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The poverty impacts of improved soybean technologies in Malawi

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ABSTRACT

Improved soybean varieties and agronomic practices have been widely disseminated to smallholder farmers in Malawi over the last 15 years. However, there is no empirical evidence on the welfare impacts of adopting improved soybean technologies. This paper estimated the poverty impacts of adopting improved soybean technologies using data from 1,234 households in six soybean growing districts accounting for over 80% of the total soybean production in the country. The results from an endogenous switching regression model showed that 32% of the sample households adopted improved soybean varieties and agronomic practices. The adoption benefits were higher for female-headed households and increased with the household head's education and cultivated land areas. A comparison of the observed and counterfactual incomes for adopters based on the international poverty line of US$1.90 per capita per day showed a 4.16 percentage-point reduction in poverty among the sample households, translating to over 150,000 people lifted out of poverty. The household head's education level, household size, cultivated land area, livestock size, and asset ownership are associated with the daily per capita income. The results point to the need for scaling up of improved soybean varieties and agronomic practices for greater impacts on poverty reduction among smallholders in Malawi.

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1. Introduction

The agricultural sector in Malawi employs 80% of the population, produces one-third of the total GDP, and generates over 80% of total export revenues (IMF 2017). However, agricultural productivity remains low mainly due to (1) declining soil fertility, changing rainfall patterns, extended drought seasons; (2) poor health of the farming community; and (3) limited access to farm inputs such as improved seeds, fertilisers, and other resources such as credit, market information, and improved agronomic practices (Ajayi et al. 2015; Denning et al. 2009; Dorward and Chirwa 2011; Khojely et al. 2018; Mubichi 2017; Sánchez 2010; Zeller, Diagne, and Mataya 1998). As a result, farmers face high input prices, low traded volumes, thin markets, high variability in agricultural produce prices, and low incomes.

Income growth in agriculture is two to three times more effective in reducing poverty than equivalent income growth in non-agricultural sectors (Christiaensen, Demery, and Kuhl 2011;

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Christiaensen and Martin 2018; Ligon and Sadoulet 2008; Loayza and Raddatz 2010; Minten and Barrett 2008; Ravallion and Datt 1996; Thirtle, Lin, and Piesse 2003). This effect is the largest for the poorest people in a society (Christiaensen, Demery, and Kuhl 2011; Ligon and Sadoulet 2008) and those in a lower literacy level (Ligon and Sadoulet 2008). This means that the poverty-reducing effect of agriculture is highest among African countries where many people are engaged in agriculture, and the contribution of agriculture to the whole economy is substantial. Therefore, increasing the production and productivity of agriculture by promoting improved agricultural technologies is important to increase income and reduce poverty in Africa (Alene and Coulibaly 2007; Debnath 2013; Thirtle, Lin, and Piesse 2003).

Many agricultural technologies have been developed and disseminated to end-users in Sub-Saharan Africa (SSA) and elsewhere by national and international organisations. The Consultative Group on International Agricultural Research (CGIAR) has contributed to the development of improved varieties and complementary agronomic practices since 1965. Between 1965 and 1998, CGIAR contributed to the development of 8,000 crop varieties released in developing countries across the world (Evenson and Gollin 2003). As of 2011, CGIAR contributed to the development of about 1,500 crop varieties in SSA alone (Walker and Alwang 2015). The development of these improved crop varieties and complementary management practices has significantly contributed to increase in agricultural productivity in the SSA (Alene et al. 2015; Darko et al. 2018; Evenson and Gollin 2003; Khojely et al. 2018; Zeller, Diagne, and Mataya 1998).

Soybean is among the major legume crops that provide multiple benefits to smallholder farmers in Malawi. It is a source of cash, nutritious food, and biological nitrogen (Giller et al. 2011; Sinclair et al. 2014; van Vugt, Franke, and Giller 2016). Smallholder farmers sell soybeans to processors who process it into human food such as maize-soybean blend and weaning baby foods, feed for animals, and vegetable oil. Soybean is also consumed at the household level mixed with maize. Soybean production helps improve soil fertility if grown in rotation with maize, the crop to which up to 90% of the farmland is allocated. This practice helps to reduced dependence on mineral N fertiliser and thus reduces farmers' production costs. Despite these benefits of soybean production, soybean yields remain low at less than 1 ton/ha (Khojely et al. 2018).

Over the last 15 years, improved soybean varieties, and complementary agronomic practices such as inoculants, correct plant density, close spacing, proper application of inorganic fertiliser have been widely disseminated to smallholder farmers through demonstrations, training on good agronomy and postharvest handling practices, seed fairs, and handouts of small seed packs (Tufa et al. 2019). These agricultural innovations can reduce poverty directly through increased soybean production for home consumption, sales, and cost savings; and indirectly through lower food prices, employment creation, and higher wages (De Janvry and Sadoulet 2002; Minten and Barrett 2008).

Despite large-scale technology dissemination, however, there is no empirical evidence on the adoption and poverty impacts of improved soybean technologies (ISTs) in Malawi. This study, therefore, assesses the adoption and poverty impacts of ISTs in Malawi. Adoption of ISTs is defined in this paper as growing one or more of the widely grown improved soybean varieties (Tikolore, Mackwacha, Nasoko, or Serenade) in double row spacing. Double row spacing is an agronomic practice that uses two rows on the same ridge for optimum plant density compared to the traditional farmer practice of planting one row per ridge. It enhances the productivity of improved soybean varieties through increased plant population and smothering weeds. The results of on-farm experimentations and participatory evaluation of soybean crop management practices conducted in Malawi show that management practices (e.g., plant population) when combined with improved varieties, can increase soybean grain yields by more than two-fold (Van Vugt et al., 2017). This emphasises the importance of adopting soybean technologies as a package to exploit the complementarities among the technical components.

This study contrasts with many past impact studies that considered only improved varieties (Asfaw et al. 2012; Becerril and Abdulai 2010; Kassie et al. 2011, 2018; Katungi et al. 2018; Mendola 2007; Shiferaw et al. 2014). Most of these studies also used the propensity score matching

(PSM) technique that controls only for observable characteristics of the adopters and non-adopters (for example, Becerril and Abdulai 2010; Kassie, Shiferaw, and Muricho 2011; Mendola 2007). The use of PSM may yield biased estimates because of the influence of unobservable characteristics such as skills or innovativeness (Heckman and Navarro-lozano 2004). These unobserved characteristics may simultaneously affect smallholder farmers' IST adoption decisions and income. Further, the results of PSM may be biased due to the misspecification of the propensity score model. We used the endogenous switching regression model (ESRM) to control for observable and unobservable variation between the adopters and non-adopters of soybean technologies and estimate the causal effect of IST adoption on daily per capita income and poverty. The ESRM accounts for the endogeneity of the adoption decision by estimating simultaneous equations models of IST adoption and daily per capita income and poverty. We used the international poverty line to estimate poverty indices and the number of people lifted out of poverty due to the adoption of ISTs.

The rest of this paper is organised as follows. The following section presents a brief introduction to soybean production and research in Malawi. The third section describes the theoretical model and empirical procedure, whereas the fourth section presents the survey design and data collection and presents and discusses the descriptive statistics. The fifth section presents and discusses the results, and the last section concludes with policy implications.

2. Soybean production and research in Malawi

2.1 Soybean production and productivity

Introduced in 1910 from an unknown source (Shurtleff and Aoyagi, 2009), soybean production in Malawi has increased over the last decade due to an increase in yield and production area (Figure 1). In Malawi, smallholder farmers contribute to 95% of total soybean production (Opperman and Varia, 2011). The increase in area under soybean production in the last decades came about mainly at the expense of other crops such as tobacco (Meyer et al. 2018). There is no more new land to be put under cultivation even though soybean can be grown in all parts of the country. Soybean is less labour-intensive and less risky than tobacco, which is the major cash crop in Malawi and gives higher returns for poorer households (Franke, van den Brand, and Giller 2014). Some of the tobacco producers switched over to soybeans (Meyer et al. 2018).

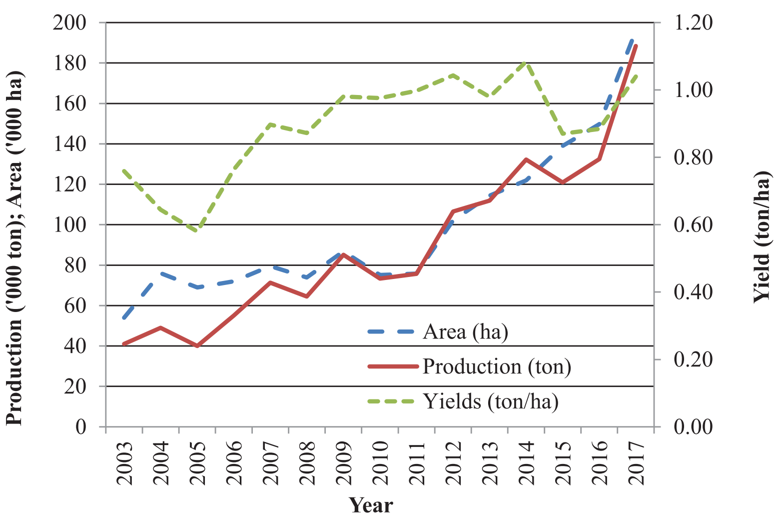

Figure 1. Soybean production and yield trends (2003–2017). Source: FAOSTAT database (FAO, 2019).

The increase in soybean production in Malawi is mainly induced by the growing demand for soybean as food and feed; and the availability of a favourable policy that promotes soybean to address declining soil fertility, malnutrition, and poverty (Meyer et al. 2018). A study conducted in Malawi showed that 63 kg/ha of nitrogen was derived from the atmosphere due to the production of soybean (van Vugt, Franke, and Giller 2016). Thus, soybean production can provide cash and nutritious food to smallholder farmers and in enhancing the productivity of rotation crops. However, smallholder farmers in Malawi are not benefiting much from soybean production due to several constraints. The constraints include lack of resistant varieties to foliar diseases, shortage of drought-tolerant varieties, poor market access due to poor infrastructure, price volatility, lack of organised markets, lack of knowledge in soybean processing and utilisation, low farm gate prices, unpredictable demand, weak extension services, and limited access to quality seeds of improved varieties (ICRISAT, 2013).

2.2 Soybean research

In Malawi, soybean variety trials were conducted for the first time from 1961 to 1964 at Bvumbe research station on five soybean varieties, namely, Hernon-107 1153, Pelican 1091, Hernon-147 1072, Volstate 1027, and Hood 258 (Shurtleff and Aoyagi, 2009). In the 1980s soybean research became a fully-fledged and focused programme and released improved varieties such as Impala, Kudu, Geduld, Bossier, Hernon 147, and Hardee. However, these varieties had very high shattering rates and were also unsuitable for processing (ICRISAT, 2013). The soybean traits needed for processing are cream-white hilum and large seed size.

Even though soybean research started in 1960, the varieties with cream-white hilum and large seed sizes were released after the 1990s (Alene et al. 2015). According to Alene et al. (2015), 15 soybean varieties were released for commercial production with improved complementary agronomic practices between 1985 and 2011. The average yields of these varieties were in the range of 2.5 to 3 ton/ha on experimental fields, depending on the type of variety. However, current soybean yields on smallholder farmers' fields are only about 1 t/ha. The soybean varieties currently grown at scale by smallholder farmers are Tikolore, Makwacha, Nasoko, and Serenade. This paper shows that 56% of the soybean producers in the six major soybean growing districts such as Lilongwe, Mchinji, Dedza, Ntchisi, Kasungu, and Mzimba planted one of the four improved soybean varieties in the 2016/2017 cropping season. The total land under soybean production in the 2016/2017 cropping season was 188,407 ha, with over 100,000 ha was planted to each of the four varieties. These four varieties are high-yielding and have characteristics desired by processors. The varieties also have other traits such as short maturity, high yield under moisture stress, and excessive moisture.

3. Theoretical model and empirical procedure

3.1 Theoretical model

In this study, we consider the direct effect of the adoption of ISTs, on daily per capita income and poverty. Similar to previous studies (e.g., Becerril and Abdulai 2010; Jaleta et al. 2018; Khonje et al. 2015, 2018; Tufa et al. 2019), we use the random utility framework to model a smallholder farmer's decision to adopt or not an IST. This decision is based on the expected benefits of the adoption of ISTs. Therefore, a soybean grower will adopt an IST if $G^* = R_A - R_N > 0$. G^* is a variable that represents the difference between benefits from the adoption of IST (R_A) and non-adoption (R_N). Non-adoption is the decision not to grow one of the four improved soybean varieties using double row spacing (i.e., the decision to grow improved or local soybean varieties without using double row spacing or it can also be the decision to grow local varieties with double-row spacing). Therefore, G^* is a latent variable that can be stated in terms of observable variables expressed as follows:

$$G^* = \gamma Z + \varepsilon \text{ and } G = \begin{cases} i & \text{if } G^* > 0 \\ \leq 0 & \text{otherwise} \end{cases} \tag{1}$$

where G is a binary variable that equals 1 if a soybean grower chooses to adopt IST and zero otherwise; γ is a vector of parameters to be estimated; Z is a vector of explanatory variables, (e.g., demographic and socioeconomic characteristics of household) and ε is the error term which includes measurement error and unobserved factors.

We expect that the adoption of ISTs increases daily per capita income,[1] and daily per capita income is a linear function of the adoption of ISTs (G) and other explanatory variables (X). This relationship can be specified as

$$Y = \alpha X + \beta G + v \tag{2}$$

Where Y represents daily per capita income, α and β are parameters to be estimated, υ is error term. The estimates of parameter β measure the impacts of the adoption of ISTs. In this study, we used observational data where soybean growers were not randomly assigned to adoption and non-adoption groups. Thus parameter β cannot measure the impacts of adoption accurately. The decision to adopt ISTs could be based on soybean growers' differences in innate abilities and other circumstances (e.g., distance to market) that could be correlated with daily per capita income, that is, υ in Equation (2) might be correlated with G and ε in Equation (1). This correlation biases the results of the estimations in Equation (2).

The impact evaluation methods used to minimise these biases are propensity score matching (PSM) (Kabunga, Ghosh, and Webb 2017; Shiferaw et al. 2014) and instrumental variable (IV) approaches. PSM estimates impacts of adopting of technologies based only on observable variables. They do not account for unobservable variables that may simultaneously affect smallholder farmers' decision to adopt and daily per capita income. Hence the results of PSM estimation may be biased due to errors in the specification of the propensity score model. This study uses a type of instrumental variable (IV) approach called endogenous switching regression model (ESRM). The ESRM controls for both observable and unobservable factors and thus provides unbiased estimates (e.g., Abdoulaye, Wossen, and Awotide 2018; Abdulai and Huffman 2014; Alene and Manyong 2007; Fuglie and Bosch 1995; Khonje et al. 2018; Lee 1978; Lokshin and Sajaia 2004). Therefore, ESRM estimates net gain in daily per capita income due to the adoption of ISTs.

3.2 Empirical procedure

3.2.1 Endogenous switching regression

The ESRM uses the full information maximum likelihood estimation (FIML) approach to estimate the impacts of treatments to which subjects are not randomly assigned like the case at hand. The impact of the adoption of ISTs can be estimated using The 2SLS, in two stages (Fuglie and Bosch 1995; Lokshin and Sajaia 2004). The first stage estimation determines the probability of adoption, parameter γ in Equation (1) using a probit regression model. The second stage estimation determines the relationships between the outcome variables (daily per capita income of the household) and soybean growers' observed characteristics (see Table 1) under two separate regimes (Regimes 1 and 2) using ordinary least squares (OLS) regressions for which selectivity is corrected. However, the simultaneous estimation using the FIML estimation is more efficient than the 2SLS estimation (Lokshin and Sajaia 2004). Hence, we opt to use the FIML. The two separate regimes are given as follow:

$$\text{Regime 1 (adopter):} \quad y_A = \beta_A X_A + \upsilon_A \quad \text{if } G = 1 \tag{3a}$$

Table 1. Descriptive statistics of the variables used in the analysis.

Variable	Description	All (n = 1234)	Adopter (A) (n = 392)	Non-adopters (N) (n = 842)	Difference (A-N)
Adoption status	Adoption of soybean improved varieties and agronomic practices	0.32	1	0	
Income	Household daily Per capita income (UD$)	1.65	1.65	1.64	0.01
Poverty	Head count ration (UD$ 1.90 per capita per day)	0.738	0.722	0.746	−0.024
Age	Age of household head (number of years)	44.75	44.45	44.88	−0.43
Education	The education level of household head (number of years in school)	5.30	5.45	5.23	0.22
Sex	Sex of household head (1 = male)	0.81	0.84	0.80	0.04**
Household size	Number of household members	5.23	5.22	5.23	−0.01
Land	Total area of cultivated land (ha)	1.22	1.26	1.20	0.06
Roofing	Ownership of iron roofed house (1 = yes)	0.33	0.32	0.33	−0.01
Bicycle	Ownership of bicycle (1 = yes)	0.50	0.55	0.48	0.08***
Cart	Ownership of cart (1 = yes)	0.05	0.04	0.06	−0.02
TLU	Ownership of livestock in TLU	0.64	0.49	0.70	−0.21
Market	Participation in a formal seed market (1 = yes)	0.71	0.78	0.67	0.11***
Support	Rely on government support if crop fails (1 = yes)	0.66	0.63	0.67	−0.04*
Transport	Average one-way transport cost to the main market by car (Mk/person)	857.78	861.03	856.26	4.77
Member	Household head or spouse member of organisation (1 = yes)	0.37	0.44	0.33	0.11***
Village adoption	The proportion of adopters in the previous season in the villages	26.47	47.56	16.69	30.88***
Information	Number of sources of information about the technology	1.13	1.30	1.06	0.25***

$$\text{Regime 2(non}-\text{adopter):}\quad y_N = \beta_N X_N + \upsilon_N \quad \text{if } G = 0 \tag{3b}$$

where y_A and y_N are continuous variables representing daily per capita income, X_A and X_N are characteristics of soybean producers, β_A and β_N are parameters to be estimated, υ_A and υ_N are error terms, for adopters and non-adopters, respectively.

We expect non-zero values for the correlation between υ_A and υ_N as the adoption of ISTs may suffer from self-selection and thus be biased from the OLS estimation (Maddala 1983). We assume $\varepsilon,\ \upsilon_A,$ and υ_N to have a tri-variate normal distribution that has zero mean, and variance-covariance structure expressed as follow:

$$\text{cov}(\varepsilon,\ \upsilon_A,\ \upsilon_N) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\upsilon_A} & \sigma_{\varepsilon\upsilon_N} \\ \sigma_{\upsilon_A\varepsilon} & \sigma_{\upsilon_A}^2 & \sigma_{\upsilon_A\upsilon_N} \\ \sigma_{\upsilon_N\varepsilon} & \sigma_{\upsilon_N\upsilon_A} & \sigma_{\upsilon_N}^2 \end{bmatrix} \tag{4}$$

where σ_ε^2 is the variance of the error term in the selection equation (Equation 1); and $\sigma_{\upsilon_A}^2$, and $\sigma_{\upsilon_N}^2$ are the variance of the error terms in outcome Equations (3a) and (3b) correspondingly; and $\sigma_{\upsilon_A\varepsilon}$ is the covariance of ε and υ_A, and $\sigma_{\upsilon_N\varepsilon}$ is the covariance of ε and υ_N. The correlation between the error terms, ρ, can be specified as $\rho_{\upsilon_A\varepsilon} = corr(\upsilon_A,\ \varepsilon)$ for adopters and $\rho_{\upsilon_N\varepsilon} = corr(\upsilon_N,\ \varepsilon)$ for non-adopters. These correlations can also be specified as $\rho_{\upsilon_A\varepsilon} = \sigma_{\upsilon_A\varepsilon}/\sigma_{\upsilon_A}\sigma_\varepsilon$ for adopters and $\rho_{\upsilon_N\varepsilon} = \sigma_{\upsilon_N\varepsilon}/\sigma_{\upsilon_N}\sigma_\varepsilon$ for non-adopters. The covariance between υ_A and υ_N is undefined as y_A and y_N do not occur at the same time. This assumption leads to the expression of the expected values of the truncated error terms

$E(\upsilon_A|G = 1)$ and $E(\upsilon_N|G = 0)$ as follows

$$E(\upsilon_A|G=1) = \sigma_{\upsilon_A\varepsilon}\frac{\phi(\gamma Z/\sigma)}{\Phi(\gamma Z/\sigma)} \equiv \sigma_{\upsilon_A\varepsilon}\lambda_A \tag{5}$$

$$E(\upsilon_N|G=0) = \sigma_{\upsilon_N\varepsilon}\frac{-\phi(\gamma Z/\sigma)}{1-\Phi(\gamma Z/\sigma)} \equiv \sigma_{\upsilon_N\varepsilon}\lambda_N, \tag{6}$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative density function, and $\lambda_A = \frac{\phi(\gamma Z/\sigma)}{\Phi(\gamma Z/\sigma)}$, and $\lambda_N = \frac{-\phi(\gamma Z/\sigma)}{1-\Phi(\gamma Z/\sigma)}$ where λ_A and λ_N are inverse mills ratio. λ_A and λ_N can be treated as missing variables (Lee 1978) in Equations (3a) and (3b). By finding instrumental variables for λ_A and λ_N, they can be included in the specifications of Equations (3a) and (3b) so that the equations can be consistently estimated using OLS (Fuglie and Bosch 1995). A correct specification of ESRM needs the inclusion of at least one instrumental variable in the selection model. The instrumental variable should affect the adoption of IST but not the daily per capita income for non-adopters (Abdulai and Huffman 2014; Kabunga, Dubois, and Qaim 2012).

We use three instrumental variables, namely membership in farmers' groups, the adoption rate of ISTs at a village-level, and the source of information about ISTs. The adoption rate of IST at the village level is defined as the percent of adopters of IST in the village in the preceding cropping season. Membership in a farmers' group refers to whether the household head or the spouse was a member of farmers' organisations such as farmers' cooperatives or other informal or formal farmers' groups. Source of information represents the number of self-reported information sources (e.g., government extension agents, NGOs, fellow farmers, radio, etc.) about IST. The use of these variables as instruments is based on the idea of social networks. Farmers' adoption decisions are usually influenced by their network of friends and relatives (Adegbola and Gardebroek 2007; Bandiera and Rasul 2006; Krishnan and Patnam 2013). Besides, we selected these instruments based on the results of the suitability test as suggested by Di Falco, Veronesi, and Yesuf (2011)[2]. The results of a simple falsification test in Table A1 in the appendix show that the selected variables jointly influence the adoption of IST (Model 1, $\chi^2 = 11.46,\ \rho = 0.003$) but not daily per capita income (Model 2, F-stat=1.79, $p = 0.168$), indicating that these are valid instrumental variables. The instrumental variables used in other studies were, for instance, membership in farmer's group (Kabunga, Dubois, and Qaim 2012), adoption rate at the village level in the preceding cropping calendar (Katungi et al. 2018), and information source about technologies (Manda et al. 2016; Shiferaw et al. 2014).

Endogenous switching exists if $\rho_{\upsilon_A\varepsilon}$ or $\rho_{N\varepsilon}$ is significantly different from zero (Abdulai and Huffman 2014). The selection bias can be positive or negative. Negative selection bias occurs if $\rho_{\upsilon_A\varepsilon}$ or $\rho_{N\varepsilon}$ is positive and implies that soybean growers with below-average daily per capita income are most likely to adopt ISTs. A negative $\rho_{\upsilon_A\varepsilon}$ or $\rho_{\upsilon_N\varepsilon}$ shows a positive selection bias and suggests more likelihood of adopting of ISTs by soybean producers with above-average daily per capita income.

3.2.2 Impact of IST adoption on income

The impacts of the adoption of IST can be estimated by stating the daily per capita income, under two scenarios: real and hypothetical. The real scenario expresses the expected values of the daily per capita income for adopters, y_A, as follows

$$E[y_A|G=1] = X\beta_A - \sigma_{\upsilon_A\varepsilon}\lambda_A \tag{7}$$

In Equation (7), $\sigma_{\upsilon_A\varepsilon}\lambda_A$ accounts for selection bias. This shows that adopters of IST may have exhibited different behaviour compared to an average soybean grower with similar characteristics because of unobserved factors. The counterfactual outcome values, i.e., the expected outcome values for adopters exhibit had they decided not to adopt can be stated as

$$E[y_N|G = 1] = X\beta_N - \sigma_{\upsilon_N\varepsilon}\lambda_A \quad (8)$$

The average treatment effect on treated (ATT) which is the impact of adoption on daily per capita income is Equation (7) less Equation (8) and can be expressed as follows

$$ATT = E[y_A|G = 1] - E[y_N|G = 1] = X(\beta_A - \beta_N) + (\sigma_{\upsilon_A\varepsilon} - \sigma_{N\varepsilon})\lambda_A \quad (9)$$

The expected outcome values for non-adopters without adoption is given as

$$E[y_N|G = 0] = X\beta_N - \sigma_{\upsilon_N\varepsilon}\lambda_N \quad (10)$$

ESRM reduces bias in ATT estimates by accounting for unobserved variations and also structural differences in the outcome equations.

3.2.3 Poverty estimation procedure

We used Foster, Greer & Thorbecke (FGT) class of poverty measures to estimate poverty indices – poverty headcount, poverty gap, and the squared poverty gap (Foster, Greer, and Thorbecke 1984). FGT indices have been widely used in the welfare analyses literature (Howes and Lanjouw 1998; Jolliffe, Datt, and Sharma 2004; Jolliffe and Serajuddin 2018; Kassie, Shiferaw, and Muricho 2011; Ravallion and Bidani 1994; Zeng et al. 2015) because they are additively decomposable allowing evaluation of impacts by subgroups such as adopters and non-adopters. The general FGT class of poverty measure can be expressed as

$$P_\alpha = \frac{l}{n}\sum_{i=1}^{q}\left(\frac{l - y_i}{l}\right)^{\alpha} \quad (11)$$

where l is a poverty line, y_i is daily per capita income of i^{th} person, n is the total number of people, q is the number of poor people, and α is a poverty aversion parameter. P_α in Equation (11) estimates all the three indices conditional on the value α assumes. When $\alpha = 0$, P_α measures poverty headcount index, which is a percentage of people with daily per capita income less than the poverty line. When $\alpha = 1$, P_α measures poverty gap index which is the mean distance below the poverty line stated as a proportion of that line, where the mean is formed over the entire population, counting the non-poor as having zero poverty gap. The poverty gap measures the amount of income required to raise people in poverty up to the poverty line. When $\alpha = 2$, P_α measures the squared poverty gap index (also called severity of poverty).

We used the international poverty line of US$1.90 and Malawi's national poverty line of US$1.27 to categorise the sample households into poor and non-poor based on household daily per capita income. Household consumption expenditures were used to estimate household daily per capita income. Consumption expenditure is a better poverty measurement than household income for developing countries like Malawi as measuring household income is difficult because of seasonal variability in earnings and portion of incomes are from self-employment on-farm and off-farm (Jayne et al. 2003; Sahn and Stifel 2003). The consumption expenditure used in this study comprises all expenditures on food and non-food items incurred by the households for the 2016/17 cropping calendar year. Purchasing power parity for 2017 was used to convert Malawi Kwacha (MWK) into US$ (1US$ = 205.60 MWK) which was equivalent to the international poverty line of MWK142583.60 (=205.60*1.9*365) per person per year. The reference year for the purchasing power parity was 2011.

The daily per capita income values used for the poverty analysis are predictions from the ESRMs. The per capita income values for the adopters were predicted from Equation (7) for observed per capita incomes, and Equation (8) for counterfactual per capita incomes. The per capita counterfactual incomes are the expected per capita incomes of adopters had they decided not to adopt. For non-adopters, the per capita incomes were estimated based on Equation (10). We used natural logarithm transformed values of per capita income values (as dependent variable) to run the ESRM (see Table 2). We

Table 2. Full information maximum likelihood results of endogenous switching regression.

Variable	Selection model	Non-adopters	Adopters
Age	0.01 (0.02)	0.01 (0.01)	−0.01 (0.01)
Age squared	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
Education	0.01 (0.01)	0.02*** (0.01)	0.03*** (0.01)
Sex	−0.05 (0.13)	0.07 (0.06)	−0.11 (0.08)
Household size	−0.02 (0.03)	−0.15*** (0.01)	−0.15*** (0.02)
Ln Land	0.11 (0.09)	0.24*** (0.04)	0.25*** (0.06)
Roofing	0.00 (0.11)	0.14*** (0.05)	0.12* (0.07)
Bicycle	0.02 (0.10)	0.21*** (0.05)	0.20*** (0.06)
Cart	−0.32 (0.21)	0.31*** (0.10)	0.24 (0.14)
Ln TLU	0.00* (0.00)	0.00*** (0.00)	0.00*** (0.00)
Market	0.26** (0.10)	0.05 (0.05)	0.12* (0.07)
Support	−0.11 (0.09)	−0.03 (0.04)	−0.04 (0.06)
Transport	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
Lilongwe district	0.27 (0.25)	−0.24** (0.10)	−0.12 (0.22)
Mchinji district	0.17 (0.25)	−0.13 (0.09)	−0.07 (0.22)
Kasungu district	−0.02 (0.27)	−0.07 (0.10)	0.12 (0.24)
Dedza district	0.17 (0.26)	−0.08 (0.09)	−0.10 (0.23)
Ntchisi district	0.11 (0.26)	−0.18* (0.09)	−0.11 (0.22)
Member	0.32*** (0.10)		
Village adoption	0.04*** (0.00)		
Information	0.24*** (0.07)		
Constant	−2.28*** (0.51)	0.44* (0.23)	1.13*** (0.35)
σ_N (non-adopters)		−0.51*** (0.03)	
$\rho_{N\varepsilon}$		−0.34** (0.13)	
σ_A(adopters)			−0.63*** (0.04)
$\rho_{A\varepsilon}$			−0.12 (0.12)
Model diagnosis			
Log likelihood	−1583.33		
Wald χ^2	395.77***		
LR test of independent equations $\chi^2(2)$	7.68**		
N	1,234	842	392

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

then obtained predicted values of per capita income. We used the antilogs of the per capita incomes to estimate the ATTs (see Table 3) because the ATTs estimated this way are easier to interpret. This method is also used in several past studies (e.g., Shiferaw et al. 2014; Tufa et al. 2019). We computed the FGT poverty indices on a complete set of data for two categories: with the intervention of IST technologies (full sample households with the adopter and non-adopter category) and without the intervention. The poverty

Table 3. Observed and counterfactual household daily per capita incomes of adopters disaggregated by gender and level of education.

Disaggregates		Household daily per capita income (USD) Adopt	Not to adopt	ATT
Gender	Full sample ($n = 392$)	1.41 (0.03)	1.10 (.02)	0.31*** (0.01)
	Male ($n = 330$)	1.46 (0.03)	1.15 (.03)	0.30*** (0.01)
	Female ($n = 62$)	1.20 (0.06)	0.82 (.04)	0.38*** (0.02)
The education level of the household head	Illiterate ($n = 51$)	1.08 (0.06)	0.87 (0.05)	0.21*** (0.02)
	Standards 1 to 3 ($n = 88$)	1.22 (0.06)	0.98 (0.05)	0.24*** (0.02)
	Standards 4 to 6 ($n = 90$)	1.34 (0.05)	1.06 (0.05)	0.28*** (0.02)
	Standards 7 to 8 and Form 1 ($n = 101$)	1.56 (0.06)	1.18 (0.04)	0.37*** (0.02)
	Higher than Form 1 ($n = 62$)	1.85 (0.08)	1.39 (0.06)	0.46*** (0.03)
Total cultivated land	1st quintile (<=0.685 ha), ($n = 78$)	1.05 (0.04)	0.77 (0.03)	0.28*** (0.02)
	2nd quintile (0.685, 0.91] ha, ($n = 79$)	1.26 (0.06)	1.00 (0.04)	0.26*** (0.02)
	3rd quintile (0.91, 1.25] ha, ($n = 79$)	1.31 (0.05)	1.02 (0.03)	0.29*** (0.03)
	4th quintile (1.25, 1.72] ha, ($n = 77$)	1.62 (0.06)	1.27 (0.05)	0.35*** (0.03)
	5th quintile (>1.72 ha), ($n = 79$)	1.84 (0.08)	1.45 (0.07)	0.39*** (0.03)

Standard deviations in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

impacts of the adoption of IST in terms of reduction in the poverty headcount index, depth, and severity are measured as the differences in the respective poverty indices.

4. Sampling procedure, data, and descriptive analysis

This study employed a stratified random sampling technique to select the sample households for the survey. First, we purposively selected Lilongwe, Mchinji, Dedza, Ntchisi, Kasungu, and Mzimba districts accounting for over 80% of the total soybean produced in Malawi. Second, we selected the extension planning area (EPAs) (administrative structure next to district). A list of all EPAs in the six districts was prepared and used to select 20 EPAs using probability proportional to size (PPS), where the size is the area under soybean in the 2015/2016 cropping season. We selected sections, villages and households using random sampling technique with pre-specified sizes per stratum. Accordingly, we selected 80 sections from 20 EPAs, 320 villages from 80 sections, and 1,600 households from 320 villages. From 1,600 households, 1,234 were soybean growers in the 2016/2017 cropping season. The data comprise sex, age, and education of household head; the number of household members, land and non-land assets; and institutional characteristics (e.g., distance from residence to local markets, membership in farmer organisations, and sources of information). The survey questionnaire was programmed in the *Surveybe* software,[3] a computer-assisted personal interview (CAPI) tool, and trained enumerators were used to collect the data. Table 1 gives summary statistics of the variables used in the analysis by adoption status of IST.

The household characteristics considered in this study include age, education, sex of the household head, and household size. These household characteristics influence the adoption decision of improved agricultural technologies in developing countries (Feder et al., 1985). The age of the household head influences the adoption of improved agricultural technologies, even though the direction of the influence is not conclusive. Older farmers have more experience and physical wealth required to adopt improved agricultural technologies, whereas younger farmers have more flexibility in adopting innovations (Kassie et al. 2013). The role of education in adopting improved technologies is usually positive as better-educated household heads are expected to be more aware of the benefits of adopting improved agricultural technologies. Household heads with a better education level are expected to know the benefits of adopting improved agricultural technologies and to allocate resources efficiently (Pender and Gebremedhin, 2007). The adoption rate of improved agricultural technologies also varies between female- and male-headed households. Studies (e.g., Doss and Morris, 2001; Peterman et al., 2014) showed that men are more likely to adopt improved technologies than women because women have less access to agricultural inputs and services compared to men. Household size is a proxy for the availability of labour in the household for agricultural production. It is expected that a household with a larger family size can supply more labour for farming activities compared to a household with a smaller family size. It is expected that labour availability will increase the likelihood of adopting improved agricultural technologies, including IST. The size of land owned and ownership of other assets like iron sheet roofed houses, bicycles, carts, and livestock are indicators of the household wealth of households. Previous studies (e.g., Kassie et al. 2013; Khonje et al. 2015) have shown that wealthier households are more likely to adopt improved agricultural technologies than poorer households.

It is expected that participation in any formal seed market increases household's access to seeds of improved soybean varieties. Membership in a farmers' group facilitates access to information about the improved technologies through learning from each other (Adegbola and Gardebroek 2007). Farmer groups are also used to transfer information and agricultural technologies by agricultural extension service providers. Besides, the number of sources of information about improved technologies is a proxy for access to extension services. Transport costs are related to transaction costs of obtaining inputs, including improved seeds of soybean varieties. Therefore, membership in farmers' organisations and more information sources are expected to increase the probability of adopting ISTs while transportation costs are expected to have an opposite effect. It is common for governments and international organisations to provide support (e.g., subsidies) to farmers when crop production fails thereby helping households to smooth out consumption and maintain productive capacity (Kassie et al. 2013). We hypothesise that the adoption of IST is likely to increase with government support.

The descriptive results of this study indicate that 32% of the sample households adopted ISTs [see district adoption rates (Appendix Table A2) and village level adoption rates (Appendix Figure A1)]. The results also show that adopters were generally younger, more literate, and had more land and daily per capita income than non-adopters. The results also show that the number of adopters who reported relying on government support should their crops fail was less than that of non-adopters. The results also show that more adopters participate in a seed market than the non-adopters, and adopters were farther to the nearest local market than the non-adopters.

5. Results and discussion

5.1 Determinants of adoption and per capita income

Table 2 presents the ESRM estimates of the factors that affect the adoption of IST and daily per capita income for adopters and non-adopters. Results show that the estimate for the parameter $\rho_{N\varepsilon}$, the correlation between ε and υ_N, was significant, implying that there were initial differences between adopters and non-adopters that caused self-selection in the adoption of ISTs. Besides, the joint independence test of the selection equation, outcome equation for adopters, and outcome equation for non-adopters indicate that the daily per capita income functions for adopters and non-adopters are not the same. This is evident in the differences in the coefficient estimates of the independent variables in the two outcome equations (columns (3) and (4) of Table 2). For example, the parameter estimates for variables such as ownership of an iron-roofed house and cart, participation in a seed market, and location dummies for Lilongwe and Ntchisi districts are different for adopters and non-adopters. This finding indicates that the ESRM is superior to a simple treatment effect model (Kabunga, Dubois, and Qaim 2012).

The results of the selection equation (column 2 of Table 2) show that variables such as seed market participation, farmers' cooperative or group membership, and IST adoption rate at the village level affected the probability of adoption of ISTs at household level. The relationship between participation in the formal seed market by soybean growers and adoption of ISTs was positive and significant. This shows that soybean farmers who bought any seeds from the formal market were more likely to adopt ISTs than those soybean farmers who did not buy seeds of any crop from the formal sources. This could be because soybean farmers who participate in the formal seed market have more access to seeds of improved soybean varieties than those who did not buy seeds. Other studies also found that access to information about the technologies increases the likelihood of adopting those technologies (e.g., Teklewold et al., 2013). Soybean growers may also acquire knowledge about ISTs by being a member of cooperatives. Results also showed that being a member of a farmers' organisation significantly increases the likelihood of adopting ISTs. Other studies (e.g., Amare et al., 2012; Ma and Abdulai, 2016; Wossen et al., 2017) also found that cooperative membership had positive and significant effects on the probability of adopting improved technologies.

The results of the outcome models (columns 3 and 4 of Table 2) show that education of household head, household size, size of cultivated land, ownership of bicycle, and size of livestock (in TLU) significantly influenced per capita income for adopters and non-adopters of IST. For instance, an increase in schooling by one year was associated with a 2.70% increase in daily per capita income for adopters and 2.40% for non-adopters.

5.2 The effect of adoption of IST on per capita income

As discussed in Section 4, IST adopters and non-adopters are different in observable and unobservable characteristics. This shows that the mean difference in the daily per capita income presented in Table 1 cannot be the true impact of the adoption of IST. The true impact of the adoption of IST is presented in Table 3. The ATTs presented in Table 3 show the change in daily per capita income after accounting for selection bias arising from systematic differences between the adopters and non-adopters. The results show that the adoption of IST significantly increased daily per capita income. The estimated income for farmers who adopted IST was US$1.41 per day. Had they not adopted IST, the daily per capita income would have been only US$1.10. The impact of the adoption of ISTs is thus US$0.31, representing an increase of 28.43%.

Adoption of ISTs had differential effects on the net per capita income for male- and female-headed households, household heads with different levels of education, and area of cultivated land by the households. Per capita income for both male-headed and female-headed households had significantly increased due to the adoption of ISTs. In particular, the daily net gain in per capita income due to the adoption of ISTs was higher for female-headed households (US$0.38) than for male-headed households (US$0.30), suggesting that female-headed households benefited more from the adoption of ISTs than male-headed households. However, the daily per capita incomes were higher for male-headed households than for female-headed households for both adopters and non-adopters. This could be due to several factors such as access to agricultural inputs, markets, and credit; use of agricultural inputs; land tenure situation; and ownership of human and physical capital (Alene et al., 2012 ; Goldstein and Udry 2008; Peterman et al. 2011). A study conducted in Malawi on the gender gap shows that agricultural productivity of female-headed households was lower than that of male-headed households because of the differences in the use of agricultural inputs, asset ownership, and time devoted to productive activities (Kilic, Palacios-López, and Goldstein 2015).

The ATT had increased with levels of education of household head, and the increase was significant for all levels from illiterate to Form 9[4]. The ATT (US$0.458) realised by the households whose household head had attained an education level higher than Form 1 (equivalent to Grade 10 and above) was more than double that of the ATT (US$0.209) realised by a household whose household head was illiterate. This is in line with the finding by Alene and Manyong (2007) in Nigeria. In their study, Alene and Manyong (2007) found that education enhanced improved cowpea productivity. As expected the ATT had increased with the land area cultivated by the household. The increase was significant in all quintiles for both adopters and non-adopters.

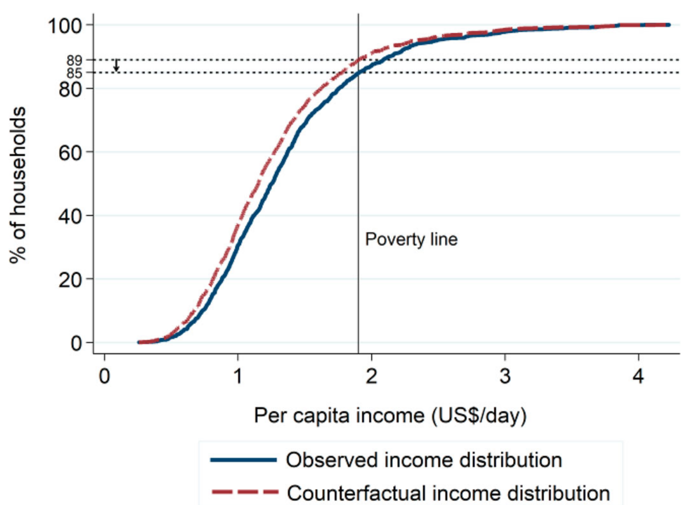

Figure 2. Observed and counterfactual income distributions for the sample households. Source: Own survey.

5.3 Effect of IST adoption on poverty reduction

Figure 2 presents observed and counterfactual income distributions for the sample households. The results of poverty estimation show that adoption of IST increased the daily per capita income that helped to reduce poverty. Using the international poverty line of US$1.90 per capita per day, the proportion of poor[5] people was 84.67%, and this poverty rate would have been 88.83% without the adoption of ISTs. This represents a 4.16 percentage-point reduction in poverty for the sample households due to the adoption of ISTs. The estimates suggest that 4.68% of the poor soybean growers in rural Malawi escaped poverty in the 2016/17 cropping season due to the adoption of IST.[6] The number of soybean growers in Malawi during the study year was close to 0.70 million, and our survey results show that the household size for soybean growers for 2016/2017 cropping season was 5.23 people. Therefore, the 4.16 percentage-point reduction in poverty translates to about 150,000 people lifted out of poverty.

Adoption of ISTs also reduced the depth of poverty by 4.12 percentage points and severity of poverty by 2.89 percentage points for the sampled households using the international poverty line (Figure 3). These results are consistent with the findings of several past studies on the impacts of improved crop varieties such as groundnut in Uganda (Kassie, Shiferaw, and Muricho 2011); rice in Bangladesh (Mendola 2007), and China (Wu et al. 2010); cassava in Tanzania, Democratic Republic of Congo, Sierra Leone, and Zambia (Feleke et al. 2016); maize in Mexico (Becerril and Abdulai 2010), Ethiopia (Zeng et al. 2015), Kenya (Mathenge, Smale, and Olwande 2014), Zambia (Khonje et al. 2015), Nigeria (Abdoulaye, Wossen, and Awotide 2018), and Malawi (Darko et al. 2018). The consistency of poverty indices of our study to these previous studies is more of direction than magnitude because of the difference in crop technologies, empirical procedures (propensity score matching, endogenous switching regression, fixed effects model vs correlated random effect), data (cross-sectional vs panel), and study type (ex-post vs ex-ante). The study conducted in Malawi by Darko et al. (2018), for instance, used the simulation (ex-ante) method and found that a 50% increase in maize yield can potentially reduce poverty by 6.77 percentage points among rural agricultural households, which supports the results of our study at least by the direction

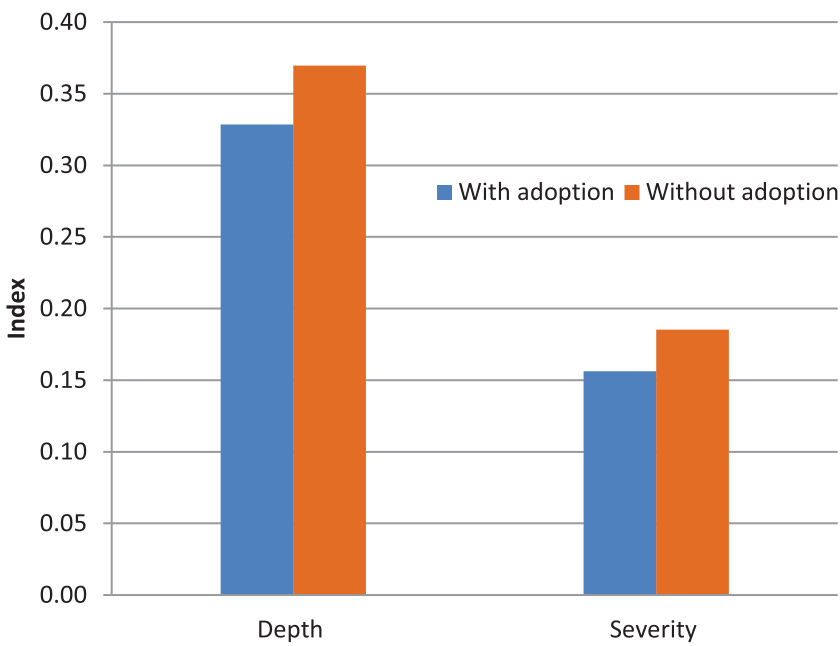

Figure 3 Poverty depth and severity with and without adoption for sample households. Source: Own survey.

of the effect. It is difficult to make the same claim for the magnitude of the effect because the two studies are different – our study estimated the actual effect of the adoption of improved soybean technologies on poverty reduction while Darko et al. (2018) estimated the potential effect of the increase in maize yield on poverty reduction.

6. Conclusion and policy implication

In this study, we estimated the causal effects of adopting ISTs on daily per capita income and poverty in rural Malawi using data collected from 1,234 soybean growers. We used the ESRM to estimate the net gain in daily per capita income due to IST adoption. The ESRM controls for observed and unobserved variations between IST adopters and non-adopters. We used the observed and counterfactual daily per capita income estimates from the ESRM to estimate the FGT class of poverty indices.

The adoption rate of ISTs was 32%. A farmer's decision to adopt an IST was influenced by membership in a farmer organisation and access to information about IST. This implies that increasing smallholder farmers' access to information through field demonstrations, information exchange visits, and training may help increase adoption of ISTs. Besides, the household head's education level, household size, size of cultivated land, livestock size, and asset ownership are associated with the daily per capita income. The increase in the daily net per capita income with the increase in the formal education level of the household head points to the importance of policies that encourage the promotion of formal education. The results also suggest that the policies that enhance asset ownership can also help improve the daily per capita income of soybean growing households.

IST adoption has differential effects on daily per capita income for male-headed and female-headed households. Female-headed households benefited more compared to male-headed households. This suggests that projects and programmes aimed at improving the welfare of women farmer in Malawi could be more effective at maximising the average impacts of the ISTs in the country. Targeted interventions should consider wider dissemination of ISTs to female farmers. IST adoption significantly reduced the poverty headcount ratio, depth, and severity in rural Malawi. Overall, the results point to the need to further scale of improved soybean varieties and double row spacing for greater impacts on poverty reduction among smallholder farmers in Malawi.

Notes

1. Daily per capita income is defined as the total amount of annual food and non-food household expenditure adjusted for purchasing power parity and then divided by household size and number of days in a year.
2. Based on simple falsification test, a variable can be a valid selection instrument if it will affect adoption decision but it will not affect the outcome variables in our case daily per capita income among farm households that did not adopt (Di Falco, Veronesi, and Yesuf 2011).
3. *Surveybe* software is a tool that helps to design electronic computer-assisted personal interview (CAPI) questionnaires and collect and export analysis-ready data (https://surveybe.com/).
4. Malawi education system categories as illiterate those who do not read and write; Standards 1 to 8 are similar to Grades 1 to 8; Forms 1 to 4 are similar to Grades 9 to 12.
5. The national poverty level for Malawi is 70.8% which is different from the poverty level in this paper. This could be because we used data collected only from rural Malawi and the effect of crop failure a year before the survey.
6. Computed as the percentage reduction divided by the counterfactual poverty headcount ratio, that is, $\frac{0.8883 - 0.8467}{0.8883} \times 100$.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1. Parameter estimates – test on the validity of the selection instruments.

Variable	Model 1 Adoption 1/0	Model 2 Daily per capita income (US$) for non-adopters
Age	0.01 (0.02)	0.06** (0.02)
Age squared	−0.00 (0.00)	−0.00** (0.00)
Education	0.01 (0.01)	0.05*** (0.02)
Sex	−0.04 (0.13)	0.02 (0.16)
Household size	−0.02 (0.03)	−0.27*** (0.03)
Ln land	0.10 (0.09)	0.59*** (0.11)
Member of a farmers' organisation (1 = yes)	0.25*** (0.09)	0.23* (0.13)
Participate in a seed market (1 = yes)	0.25** (0.10)	0.15 (0.13)
Relied on government support (1 = yes)	−0.10 (0.09)	−0.17 (0.12)
One way transport cost	−0.00 (0.00)	−0.00 (0.00)
Lilongwe district	0.26 (0.25)	0.05 (0.26)
Mchinji district	0.14 (0.25)	0.15 (0.25)
Kasungu district	−0.02 (0.27)	0.23 (0.27)
Dedza district	0.17 (0.26)	0.12 (0.26)
Ntchisi district	0.10 (0.26)	−0.06 (0.26)
The proportion of adopters in the previous season in the villages	0.04*** (0.00)	0.001 (0.00)
Number of sources of information about the technology	0.22*** (0.08)	0.06 (0.10)
Ln TLU	0.00* (0.00)	0.00 (0.00)
Own cycle	0.02 (0.10)	0.12 (0.13)
Own cart	−0.30 (0.21)	0.73*** (0.27)
Own iron-roofed	−0.01 (0.11)	0.16 (0.14)
Constant	−2.31*** (0.51)	1.18* (0.64)
N	1234	842
Wald test on information sources	$\chi^2 = 11.46^{***}$	F-stat = 0.17

Standard errors in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Note: Model 1: Probit model (Pseudo $R^2 = 0.322$); Model 2 ordinary least squares ($R^2 = 0.167$). Standard errors are in the parentheses.

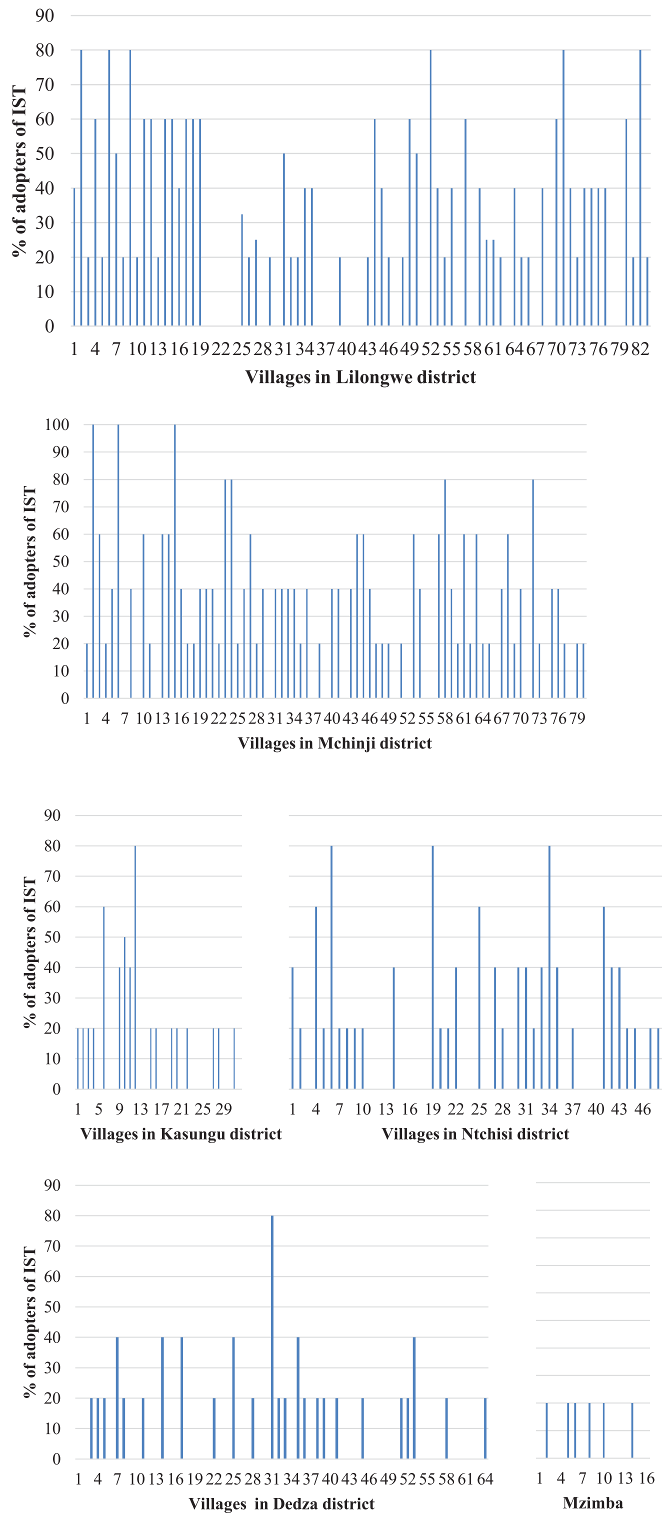

Figure A1. Village level adoption rates of IST in the districts of Lilongwe, Mchinji, Kasungu. Ntchisi, Dedza and Mzimba.

Table A2. Number of adopter of IST by districts.

District	Number of adopters	Adoption rate
Lilongwe	127	0.42
Mchinji	137	0.42
Kasungu	26	0.20
Dedza	38	0.18
Ntchisi	57	0.28
Mzimba	7	0.10