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Agricultural Technology Adoption in Ghana: Improved Tomato Seed Variety Adoption in Perspective

Adinan Bahahudeen Shafiwu

University for Development Studies
Department of Agricultural and Food Economics
shafiwu@uds.edu.gh

ABSTRACT

This study investigates the factors that influence farmers' adoption of Improved Tomatoes Seed Variety (ITSV) and how they affect farmers' production efficiency. With the help of multi-stage sampling procedure, a total of 508 farmers were chosen for interviews from three agro-ecological zones in Ghana. The factors influencing the adoption of ITSV were assessed using a multinomial logit (ML), while the effect and evaluation, validation and accounting for selectivity bias were carried-out using the stochastic metafrontier (SMF) models, propensity score-matching (PSM) technique, Inverse Probability Weight (IPW), and Augmented Inverse Probability Weight (AIPW). The results of the ML model indicated that farmers were more likely to select ITSV over the local variety if they were male, resided in the Forest Savannah Transitional Zone (FSTZ), were relatively wealthy and benefited from financing, and thought that improved varieties increased yields. In particular, the mean technical efficiency (TE) of farmers who adopted Pectomer, Pectomer and Power-Roma was 90.9% and 93.1%, respectively, compared to 86.2% and 88.8% if they had not adopted; this suggests that adopters are more efficient than those who did not adopt. Land, seed, insecticide, and tractor services positively influenced tomato production among adopters of the ITSV. The study suggests that using qualified extension agents and giving farmers credit could increase the adoption of improved tomato varieties by tomato farmers. Hence, this study advocates for government through the Ministry of Food and Agriculture (MoFA) to provide more capacity training to extension officer in order for them to effectively deliver their mandate.

Keywords: *Adoption, Tomato seeds, Production Efficiency, Selectivity bias, Agro-ecological Zones*

Introduction

The tomato industry contributes significantly to most West African farmers' nutritional status and livelihoods in the rural and peri-urban areas (Nnaemeka, 2024). In Ghana, it contributes significantly to the income of small-scale farmers in the savanna and forest transition zones and mostly seen as an indispensable ingredient found across every region and used in the preparation of dishes such as soups, sauces and salads (Shafiwu, et al. 2022). Its production has increased over the years to meet the growing demand. Tomato production increased from 196,991 tons in 2000 to 381,015 tons (see Figure 1.1). Production was stable in the early 2000s until 2005 when the country reported a sharp decline in production from about 100,000 tons per year to around 50,000 tons per year. The variations in production were primarily due to changes in cultivated land

rather than output. Output grew virtually exponentially between 2008 and 2018, as shown in Figure 1.1.
Despite the increase in tomato production, the national demand for tomatoes has long outstripped domestic supply, a situation that attracts large imports from neighbouring countries (Melomey *et al.,* 2019). In 2017, for instance, some 75,000 tonnes of tomatoes were imported to meet domestic demand. Asharani (2016), attributes the shortages in supply to poor yields, which range from 63,500 kg/Ha to 65000 kg/Ha on average. Inefficient use of resources in agricultural production and a lack of acceptance of modern agricultural technologies, such as crop varieties, are contributing factors to low agricultural productivity (Owusu, 2016). The main causes of the low productivity of tomatoes and rice are the over-reliance on rain-fed agriculture systems, as well as the low adoption of farm inputs and better technology (Abdulai et al., 2018; Bidzakin et al., 2018; Mabe, 2018., Ragasa et al. 2013). Specifically, the use of fertilizer and seeds nowadays is still less than is advised. According to reports, 90% of African farmers produce their crops using native seeds (McMichael, 2013). More than half of Ghanaian farmers, for example, produce their crops using native seeds, according to (Shafiwu et al. 2022).

Low-quality, locally grown seed varieties reduce productivity and tomato quality, which impacts tomato prices (Oladoyin, 2024). Despite the crop's many advantages, most poor nations—especially those in Africa—face numerous obstacles while trying to cultivate it, making its production unprofitable. To increase tomato productivity, farmers will need to adopt new technology in addition to changing various institutions, such as the land tenure systems, input, and credit provision (Karuku, et al.2017). Because of the inefficiencies in these nations' manufacturing processes, efficiency measurement is a topic of ongoing, substantial research (Betty, 2005). For example, some research has focused on growing Ghana's tomato production (Shafiwu, et al. 2022)) with Some (Ahmed and Anang, 2019; Anang et al., 2019) who also, uncovered the factors influencing tomato producers' efficiency performances.

Furthermore, there is a dearth of empirical data about the effect of increased technology adoption on tomato farmers' production efficiency, despite the substantial body of research exploring the variables influencing farmers' productivity in Ghana, this study looks into how farmers' production efficiency in particular Ghanaian ecological zones is affected by the use of enhanced tomato seed varieties. The present investigation aims to explore the factors that influence farmers' adoption of enhanced tomato seed varieties and to calculate the impact of these varieties on tomato farmers' production efficiency within certain agro-ecological zones in Ghana.

By giving policy makers advice on the variables influencing farmers' adoption of improved agricultural technologies like ITSV, this study advances the national enhanced technology dissemination goal. Although there is consensus on the positive welfare effects of technology adoption on crop producing households, the literature is silent on tomato farmers. Thus, findings from my second objective will communicate empirical evidence of the potential of adoption of ITSVs to enhance farm household production efficiency and welfare. The rest of this paper is structured as follows. Section 2 outlines the materials and methods. Section 3 presents a discussion of the results. Finally, section 4 highlights the study conclusions and proffers policy recommendations.

Ghana's tomato industry is neither able to reach its full potential in terms of yields and production, nor in terms of assisting processing enterprises, as compared to other nations. Consequently, the industry has not succeeded in raising the standard of living for the households engaged in its manufacturing and distribution (Anang et al., 2013). Despite substantial government investments in the tomato industry, including the construction of multiple processing facilities, farmers prefer to grow local varieties with high water content, high seed counts, poor color, and low brix rather than the quality and quantity of tomatoes required for commercial processing. Most tomato growers are unable to sell their produce due to the seasonality of production, high perishability, limited market access, and competition from imports; as a result, the tomatoes are allowed to decay on their fields (Ghana veg Report, 2016). Conversely, growers that continue to reap financial rewards from growing tomatoes instead of other crops do so because they can produce larger yields of tomatoes (Hilmi, 2022). High input prices per unit are one of the main issues facing Ghanaian tomato growers, according to Shafiwu, (2021). Therefore, for Ghanaian agro-tomato processing to be competitive, a lower average production cost per unit is required. At low but fixed prices provided by processors, farmers can profitably sell their tomatoes (Shafiwu, et al 2022)

In Ghana, tomatoes are both a food and a cash crop. Increasing competitiveness of tomato production can enhance economic growth in Ghana (Otokunor, et al.2023) Despite its potential, tomato production continues to decline, while imports of tomato paste surge (Robinson *et al.,* 2012). The country is ranked as the second largest importer in Africa with about 7,000 Mt of fresh tomatoes and 27,000 Mt of processed tomatoes imported annually from the neighboring Burkina Faso and European market (MoFA, 2017).

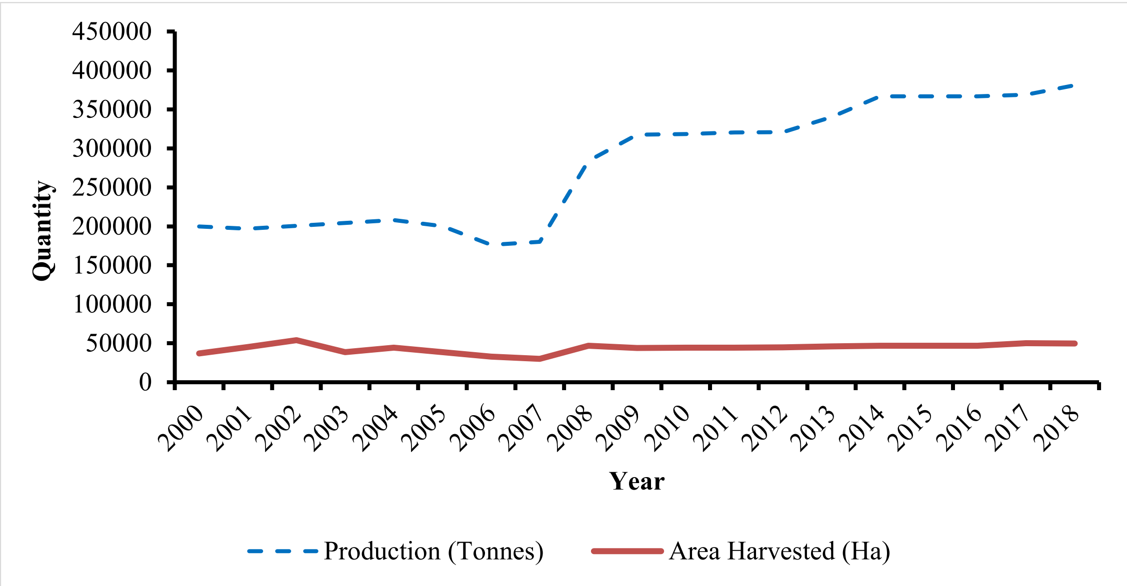


Figure 1. 1: Tomato production trends and yields

Source: FAOSTAT, 2018

Materials and Methods

Study location and sampling

The study was cross-sectional and used Primary data sourced from farmers using a semi-structured questionnaire. A total of 508 tomato farmers were selected through a multi-stage sampling technique. Three agro-ecological zones: Guinea Savannah, Forest Savannah Transition, and the Coastal Savannah zones of Ghana, were selected based on their high tomato production (IFPRI, 2013). First, a municipality was selected from each zone using the purposive sampling technique, they were, Sagnarigu, Techiman and Kesena Nankana (Navrongo) municipality being, the Northern, Bono East and Upper East regions of Ghana. In the second stage, a stratified sampling technique was employed to select communities from each selected municipality. In the third stage, a proportion-to-size sampling approach was employed to select thirty or twenty (30/20) farmers from each community based on the tomato farming population of the community. Finally, a simple random sampling technique was employed to select the individual respondents from the households who are into tomato farming. The Slovin's formula as used by Rivera (2007) was employed to determine the sample size for this study. It is expressed as:

$$n = \frac{N}{(1 + Ne^2)} \qquad (1)$$

where n is the sample of farmers to be included in the study, N is the population of potential farmers in Ghana which MoFA (2016) estimates as 2,503,006; and e is the margin of error or precision level. 4.4% was my chosen margin of error. Using the formula, 516 farmers were found in all, all of whom had the same amount of land. After gathering information from the 516 responders, it was cleaned up to produce a list of 508 farmers. In the analysis, I used quantitative methods. Stata software (version 16) was used for quantitative analyses, such as maximum likelihood model estimation and respondent descriptive statistics.

Conceptual Framework of the study

The conceptual framework for the study is presented in Fig 2. A conceptual framework tries to explain the linkages that exist among various concepts or variables used in the study. It starts from an inductive viewpoint to a deductive or from a simple to complex model below.

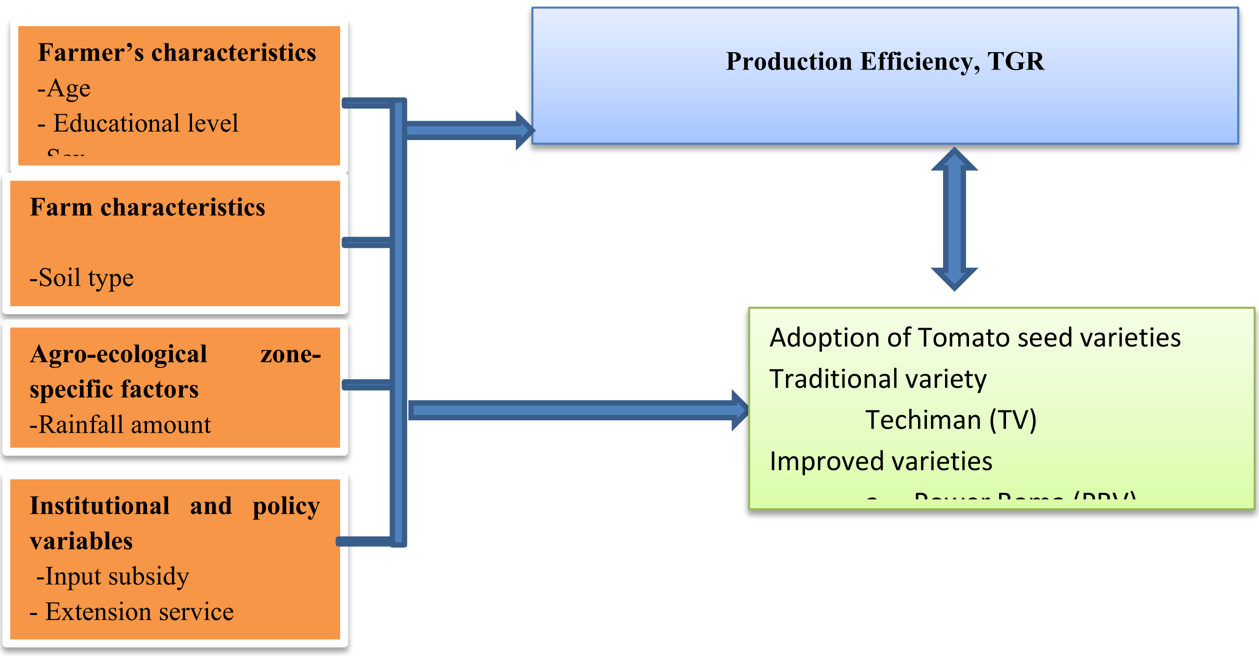


Figure 2. Conceptual Framework of the Study

The conceptual framework shown in Figure 2 is adapted from the works of Kiatpathomchai (2008) and Alemaw (2014). Alemaw (2014) showed how farmer specific characteristics, institutional and policy factors and psychological factors affect the adoption of a new maize technology (improved maize variety). Also, the conceptual framework designed and used by Kiatpathomchai (2008) examined the effects of farm household characteristics and rice farming practices on efficiency. This study combined the conceptual framework of Kiatpathomchai (2008) and Alemaw (2014) and added agro-ecological zone-specific characteristics which were termed as environmental factors by Shiferaw *et al.* (2014) in order to take care of heterogeneity owing to the adoption of different ITSV by the various agro-ecological zones. The study also added the effect of technology adoption on production efficiency.

Three main tomato seed varieties were predetermined for the study, namely; Techiman (TMSV), Power Roma (PRV) and Pectomer (PV). While TMSV is the traditional variety, Power Roma (PRSV) and Pectomer (PSV) are the modern varieties. Literature on adoption (e.g., Feder, Just, & Zilberman, 1985; Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013; Kassie, Teklewold, & Jaleta, 2015; Makate, Makate, & Mango, 2017; Manda, Alene, Gardebroek, Kassie, & Tembo, 2016) often argue that farmers' decisions regarding farm technologies are influenced by socio-demographics and economic characteristics. The current study follows the same line of argument that farmers' adoption of ITSV will depend on socio-demographics and economic characteristics including age, sex, occupation, household size, education, income, among others. Beyond the socio-demographic and economic characteristics, a farmer's decision to adopt a particular ITSV could also be influenced by farm-specific factors, institutional, policy variables of the country and the agro-ecological/location factors (Binswanger & Rosenzweig, 1986; Binswanger & Pingali, 1988; Erenstein, 2006). In this study, these factors are captured using farm size, soil type, cropping system, irrigation, input subsidy, extension service, market access, rainfall and temperature, among others. The relationship between these variables and adoption is shown in Figure 2 above.

Theoretical Frameworks

This study is based on the random utility theory, which is founded on utility maximization. It is adopted to explain farmers' adoption of ITSV. The decision to adopt in agriculture helps farmers and consumers to estimate their profit maximization or utility maximization. A farmer producing tomatoes has an option of being a net adopter of some improved variety of seeds. This involves making decisions on the assumption that, ranks can be made for the utility a farmer derives from adopting a particular seed variety.

The rational choice theory suggests that when an individual or economic agent is faced with a number of choices, he/she will prefer a choice that maximizes his/her expected utility[i] of wealth. By so doing, the theory assumes that rational behavior governs decisions of an individual or economic agent. Thus in accordance with the theory, an individual or economic agent i will choose any package j over any alternative package m if $U_{ij}(\pi) > U_{im}(\pi)$ or $\Delta U_{im} = U_{ij}(\pi) - U_{im}(\pi) > 0$ and $m \neq j$ in all cases. This is under the assumption that the individual or economic agents are risk neutral and take into account the net benefit derived from such practice during the decision-making process. However, the benefit or utility of wealth $U_{ij}^{*}(\pi)$ derived from choosing package j is a latent variable and as a researcher one cannot directly observe the parameters of such package. The econometric inference problem then becomes a question of parameterizing the equation that defines the net utility of wealth. According to Green (2002), although the preferences of the individual or the agent are not known to the researcher, his/her characteristics and as well as the attributes of the program (adoption of ITSV in the case of this study), X are observed during the survey. Green (2002) further pointed out that such characteristics (X) can be used to determine the choice of the individual in the following fashion:

$$U_{ij}^{*} = \delta_j \mathrm{X}_\mathrm{i} + \varepsilon_{ij} \quad \textit{(2)}$$

Assuming $ITSV$ is the index variable for each of the unobserved preferences, equation *(2)* translates into the observed binary outcome equation for each choice as follows:

$$TV = \begin{cases} 1 & if \quad U_{i1}^{*}(\pi) > \max\limits_{m\neq j}[U_{im}^{*}(\pi)] \\ :: & :: \quad :: \\ J & if \quad U_{ij}^{*}(\pi) > \max\limits_{m\neq j}[U_{im}^{*}(\pi)] \end{cases}$$

$or\ \eta_{i1} < 0$

for all $m \neq j$ *(3)*

$or\ \eta_{ij} < 0$

Where $\eta_{ij} = \max\limits_{m\neq j}[U_{im}^{*}(\pi) - U_{ij}^{*}(\pi)] < 0$ in (30.0) as indicated by Bourguignon et al. (2007); further, equation *(3)* implies that the decision maker will choose package j to maximize his/her expected utility of wealth if package j provides greater expected utility of wealth than any other package $m \neq j$, that is if $\eta_{ij} = \max\limits_{m\neq j}[U_{ij}^{*}(\pi) - U_{im}^{*}(\pi)] > 0$. Giving that ε in equation *(3)* is identically and independently Gumbel distributed, McFadden (1973) argued that the probability that the decision maker will choose package j can be specified by a multinomial Logit model which is discussed in the subsequent section.

Analytical Framework

Multinomial Logit

The socio-economic determinants influencing tomato growers' decisions to adopt a certain tomato seed variety (TSV) were identified and estimated using the multinomial logit. Tomato seed variety in this study were predetermined and categorise into three categories. These categories were Adoptors of Pectomer seed variety (PSV), Power Roma (PRSV) and adoptors of both Pectomer and the Power Roma varieties (PPRSV) jointly against the traditional variety ("Techiman"). The categorization was mutual exclusive and was based on preference, hence warranted the use of multinomial logit model. A logical buyer or producer looking to maximize output or profit would select one of the several enhanced tomato cultivars that provide the highest yield. The resulting utility can be broken down into components that are noticed and those that are not (Greene, 2003). It is expressed as:

$$U_{ij}(X_{ij};Z_{ij}) = V_j(X_{ij};\beta) + \varepsilon \quad \textit{(4)}$$

Where: $U_{ij}(X_{ij};Z_{ij})$ is the utility of i^{th} individual choosing alternative j while $;V_{ij}(X_{ij;}Z_{ij})$ denotes the deterministic component of the utility.

The deterministic portion is modeled using a multinomial logit. In accordance with Greene (2003), Cameron and Trivedi (2005), Mpuga (2008), and Eneyew (2012), the multinomial logit model's conditional probability is given as follows:

$$prob(Y_i = j / X_i)\frac{\exp(x_i\beta_j)}{\sum_{j=0}^{k}\exp(x_i\beta_j)} \quad \textit{(5)}$$

Where j=1, 2, …, k. empirically, are the categories of ITSV. The base category is used to compare other choices by restricting the base category's parameters to all zero ($\beta = 0$). The estimation of the multinomial logit is by maximum likelihood method. The log-likelihood function is expressed

$$\ln L = \sum_{i=1}^{n}\sum_{j=1}^{k} d_{ij} \log(p_{ij}) \quad \textbf{\textit{(6)}}$$

The multinomial logit is interpreted in terms of odds. The odd of outcome *m* versus outcome *n* given *U* shown by $wm/n(U_i)$ is expressed as:

$$wm/n(X_i) = \frac{pro(y_i = m/X_i)}{pro(y_i = n/X_i)} = \frac{\ell(x,\beta_m)}{\ell(x,\beta_n)} \quad \textbf{\textit{(7)}}$$

Simplifying equation *(5)* gives

$$wm/n(X) = \ell(x,\beta_m - x,\beta_n) = \ell[x,(\beta_m - \beta_n)] \quad \textbf{\textit{(8)}}$$

Taking the natural logarithm of equation [8], the multinomial logit is expressed as linear in logit:

$$\ln[(wm/n(X_i)] = X_i(\beta_m - \beta_n) \quad \textbf{\textit{(9)}}$$

Equation (*7)* gives the effect of *X* on the logit of outcome *m* against outcome *n*. Also, the partial derivatives of the equation [7.0] give the marginal effects expressed as:

$$\frac{\partial \ln[wm/n(X_i)]}{\partial X_k} = \frac{\partial X_i(\beta_m - \beta_n)}{\partial X_k} = \beta_{km} - \beta_{kn} \quad \textbf{\textit{(10)}}$$

Where $\beta_{km} - \beta_{kn}$ means, for a unit change in x_K the logit of outcome *m* versus outcome *n* is expected to change by $\beta_{km} - \beta_{kn}$ units.

The New Two-Step Stochastic Meta-Frontier Models

The proposed new two-step stochastic meta-frontier by Huang et al. (2014) is the current estimation method for production efficiency analysis. Both the group specific stochastic frontier and the stochastic meta-frontier regressions are used. The group specific stochastic frontier regression is specified as:

$$y_i^k = f(x_i,\beta_i^k)\ell^{V_i^k - U_i^k} = \ell^{x\beta_i^k + V_i^k - U_i^k} \quad \textbf{\textit{(11)}}$$

Where y^k is group k output, x is the vector of inputs, v_i^k and u_i^k are the error terms for firms in group k, β^k is a vector of unknown parameters for group k firms.

From the above model *(11),* the group specific stochastic frontier will be first estimated and the estimated parameters and error terms pooled together for the estimation of the stochastic meta-frontier model. This is expressed as:

$$y_i^k = f(x_i,\beta_i^k)\ell^{V_i^k - U_i^k} = y^* = f(x_i,\beta_i{*})\ell^{V_i^{*} - U_i^{*}} = \ell^{x_i\beta_i^* + V_i^* - U_i^*} \quad \textbf{\textit{(12)}}$$

Similarly, y^k is group k output, x is the vector of inputs, v_i^k and u_i^k are the error terms for firms in group k, β^k is a vector of unknown parameters for group k firms. On the contrary, y^* is meta-frontier output and v_i^* and u_i^k are error terms for meta-frontier and β^* is the vector of meta-frontier parameters.

The group specific stochastic frontier will be calculated first from the aforementioned model *(10),* and the estimated parameters and error terms will then be combined to estimate the stochastic meta-frontier model.

Therefore, the technical efficiency (*T.E (1))* of a group (GSZ) can be expressed as:

$$TE_A^1 = \frac{Observed-output-of-ecological-zone1}{Frontier-output-of-group(1)ecology} = \frac{y_A^1}{y^1} = \frac{f_A^1(x,\beta_A^1)e^{v^1-u^1}}{f^1(x,\beta^1)e^{v^1}} = e^{-u^1}$$

(13)

For output-oriented efficiency, the technology gap ratio of farmers in eco1ogical group1 (GSZ) can be estimated as:

$$TGR(1)\frac{Frontier-output-of-firms-ecological-zone1}{metafrontier-output} = \frac{y^1}{y^*}$$

(14)

Finally, the meta-frontier technical efficiency *(TE*)* can be measured using the equation

$$TE^* = \frac{Observed-output-of-ecological-zone1}{metafrontier-output} = \frac{y_A^1}{y^*}$$

(15)

Following Huang *et al.* (2014), for any estimated meta-frontier efficiency to be exact then, $MFTE_i^k$ justifies the definition of metafrontier as an envelope of individual frontiers. Hence, the estimated metafrontier is given as:

$$MFTE_i^k = TGR_i^k \times TE_i^k$$

(16)

Where

$$0 \le MFTE_i^k \le 1, 0 \le TE_i^k \le 1 and 0 \le TGR_i^k \le 1$$

while $MFTE_i^k$, are all predicted.

Propensity Score matching technique

One of the widely used techniques in measuring the impact of agrarian intervention programme or innovation on an outcome variable of interest is the PSM. The PSM is a non-parametric estimation approach that does not require specification of any functional form and a random error term distribution. This approach is theoretically appealing because it enables a comparison of the impacts of a treatment on the potential outcome of the treated variable and the control group (Heckman and Vytlacil 2005; Amare et al., 2012). The fundamental principles of the PSM are to match the treated group against the control concerning a predicted propensity of being treated conditioned on some observed covariates (Wooldridge 2003; Heckman and Vytlacil, 2005). There are two critical assumptions underlying the estimation of impact using the PSM. The first assumption is the Conditional Independence Assumption (CIA). According to the CIA, the decision to be treated is a random condition on some observed covariates (Abadie and Imbens, 2006; Takahashi and Barrett, 2013). Thus, given some observed characteristics of the respondents, the potential outcome and the treatment status in the absence of treatment are statistically independent (Takahashi and Barrett, 2013).

The second most important assumption in PSM is the Common Support Assumption (CSA). The CSA states that there should be considerable similarity in observed characteristics between participants and non-participants of a programme. Thus, respondents being compared have equal probability of belonging to the treated and the control group (Amare et al., 2012; Takahashi and Barret, 2013). If these two assumptions are met, then the magnitudes of the effects of the treatment on the treated; called the average treatment effects on the treated (ATT), can be validly estimated (Smith et al., 2005; Wossen et al., 2015). The ATT can be defined as the differences in the mean of the potential outcome of the treated group with and without treatment defined within the region of common support. The PSM technique follows a two-step estimation procedure. First, the treatment variable is modeled as a choice dependent variable using probit or logit after which the propensity for each observation is calculated. Second, each treated sample is matched with non-treated sample with same or similar propensity score value and the ATT are estimated (Abadie and Imbens, 2006). One drawback of the PSM is that it cannot account for hidden biases, it can only correct for observed heterogeneity to the extent that they are accurately estimated (Oduol *et al.,* 2011; Amare *et al.,* 2012). For the purposes of robustness, validity and sensitivity analysis to complement (PSM), both the IPW and AIPW were conducted.

Inverse-probability weights (IPW) and augmented inverse-probability weights (AIPW)

As robustness checks, the IPW and AIPW estimators were further estimated to assess the impact of improved tomatoes seed variety adoption on production efficiency to validate PSM estimates. According to Amfo, et al. (2024), weighted averages of observed outcomes for computing potential outcomes are used in IPW while AIPW models outcome and treatment probabilities. In effect, AIPW is said to be IPW which combines a term for augmentation to correct the estimator if treatment model is wrongly specified (Amfo, et al. (2024). Following Wooldridge (2010), the probability of treatment in IPW and AIPW estimations is

$$p(N) = \Pr(B_i = 1 \mid N) = Y\{z(N)\} = H(B_i \mid N) \quad \textbf{\textit{(17)}}$$

where N is pre-treatment covariates' multidimensional vector from observable characteristics, $Y\{z(N)\}$ is cumulative distribution function, N is a vector for obtaining treatment effects. The resulting propensity scores generate independent and artificial samples from treatment allocations. Hence, for treatments having an inverse weight of 1 and $\frac{\hat{P}(N)}{(1-\hat{P}(N))}$ for non-treatments, the weight would be:

$$g = W_a + (1-W_a)\frac{\hat{P}(N)}{(1-\hat{P}(N))} \quad \textbf{\textit{(18)}}$$

where $\hat{P}$ represents computed propensity scores. IPW model for ATE is specified below:

$$ATE_{IPW} = j_d^{-1}\sum_{a=1}^{s} W_a\left[r_d(N,\varpi_d) - r_L(N,\varpi_L)\right] \quad \textbf{\textit{(19)}}$$

where J_d is number of tomato farmers who adopted ITSV, $r(N)$ is regression model for adopters of ITSV and non-adopters of ITSV and $\varpi_L = (\delta_a, \nu_a)$. Integrating the weighting of equation 18 and equation 19 establishes the AIPW. AIPW model for ATE is specified below:

$$ATE_{AIPW} = j_d^{-1}\sum_{a=1}^{s} W_a\left[r_d^*(N^*,\varpi_d^*) - r_L^*(N^*,\varpi_L^*)\right] \quad \textbf{(20)}$$

where $\varpi_d^* = (\delta_d^*, \nu_d^*)$ is attained through estimation of weighted regression.

Accounting for technological heterogeneity and self-selection

Unlike studies by Villano et al. (2015) and Issahaku and Abdulai (2020), where the decision variable is binary and uses the Greene (2010) approach to account for selectivity bias in stochastic frontier, this study's decision variable (ITSV) has more than two categories: Pectomer, Power Roma, and Pectomer/Power Roma. Consequently, to get the MTE scores, the study used the metafrontier technological efficiency based on technology difference. The treated group (adopters) was then matched against the non-treated group (non-adopters) who shared similar traits using propensity score matching. Because tomato seed varieties have varying yield potentials and complementing services connected with the technological package, their effects on the frontier production function and efficiency can vary. The stochastic metafrontier (SMF) model was estimated to take into consideration this possible technological difference in the SPF model as well as its interactions with production inputs. In accordance with Battese et al. (2004) and Geffersa et al. (2019), the following is the specification of the econometric model for selectivity correction and translog metafrontier production functions:

$$\ln T_i = \beta_0 + \sum_{j=1}^{7} \beta_j \ln X_{ij} + \frac{1}{2}\sum_{j=1}^{7}\sum_{k=1x}^{7} \beta_{lk} (\ln X_{ij})(\ln X_{ik}) + u_i \ln \beta_{1i} + \phi_1 ITSV_i$$

$$+ \frac{1}{2}\sum_{j=1}^{7} \phi_j (\ln X_{ij})(ITSV_{ij}) + (v_i - u_i) \qquad \textbf{\textit{(21)}}$$

$$\sigma_{ui}^2 = \exp(\delta Z_i^i) \qquad \textbf{\textit{(22a)}}$$

$$\sigma_{vi}^2 = \exp(\eta Z_i^i) \qquad \textbf{\textit{(22b)}}$$

The decision variable, technology adoption (ITSV), when included in eqn. *(22.a),* presents a likely endogeneity problem due to the farmers' self-selectivity, as the two groups of farmers (adopters and non-adopters of each seed variety in the context of this study) may differ in terms of specific household and farm characteristics. The study used a propensity score-matching (PSM) technique, which considers the variations in observed variables between ITSV adopters and non-adopters, to solve this endogeneity concern. Based on specific attributes, the PSM calculates the farmers' probability or propensity score (p-score). This study used an empirical technique consisting of three steps to estimate the PSM. Initially, we computed a probability model for farmers who would adopt ITSV and p-scores for those who would accept each of the four tomato seed varieties. In accordance with Imbens and Wooldridge's (2009) research, the p-score is described as follows:

$$p(y=1 \mid X) \equiv \Pr(Ti = 1 \mid x_1, x_2 ...., x_j) = E[Ti \mid Xi] \qquad \textbf{\textit{(22c)}}$$

where y is a response variable representing technology adoption, x denotes a set of explanatory variables for a given farm household, and T refers to a given technology. The prediction of p-scores follows a non-linear binary (probit or logit) model:

$$ITSV_i^* = Z_i\alpha + \psi_i \quad \text{for} \quad \{\text{ITSV}= \frac{1 if Z_i\alpha + u_i > 0}{0 otherwise}\} \qquad \textbf{\textit{(22d)}}$$

where $ITSV_i^*$ is a binary variable defined above, Z_i is a vector of factors that may influence farmers' adoption decision, and ψ_i is an error term assumed to be normally distributed with mean 0 and variance σ^2.

In the second phase, we compared the results of adopting a certain seed variety (treated) to the hypothetical scenario in which they had not adopted, using the p-scores. Using the anticipated p-scores, we matched producers of ITSV with the conventional variety (TMSV) subsample in the third stage. Once more, all conventional variety growers were excluded from additional examinations. As a result, a condition that was roughly like one another in terms of visible traits was established for the two farmer groups. It is well known that PSM eliminates baseline inequalities in adoption choices made by farmers. It does not, however, take into consideration the unobservable factors that could affect the choice of technology.

Table 1: Variable Description and *A-priori* Expectation

Variable	Description/ Measurement	
Sex	Sex of the farmer	Dummy: 1 if the respondent is male, 0 if otherwise
HH_Size	Household size	Nunmber of people eating from the same pot
Education	Education of the farmer	Number of years in school
Primary_Occupation	Main occupation of the farmer	Dummy: 1 if tomato farming is the main occupation, 0 if otherwise
Income	Annual household income	Ghana Cedi
Ext_Access	Access to extension service	Dummy; 1 if the respondent had extension visit (s), 0 if otherwise
Credit_Access	Access to credit	Dummy; 1 if the respondent had credit, 0 if otherwise
Cropping_Type	Type of cropping	Dummy; 1 if the respondent practices mono-cropping, 0 if otherwise
Potential_Yield	Perception yield	Dummy; 1 if a farmer had good yield, 0 if otherwise
Availability_Mkt	Market access	Dummy; 1 if a farmer had access to market, 0 if otherwise
Seed_Access	access to seed	Dummy; 1 if a farmer had access, 0 if otherwise
Resistance_Pest	Resistance to pest	Dummy; 1 if a crop is Resistance to pest, 0 if otherwise
Early_Maturity	Early maturity	Dummy; 1 if a crop grows earlier, 0 if otherwise
Storage_Access	storage ability	Dummy; 1 if a farmer had access to storage, 0 if otherwise
Resistance_Bad Weather	Resistance	Dummy; 1 if a farmer had good weather, 0 if otherwise
CSZ	Coastal Savanna Zone	Dummy; 1 if the respondent is located in CSZ, 0 if otherwise
GSZ	Guinea Savannah zone	Dummy; 1 if the respondent is located in GSZ, 0 if otherwise
FTSZ	Forest Transition Savannah zone	Dummy; 1 if the respondent is located in FTSZ, 0 if otherwise
FBO	Membership in FBO	Dummy; 1 if the respondent belonged to an FBO, 0 if otherwise
Insurance	Membership in insurance program	Dummy; 1 if the respondent participated in insurance program, 0 if otherwise

Results and Discussion

Demographic Characteristics

The results show that respondents have a mean age of 40.53 years with a minimum of 22 years and a maximum of 77 years. Also, 89.6% of the respondents are male while the remaining 10.4% are female, suggesting a male dominance in tomato production in Ghana. The mean formal education is 2.23 years with a minimum of zero and a maximum of seven, showing a very low level of education. The mean farming experience is 13.01 years while the average household size is eight persons per household with a minimum of one and a maximum of twenty-three. This finding is in-line with GPHS (2020) findings, which revealed that Ghana practices the extended family system where a household has an average population of 5 or more. In line with (Martey,2012) Large household sizes could mean adequate family labor in farming or households can earn additional income if other members are engaged in non-farm activities (Al-Hassan, 2008).

Furthermore, majority (83.9%) of the farmers are engaged in tomato production as their primary occupation. About 97% of the farmers belong to FBOs which helps them identify new technologies, ideas, and access credit to mitigate the acquisition and use of farm inputs. Membership of FBOs also enables farmers to navigate market imperfections whiles accessing other essential agricultural knowledge through training and demonstration (Osman et al., 2018). On the other hand, the majority (63.2%) of tomato farmers had access to extension services but just 12.2% have access to credit for their tomato production. Also, less than 5.0% of the entire sample belongs to an insurance program.

Table 2 also shows that the mean age of: “techiman”seed variety (TMSV), Power-Roma seed variety (PRSV), and Pectomer (PSV) adopters are 39.9 years, 41, and 40 years respectively. The percentage of male farmers cultivating TMSV is 84% while the percentages of farmers adopting PRSV and PSV are 87% and 79% respectively. The average farming experiences are 12.032 years, 13.397 years, and 13.000 years for TMSV, PRSV, and PSV. The mean education is uniform for TMSV, PRSV and PSV adopters. Adopters of PSV gained the highest farm income (GH¢705.497), followed by adopters of TMSV (GH¢673.553) and PRSV (GH¢597.755). There were few tomato farmers in FBOs and those with access to credit and extension services. Also, farmers have different perceptions about tomato seed varieties.

Table 2: Summary Statistics of Variables in MESR Model, by Variety

	TMSV		PRSV		PSV		PSV/PRSV	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Age of the Farmer	38.947	9.783	41.384	11.180	40.232	9.918	39.947	9.983
Sex of the Farmer	0.840	0.368	0.873	0.333	0.797	0.404	0.841	0.468
Farming Experience	12.032	8.338	13.397	9.887	13.000	9.291	13.012	8.338
Education	2.415	1.780	2.059	2.152	2.373	1.968	2.159	2.252
Income	673.553	638.380	597.755	559.506	705.497	520.298	600.755	501.506
Primary Occupation	0.809	0.396	0.823	0.383	0.876	0.331	0.811	0.369
Cropping Type	0.404	0.493	0.367	0.483	0.362	0.482	0.437	0.513
Membership in FBO	0.979	0.145	0.970	0.170	0.949	0.220	0.770	0.070
Membership in Insurance Policy	0.032	0.177	0.068	0.251	0.034	0.181	0.132	0.277
Credit Access	0.085	0.281	0.148	0.356	0.107	0.310	0.185	0.381
Extension Contact	0.637	0.482	0.634	0.484	0.544	0.501	0.337	0.382
Potential Yield	0.479	0.502	0.489	0.501	0.540	0.500	0.477	0.510
Market Availability	3.691	2.636	2.743	2.191	3.747	2.593	3.944	2.573
Seed Access	3.926	2.591	2.882	2.199	3.787	2.557	3.887	2.657
Pest Resistance	2.883	1.945	2.793	1.879	3.045	2.072	3.145	2.172
Early Maturity	2.617	1.890	2.844	1.789	3.183	1.968	2.517	1.790
Storage Ability	2.628	1.697	3.055	1.975	2.994	1.890	2.728	1.791
Resistance to Bad Weather	2.957	2.165	3.072	2.298	3.582	5.124	2.759	2.1535

Tomato Seed Variety Adoption

Table 3 provides the distribution of respondents according to ITSV adoption. These are Pectomer seed variety (PSV), Power-Roma seed variety (PRSV) or a combination of the two and the local variety (Techiman seed variety (TMSV)). The adoption of ITSV is a single response variable, thus mutually exclusive. This gives multinomial responses or unordered categories. The results reveal that the highest proportion (40.55%) of farmers adopted PSV, followed by those who adopted PSV/PRSV (32.28%), PRSV (21.46%), and TMSV (5.71%). The two improved tomato seed varieties have similar characteristics in size and mean of cultivation. Still, they have different potential in early maturity and other agroecology-specific characteristics.

Improved Tomato	Frequency	Percentage (%)
Pectomer	206	40.55
Power Roma	109	21.46
Pectomer/Power Roma	164	32.28
Non-Adopters ("Techiman")	29	5.71
Total	508	100.0

Table 3: Tomato Seeds Adoption

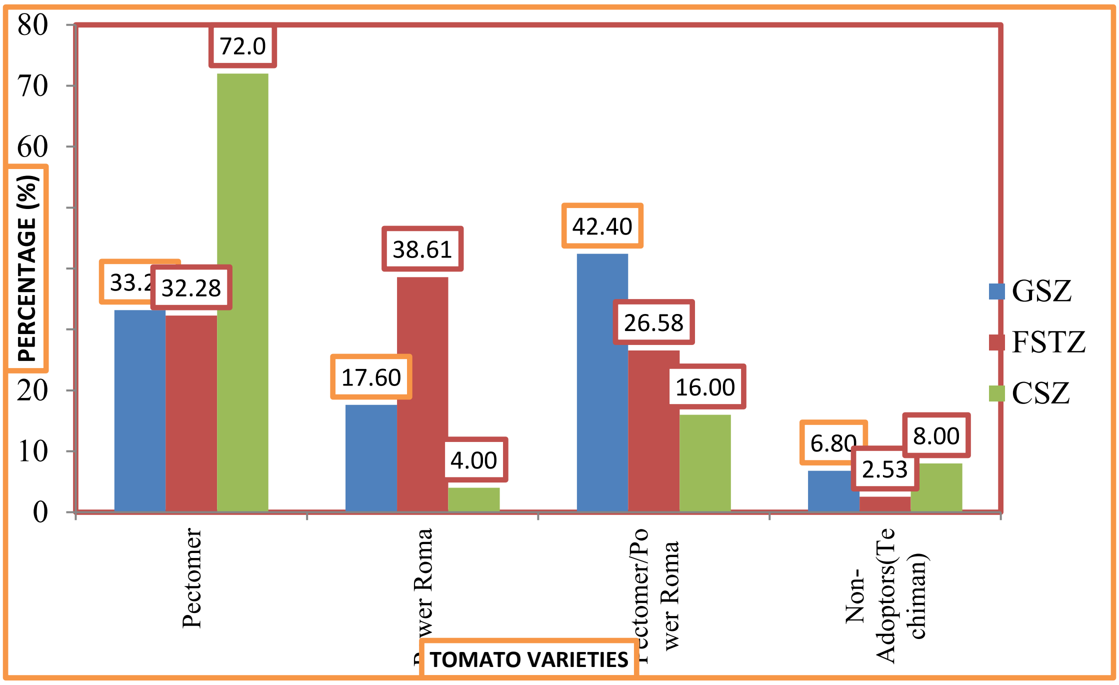
Improved Seeds Adopted in Various Agro-Ecological Zones

Farmers in each of the three agro-ecological zones are adopting better tomato seed varieties, as seen in Figure 1. The distributions of responders across the three agro-ecological zones in the figure below are the same about the adoption of enhanced tomato seed varieties. Around 42.4% of the farmers in GSZ chose PSV/PRSV, whereas the traditional variety, TMSV, was adopted by 33.2%, 17.6%, and 6.8% of the farmers, respectively.

PSV/PRSV was accepted by 26.6% of farmers in the FSTZ, whereas PSV, PRSV, and the original variety TMSV were adopted by 32.3%, 38.6%, and 2.5% of farmers, respectively. Furthermore, whereas 72.0%, 4.0%, and 8.0% of CSZ farmers adopted PSV, PRSV, and the classic variety TMSV, respectively, only 16.0% of them chose PSV/PRSV. The findings usually imply that in Ghana's several agro-ecological zones, farmers cultivate a greater number of improved varieties than the native type.

The determinants of adoption of improved tomato seed variety (ITSV)

The econometric results of the determinants of farmers' adoption of tomato seed variety are presented in Table 4. The table contains the marginal effects of the parameters of the multinomial logit (MNL) model of ITSV adoption. The marginal effect represents the unit change in the dependent variable being in a particular category vis-a-vis the reference category when a corresponding independent variable changes by one unit. As a rule of thumb, the non-adopters, that is those who cultivated traditional variety ("Techiman" seed variety), is chosen as the base or reference category. This identification procedure allowed for the determination of marginal effects for all the independent variables relating to the adoption of PSV, PRSV or both PSV and PRSV. According to the LR chi-squared test, the fitted MNL model is statistically significant at 1% significance level, meaning that at least one of the regression coefficients is not equal to zero. However, it also means that the model fits the data very well. The results show that adoption of PSV is significantly associated with the gender of the farmer, tertiary education, household income, extension contact, access to credit, perception about potential yield, and farmer residency in either GSZ or FSTZ. In contrast, the adoption of PRSV is significantly affected by the gender of the farmer, household size, primary occupation, household income, extension contact, access to credit, membership of FBO, perception about potential yield, and farmer residency in FSTZ. Furthermore, the gender of the farmer, household size, tertiary education, household income, access to credit, perception about potential yield, perception about market availability, and farmer residency in either GSZ or FSTZ significantly influenced tomato farmers' adoption of both PSV and PRSV.



Legend: Figure 1: Improved Seeds Adopted in Various Agro-Ecological Zones

Table 4: Marginal Effects of the Determinants of ITSV adoption

	Pectomech	Power Roma	Pectomech/Power Roma (Joint Adoption)
Variable	Marginal Effect	Marginal Effect	Marginal Effect
Sex of the Farmer	0.0358**	0.0352***	-0.0217**
Age of the Farmer	-0.0006	-0.0005	0.0013
Household Size	-0.0033	0.0034*	0.0022*
Basic Education	-0.0947	0.1056	-0.0177
Secondary Education	-0.0481	0.1222	-0.0908
Tertiary Education	-0.1425*	0.2189	-0.1161**
Primary Occupation	0.0615	0.1552*	-0.2037
Income	0.0865***	0.1884***	0.0805***
Extension Contact	-0.0249*	-0.0154*	0.0205
Credit Access	0.0001**	0.0521***	-0.0359*
Membership in Insurance Policy	-0.1260	0.2577	-0.1208
Cropping Type	0.0198	-0.0495	0.0366
Membership in FBO	0.0379	0.1757**	0.0712
Potential Yield	-0.0103**	-0.0004**	0.0037**
Market Availability	0.0072	-0.0327	0.0292**

Seed Access	-0.0033	0.0115	-0.0102
Pest Resistance	-0.0037	0.0009	0.0019
Early Maturity	-0.0031	0.0099	-0.0071
Storage Ability	0.0096	-0.0118	0.0051
Resistance to Bad Weather	0.0122	0.0122	0.0005
GSZ	0.2603***	-0.5210	0.2877***
FTSZ	0.0489***	-0.4360***	0.4491***

Legend: ***, **, and * indicate significance levels at 1%, 5%, and 10% respectively.
NB: *Base category is Non-adopters ('Techiman' variety), sample size is (508) farmers selected from three Agro Ecological zones with (100) Bootstrapping*

Estimates of the New-Two Step Stochastic Metafrontier Translog Model of ITSV

Table 4 shows the result of maximum likelihood estimates of the new-two-step stochastic metafrontier translog model of the interaction between the conversional inputs and the adoption of the improved tomato seed varieties. In all the estimations, the translog production frontiers fit the data reasonably well (based on the likelihood ratio tests), with statistically significant variables. The likelihood ratio (LR) chi-squared test also rejects the null hypothesis that tomato farmers in the three selected agro-ecological zones operate with similar or homogenous production technologies. In contrast, the study rejects the null hypothesis that tomato farmers in the three selected agro-ecological zones operate with homogeneous production technologies. The results also imply that using the SMF model helped to correct all potential biases in technical efficiency due to differences in tomato seed variety adoption. The SMF model was used to estimate technical efficiencies for ITSV adoption based on the notion that the varieties have varying yield potency or effect due to specific characteristics.

The dependent variable (output) with its correspondents' input variables were all log-transformed and mean-corrected to zero. This implies the first-order coefficient estimates of the model represent the corresponding elasticity and gives room for the interpretation of the result as partial output elasticities. Therefore, the coefficients are interpreted as the percentage change in output due to a one-percent change in input.

For the adoption of the ITSV (PSV, PRSV and the joint adoption), inputs such as the land size, fertilizer, tractor services, quantity of seed planted by farmers, application of insecticides and herbicides are found to be statistically significant at various levels and positive, implying that for farmers who adopted any of the two ITSV s or jointly adopted the two ITSV, a one percentage increase in any of the above inputs leads to an increase in tomato output by more than one-percent. On the other hand, for the adoption of any of the ITSV or the joint adoption, the partial elasticities of labour show that a 1% increase in labour will decrease tomato output. The positive effect of land and seed agrees with Geffersa et al. (2019) and Awunyo-Vitor (2019) reported a positive and significant effect of land and seed on and maize and rice production in Ethiopia and Ghana but disagrees with the findings of Abro et al. (2014). The negative effect of labour also disagrees with the findings of Asravor et al. (2019) but agrees with Owusu (2016) and Wongnaa and Awunyo-Vitor (2019). The positive effects of land, fertilizer application, insecticides and herbicides application, and the quantity of seed used by a farmer on output, suggest that farmers if given the right training and credit facilities to own these inputs could help improve upon their output.

It is worth noting that the result of the maximum likelihood estimation of metafrontier in both the case of adoption of ITSV and the agro-ecological zones are similar. In both estimations, inputs such as land size, seed, fertilizer, insecticides, and pesticides are found to be statistically significant at various levels and contribute to increased output while labour is found to be significant but negative thus, it reduces output. Deductively, it can be said that different environmental and technology conditions exist in the various agro-ecological zones. These, as well as the heterogeneous nature of the ITSVs, influence how farmers adopt ITSVs.

Table 5: Estimates of the New-Two Step Stochastic Metafrontier Translog Model of ITSV

Variables	PSV		PRSV		Both PSV/PRSV		Metafrontier Model	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
lnLand	0.1819***	0.1275	0.2318	1.8054	0.2022***	0.0462	-0.0599	0.2164
lnLabour	-0.0118	0.0608	-0.1283*	0.0658	-0.0703***	0.0153	-0.0676**	0.0304
lnFertilizer	0.2549*	0.1501	0.0128	0.0933	0.0496	0.0320	0.2428	0.1879
lnSeed	0.2021	1.3977	0.1714**	0.0632	0.0334	0.0363	0.8298	0.7929
lnHerbicide	0.0437	0.0621	0.3269***	0.0979	0.0913***	0.0224	-0.1716	0.1553
lnInsecticide	0.0852	0.0658	-0.0849	0.1314	-0.0426	0.0301	0.0647	0.1753
lnTractor	0.0247	0.0618	0.0068	0.0566	0.0556**	0.0203	-0.0357	0.0682
$lnLand^2$	0.1896	0.1271	-0.3529*	0.1852	0.0617	0.0409	-0.0125	0.1775
$lnLabour^2$	0.0086	0.0311	-0.0077	0.0371	0.0393***	0.009	-0.1019**	0.3767
$lnFertizer^2$	0.2539**	0.1263	-0.1186	0.0601	0.0204*	0.0171	0.1892	0.1925
$lnSeed^2$	0.1168	0.2069	-0.2406	0.2127	-0.0665	0.0650	0.1412	0.2480
$lnHerbicide^2$	0.0563	-0.1998	-0.1648	0.1309	-0.0242	0.0427	0.2698	0.1654
$lnInsecticide^2$	0.0827	0.2047	-0.0779	0.2154	0.0291	0.0506	0.5077**	0.2366
$lnTractor^2$	0.0002**	0.1229	0.0037	0.0112	0.0140***	0.0042	-0.0114	0.0144
lnLand× Labour	0.3222	0.0888	0.1411	0.1309	-0.0006	0.0330	-0.1653	0.1437
lnLand× Fertilizer	0.0808*	0.0931	0.2376	0.1453	0.2277***	0.0300	0.1859*	0.0974
lnLand× Seed	-0.0499	0.1546	-0.2007*	0.1635	-0.1000	0.0629	-0.0497	0.2533
lnLand× Herbicide	0.0402	0.1369	-0.0718	0.1529	-0.0569	0.0429	0.3438**	0.1400

lnLand × Insecticide	0.0767*	0.1448	-0.2375	0.1773	0.0106	0.0471	0.3469*	0.1909
lnLand × Tractor	-0.0099	0.0179	-0.0059	0.0193	-0.0023	0.0056	-0.0086	0.0163
lnLabour × Fertilizer	0.1333**	0.0787	-0.1429	0.0875	-0.1061***	0.0236	0.0467	0.0935
lnLabour × Seed	-0.3844**	0.2057	-0.4564	0.2453	-0.2029***	0.0622	0.2488	0.3594
lnLabour × Herbicide	0.0216	0.1053	0.0024	0.1357	0.0201	0.0341	0.0182	0.1111
lnLabour × Insecticide	0.0471*	0.1141	0.0922	0.1632	0.0300	0.0400	-0.1613	0.1203
lnLabour × Tractor	0.0111	0.0161	0.0049	0.0213	0.0120*	0.0061	0.0224	0.2475
lnFertilizer × Seed	0.2025	0.2258	0.2233	0.1855	0.0122*	0.0611	0.0464	0.2865
lnFertilizer × Herbicide	0.2499**	0.1264	0.0882	0.1325	0.0200	0.0375	-0.3007**	0.1110
lnFertilizer × Insecticide	0.1641	0.1349	0.0400	0.1166	-0.0074	0.0300	0.1764	0.1434
lnFertilizer × Tractor	0.0082	0.0151	-0.0144	0.0122	0.0064	0.0044	0.0374*	0.0221
lnSeed × Herbicide	0.3119	0.2126	0.3748*	0.2120	0.1065*	0.0509	-0.2949	0.2323
lnSeed × Insecticide	0.1716	0.2308	0.2803	0.2264	0.0678	0.0600	0.0562	0.3086
lnSeed × Tractor	0.0451*	0.0255	0.0144	0.0255	0.0138*	0.0076	0.0409	0.0277
lnHerbicide × Insecticide	0.0596	0.1150	-0.0195	0.1598	-0.0762*	0.0422	-0.5283***	0.1748
InHerbicide × Tractor	0.0306*	0.0153	-0.0106	0.0192	-0.0248***	0.0040	-0.0274*	0.0159
InInsecticide × Tractor	0.0034	0.0179	-0.0123	0.0216	-0.0100	0.0056	0.0189	0.0176
Constant	-0.0248	0.3715	0.0156	0.3933	-0.3021**	0.1117	-0.9149**	0.4261
RTS	1.5644		0.3146		1.1439			
Log-Likelihood	175.89		112.03		146.60		43.32	
Wald $\chi^2(35)$	85.31***		125.84***		537.27***		103.23***	

Legend: ****, **, and * indicate significance levels at 1%, 5%, and 10% respectively*

Effect of ITSV adoption on production efficiency of tomato farmers

Table 6 shows the effect of adoption of ITSV on farmers' production efficiency. It contains the sample statistics (ATT estimates) of efficiency scores for the three tomato seed varieties

Furthermore, ATT of tomato seed adoption on farmers' TE was estimated using the PSM technique. Accounting for potential selection bias of the adoption variable, the results showed that the group-specific TE scores increased with improved tomato seed varieties adoption. Thus, adopters of improved tomato seed variables seem to be more technically efficient than adopters of the local variety. However, with the exception of Power-Roma adoption, when compared with the traditional variety, adopters of Pectomer and both Pectomer and Power-Roma would have achieved a lower TE if they had not adopted the improved varieties. For example, farmers who adopted Pectomer and both Pectomer and power roma, had mean TE of 93.1% and 90.9% respectively, compared to 86.2% and 88.8%, had they not adopted. In other words, farmers who adopted Pectomer and both Pectomer and Power-Roma would have become 6.9% and 2.1% less efficient had they not adopted. Likewise, under the counterfactual conditions that adopters of Power-Roma and the local variety had not adopted, they would have gained a higher TE if they had adopted the other improved varieties. The highest TE was achieved through the adoption of Pectomer. This result is in line with Anang et al. (2020), who found that improved maize variety increases TE in smallholder maize production in Ghana. In Nigeria, Obayelu et al. (2016) found that the adoption of improved protein maize increased TE of smallholder farmers. Ahmed et al. (2017) also revealed that farmers in Ethiopia who adopted improved maize varieties attained higher TE (82.34%), compared with their non-adopter counterparts (79.54%). Geffersa et al. (2019) also found that farmers using improved varieties attained a mean TE of 67.87%, while farmers using local maize variety attained a mean TE of 64.53%.

Table 6: Impact of ITSV adoption on production efficiency of tomato farmers

		Mean Technical Efficiency Scores			
Adoption decision	**Seed Variety**	**Local variety**	**PSV**	**PRSV**	**Joint Adoption**
Adopting the technology	**A**	0.818	0.931	0.820	0.909
Not adopting the technology	**B**	0.910	0.862	0.914	0.888
(diff (ATT) =A-B)	**C**	-0.093***	0.069***	-0.095***	0.021*
		(0.060)	(0.012)	(0.014)	(0.013)

Legend: ****, **, and * indicate significance levels at 1%, 5%, and 10% respectively*
NB: Standard Errors in parenthesis

Table 7 shows the IPW and AIPW for robust check and validation of the PSM. IPW and ATE by IPW estimator indicates that adoption of ITSV leads to an increase in productivity by an average of 0.069 and 0.021 for PSV and joint adoption (PSV/PRSV) respectively. General adoption of ITSV leads to an increment in tomato production by 1.840kg from an average of 1.750 kg which would have been recorded had the farmers failed to adopt ITSV. The IPW, on average, shows that adoption of ITSV significantly increases tomato production by 9%. Additionally, the result from the AIPW for the ATE indicates adopters of ITSV obtain an average efficiency increment of about 3% over the non-adopters. This difference is significant at 1% level and indicates the superior production performance accruing to adopters of ITSV over the non-adopters.

Table 7: ATE by IPW and AIPW for impact of ITSV adoption on production Efficiency

Treatment-effects/ATE estimator	Coefficient (robust standard error)			
	ATE	*Outcome mean*		*Percentage increase*
		Adopters of ITSV	*Non-Adopters of ITSV*	
IPW	0.818 (0.060)**	1.840 (0.512)***	1.750 (0.182)***	0.09 (0.213)**
AIPW	0.910 (0.920)*	2.143(0.808)***	2.110 (0.832)***	0.033(0.425)***

***, ** and * denote significance at 1%, 5% and 10% respectively.

Results from PSM, IPW and AIPW suggest that tomato farmers who adopted ITSV produce higher than the non-adopters, ITSV could be said to be the reason for the rise in tomato production among farmers in the selected agro-ecological zones.

Conclusions and Recommendations

Tomato is one of the most highly consumed vegetables in Ghana. However, available evidence shows that domestic production falls short of the national demand. This necessitates the promotion of improved technologies that can improve production. In summary, the paper comprises the adoption of ITSV and the impact of adoption on production efficiency using metafrontier stochastic frontier model to estimate MTE and employed propensity score-matching technique to address self-selection bias and used Inverse probability weight (IPW) and augmented inverse probability weight (AIPW) to affirm and validate the findings of the PSM results. Tomato production in Ghana is an important activity, especially for the youth and people with no formal education. It is predominantly rainfed and thus seasonal in its production. It, however, contributes to nutritional needs and employs a greater percentage of the youth spanding from production to consumer in the tomato value chain. The cultivation of improved varieties (Pectomer, Power-Roma, and a combination of both), or the traditional variety ("Techiman") by farmers was based on their perceptions of the varietal characteristics and some socioeconomic factors. The adoption of ITSV led to increased farmers' production efficiency.

The study suggests that both public and private sector should promote improved tomato seed varieties to improve adoption in all three agro-ecological zones studied. The study recommends for the government through the ministry of food and agriculture to provide capacity and in-service training to extension officers to help improve their skill and to enable them to deliver on their mandate effectively. Also, stakeholders such as MSR, Policy link, IFPRI who provide financial services to farmers should increase their credit access to farmers in order to help them expand their farms and explore new variety.

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