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Does adoption of improved soybean varieties and their complementary agronomic practices enhance household food security among smallholder farmers in Malawi

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Abstract

Soybean is one of the key legume crops that provides several financial benefits for farming households in Malawi. However, Malawi's persisting efforts to improve smallholder productivity and diversification have only translated into moderate improvements in food security outcomes. Hence, the study aims to assess whether adopting improved soybean varieties and their complementary agronomic practices enhances food security among smallholder farmers in Malawi. Furthermore, using 1 500 sampled households, the study employed the endogenous switching regression to assess farmers' adoption decisions, and a Cox hazard proportion model to determine the survival and hazard ratio of dis-adoption. In addition, the study identified food consumption score, household dietary diversity score and household food insecurity access score as outcome variables for food security measures. The study's findings indicate that adopting improved soybean varieties and agronomic practices decreases the household food insecurity access scale and increases the food consumption *score and household dietary diversity score. In addition, from the result of the Cox hazard proportion model it can be seen that farmers are less likely to dis-adopt soybean varieties if they own a bicycle, live in a home with an iron roof, or are from the Lilongwe, Ntchisi or Dedza districts. Finally, the study recommends enhancing access to soybean varieties by improving distribution systems and providing transportation solutions for farmers, and suggests conducting a similar study using panel data to more accurately capture the true impact of adoption of improved varieties on food security.*

Key words: soybean varieties, household food security, endogenous switching regression, food consumption scores, agronomic practices, FCS, HFIAS, HDDS

1. Introduction

Food security is a multidimensional phenomenon where households produce food sustainably, have the economic means to access it, and utilise it to meet their nutritional needs (Sileshi *et al*. 2023). In 2019, 250.3 million people in Africa lacked adequate food, with 94% of these in Sub-Saharan Africa (SSA) (Salima *et al*. 2023). Even worse, one in five people in Africa experienced food insecurity in 2021 (FAO 2022). Hence, food insecurity remains a significant issue in the region. Efforts in Sub-Saharan Africa to achieve Sustainable Development Goals 2.1 and 2.2 – ending hunger, food insecurity, and all forms of malnutrition – are moving in the wrong direction, with projections showing nearly 670 million people facing hunger by 2030 (FAO 2022). The region lags in reducing hunger due to rapid population growth and rural areas' vulnerability to climate change (Barrios *et al*. 2008; Kotir 2011).

Malawi is one of the Sub-Saharan countries struggling with food security (Salima *et al*. 2023). Between 2019 and 2020, approximately 63.5% of families were food insecure, a significant increase from the 38.5% reported a decade earlier (National Statistical Office [NSO] 2020). This is due to a rapidly growing population that is overly dependent on agriculture and lacking coping strategies for recurring and extreme climate shocks, like floods and droughts (Gholami *et al*. 2022). Hence, minor shocks significantly affect Malawian livelihoods, causing inefficiency and losses among smallholder farmers (Gono & Takane 2018). This suggests that poverty and vulnerability are closely associated with food insecurity, especially in agricultural families living in rural areas where income and crop yield are converging (Devereux 2016).

To address food security, the Government of Malawi introduced the Farm Input Subsidy Programme (FISP) in the 2005/2006 growing season to help small-scale farmers who lack resources to buy inputs (Sibande *et al*. 2017), However, not all farmers have access to these subsidised inputs. According to De Weerdt and Duchoslav (2022), beneficiaries are often from rural middle- and higher-income households, not poor productive farmers. Worse still, ultra-poor farmers usually sell their vouchers to meet immediate basic needs (Duchoslav *et al*. 2023).

In response, the government and research institutions have intensified crop diversification efforts, particularly advocating for soybeans. Soybean is a key legume crop providing several financial benefits to farming households in Malawi. It improves soil fertility when grown in rotation with maize, reducing the need for mineral nitrogen fertiliser and lowering production costs (Van Vugt *et al*. 2018). In addition, soybeans have better grain storage quality compared to cereals, and are more resistant to pests and diseases, making cultivation less costly (Giller *et al*. 2011).

Alternatively, several agronomic management practices, such as using certified seeds, box ridges, fertilisers, inoculants, double row spacing, optimising plant population and adhering to effective planting dates have been widely introduced and promoted in Malawi due to their economic and agronomic benefits. According to Van Vugt *et al*. (2017), combining these practices with enhanced soybean varieties allows farming households to maximise their production.

Nonetheless, Malawi's smallholder farmer fields currently produce only about 1 t/ha of soybeans, significantly less than the continent's and the world's average yields (Tufa *et al*. 2021). According to Van Vugt *et al*. (2017), minimal utilisation of modern technology and ineffective production methods with low-quality seeds have contributed to poor soybean productivity in Malawi.

However, despite an increase in the popularity of soybeans and their complementary agronomic practices, there is inconclusive information on their effectiveness in enhancing household food security. There is a gap in information on factors that influence a farmer's decision to adopt better soybean varieties and agronomic practices, whether improved soybean varieties and agronomic practices enhance food security, and the survival estimates and dis-adoption hazard ratios of these soybean varieties.

A household's decision to adopt improved soybean varieties and agronomic practices can be influenced significantly by food security factors such as availability, utilisation and food accessibility. By adopting these improved varieties, households can maximise their output and profits, thereby increasing their disposable income to purchase food during shortages. This decision ensures not only the availability of food through increased production, but also food accessibility through the income generated from soybean sales. In addition, improved soybean varieties provide numerous nutritional benefits, enhancing food utilisation within the household. Furthermore, adopting these varieties yields positive livelihood outcomes, ensuring household food security through better output, income generation and nutritional benefits.

Tikolore, Makwacha, Nasoko and Serenade are the soybean varieties that smallholder farmers cultivate on a large scale. This paper demonstrates that, during the 2016/2017 cropping season, one of the four improved soybean varieties was planted by 56% of the soybean producers in the six main soybean-growing districts, including Lilongwe, Mchinji, Dedza, Ntchisi, Kasungu and Mzimba. During the 2016/2017 cropping season, 188 407 ha of land was planted to soybeans, with more than 100 000 ha allocated to the four varieties. These four cultivars yield well and have qualities that processors find desirable. Other characteristics of the varieties include high yield under moisture stress, short maturity, and excessive moisture.

This paper acknowledges that using the propensity score matching (PSM) method might yield biased estimates due to model misspecification, as PSM only accounts for observable characteristics. In contrast, this paper uses endogenous switching regression, which considers both observable characteristics, such as access to extension services and membership in an organisation, and unobserved characteristics, like farmers' skills, innovativeness and utility. These influence the choice to adopt improved soybean varieties and agronomic practices.

Traditionally, adoption studies focus on seasonal adoption decisions, regardless of the dataset used. Critics, including Dillon *et al*. (2020) and Mgomezulu *et al*. (2023), argue that evaluations should be conducted at least two years after introducing agricultural technology, as the benefits of adoption may not be apparent within a single season. Thus, this study defines adoption as a farmer's awareness of the varieties and their complementary agronomic practices, along with continuous use of the variety over the preceding three years with double-row spacing as an agronomic practice (Mgomezulu *et al*. 2023).

Furthermore, measuring food security is complex, and no single indicator can capture all aspects, such as sustainability, accessibility, availability and utilisation (Magrini & Vigani 2016). Therefore, in contrast to other studies that use only one food security indicator (Sileshi *et al*. 2023), this study employs the food consumption score (FCS), household food insecurity access scale (HFIAS), and household dietary diversity score (HDDS) to assess food accessibility and nutrition aspects.

This paper is organised into the following sections: the first section introduces soybean complementary agronomic and food security in Malawi; the second section describes the theoretical model and empirical procedure; the third section presents the survey design and data collection, along with descriptive statistics; and the final section summarises the study's findings and provides policy recommendations.

2. Theoretical framework

2.1 Utility maximisation theory

Utility is a means to describe individuals' preferences (Varian 2010). It is common to imagine people making decisions to maximise their utility or to maximise their level of happiness. Hence, a household's decision to adopt improved soybean technologies can be modelled using the utility maximisation theory, as evidenced by Tufa *et al*. (2021) and Mgomezulu *et al*. (2023).

Utility can be derived through one's decision to adopt improved soybean varieties and their complementary agronomic practices, which might maximise production and enhance household food security. Furthermore, households might want to maximise their disposable incomes to buy household assets and food, or anything they want from the market in times of need. Farmers' decisions to adopt improved soybean technologies might be influenced by aspects such as production factors, whereby households want to consume their own produced food; market factors, whereby households want to increase their income for purchasing goods and services at the market; and household and institutional factors. Farmers may adopt improved soybean varieties and the associated agronomic practices if the utility obtained exceeds other alternative sources available. Equation (1) represents the utility maximisation theory:

$$G^*{}_i = B_{iA} - B_{iN} > 0, \tag{1}$$

where $(G^*{}_i)$ is a latent variable that shows the difference between adoption benefits (B_{iA}) and the non-adoption (B_{iN}) of improved soybean varieties. Further, G^* can be presented as a function of observable characteristics, as defined below:

$$G^*{}_i = \beta X_i + \varepsilon_i, \text{ with } G^*{}_i = \begin{cases} 1 \; if \; \dot{G}_i > 0 \\ 0 \; otherwise \end{cases}, \tag{2}$$

where β is a vector parameter to be estimated, X_i is a vector of explanatory variables, and ε_i is the error term. Further, this paper defines an adopter as any soybean grower who is aware of and plants any improved soybean variety with double row spacing as an agronomic practice.

2.2 Empirical framework

The study uses observational data without randomisation into adoption or non-adoption groups. Thus, soybean growers with comparative advantages in terms of observed characteristics (e.g., distance to the market) and unobserved characteristics (e.g., household utility preferences) may adopt improved varieties, resulting in higher HDDS, FCS and lower HFIAS. This indicates potential self-selection bias, possibly causing parameter (β) estimations to underestimate the true effects of adoption. Consequently, this bias may affect the real impact of improved varieties and practices. The research also notes that adoption decisions are influenced significantly by extension workers and lead farmers (Mgomezulu *et al*. 2023). Farmers may self-select based on household preferences, and unobservable factors such as relationships with extension workers, farming skills and personal motivation could further bias estimates. This suggests the need for an endogenous switching regression (ESR) model to account for both observable and unobservable variations (Wooldridge 2015).

2.2.1 The selectivity-corrected endogenous switching regression model

When individuals are not assigned randomly, as in this study, the ESRM uses the full information maximum likelihood estimation (FIML) approach to estimate the effects of treatments. According to Lokshin and Sajaia (2004), a two-stage least squares (2SLS) method can be applied in two steps to evaluate the impact of implementing improved soybean varieties. The first step involves applying a probit regression model to ascertain the likelihood of adoption. The second stage looks at the relationships between the observable traits of soybean growers and the outcome variables. The two separate regimes are given as follows:

$$Y_{iA}^{*} = \beta_{iA} X_{iA} + v_{iA} \text{ if } G_i = 1 \text{ for adopters in regime 1} \tag{3}$$

$$Y_{iN}^{*} = \beta_{iN} X_{iN} + v_{iN} \text{ if } G_i = 0 \text{ for non- adopters in regime 2} \tag{4}$$

The latent variable, Y_{iA}^{*}, represents the likelihood that a farming household will adopt an improved soybean variety and an agronomic practice over the course of three years. The vectors X_{iA} and X_{iN} represent production socioeconomic and institutional regressors for adopters and non-adopters, β_{iA} and β_{iN} represents a vector of parameters that need to be estimated for both adopters and non-adopters, and v_{iA} and v_{iN} represents the stochastic error term.

Due to selection bias and endogeneity, the study assumes non-zero values of correlation between v_{iN} and v_{iA}. Furthermore, the study assumes that the three errors, thus ε_i, v_{iN} and v_{iA}, have a trivariate normal distribution with zero mean, and a variance covariance structure presented as follows:

$$\text{Covariance } (\varepsilon_i, v_{iN}, v_{iA}) = \begin{Bmatrix} \sigma_{\varepsilon}^2 & \sigma_{A\varepsilon} & \sigma_{N\varepsilon} \\ \sigma_{A\varepsilon} & \sigma_A^2 & \sigma_{NA} \\ \sigma_{N\varepsilon} & \sigma_{NA} & \sigma_N^2 \end{Bmatrix}, \tag{5}$$

where σ_{ε}^2, σ_A^2 and σ_N^2 are variances of the error terms in the selection equation and outcome models for adopters and non-adopters. Furthermore, $\sigma_{A\varepsilon}$ is the covariance between ε_i and v_{iA}, and $\sigma_{N\varepsilon}$ is the covariance between ε_i and v_{iN}. Since Y_A^{*} and Y_N^{*} do not occur at the same time, the covariance between v_{iN} and v_{iA} is undefined. This results in the mean values of the truncated error terms being presented as:

$$E[v_A | \, G = 1] = \sigma_{A\varepsilon} = \sigma_{A\varepsilon}\gamma_A \tag{6}$$

and

$$E[v_N | \, G = 0] = \sigma_{N\varepsilon} = \sigma_{A\varepsilon}\gamma_N \tag{7}$$

In the first stage, γ_A and γ_N can be estimated and included in the outcome equations for adopters and non-adopters if an exogenous instrument relevant to the situation is provided. For the proper design of the ESR model, the selection model must have at least one variable that influences the decision to adopt improved soybean technologies, but that does not affect the outcome variable (FCS, HDDS and HFIAS).

2.2.2 The impact of adoption of improved soybean varieties and agronomic practices on food security

The impact of adopting improved soybean technologies can be modelled by estimating the FCS, HDDS and HFIAS under observed and counterfactual scenarios. In the observed scenario, the expected value of the outcome variables (FCS, HDDS and HFIAS) for adopters (Y_{iA}^*) can be expressed as:

$$E[Y_A^*|\, G = 1] = \beta X_A - \sigma_{A\varepsilon}\gamma_A \tag{8}$$

Soybean growers who adopted improved varieties may behave differently from average soybean growers with the same characteristics due to unobserved characteristics. Hence, $\sigma_{A\varepsilon}\gamma_A$, in the equation above, considers selection bias.

The expected outcome (FCS, HDDS and HFIAS) for adopters had they decided not to adopt is modelled as follows:

$$E[Y_N^*|\, G = 1] = \beta X_N - \sigma_{N\varepsilon}\gamma_A \tag{9}$$

Therefore, the impact of adoption on food security is the difference between the two equations above; thus, the average treatment effect on the treated (ATT) is presented as follows:

$$ATT = E[Y_A^*|\, G = 1] - E[Y_N^*|\, G = 1] = X(\beta_A - \beta_N) + (\sigma_{A\varepsilon} - \sigma_{N\varepsilon})_{\gamma_A} \tag{10}$$

2.2.3 Description of outcome variables and their covariates

According to McGuire (2015), the study adopts the household dietary diversity score (HDDS) as a measure of food security, which is presented as:

$$HDDS = \textstyle\sum_i k_i \;\; i = 1,2,3 \ldots ,0, \tag{11}$$

where k_i represents the food group consumed; it equals 1 when a household consumed a particular food group, and zero otherwise. A household with an HDDS of 10 would have consumed every food group during the previous survey week, offering a useful indicator of food access by recording the quality, and not just the quantity, of food (FAO 2016). The considered food groups are fish and meat, pulses, eggs, fats and oils, cereals and grains, fruits and vegetables, dairy, roots and tubers, sugars, and condiments.

The food consumption score (FCS), another outcome variable used to measure food security, is the product of the assigned weight and consumption frequency of a food group. According to the FAO (2016), the FCS provides a composite score considering food consumption frequency, dietary diversity, and nutritional value, unlike the HDDS. Food group weights are cereals and grains (4), pulses (3), vegetables (1), fruits (1), meat/fish (4), milk/dairy products (4), sugars (0.5), fats and oils

(0.5), and condiments (0). The HDDS recall period is 24 hours, while the FCS recall period is seven days (Maxwell *et al*. 2014). A higher FCS indicates more food security.

The household food insecurity access scale (HFIAS), developed by FANTA, determines household food insecurity over the previous 30 days. A higher HFIAS score reveals poorer access to food and higher household food insecurity. The HFIAS has nine questions identifying food-insecure or secure households (FAO 2016). Responses are limited to three options based on how often food access was a concern: seldom (once or twice), sometimes (three to 10 times), and often (more than 10 times). A household scores up to 27 if it answers 'often' to all nine questions, and 0 if it did not encounter any of those circumstances, with a higher score indicating food insecurity (Maxwell *et al*. 2014).

In Malawi, the adoption of improved agricultural technologies is influenced by socioeconomic and institutional factors, such as the age, education and gender of the household head, household size, and ownership of assets like bicycles and radios. In addition, access to extension services and membership in farmer organisations also play a role (Feder *et al*. 1985).

Older household heads may adopt innovations due to experience and resources, while younger ones are more adaptable (Kassie *et al*. 2013; Ayinde *et al*. 2017; Mgomezulu *et al*. 2018; Pangapanga-Phiri & Mungatana 2021; Tufa *et al*. 2022). Furthermore, educated household heads are better at managing resources and understanding the benefits of using advanced agricultural methods, making them more likely to implement improved technologies (Mgomezulu *et al*. 2018; Vaiknoras *et al*. 2019; Pangapanga-Phiri & Mungatana 2021). Men generally adopt new technologies more than women due to better access to inputs, although female-headed households also show strong potential (Peterman *et al*. 2014; Low & Thiele 2019; Mapanje *et al*. 2021).

Larger households furthermore provide more labour, increasing the likelihood of adoption (Ayinde *et al*. 2017; Low & Thiele 2019; Mapanje *et al*. 2021). Wealth indicators, such as land and livestock ownership, correlate with higher adoption rates (Kassie *et al*. 2013; Musa *et al*. 2015; Ojha & Khanal 2021). Membership of farmer organisations and access to extension services facilitate learning and technology dissemination (Vaiknoras *et al*. 2019; Mapanje *et al*. 2021; Pangapanga-Phiri & Mungatana 2021). Bicycle ownership reduces transportation costs, further increasing the likelihood of adopting improved soybean technologies.

2.2.4 The Cox proportional hazard model

Using a Cox proportional hazard model, the study calculated adoption hazard rates. This is because farmers are unable to fully reap the benefits of soybean technologies due to inconsistent and ineffective adoption. According to the study, survival analysis offers the best-fit check, since it can account for both the hazard rates and the adoption time. Following Lancaster (1992), let T represent the duration of adoption for each farmer, where the observed durations are the periods over which each farmer actively uses the soybean varieties. Here, T is a nonnegative random variable quantifying these adoption durations. The cumulative density function, $F(t)$, can thus be expressed as follows, and the probability density function of t can be expressed as $f(t)$:

$$F(t) = \int_0^t f(s)ds, \tag{12}$$

where $f(s)$ is the adoption duration, and $S(t)$ is the survival function, given as follows:

$$S(t) = P(T > t) = 1 - F(t) \tag{13}$$

The likelihood (P) that the adoption of soybean technologies will occur in an infinite timeframe (Δt) following the adoption survival function, after the decision to not adopt the technologies has lasted for time t, can be determined as follows:

$$P\ (t \leq T < t + \Delta t | T > t) \tag{14}$$

The hazard function ($h(t)$) below shows the likelihood that a farmer adopts the soybean technologies at time t, such that T = t, provided that the farmer did not adopt the technologies before t:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T > t)}{\Delta t} = \frac{f(t)}{S(t)} \tag{15}$$

Moreover, the allocation of the adoption period is influenced by several independent variables, including production, market and socioeconomic factors:

$$h(t, x, \theta, \beta) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T > t)}{\Delta t}, \tag{16}$$

where β is a vector of parameters that need to be estimated, θ is a vector of parameters that determine the probability distribution of the hazard rates, and x is a vector of socioeconomic, production and market factors. Every smallholder agricultural adoption period is projected to have its distinctive hazard function, based on the semi-parametric model in Equation (17):

$$h_i(t) = h(t; x_i) = h_0(t) \exp(x_i \beta) = h_0(t) \exp(\beta_1 x_{i1} + \ldots + \beta_k x_{ik}) \tag{17}$$

Therefore, the function becomes

$$\log h_i(t) = \alpha(t) + \beta_1 x_{i1} + \ \ldots + \beta_k x_{ik}, \tag{18}$$

in which the proportionate influence of each of the uncorrelated variables on the likelihood of adoption are expressed by β and $\alpha(t) = \log h_0\ (t)$.

3. Sampling procedure and data

The International Institute for Tropical Agriculture (IITA) provided secondary data for this study, which was used to select sample households using a stratified random sampling technique. Extension planning areas (EPAs) within the districts of Lilongwe, Mchinji, Dedza, Ntchisi, Kasungu and Mzimba, which produce over 80% of Malawi's soybeans, were chosen carefully. Twenty EPAs were selected using probability proportional to size (PPS) sampling, based on the area planted to soybeans during the 2016/2017 season. Within these EPAs, sections, villages and households were randomly selected, resulting in 320 villages from 80 sections, and 1 600 households from 320 villages. Of these, 1 500 households were soybean growers during the 2016/2017 season. The data includes household head demographics (age, sex, education), household size, assets, and institutional characteristics (e.g., farmer organisation membership, distance to local markets, and information sources). Skilled enumerators collected the data using Surveybe software, a computer-assisted personal interviewing tool.

4. Results and discussion

4.1. Descriptive statistics

Table 1 presents the summary statistics of the surveyed farmers. From the results it is clear that 77% of the surveyed households were male-headed, with an average age of 44.37 years. These household heads had an average of 7.8 years of schooling, and the average household size was 5.14 members. Notably, farming households cultivated an average of 1.21 hectares of cropland, with 0.21 hectares dedicated to soybean production, representing 17% of the total cropped area. Soybean farmers yielded around 212.41 kilograms per hectare, utilising 162.48 person-days of labour per hectare. In terms of food security, households reported average scores of 6.24 for the household food insecurity access scale (HFIAS), 11.21 for the food consumption score (FCS), and 6.81 for the household dietary diversity score (HDDS). Adopters of improved soybean varieties and agronomic practices represented 8% of the surveyed households. They achieved significantly higher soybean yields, of 80.37 kilograms per hectare, and a total crop production value of 6 499 kwacha per hectare more than non-adopters. Adopters also allocated an additional 0.06 hectares of land to soybean production and had 8% greater access to extension services compared to non-adopters. Furthermore, among adopters of improved soybean varieties and practices, 62% owned bicycles, facilitating market access and input procurement, while 45% had radios, providing farming information. Lead farmers made up 6% of adopters, likely promoting adoption in their communities. In addition, about 69% of the sampled households had access to agricultural extension services, 49% farmed on medium slopes and 88% had access to formal markets.

Table 1: Descriptive statistics of the surveyed farmers

Variable	Variable description	Full sample N = 1 510	Adopters (A) n = 124	Non-adopters (N) n = 1386	Difference (A-N)
Soybean yield	Kilograms per hectare (kg/ha)	212.41 (8.38)	286.20 (30.93)	205.81 (8.68)	-80.37*** (30.47)
Productivity	Total value of crop production (MWK/ha)	18 453.49 (819.08)	24 418.78 (3 402.61)	17 919.41 (837.74)	-6 499.37** (2 978.78)
HFIAS	Household food insecurity access score	6.24 (0.14)	5.15 (0.40)	6.33 (0.15)	1.18** (0.54)
FCS	Food consumption score	11.21 (0.10)	12.02 (0.36)	11.14 (0.11)	-0.87** (0.39)
HDDS	Household dietary diversity score	6.81 (0.05)	7.25 (0.16)	6.77 (0.05)	-0.48*** (0.18)
Extension	Extension contacts (1 = yes)	0.69	0.76	0.68	0.08*
Gender	Gender of household head	0.77	0.78	0.77	0.01
Age	Age of household head	44.37 (0.39)	44.16 (1.31)	44.38 (0.41)	0.21 (1.44)
Education	Education status of household head (years of schooling)	7.80 (0.11)	7.42 (0.35)	7.83 (0.12)	0.40 (0.42)
Household size	Number of persons per household	5.14 (0.05)	5.09 (0.16)	5.14 (0.05)	0.04 (0.18)
Soybean area	Area under soybean production (ha)	0.21 (0.01)	0.27 (0.02)	0.21 (0.01)	-0.06*** (0.02)
Area	Total area under cultivation (ha)	1.21 (0.04)	1.27 (0.07)	1.20 (0.04)	-0.07 (0.14)
Labour	Total quantity of labour (man-days per hectare)	162.48 (4.26)	178.26 (13.05)	161.06 (4.49)	-17.19 (15.52)

Notes: * = significant at 10% (0.1), ** = significant at 5% (0.05), *** = significant at 1% (0.01); standard errors in parentheses

4.2 Determinants of adoption of improved soybeans and agronomic practices

Table 2 displays the endogenous switching regression (ESRM) results, including estimates for factors influencing the adoption of improved soybean varieties and agronomic practices, along with the outcome variables FCS, HDDS and HFIAS, for both adopters and non-adopters. All three models are significant at 1%. The paired independence test shows differences in the FCS, HFIAS and HDDS functions between adopters and non-adopters, highlighting variations in coefficient estimates for factors such as ownership of iron-roofed houses, radios, bicycles, and district location. This indicates that ESRM is superior to a simple treatment effect model. The results of the selection model show that farmers from the Ntchisi district who own a bicycle and have high adoption intensity are more likely to adopt improved soybean varieties and agronomic practices. Specifically, a farmer from Ntchisi has a 41.74% higher probability of adoption compared to one from Mzimba, likely due to fewer extension workers and market access in Mzimba. Bicycle owners have a 30.61% higher likelihood of adoption, as bicycles facilitate access to markets for improved seeds. The FCS and HFIAS outcome models reveal that household size, fertile land ownership, radio ownership, and iron-roofed houses affect food insecurity scores for both adopters and non-adopters. For example, a percentage increase in land raises the FCS by 0.69 for non-adopters and 2.07 for adopters. Household size increases HFIAS by 0.46 for non-adopters and 0.67 for adopters, while fertile land reduces HFIAS by 1.27 for non-adopters and 1.87 for adopters. Homes with iron roofs lower HFIAS by 2.39 for non-adopters and 2.90 for adopters.

4.3 Endogeneity test and weak instrument test

Based on theoretical foundations and prior research (Amadu *et al*. 2020), this study selected adoption intensity, defined as the number of improved soybean varieties a farmer has adopted, as an instrumental variable to address potential endogeneity. Adoption intensity is strongly correlated with the likelihood of adopting improved soybean varieties and their associated agronomic practices, as it reflects a farmer's commitment and resources devoted to adoption. Importantly, adoption intensity does not have a direct effect on food security outcome variables – such as the food consumption score (FCS), household food insecurity access scale (HFIAS), and household dietary diversity score (HDDS) – other than through its influence on the adoption decision itself. To ensure the validity of this instrument, we conducted both endogeneity and weak instrument tests. Following econometric principles (Wooldridge 2015), we tested the null hypothesis of exogeneity for the soybean and agronomic adoption variables and assessed the strength of the instrument using the zero-first-stage test (Wooldridge 2015; Mgomezulu *et al*. 2023). As shown in Table 3, the null hypothesis of exogeneity was rejected at the 1% level of significance, indicating the presence of endogeneity. Moreover, the weak instrument test was also rejected, confirming that adoption intensity is a strong instrument.

Table 2: Results from endogenous switching regression

Variables	FCS			HDDS			HFIAS		
	Adopter	Non-adopter	Selection model	Non-adopter	Adopter	Selection model	Selection model	Adopter	Non-adopter
Age	-0.0587	-0.0111	0.0235	-0.0005	0.0010	0.0166	0.0149	-0.0992	0.0641
	(0.241)	(0.044)	(0.023)	(0.003)	(0.009)	(0.019)	(0.018)	(0.174)	(0.055)
Age^2	-0.0003	-0.0001	-0.0002	-0.0000	-0.0001	-0.0002	-0.0002	0.0017	-0.0004
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
Education	0.1240	-0.0182	-0.0139	-0.0024	0.0057	-0.0118	-0.0116	0.0762	-0.0064
	(0.138)	(0.030)	(0.010)	(0.002)	(0.005)	(0.011)	(0.011)	(0.105)	(0.035)
Sex of household head	-0.4450	0.6258*	-0.1240	0.0186	-0.0166	-0.1785	-0.1849	-0.4387	-0.2404
	(0.966)	(0.372)	(0.219)	(0.020)	(0.056)	(0.130)	(0.130)	(0.994)	(0.404)
Household size	-0.4178*	-0.0774	-0.0107	-0.0111***	-0.0260**	-0.0222	-0.0270	0.6370***	0.3748***
	(0.215)	(0.075)	(0.037)	(0.004)	(0.012)	(0.028)	(0.029)	(0.231)	(0.087)
Lilongwe district	-0.6870	-0.8005	0.2273	-0.0297	-0.1286	0.2141	0.1909	-1.1678	1.5224**
	(1.980)	(0.736)	(0.424)	(0.036)	(0.080)	(0.251)	(0.251)	(2.268)	(0.682)
Mchinji district	0.5427	-1.1702**	0.1866	-0.0742**	-0.0553	0.0472	0.0449	-1.5387	0.3334
	(1.748)	(0.594)	(0.220)	(0.034)	(0.075)	(0.244)	(0.243)	(2.305)	(0.617)
Kasungu district	-1.6232	-0.8628	0.0975	-0.0437	-0.2099**	0.0502	0.0503	-1.7686	-1.0570
	(2.150)	(0.661)	(0.335)	(0.037)	(0.098)	(0.269)	(0.268)	(2.502)	(0.671)
Dedza district	-1.2241	-1.9807***	0.2226	-0.1079***	-0.1623**	0.0485	0.0361	-1.0010	1.0928
	(1.760)	(0.630)	(0.338)	(0.036)	(0.067)	(0.261)	(0.261)	(2.271)	(0.678)
Ntchisi district	-1.6396	-2.0147***	0.4081*	-0.1173***	-0.1800***	0.3245	0.3334	-0.7755	0.9373
	(2.330)	(0.701)	(0.227)	(0.037)	(0.069)	(0.254)	(0.252)	(2.360)	(0.669)
Very fertile land	-1.1587	0.4637*	0.0177	0.0338**	-0.0404	0.0247	0.0205	-1.3581*	-1.0277***
	(0.837)	(0.261)	(0.135)	(0.016)	(0.044)	(0.103)	(0.104)	(0.694)	(0.302)
Natural log of land (ha)	2.0913**	0.4844**	-0.0830	0.0564***	0.1029**	-0.0304	-0.0387	-1.0304	-1.5949***
	(0.908)	(0.218)	(0.112)	(0.013)	(0.042)	(0.087)	(0.086)	(0.767)	(0.278)
Radio	-0.4914	1.0079***	0.0431	0.0993***	0.0077	0.1110	0.0903	-1.5898**	-1.4358***
	(0.921)	(0.373)	(0.256)	(0.016)	(0.042)	(0.111)	(0.112)	(0.732)	(0.315)
Iron roofing	-0.1443	0.5178*	0.0606	0.0537***	0.0514	0.0502	0.0512	-2.6307***	-2.1587***
	(0.896)	(0.297)	(0.104)	(0.016)	(0.045)	(0.112)	(0.113)	(0.873)	(0.321)
Extension	-0.1629	0.3531	0.0604	0.0226	-0.0023	-0.0104	-0.0129	-0.2599	0.6182*
	(0.949)	(0.288)	(0.270)	(0.016)	(0.044)	(0.119)	(0.119)	(0.686)	(0.340)
Organisation member	1.1493	0.8559***	-0.0939	0.0693***	0.0799*	-0.1057	-0.1092	-0.1481	-1.0861***
	(0.824)	(0.274)	(0.119)	(0.016)	(0.044)	(0.110)	(0.110)	(0.686)	(0.310)
Lead farmer	1.5207	1.3458**	0.0830	0.0902***	0.1818**	0.0646	0.0545	-0.4542	-0.7926
	(1.897)	(0.672)	(0.210)	(0.029)	(0.074)	(0.228)	(0.226)	(1.309)	(0.657)

Medium slope	-0.8418	0.1271	0.1978*	0.0240	-0.0303	0.2098**	0.2148**	1.1929	0.1944
	(1.191)	(0.372)	(0.105)	(0.016)	(0.043)	(0.104)	(0.104)	(0.874)	(0.305)
Formal market	-2.2305	0.1647	0.2966**	0.0286	-0.1158*	0.3344**	0.3346**	0.7489	0.7674**
	(1.582)	(0.422)	(0.140)	(0.019)	(0.061)	(0.140)	(0.140)	(1.480)	(0.373)
Adoption intensity			0.2169*			0.3074***	0.3075***		
			(0.297)			(0.052)	(0.052)		
Bicycle			0.2854*			0.2421**	0.3215**		
			(0.171)			(0.121)	(0.138)		
Insigma0			1.3408**			-6.1083***	1.2473***		
			(0.566)			(0.679)	(0.102)		
Insigma1			1.4729***			-4.2837***	1.6052***		
			(0.229)			(0.774)	(0.006)		
athrho0			-0.4857			-1.5639***	-0.1852		
			(1.648)			(0.300)	(0.803)		
athrho1			-1.4776			-1.5284***	0.2772**		
			(3.168)			(0.133)	(0.126)		
_constant	23.0807	11.4547***	-2.6526***	1.9849***	2.3858***	-2.3322***	-2.2867***	5.6732	2.8870**
	(17.570)	(1.291)	(0.689)	(0.074)	(0.220)	(0.531)	(0.520)	(7.425)	(1.455)
Wald chi	46.1544			316.2271			87.7684		
Prob > chi^2	0.0005			0.0000			0.0000		
Observations	1 500			1 500			1 500		

Source: Authors' analysis using an endogenous switching regression.
Notes: The three models were run on 1 500 observations. The first column presents results with the dependent variable, food consumption score (FCS), the second column presents results with the household dietary diversity score (HDDS), and the third column presents results with the household food insecurity access scale (HFIAS) as dependent variables. Furthermore, asterisks denote significance levels: * is significant at 10% (0.1), ** is significant at 5% (0.05), and *** is significant at 1% (0.01). Standard errors are in parentheses.
lnsigma0: This is the natural logarithm of the standard deviation of the error term in the outcome equation for non-adopters
lnsigma1: This is the natural logarithm of the standard deviation of the error term in the outcome equation for adopters
athrho0: This is the hyperbolic arctangent of the correlation coefficient between the errors of the selection equation and the outcome equation for non-adopters
athrho1: This is the hyperbolic arctangent of the correlation coefficient between the errors of the selection equation and the outcome equation for adopters

Table 3: Endogeneity test and weak instrument test

Test	F-statistic	P-value
Endogeneity test	9.9025	0.0017
Weak instrument test	18.107	0.0000

4.4 Impact of adoption on household food security

The objective of this research was to assess the impact of adopting improved soybean varieties and agronomic practices on household food security. The findings indicate that adopters had a food consumption score (FCS) that was 8.00 points higher than that of non-adopters. This suggests that the FCS for non-adopters could increase by 8.00 points if they were to sustainably adopt improved soybean varieties and related agronomic practices. Similarly, the household dietary diversity score (HDDS) for adopters was 3.86 points higher compared to non-adopters. Thus, if non-adopters adopted improved soybeans and their related agronomic practices, their HDDS could potentially increase by 3.86 points. The study also examined food access using the household food insecurity access scale (HFIAS). The results show that adopters had an HFIAS score that was 3.85 points lower than that of non-adopters. This implies that the HFIAS score for non-adopters could decrease by 3.85 points if they were to adopt improved soybean varieties and their complementary agronomic practices. Table 4 shows the treatment effects of the adoption of improved soybean and agronomic practices on FCS, HDDS and HFIAS.

Overall, the study concludes that adopting improved soybean varieties and agronomic practices significantly enhances food security among farming households, as evidenced by improvements in both FCS and HDDS and a reduction in HFIAS.

Table 4: Average treatment effect of improved soybean and agronomic practice adoption on FCS, HDDS and HFIAS

Soybean and agronomic practice adoption	Actual FCS dependent on the adoption of improved soybean and agronomic practice adoption	Counter-factual FCS independent of improved and agronomic practice soybean adoption	ATE	Actual HDDS dependent on the adoption of improved soybean and agronomic practices	Counter-factual HDDS independent of improved soybean and agronomic practice adoption	ATE	Actual HFAIS dependent on the adoption of improved soybean and agronomic practices	Counter-factual HFAIS independent of improved soybean and agronomic practice adoption	ATE
(ATT)	12.02	4.01	8.00***	7.25	3.39	3.86***	5.15	9.00	-3.85***
	(0.17)	(0.14)		(0.08)	(0.07)		(0.24)	(1.26)	

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

4.5 Cox proportional hazard model for soybean adoption

We applied a Cox proportional hazard model to estimate the hazard rates associated with soybean adoption. The Nelson-Aalen cumulative hazard and Kaplan-Meier survival estimates for the soybean varieties Makwacha, Serenade Tikolore and Nasoko are displayed in the figures below. The survival durations for Makwacha, Serenade, Tikolore and Nasoko are 10, 26, 17 and 11 years, respectively, based on the Kaplan-Meier survival projections.

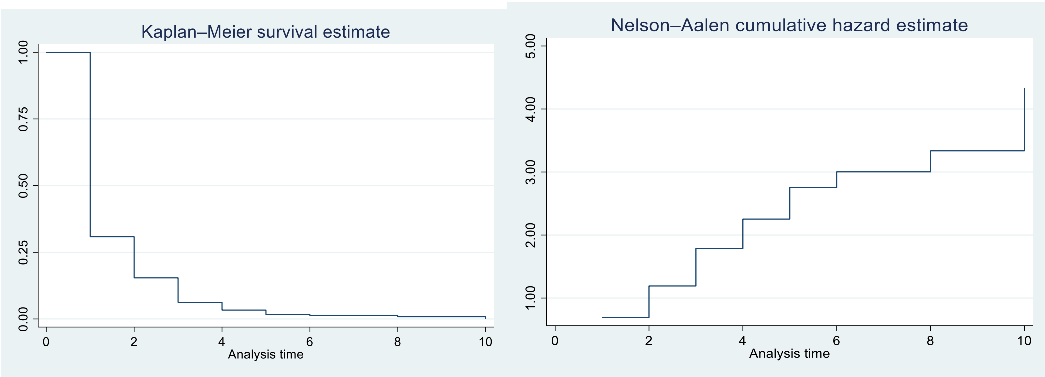

Figure 1: Kaplan Meier survival estimates and Nelson-Aalen hazard estimates of adoption of Makwacha soybean variety

The adoption of the Makwacha soybean variety is shown in the graphs in Figure 1 above, with adoption rates decreasing from 100% in the first year to approximately 20% in the second year and 0% after six to ten years. Concurrently, the risk of dis-adopting the variety rises at an accelerating rate, from 0.1 in the first year to 2.2 in the following four years, 3 in the following six years, and 4 in the following 10 years.

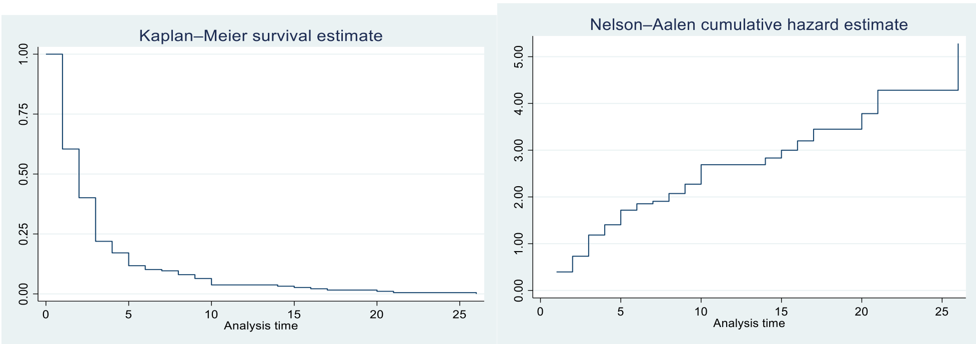

Figure 2: Kaplan Meier survival estimates and Nelson-Aalen hazard estimates of adoption of Serenade soybean variety

The probability of survival for Serenade in Figure 2 above decreases from 100% in the first year to 20% in the following five years, less than 10% in the following 10 years, and 0% in the following 25 years. Concurrently, the risk of not adopting the serenade variety rises from 0.3 in the first year to 1.5 in the following five years, 3 in the following 15 years, and 5 in the following 25 years.

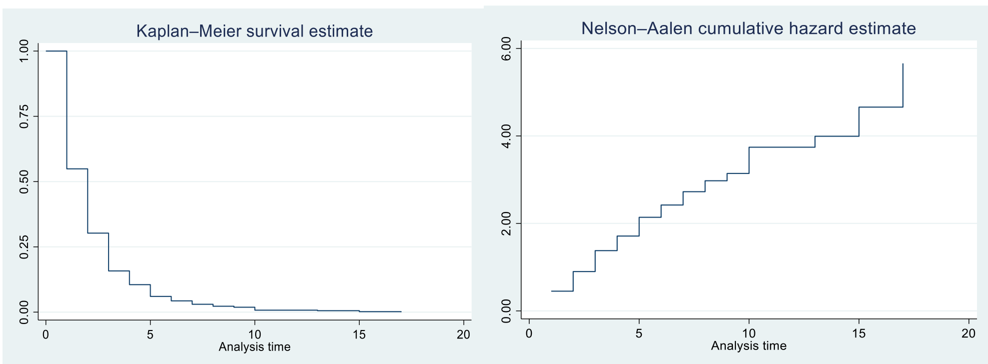

Figure 3: Kaplan Meier survival estimates and Nelson-Aalen hazard estimates of adoption of Tikolore soybean variety

According to the Kaplan-Meier survival estimates, shown in Figure 3 above, the Tikolore variety experienced a decrease from 100% in the first year to 55% in the second, 22% in the third, and less than 5% in the following 10 and 0% in the following 15 years. In addition, the risk of not adopting the Tikolore variety rises using the Nelson Aalen hazard estimates, from 0.2 in year one to 2.1 in year five, 3.8 in the following 10 years, and five in the following 17 years.

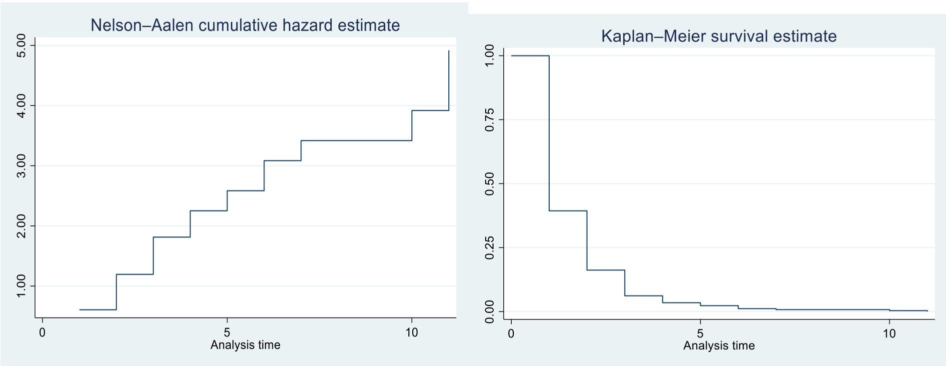

Figure 4: Kaplan Meier survival estimates and Nelson-Aalen hazard estimates of adoption of the Nasoko soybean variety

The adoption survival rate of the Nasoko variety (see Figure 4 above) declined from 100% in the first year to 35% in the next two, and then to less than 5% in the following five years, and 0% in the following 10, according to Kaplan-Meier estimates. In addition, the dis-adoption rate rises from 0.2% in the first year to 3% in the following five years, and 4% in the following 10 years based on the Nelson-Aalen hazard rate of dis-adopting the Nasoko variety.

Table 5 presents the results of a time-to-failure analysis using a semi-parametric Cox proportional hazard model to assess the relative risk of dis-adopting the Makwacha, Serenade, Tikolore and Nasoko varieties over time. The Nasoko model is significant at 1%, as are the Serenade and Tikolore models. Furthermore, it is also important to remember that estimates are the hazard ratios minus one to calculate the relative risk, because hazard ratios occur out of one. A farmer with very fertile land has a 21.97% lower risk of dis-adopting Serenade, as fertile land boosts productivity and profits compared to less fertile land. Alternatively, owning land on a slope increases the risk of dis-adopting Serenade by 18.09% due to vulnerability to soil erosion, which can further influence the effectiveness of herbicides and different water management practices. Households with bicycles as a mode of transportation have a 21% lower risk of dis-adopting Tikolore, as bicycles facilitate access to inputs and output markets. Farmers in Dedza district have a 39.65%, 32.45% and 84.80% lower risk of dis-adopting Serenade, Tikolore and Nasoko, respectively, compared to farmers in Mzimba district. In contrast, farmers in Ntchisi district have a 65.92%, 76.12% and 41.61% lower risk of dis-adopting these varieties. Farmers in Kasungu and Lilongwe have a 32.13% and 24.59% lower risk of dis-adopting Tikolore compared to those in Mzimba. Increasing labour by one man-day per hectare lowers the risk of dis-adopting Nasoko by 0.12%, as more labour improves care and management. However, the risk increases by 32.64% if the farmer has an iron-roofed house.

Table 5: Estimating hazard ratios for the dis-adoption of soybean technologies among smallholder farmers in Malawi

	Makwacha	Serenade	Tikolore	Nasoko
Independent variables	**Hazard ratio**	**Hazard ratio**	**Hazard ratio**	**Hazard ratio**
Age	-0.0017	-0.0004	-0.0040	0.0007
	(0.003)	(0.004)	(0.003)	(0.005)
Education	0.0013	0.0136	0.0079	-0.0064
	(0.009)	(0.015)	(0.011)	(0.018)
Sex of household head	-0.0107	0.0788	-0.0037	0.3150*
	(0.092)	(0.182)	(0.124)	(0.186)
Access to formal market	-0.0221	-0.4051**	0.0389	0.1158
	(0.112)	(0.181)	(0.123)	(0.190)
Fertile land	-0.0288	-0.2952**	0.1580	-0.0513
	(0.079)	(0.125)	(0.099)	(0.145)
Total area	-0.0141	-0.0437	-0.0263	0.0255
	(0.065)	(0.083)	(0.025)	(0.024)
Total labour quantity	-0.0002	-0.0006	0.0002	-0.0017***
	(0.000)	(0.000)	(0.000)	(0.001)
Extension	-0.0626	-0.2708**	-0.1095	-0.1820
	(0.078)	(0.136)	(0.097)	(0.163)
Bicycle	0.0113	0.0320	-0.2300**	-0.3079*
	(0.079)	(0.152)	(0.106)	(0.160)
Iron roofing	0.0012	-0.0110	-0.0827	0.4723***
	(0.099)	(0.136)	(0.108)	(0.164)
Radio	0.0605	-0.1194	-0.0516	0.0714
	(0.088)	(0.141)	(0.106)	(0.164)
Medium depth	-0.0195	-0.1327	-0.0829	0.2179
	(0.077)	(0.125)	(0.098)	(0.150)
Dedza district	0.0266	-0.6445***	-0.3341**	-0.9159***
	(0.117)	(0.193)	(0.152)	(0.226)
Medium slope	0.0736	0.1571	-0.0917	0.0840
	(0.075)	(0.116)	(0.101)	(0.147)
Household size	0.0054	0.0024	0.0073	0.0307
	(0.024)	(0.030)	(0.026)	(0.039)
Lilongwe district	-0.1394	0.1208	-0.2716**	-0.0282
	(0.116)	(0.166)	(0.127)	(0.216)
Kasungu district	-0.0206	-0.4610	-0.2532*	-0.3981
	(0.131)	(0.300)	(0.145)	(0.286)
Ntchisi district	0.0431	-0.7653***	-0.7629***	-0.2666
	(0.105)	(0.198)	(0.168)	(0.206)
Wald chi	6.1799	52.4637	45.5012	42.4638
Prob > chi^2	0.9954	0.0000	0.0004	0.0010
Observations	224	174	496	241

Notes: Standard errors in parentheses; * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$

5. Conclusions and recommendations

The main objective of this study was to assess whether the adoption of improved soybean varieties and their complementary agronomic practices enhance household food security among smallholder farmers in Malawi. Firstly, the study used endogenous switching regression to assess what influences the decision to adopt improved soybean varieties and agronomic practices; secondly, using treatment effects, the study sought to determine the effect of improved soybean varieties and agronomic practices on food security; and lastly, the study used a Cox hazard proportion model to determine the survival estimates and hazard relative risks of dis-adopting soybean varieties. The study modelled adoption based on a farmer's awareness of the soybean varieties and their complementary agronomic practices, as well as their continued use of the variety over the preceding three years, including the practice of double-row spacing.

The results indicate that adopting improved soybean technologies significantly enhanced household food security among smallholder farmers. Specifically, the food consumption score and household dietary diversity score increased by 8 and 3.86, respectively. In addition, households that adopted these technologies experienced a reduction of 3.85 in their food insecurity access score. The findings from the Cox proportional hazards model show that various factors reduce the relative risk of dis-adoption, such as bicycle ownership, access to formal markets, extension services, being a male farmer, having fertile land, increasing labour on the farm, and residence in Kasungu, Lilongwe, Ntchisi or Dedza districts. The results from the endogenous switching regression further show that the likelihood of adopting improved soybean varieties and agronomic practices increases for farmers who own a bicycle, have land on a medium slope and have access to formal markets, compared to farmers without these resources. In addition, compared to farmers in Mzimba district, those residing in Ntchisi district demonstrated a higher probability of adopting improved soybean varieties and agronomic practices.

In conclusion, the study gives rise to the following recommendations: Firstly, the study suggests strengthening links to formal markets, which are critical for maintaining soybean production. In addition, increasing extension services designed specifically for soybean production promotes the adoption of better practices and gives farmers the technical know-how required for efficient crop management. Lastly, the study recommends conducting a similar study using panel data to capture the true impact of adoption on food security more accurately.

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