	Total amount of fertilizer applied (kg/acre)	77.55 (71.21)
Chemical	Total amount of active ingredient of chemical applied (kg/acre)	1.59 (1.07)
Labor	Total amount of labor used in vegetable production (worker-days/acre)	70.08 (7.35)
Soil fertility	1 if a farmer perceives soil to be fertile, 0 otherwise	0.96 (0.18)

Note: GH¢ is Ghanaian currency (US$1 = GH¢ 5.70 as of December 2019).
Abbreviations: SD, Standard Deviation; SPF, stochastic production frontier.

participate in agrifood systems. Motorable roads enable easy access to market centers and growing communities by product buyers. The results also show that farmers who belong to farmer groups and those who receive a relatively higher number of extension visits are 47.9% and 19.8% more likely to participate in agrifood systems. Farmer group members derive benefits in the form of access to credit, production inputs, and markets for their produce (Fischer &

TABLE 2 Differences in characteristics of vegetable farmers by agrifood system participation

Variable	Unmatched sample					Matched sample				
	Participants		Nonparticipants		Difference	Participants		Nonparticipants		Difference
	Mean	SD	Mean	SD	(*t* statistics)	Mean	SD	Mean	SD	(*t* statistics)
Age	41.34	10.55	37.67	10.99	3.47***	41.34	10.55	42.99	11.14	−1.65
Education	3.62	5.34	3.17	4.22	0.96	3.62	5.34	3.23	4.29	1.41
Gender	0.67	0.47	0.61	0.48	1.23	0.67	0.47	0.62	0.48	0.91
Household size	13.72	8.74	7.83	3.66	9.31***	13.72	8.74	9.96	3.74	1.62
Total farm size	6.77	5.26	3.97	3.94	6.24***	6.77	5.26	6.80	4.05	−0.96
Access to credit	0.55	0.30	0.41	0.45	−4.94***	0.55	0.30	0.53	0.44	1.31
Farmer group	0.51	0.50	0.17	0.37	7.95***	0.51	0.50	0.50	0.70	0.50
Extension visits	3.00	6.11	0.41	0.97	6.35***	3.00	6.11	2.67	1.01	0.86
Mobile phone	0.87	0.33	0.58	0.49	6.88***	0.87	0.33	0.76	0.50	1.58
Distance to market	9.33	6.68	4.24	3.76	9.84***	9.33	6.68	8.00	3.90	0.37
Distance to main road	3.70	6.25	1.29	2.16	5.47***	3.70	6.25	3.48	2.24	0.66
Road access	0.42	0.49	0.61	0.48	−4.00***	0.42	0.49	0.48	0.47	−0.50
Irrigation	0.75	0.43	0.32	0.47	9.62***	0.75	0.43	0.70	0.41	0.74
Tolon	0.57	0.49	0.09	0.29	12.23***	0.57	0.49	0.50	0.31	−0.26
Tamale	0.12	0.33	0.11	0.32	0.429	0.12	0.33	0.12	0.32	0.20
Kumbungu	0.12	0.32	0.37	0.48	−6.34***	0.12	0.32	0.11	0.49	0.16
Savelugu	0.14	0.35	0.41	0.49	−6.26***	0.14	0.35	0.10	0.48	1.58
Sagnarigu	0.04	0.20	0.00	0.00	3.17***	0.04	0.20	0.00	0.00	3.17***
TVP	1605.74	1647.62	916.37	1379.01	4.68***	1605.74	1647.62	1773.4	1167.68	−0.83
Land	1.20	1.13	0.91	1.02	2.80***	1.20	1.13	0.97	1.06	1.26

TABLE 2 (Continued)

Variable	Unmatched sample					Matched sample				
	Participants		Nonparticipants		Difference (t statistics)	Participants		Nonparticipants		Difference (t statistics)
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Seed	3.39	23.40	6.05	29.60	−1.01	3.39	23.40	1.41	30.86	1.18
Fertilizer	88.64	67.61	68.41	72.92	2.93***	88.64	67.61	78.03	74.60	1.25
Chemical	1.91	1.16	1.32	0.92	5.77***	1.91	1.16	1.83	0.96	1.03
Labor	71.14	6.84	69.21	7.65	2.69***	71.14	6.84	71.50	7.55	−0.67
Soil fertility	0.95	0.21	0.97	0.15	−1.17	0.95	0.21	0.96	0.15	−0.98
Sample size	191		232			191		213		

Abbreviations: SD, Standard Deviation; TVP, total value of vegetable production.

*, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

TABLE 3 Factors affecting vegetable agrifood system participation: Probit model estimates

Variables	Coefficient	SE	Marginal effects	SE
Constant	−7.283***	0.896		
Age	0.134***	0.011	0.005	0.004
Education	0.052**	0.023	0.013	0.008
Gender	−0.561**	0.242	−0.214**	0.092
Household size	0.093***	0.026	0.035***	0.010
Total farm size	0.158***	0.031	0.026**	0.013
Access to credit	0.329	0.261	0.125	0.099
Farmer group	1.257***	0.251	0.479***	0.094
Extension visits	0.521***	0.091	0.198**	0.030
Mobile phone	1.119***	0.247	0.427***	0.097
Distance to market	0.053	0.041	0.020	0.015
Distance to main road	0.050	0.032	0.019	0.012
Road access	0.707*	0.414	0.270*	0.158
Irrigation	0.483**	0.239	0.069**	0.031
Tolon	−1.123	0.773	−0.428	0.294
Tamale	−1.735***	0.642	−0.662***	0.245
Kumbungu	−2.335***	0.640	−0.891***	0.245
Savelugu	−3.797***	0.711	−1.449***	0.264
Farmer group (residual)	2.362	1.823		
Access to credit (residual)	2.583	1.843		
Extension visits (residual)	−2.955	2.933		
LR $\chi^2(20)$ [Prob > χ^2 = 0.000]	355.75			
Log-likelihood	−113.33			
Number of observations	423			

Abbreviations: LR, likelihood ratio; SE, Standard Error.

*, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

Qaim, 2014; Ma et al., 2022). The location dummies also serve as significant drivers of agrifood system participation in Northern Ghana, suggesting the existence of spatial-fixed effects that affect vegetable farmers' decisions to participate in agrifood systems.

5.2 | Impacts of agrifood system participation on farm value: SPF estimate

This section presents the maximum-likelihood estimates of conventional and selection bias-corrected SPF models. The results for both the unmatched and matched samples are presented in Tables 4 and 5, respectively. As shown, the null hypothesis that the variance parameter for compound error (ψ) is not significantly different from zero (ψ = 0) is rejected, in all cases, at the 1% level. The findings indicate the stochastic nature of TE and the significant

TABLE 4 Factors affecting the farm value of vegetable production: Unmatched sample estimates

	Conventional SPF						Selection bias-corrected SPF			
	Pooled		Participants		Nonparticipants		Participants		Nonparticipants	
Variables	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	7.088***	1.831	10.228***	2.891	6.062**	2.368	10.698***	3.849	5.362**	2.292
ln land	0.110***	0.014	0.271***	0.021	0.107***	0.018	0.282***	0.028	0.280***	0.025
ln seed	0.079**	0.031	0.205**	0.089	0.159***	0.060	0.288***	0.010	0.160*	0.095
ln fertilizer	0.483***	0.047	0.512***	0.076	0.502***	0.060	0.612***	0.084	0.534**	0.068
ln chemical	0.200***	0.015	0.279***	0.019	0.356***	0.022	0.272***	0.023	0.453***	0.024
ln labor	0.107	0.417	0.813	0.672	0.367	0.517	0.931	0.900	0.339	0.647
Soil fertility	0.214***	0.023	0.259***	0.030	0.358***	0.036	0.291***	0.030	0.449***	0.027
Irrigation	0.477***	0.111	0.310***	0.020	0.244***	0.013	0.352***	0.032	0.423***	0.151
Tolon	0.679**	0.335	0.845**	0.389	0.565**	0.288	0.856*	0.466	0.971***	0.292
Savelugu	0.835**	0.326	1.152***	0.305	0.521***	0.087	1.130**	0.563	1.056***	0.285
Kumbungu	0.750**	0.336	0.898**	0.383	0.487***	0.087	0.818*	0.459	1.031***	0.288
Tamale	0.711**	0.327	0.686**	0.362	0.715***	0.089	0.568*	0.306	1.121***	0.281
AFP	0.733***	0.115	–	–	–	–	–	–	–	–
Log-likelihood	−551.76		−242.05		−295.65		−305.92		−345.84	
ψ	0.963***	0.126	1.162***	0.205	0.836***	0.167	–	–	–	–
σ^2	1.072***	0.002	1.082***	0.004	1.008***	0.003	–	–	–	–
$\sigma_{(u)}$	–	–	–	–	–	–	0.823***	0.292	0.395**	0.183
$\sigma_{(v)}$	–	–	–	–	–	–	0.706***	0.139	0.851***	0.141
ρ	–	–	–	–	–	–	−0.119***	0.035	0.443	0.310
N	423		191		232		191		232	

Abbreviations: AFP, farmer participates in a vegetable agrifood system; SE, Standard Error; SPF, stochastic production frontier.

*, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

TABLE 5 Factors affecting the farm value of vegetable production: Matched sample estimates

	Conventional SPF						Selection bias-corrected SPF			
	Pooled		Participants		Nonparticipants		Participants		Nonparticipants	
Variables	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	7.211***	1.852	10.228***	2.891	5.869**	2.398	10.535***	3.721	6.207**	2.777
ln land	0.129***	0.013	0.271***	0.021	0.112***	0.017	0.286***	0.029	0.282***	0.023
ln seed	0.081***	0.030	0.205**	0.089	0.148**	0.058	0.289***	0.011	0.161**	0.082
ln fertilizer	0.489***	0.052	0.512***	0.076	0.560***	0.060	0.614***	0.080	0.539***	0.065
ln chemical	0.211***	0.014	0.279***	0.019	0.350***	0.021	0.278***	0.021	0.453***	0.024
ln labor	0.016	0.423	0.813	0.672	0.341	0.532	0.873	0.898	0.390	0.635
Soil fertility	0.221***	0.024	0.259***	0.030	0.405***	0.048	0.298***	0.029	0.451***	0.025
Irrigation	0.483***	0.110	0.310***	0.020	0.354***	0.035	0.358***	0.033	0.493***	0.149
Tolon	0.658**	0.327	0.845**	0.389	0.546***	0.086	0.826*	0.469	0.982**	0.289
Savelugu	0.803**	0.319	1.152***	0.305	0.479***	0.083	1.117**	0.567	1.013***	0.273
Kumbungu	0.754**	0.327	0.898**	0.383	0.497***	0.084	0.814	0.567	0.985***	0.267
Tamale	0.711**	0.319	0.686**	0.362	0.727***	0.085	0.569*	0.337	1.091***	0.274
AFP	0.754***	0.113	–	–	–	–	–	–	–	–
Log-likelihood	−516.73		−242.05		−262.06		−306.54		−310.90	
ψ	0.999***	0.132	1.162***	0.205	0.881***	0.175	–	–	–	–
σ^2	1.054***	0.002	1.082***	0.004	0.975***	0.003	–	–	–	–
$\sigma_{(u)}$	–	–	–	–	–	–	0.825***	0.301	0.763***	0.150
$\sigma_{(v)}$	–	–	–	–	–	–	0.715***	0.142	0.701***	0.066
ρ	–	–	–	–	–	–	−0.109***	0.035	0.464	0.391
N	404		191		213		191		213	

Abbreviations: AFP, farmer participates in a vegetable agrifood system; SE, Standard Error; SPF, stochastic production frontier.

*, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

role of inefficiency in terms of variation of observed farm values (Bravo-Ureta et al., 2012). This finding justifies the estimation of the SPF model in our study rather than the standard production function. In addition, the results have also established statistical evidence that favors the estimation of separate SPF models for agrifood system participants and nonparticipants. This is revealed by the LR test, which rejects the null hypothesis of homogenous technology between participants and nonparticipants at the 1% level in both unmatched and matched samples (W. H. Greene, 2008). Consistent with this finding, the results reveal a positive and significant effect of agrifood system participation on the total value of vegetable production across all models for the unmatched and matched samples. The coefficient of the selection bias indicator, ρ is found to be negative and statistically different from zero at the 1% level in the participant category of the selection-bias SPF model for both subsamples (see lower parts of Tables 4 and 5). This suggests the presence of selection bias arising from unobserved factors, and that employing the selection bias-corrected SPF model over the conventional SPF model is justified because the latter would generate biased estimates (Asmare et al., 2022; Bravo-Ureta et al., 2021).

Next, we examine the factors influencing farm value, conditional on agrifood system participation. As shown in Tables 4 and 5, positive partial elasticities have been revealed across all the SPF models for the unmatched and matched samples. The partial elasticity assesses the percentage change in each input to the percentage change in the value of vegetable production. Aside labor, all the conventional inputs—land, fertilizer, seeds, and chemicals—exert positive and significant effects on the value of vegetable production. In particular, fertilizer exerts the highest effect on the value of vegetable production across all the models and samples, followed by chemicals for both participants and nonparticipants. However, the effect of the chemical is much higher for the nonparticipant group, suggesting that this category of farmers relies heavily on chemicals in controlling weeds, pests, and diseases, relative to participants. These findings are consistent with some previous studies in developing countries (Bravo-Ureta et al., 2012; Jayne et al., 2014), showing that purchased inputs play significant roles in enhancing farm outputs. Nonetheless, budget restrictions remain the major constraints for smallholder farmers in less favorable areas.

The land variable also positively and significantly affects the value of vegetable production, suggesting that a percentage increase in land size generates a larger-percentage change in the value of vegetable production. In addition, the quantity of seed exerts the least positive and significant effect on the value of vegetable production, although higher for the participant group, suggesting the use of improved vegetable seeds, as well as the application of recommended planting technologies by this group. We also find that labor plays a positive but insignificant role in the value of vegetable production. This finding is attributable to the declining marginal benefits associated with labor caused by the abundance of labor in the study area (González-Flores et al., 2014).

Other factors that enhance the value of vegetable production include soil fertility, irrigation, and location dummies. In particular, the parameter estimate for soil fertility is positive and highly significant across all the SPF models, suggesting that vegetable fields of highly perceived fertility generate a higher value of vegetable production relative to fields with the least perceived fertility. In addition, farmers who cultivate vegetables under irrigation obtain a higher value of vegetable production than farms under rainfed production. This finding confirms the important role of irrigation facilities in ensuring regular water supply to crops compared to rainfall which is erratic in the study area (Abdul-Rahaman et al., 2021; Amfo et al., 2021). Finally, relative to Sagnarigu municipal (reference district), a higher value of vegetable production is associated with farms located in areas, such as Tolon, Savelugu, Kumbungu, and Tamale. This finding reveals the importance of location-fixed effects, especially in accounting for heterogeneity in input and information access, neighborhood effects, and biophysical and environmental conditions.

5.3 | TE and predicted value of vegetable production

Table 6 presents the results of the group-specific scores of TE, TGR, and MTE for agrifood system participants and nonparticipants in the unmatched samples. These scores are derived from estimating the conventional and selection bias-corrected SPF models. The mean differences between participants and nonparticipants with respect to the TE,

TABLE 6 Technical efficiency scores across SPF models

	Conventional SPF							Selection bias-corrected SPF				
	Pooled		Participants		Nonparticipants			Participants		Nonparticipants		
Item	Mean	SD	Mean	SD	Mean	SD	Test of means	Mean	SD	Mean	SD	Test of means
Unmatched sample												
Technical efficiency (TE)	0.57	0.11	0.61	0.09	0.54	0.13	6.30***	0.68	0.04	0.58	0.13	10.23***
Technology gap ratio (TGR)	0.93	0.06	0.91	0.08	0.88	0.04	5.00***	0.95	0.04	0.91	0.06	7.88***
Metafrontier technical efficiency (MTE)	0.63	0.11	0.70	0.11	0.55	0.05	18.57***	0.73	0.13	0.57	0.04	17.75***
Matched sample												
Technical efficiency (TE)	0.57	0.11	0.61	0.10	0.54	0.13	6.10***	0.65	0.06	0.56	0.12	9.38***
Technology gap ratio (TGR)	0.95	0.04	0.93	0.02	0.91	0.01	12.90***	0.98	0.02	0.94	0.02	20.07***
Metafrontier technical efficiency (MTE)	0.54	0.11	0.56	0.12	0.51	0.10	4.57***	0.58	0.11	0.55	0.12	2.61***

Abbreviations: SD, Standard Deviation; SPF, stochastic production frontier.

***Represents significance at 1% level.

TGR, and MTE have also been conducted using statistical *t*-tests, and the results are also reported in Table 6. For both unmatched and matched samples, the results show significant mean differences between agrifood system participants and nonparticipants with respect to the TE, TGR, and MTE. Specifically, agrifood system participants obtain higher TE scores than those obtained by nonparticipants across all the models. In particular, for the conventional SPF model in the unmatched sample, the TE scores for agrifood system participants and nonparticipants stand at 61% and 54%, respectively. However, the selection bias-corrected SPF model estimation shows that agrifood system participants and nonparticipants, respectively, operate at TE levels of 68% and 58%, relative to their respective group frontiers. These findings suggest that participants perform better within their cohorts than nonparticipants (Abdul-Rahaman et al., 2021; Villano et al., 2015). Similar results have also been revealed in the case of the matched sample for both the conventional and selection bias-corrected SPF models. We also observe an increase in TE scores after correcting for biases associated with unobservable farmer attributes for the unmatched and matched samples.

Next, we examine the TGR and MTE scores derived from MF estimation across all the models and subsamples (Huang et al., 2014). The TGR is a measure of the gap between the MF and the group-specific frontiers, whilst the MTE allows for a meaningful comparison between agrifood system participants and nonparticipants. As shown in Table 6, the selection bias-corrected SPF model estimation reveals higher TGR (95%) for agrifood system participants than nonparticipants (91%) in the unmatched sample. Similarly, the TGR for agrifood system participants and nonparticipants stands at 98% and 94%, respectively, for the matched sample. These findings suggest that agrifood system participants operate closer to the best technology than nonparticipants. In addition, in the unmatched sample, the MTE score derived from the selection bias-corrected SPF model for agrifood system participants is significantly higher (73%) than that of nonparticipants (57%). The matched sample also records higher MTE (58%) for agrifood system participants than that for nonparticipants (55%). This means that participants perform better than nonparticipants in terms of farm value and efficiency. Several past studies have also recorded similar results in developing countries (De los Santos-Montero & Bravo-Ureta, 2017; Issahaku & Abdulai, 2020; Rao et al., 2012; Villano et al., 2015).

The performance of participants and nonparticipants is further examined by predicting the frontier value of vegetable production for cases without bias correction (unmatched sample) and with bias correction (matched sample). The results presented in Table 7 reveal that smallholder participation in agrifood systems contributes significantly to a 50% and about 53% increase in the predicted frontier value of vegetable production with and

TABLE 7 Predicted frontier vegetable farm value for agrifood system participants and nonparticipants

SPF model	Pooled	Participants	Nonparticipants	Farm value increase (%)	Test of means[a]
Unmatched conventional					
Mean	1392.68	2074.65	976.32	52.94	4.10***
Minimum	527.14	758.74	411.73		
Maximum	2720.65	4979.68	3112.69		
Matched sample selection					
Mean	1907.50	1918.09	958.34	50.04	3.80***
Minimum	833.49	726.55	431.89		
Maximum	4305.37	4427.51	2427.39		

Abbreviation: SPF, stochastic production frontier.

[a]*t* Test of predicted mean frontier production difference between agrifood system participants and nonparticipants.

***Represents significance at the 1% level.

without selection bias correction, respectively. This finding further confirms the higher performance of participants relative to nonparticipants.

6 | CONCLUSIONS AND POLICY IMPLICATIONS

Participation in agrifood systems has considerable implications on smallholder farm output growth, poverty reduction, and overall welfare improvement, despite the rapid structural transformation in developing countries in the last few decades. This study examined the efficiency effects of agrifood system participation among vegetable farmers in Northern Ghana. We employed recent cross-sectional data from a survey of 423 smallholder vegetable farmers from selected districts in Northern Ghana. The issues of selection bias arising from observable and unobservable farmer attributes were addressed using propensity score matching and selection bias-corrected SPF methods, respectively. We accounted for heterogeneity in technology among agrifood system participants and nonparticipants, using the MF model.

Agrifood system participation plays an important role in enhancing farm value and TE among smallholder vegetable farmers, which are very critical for poverty alleviation, enhanced food security, and rural economic transformation in Northern Ghana. The results suggest that participants benefit significantly from improved farm performance than nonparticipants. We find that correcting for selection bias remains relevant in the evaluation of smallholder agrifood system participation, particularly when survey data are used. Vegetable farmers with above-average farm value and TE are more likely to participate in agrifood systems in Northern Ghana. Significant correlates of agrifood system participation include gender, household size, mobile phone ownership, irrigation, road access, farm size, farmer group membership, and extension visits. However, the value of vegetable production is significantly influenced by factors, such as land, fertilizer, chemicals, seed, soil fertility, and irrigation. Location-fixed effects, which account for socioeconomic factors, such as neighborhood effects, and environmental and biophysical conditions, are also noted in this study as important drivers of farm value among vegetable farmers in Northern Ghana.

The findings of this study call for the adoption of the agrifood systems approach by the government, NGOs, and the private sector in the implementation of agricultural and rural development intervention, given its development potential revealed by this study. Such interventions could harness these potentials for the benefit of smallholder farmers. In practice, the government could collaborate with farmer groups to spread and diffuse the knowledge and benefits associated with agrifood systems and motivate smallholder vegetable farmers' participation. Agricultural policies should improve smallholder farmers' access to irrigation facilities, extension services, and effective input delivery and land distribution systems. This is essential because vegetable production and consumption continue to create employment, generate income and help reduce malnutrition among rural communities. Thus, continuous support for the formation and capacity development of farmer groups can enhance agrifood system participation and farm performance, as well as poverty reduction. Another policy implication is that opening up rural communities through using road infrastructure, and provision of services (e.g., financial services) will enhance effective participation in agrifood systems, particularly among vegetable farmers.

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.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

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

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How to cite this article: Abdul-Rahaman, A., Issahaku, G., & Ma, W. (2022). Agrifood system participation and production efficiency among smallholder vegetable farmers in Northern Ghana. *Agribusiness*, 1–24. https://doi.org/10.1002/agr.21793

APPENDIX A

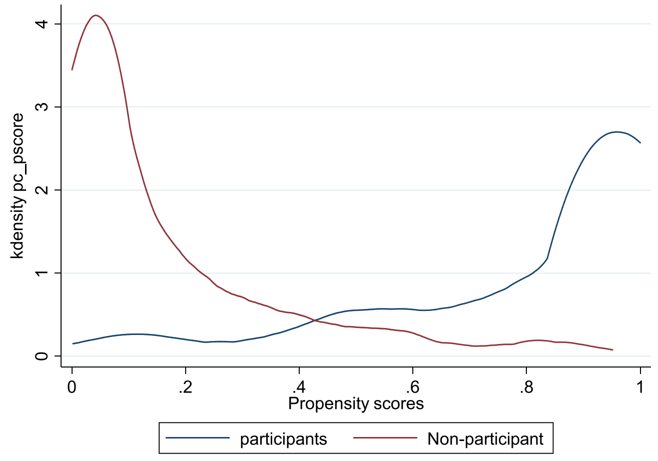

FIGURE A1 Density of propensity scores for agrifood system participants and nonparticipants