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Push–pull farming system in Kenya: Implications for economic and social welfare

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ABSTRACT

This study examines the farm-level economic benefits and aggregate welfare impacts of adopting push–pull technology (PPT)—an innovative, integrated pest and soil-fertility management strategy—with a set of household- and plot-level data collected in western Kenya. The evaluation is based on a combination of econometric and economic surplus analysis. Treatment effect estimates are used to assess the technology-induced shift in the maize supply curve, which is then used as an input to the economic surplus analysis. Finally, the aggregate poverty impact is computed using the economic surplus estimates. We observe that the adoption of PPT led to significant increases in maize yield and net maize income. The technology has significant potential benefit in terms of increasing economic surplus and reducing the number of people considered poor in western Kenya. Important factors influencing the decision to adopt PPT included access to information, household education, social capital, and social networks. We conclude that effective policies and development programmes for promoting PPT in Kenya should include information delivery and education mechanisms that are more effective.

1. Introduction

In this paper, we assess the factors that influence the adoption of push–pull technology (PPT) in western Kenya, and the effects of such adoption on farm-level outcomes and potential aggregate economic and poverty reduction benefits in the research area. PPT is an organic agricultural technology that does not rely on the increased use of chemical inputs, such as pesticides or nitrogen fertiliser. The effect of PPT adoption is critical topic because it could potentially allow farmers to increase their maize productivity and incomes without increasing their impact on the surrounding environment or their reliance on frequently unreliable agricultural input markets. Moreover, studies on the adoption of agricultural technology and its farm-level impacts are relatively common, but empirical studies on the aggregate welfare effects of adoption of such technologies (e.g. by integrating economic surplus analysis with econometrics, as we do here) are scant.

Improving food security and reducing poverty are policy priorities in sub-Saharan Africa (SSA) and have been the focal point of policies on agriculture and rural development in the region. Increasing agricultural productivity is widely recognised as a major pathway to reducing food insecurity and poverty in SSA (AGRA, 2014; Christiaensen and Demery, 2007; Gollin, 2010; Kijima et al., 2008; Owens et al., 2003; Thirtle et al., 2003). The literature on SSA (Diao et al., 2010; Minten and Barrett, 2008) suggests that growth in staple crop productivity has a greater potential to reduce poverty than any other development in the agricultural or non-agricultural sectors. However, agricultural productivity in SSA countries is still inadequate to address poverty, achieve food security, and lead to sustained economic growth (Dessy et al., 2006; Pretty et al., 2011; World Bank, 2008).

The current situation also reveals that a large gap still exists between actual and potential farm yields for major staple crops in SSA (Van Ittersum et al., 2016). For instance, between 2003 and 2012, actual yields of rain-fed maize—the dominant staple and cash crop in SSA—ranged from 1.2 t/ha to 2.2 t/ha, which represents only 15%–27% of the yield potential (Van Ittersum et al., 2016). The major constraints to increasing productivity and, hence, closing yield gaps, include socioeconomic and institutional hurdles to access farm input; poor soil fertility linked to soil erosion and nutrient depletion; poor management of pests (i.e. insects, diseases, weeds); and, more recently, climate change and variability (AGRA, 2014; De Groote et al., 2008, 2010; Gibbon et al., 2007; Kfir et al., 2002; Khan et al., 2014; Kijima et al., 2012; Minten et al., 2013; Reynolds et al., 2015; Tadele, 2017). This phenomenon is illustrated by the fact that

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low soil fertility, low soil nitrogen, and drought have been shown to reduce maize yields in Africa by 62%, 76%, and 54%, respectively (Gibbon et al., 2007). Another example is stemborer insects, which cause cereal grain yield losses ranging from 10% to 88% (Kfir et al., 2002) and the parasitic *Striga* weed (witchweed) destroying entire harvests (Kanampiu et al., 2002). To overcome these challenges and close yield gaps, farmers require multifunctional interventions that are feasible, economically sustainable, and effective.

Researchers from the International Centre of Insect Physiology and Ecology (ICIPE) in Kenya and Rothamsted Research in the United Kingdom developed PPT to improve the long-term sustainability of the agricultural system by reducing cereal crop pests such as stemborer insects and *Striga* weed while increasing soil fertility and fodder production in quality and quantity. In the PPT system, cereals such as maize are intercropped with perennial fodder legumes (*Desmodium)* that repel ('push') stemborers and suppress *Striga*. The cereal crops are also surrounded by a border of perennial fodder grass (e.g. *Pennisetum purpureum*/Napier grass or *Brachiaria* species) that attracts ('pulls') stemborers away from cereal plants (Khan et al., 2014; Pickett et al., 2014). The technology provides additional benefits such as enhancing soil fertility through nitrogen fixation and the addition of organic matter, practically eliminating soil erosion, suppressing weeds, and providing high-quality livestock forage that increases animal health and milk production, which contributes to improved incomes and nutritional security in smallholder households. The PPT approach can also, at least potentially, enhance human health and increase biodiversity through reducing the use of costly synthetic insecticides and herbicides that are unaffordable by most smallholder farmers (Pickett et al., 2014).

Despite PPT's enormous potential benefits, its adoption is limited and little is understood about its economic and welfare benefits. Understanding the PPT adoption process and its impact are relevant to design strategies that can facilitate its wider adoption. Notably, the literature on PPT mainly focuses on its efficacy (Khan et al., 2008a), how effective its dissemination pathways are (Amudavi et al., 2009; Murage et al., 2012), and its profitability (De Groote et al., 2010; Fischler, 2010; Khan et al., 2008b; Murage et al., 2015a, 2015b).

This paper contributes to the existing adoption and impact literature through systematically exploring the farm-level economic benefits and aggregate welfare impacts of PPT adoption. Specifically, this paper has three objectives: 1) assess the determinants of PPT adoption, 2) assess farm-level impacts of adoption of PPT (i.e. maize yield, cost of maize production, and net maize income), and 3) assess the ex-ante aggregate welfare effects (i.e. change in total economic surplus and poverty) of adoption of PPT in western Kenya. An ex-ante impact study was conducted because PPT is not sufficiently widespread to conduct an ex-post aggregate welfare or market-level impacts analysis.

The ex-ante analysis is based on a combination of econometric and economic surplus methods. We use econometric methods to compute the PPT-induced shift in maize supply by estimating the changes in maize yield and cost of production due to the introduction of PPT while controlling for selection biases that stem from differences in the observed and unobserved characteristics of adopters and non-adopters. In the first step, the changes in maize yield and cost of production are estimated using a cross-sectional fixed effects estimator. The second step involves plugging changes in yield and cost of maize production into an economic surplus model to compute potential economic surplus gains. Finally, the estimated economic surplus is used to compute the potential impact of adoption on aggregate poverty.

Moyo et al. (2007) and Manda et al. (2017) estimate the ex-ante economic surplus effects of the adoption of improved groundnut varieties and maize–soybean rotation practice, respectively, and use the economic surplus estimates to evaluate the ex-ante poverty impacts of the adoption of groundnut varieties and maize–soybean rotation. Ex-post impact studies in the literature link economic surplus analysis with poverty analysis and include Alene et al. (2009), Zeng et al. (2015), and Kassie et al. (2018).

In this paper, the approach employed by Alene et al. (2009) to evaluate the impact of improved maize varieties on economic surplus and poverty is used. However, instead of using econometrics to estimate the shift in supply, Alene et al. (2009) rely on a combination of on-farm variety evaluation trials, adoption surveys, and expert estimates. Zeng et al. (2015), by contrast, use a cross-sectional econometric approach to estimate the supply shift in their attempt to determine the impact of improved maize varieties on the total change in economic surplus and poverty in Ethiopia. Kassie et al. (2018) extend the approach for panel data and adoption of multiple technologies—to calculate the cost reduction per unit of output and evaluate the impact of combinations of maize production technologies and practices (i.e. maize varieties, chemical fertilisers, and cropping diversification) on the total change in economic surplus and poverty. The study we report on in this paper employs the same methods as those in Kassie et al. (2018).

2. Methodology

2.1. Estimation strategy

When using observational data to estimate the causal effect of technology adoption on farm-and market-level outcome variables, an important econometric challenge is to cater to selection bias causes by the observable and unobservable attributes that simultaneously affect household adoption decisions and outcomes of interest. Technology adopters may be systematically different from the non-adopters with respect to characteristics that are observed (e.g. resource endowments, proximity to input and output markets, access to extension, education, training, land quality) and unobserved (e.g. motivation, risk preference, managerial ability), resulting in inconsistent estimates of the effect of agricultural technology adoption on outcomes of interest. For example, the most motivated farmers with greater managerial abilities are assumed to be more likely to (i) adopt improved agricultural technologies such as PPT and (ii) engage in other yield-augmenting farm management practices. If the assumption of such a systematic difference between adopters and non-adopters is correct, the estimated effect of adoption would be biased upwards due to a positive correlation with unobserved management skills.

In this study, three measures were taken to overcome the potential selection bias. The first measure was to include several explanatory variables that influenced PPT adoption and outcomes of interest. Secondly, the data allowed for the use of household and county fixed effects to capture household and county-specific unobserved heterogeneities. The data derived from two growing seasons and repeated plot observations per household had a panel structure that enabled the use of a household cross-sectional fixed effects estimator to control for unobserved characteristics.[1] Studies that use plot-level information to construct panel data and control for farm-specific effects include Kassie and Holden (2007) and Udry (1996). The county-specific characteristics could include weather influences as well as differences in development services (e.g. access to extension, credit, markets) and the policy environment, which can influence PPT adoption and farmers' performance.

As a third measure, we used the endogenous switching regression (ESR) framework—a variant of the instrumental variables approach—to instrument the adoption decision (Abdulai and Huffman, 2014; Carter and Milon, 2005; Di Falco et al., 2011; Kassie et al., 2015a, 2017; Shiferaw et al., 2014; Teklewold et al., 2013). In the ESR framework, separate regressions were estimated for the adopters and non-adopters of PPT, respectively. This separation allows us to capture the slope

[1] Of the total usable maize plot observations (2,148), approximately 4% of plots have one observation. We ran fixed effects model including and then excluding these observations and observed no remarkable difference in the results (the results are available from the authors). We therefore included the 4% of households in our final analysis.

effect of the adoption variable because it permits full interaction of the adoption variable with other explanatory variables in the outcome equations. The separate regression estimation also has the benefit of capturing the differential returns to covariates of adopters and non-adopters in estimating the average adoption effects.

The ESR framework involves a two-stage impact estimation process. The first stage involves the adoption decision model for the PPT to understand factors influencing such adoption and to compute the inverse Mills ratios to control for selection bias. The second stage entails using the inverse Mills ratios as an additional regressor to estimate the direct effects of PPT adoption on maize yield, cost of production, and net income.

2.2. Empirical model specification

2.2.1. Measuring the farm-level economics impact of PPT adoption

As mentioned in Section 2.1, assessing the farm- and market-level impacts of PPT adoption involves a two-stage impact estimation process, as described below.

2.2.1.1. First stage: adoption equation. The decision to adopt PPT is conceptualised by following the random utility framework. We assume that farmers will use PPT if doing so maximises their net benefit (utility) given the constraints, such as inadequate resources and information and knowledge about the technology. Drawing from the adoption literature (e.g. Kassie et al., 2013, 2015b; Marenya and Barrett, 2007), we specify the utility of adoption as a function of exogenous variables, including household-, plot-, and village-level variables, as follows:

$$A_{ip}^{*} = \varphi X_{ip} + \alpha Z_i + \overline{C_i} + \varpi_{ip}, \text{ where } A_{ip} = \begin{cases} 1\, if\ A_{ip}^{*} > 0 \\ 0\, otherwise \end{cases} \tag{1}$$

In Eq. (1), i denotes an individual farmer and p denotes a specific plot. The variable A_{ip}^{*} represents the unobservable or latent variable for PPT adoption (the difference in utility associated with adopting PPT or not); A_{ip} is the actual adoption dummy variable (equal to 1 if the i^{th} farmer adopts PPT on plot p, and 0 otherwise) expressed as a function of a vector of household socioeconomic, plot, and village characteristics; X is a vector of household-, plot-, and village-level variables that affect adoption and outcomes of interest; Z represents a vector of household level variables that influences adoption but not outcomes-of-interest variables; $\overline{C_i}$ is a vector of the average of plot-varying explanatory variables to capture unobserved plot heterogeneity. φ and α are unknown parameters to be estimated, and the parameter ϖ denotes the error term. The Z variables include the number of adopters known by the respondents in a village (used as a proxy to measure farmers' exposure to PPT), the number of rural institutions in a village, the distance to the nearest input distribution centre, the distance to the nearest information source, a respondent's confidence in the skill of extension officers, and the number of PPT field days attended by the respondent farmers.

2.2.1.2. Second stage: outcome equations. The plot-level yield functions are specified in Eq. (2a) for an adopter and (2b) for a non-adopter, as follows:

$$\text{Adopter:}\quad Y_{1ip} = \beta_1 X_{1ip} + \sigma_{1\varepsilon}\hat{\lambda}_{1ip} + \omega_{1ip}\ \text{if} A_{ip} = 1 \tag{2a}$$

$$\text{Non-adopter:}\ Y_{0ip} = \beta_0 X_{0ip} + \sigma_{0\varepsilon}\hat{\lambda}_{0ip} + \omega_{0ip}\ \text{if} A_{ip} = 0 \tag{2b}$$

The variable Y_{ip} is the maize yield (kg/acre) of household i on plot p; β is a vector of parameters to be estimated; X denotes the vector of independent variables, including input variables (i.e. seed, fertiliser, pesticide, and labour), household socioeconomic variables, and plot and village characteristics; σ is the covariance between the error terms of the adoption and outcome equations; $\hat{\lambda}$ is the estimated inverse Mills ratio derived from the first stage, Eq. (1); and ω represents the error terms. The net maize income is the net of variable input costs, namely seed, fertiliser, pesticide, and hired labour.

The adoption of an agricultural technology is also expected to stimulate changes in input expenditure. For instance, adoption may lead to increased expenditure due to increased labour requirements for activities such as planting, threshing, and harvesting, and the adoption may also potentially lead to reduced expenditure due to a reduced need for pesticide. In Eqs. (3a) and (3b) for adopters and non-adopters, respectively, we specify the cost function as follows, to test whether PPT adoption can induce adjustments in input expenditure:

$$\text{Adopter:}\quad C_{1ip} = \tau_1 W_{1ip} + \sigma_{1\varepsilon}\hat{\lambda}_{1ip} + \psi_{1ip}\ if\ A_{ip} = 1 \tag{3a}$$

$$\text{Non-adopter:}\ C_{0ip} = \tau_0 W_{0ip} + \sigma_{0\varepsilon}\hat{\lambda}_{0ip} + \psi_{0ip}\ if\ A_{ip} = 0 \tag{3b}$$

In these equations, C_{ip} represents the cost of maize production in KSh per acre[2] incurred by household i on plot p; τ indicates the vector of parameters to be estimated; W represents the vector of variables, such as input prices, maize yield, household socioeconomic characteristics, and plot and village characteristics, which affect the cost functions; and ψ denotes the error terms. The cost of production includes the expenditure on inorganic fertiliser, seed, and pesticide, as well as the cost of hired labour and opportunity cost of family labour used in maize production. We use village-level wage rates to compute the value of family labour.[3]

We use a random effects probit model to estimate Eq. (1), and cross-sectional household fixed effects models to estimate all outcome equations (i.e. 2a, 2b, 3a, and 3b). The Hausman specification test of the outcome equations rejects the null hypothesis of cross-sectional random effects in favour of cross-sectional fixed effects models. Although the outcome equation estimates are consistent, they have inefficient standard errors because of the two-stage nature of the estimation procedure or generated regressor $\hat{\lambda}$. We use the bootstrap method to correct this problem.

The choices of explanatory variables, in the adoption and outcome regression models, are based on the adoption and impact literature (Abdulai and Huffman, 2014; Di Falco et al., 2011; Kassie et al., 2013, 2015a, 2015b, 2018; Marenya and Barrett, 2007; Shiferaw et al., 2014; Teklewold et al., 2013; Zeng et al., 2015).

2.2.2. Estimating the average adoption effects

We use the yield and cost functions specified in Eqs. (2a) and (2b)) and (3a) and (3b) to estimate the conditional actual and counterfactual outcomes of adoption and evaluate the adoption effects. With respect to outcomes, Eqs. (4a) and (4b) reflect the maize yield expectations (E) observed in a sample, whereas Eqs. (4c) and (4d) represent the counterfactual maize yield expectations, as follows:

$$E\left[Y_{1ip}\ |X_{1ip},\ \hat{\lambda}_{1ip}, A_{ip} = 1\right] = \beta_1 X_{1ip} + \sigma_{1\varepsilon}\hat{\lambda}_{1ip} \tag{4a}$$

$$E\left[Y_{0ip}\ |X_{0ip},\ \hat{\lambda}_{0ip}, A_{ip} = 0\right] = \beta_0 X_{0ip} + \sigma_{0\varepsilon}\hat{\lambda}_{0ip} \tag{4b}$$

$$E\left[Y_{0ip}\ |X_{1ip},\ \hat{\lambda}_{1ip}, A_{ip} = 1\right] = \beta_0 X_{1ip} + \sigma_{0\varepsilon}\hat{\lambda}_{1ip} \tag{4c}$$

$$E\left[Y_{1ip}\ |X_{0ip},\ \hat{\lambda}_{0ip},\ A_{ip} = 0\right] = \beta_1 X_{0ip} + \sigma_{0\varepsilon}\hat{\lambda}_{0ip} \tag{4d}$$

[2] The exchange rate was US\$1 = KSh100 during the survey period, namely July to August 2016.

[3] The net maize income model can be specified in the same manner as the yield and cost functions; however, the same explanatory variables are not used in the regression models.

The expected actual and counterfactual cost of maize production and net maize income can be generated in a comparable manner.

The average adoption effect on maize yield for PPT adopters (ATT_y) is derived as the difference between Eqs. (4a) and (4c), as specified in Eq. (5):

$$ATT_y = E\left[Y_{1ip}\ |X_{1ip},\ \hat{\lambda}_{1ip},\ A_{ip} = 1\right] - E\left[Y_{0ip}\ |X_{1ip},\ \hat{\lambda}_{1ip},\ A_{ip} = 1\right] = X_{1ip}(\beta_1 - \beta_0) + \hat{\lambda}_{1ip}(\sigma_{1\varepsilon} - \sigma_{0\varepsilon}) \quad (5)$$

The average adoption effect on cost of maize production for PPT adopters (ATT_c) can be specified similarly, as presented in Eq. (6):

$$ATT_c = E[C_{1ip}\ |W_{1ip},\ \hat{\lambda}_{1ip},\ A_{ip} = 1] - E[C_{0ip}\ |W_{1ip},\ \hat{\lambda}_{1ip},\ A_{ip} = 1] = W_{1ip}(\tau_1 - \tau_0) + \hat{\lambda}_{1ip}(\sigma_{1\varepsilon} - \sigma_{0\varepsilon}) \quad (6)$$

The net maize effects following adoption can be generated in analogous manner. The estimates from Eqs. (5) and (6) are then used as the input for estimating the aggregate ex-ante economic surplus and poverty reduction impacts of PPT adoption, as discussed in Sections 2.2.3 and 2.2.4.

2.2.3. Measuring the economic surplus impact of PPT adoption

An increase in the widespread adoption of PPT would affect the adopting farmers and the regions in which they live and sell their products. A change in agricultural technology will shift the supply curve for crops being produced, directly changing the welfare of adopting farmers and indirectly influencing the welfare of non-adopting farmers and consumers of that crop by causing changes in the crop price and wages. To estimate how large these effects would be if PPT is more generally adopted, we use the methodology from Alston et al. (1995): economic surplus analysis. Both the ex-ante and ex-post research evaluation literature use the economic surplus approach. The first step in applying this approach is to estimate the cost reduction per unit of output, which Alston et al. (ibid.) call the *K-shift parameter* (K), computing it as follows:

$$K = \left(\frac{ATT_y}{\varepsilon} - \frac{ATT_c}{1 + ATT_y}\right) \times A \quad (7)$$

The variables ATT_y and ATT_c, derived from Eqs. (5) and (6), are, respectively, the estimated average adoption effects for maize yield and cost of maize production, which represent yield and cost changes due to the technology. The A in Eq. (7) represents the adoption rate in the sample, namely 14.4% of the total maize area of sample households. A sensitivity analysis on the extent of adoption was performed to examine the implications for estimated ex-ante economic surplus and poverty reduction impacts. The price elasticity of supply ε is from the literature (De Groote et al., 2016).

The overall impact of PPT adoption on the producer and consumer surplus in a region depends on its openness to trade. No price changes would be observed in a region that is completely open to trade—leading to only changes in the producer surplus, and prices would decline because of the new technology in a region completely closed to trade, leading to changes in the consumer surplus as well. The actual welfare impact would be between these two extreme cases; thus, estimating the welfare impact of these two cases provides upper and lower bounds for the overall impact.

Assuming linear demand and supply curves, the ex-ante changes in producer surplus (ΔPS) and consumer surplus (ΔCS) in the closed economy case can be computed as follows, according to Alston et al. (1995):

$$\Delta PS = PQ(K - Z)(1 + 0.5Z\eta) \quad (8)$$

$$\Delta CS = PQZ(1 + 0.5Z\eta) \quad (9)$$

In Eqs. (8) and (9), P is the pre-adoption maize price; Q is the pre-adoption maize production volume; η is the price elasticity of demand; and Z is the relative change in price, defined as $Z = K*\left(\frac{\varepsilon}{\varepsilon+\eta}\right)$ (ibid.). The price elasticity of demand η is from the literature (De Groote et al., 2016; Karanja, 2003). The sum of Eqs. (8) and (9) provides the change in total change in economic surplus (ΔTS) due to the adoption of the technology. In the closed economy, consumers may benefit from a price reduction in response to a downward supply shift due to PPT adoption, whereas producers gain from the cost reduction per unit of maize output. A decrease in the price and per unit cost of production will increase incomes and has the potential to lift poor people above the poverty line.

In the case of the open economy, consumers do not benefit ($\Delta CS = 0$) from the introduction of the technology because changes in production ascribed to PPT adoption do not influence the open market price (i.e. the price remains constant). Thus, welfare benefits due to the PPT-induced shift in supply accrue only to producers. The change in total economic surplus (ΔTS) equals the change in producer surplus (ibid.), as specified in Eq. (10):

$$\Delta PS = \Delta TS = KPQ(1 + 0.5K\varepsilon) \quad (10)$$

The values of the parameters used in Equations (7)–(10) and their sources are reported in Table 1.

The change in total economic surplus (ΔTS) is used as an input to compute the potential aggregate poverty impact of the technology, as shown in Section 2.2.4.

2.2.4. Measuring the aggregate poverty reduction impact of PPT adoption

The available evidence suggests multiple pathways through which

Table 1
Parameters for economic surplus and poverty estimation.

Parameter	Value	Source
Price elasticity of supply (ε)	0.5	De Groote et al. (2016)
Price elasticity of demand (η)	0.56	De Groote et al. (2016); Karanja (2003)
Average maize production (t) (Q)	1.07 million	Ministry of Agriculture, Livestock and Fisheries (2015) for 2011–2014
Average maize price (USD/t) (P)	395	FAOSTAT 2011–2014
Poverty headcount ratio in Kenya (%)	45.2	Kenya National Bureau of Statistics and Society for International Development (2017)
Poverty headcount ratio in western Kenya region (%)	47.3	Kenya National Bureau of Statistics and Society for International Development (2017)
Total population of western Kenya region	9.8 million	Kenya National Bureau of Statistics (2012)
Number of poor in western Kenya region (N)	5.3 million	(Computed by multiplying region's population by headcount ratio)
Average value of agricultural gross domestic product ($AgGDP$)	USD 5223.45 million	World Bank (2016) for 2011–2014
Elasticity of poverty with respect to growth in staple food crops (δ)	1.19	Diao et al. (2010)

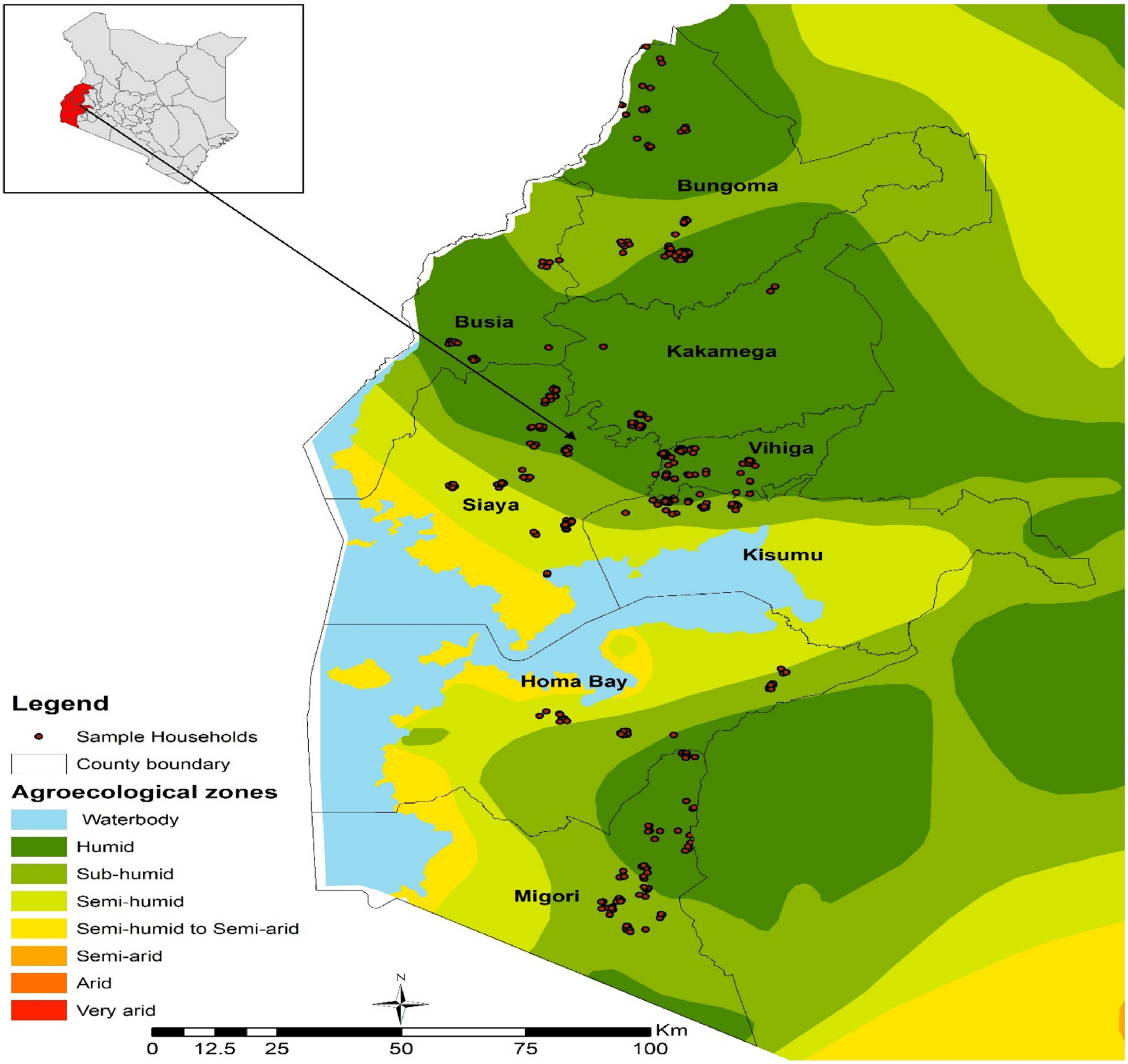

Fig. 1. Study areas and distribution of sample households.

technology adoption can reduce poverty at household and society levels, including increasing incomes, generating employment in agricultural and non-agricultural sectors, and reducing food prices (Christiaensen and Demery, 2007; De Janvry and Sadoulet, 2002; Minten and Barrett, 2008; Moyo et al., 2007; Thirtle et al., 2003). The impact of technology adoption on food security and poverty is direct and indirect (Christiaensen and Demery, 2007; De Janvry and Sadoulet, 2002). The direct effects include increased growth in productivity and a lower per-unit cost of production, which can lead to increased farm income and food security (Christiaensen and Demery, 2007; De Janvry and Sadoulet, 2002). The indirect gains include reduced prices of food staples due to outward shifts in supply, which benefit a broad spectrum of poor farm and non-farm households because of the high percentage of their budgets spent on food (De Janvry and Sadoulet, 2002; Minten and Barrett, 2008; Thirtle et al., 2003). Increased agricultural output resulting from technology adoption could also lead to the creation of employment in the agriculture and non-agriculture sectors, such as jobs in input supply and food processing (De Janvry and Sadoulet, 2002; Moyo et al., 2007; Thirtle et al., 2003).

The literature (Diao et al., 2010) indicates that growth in the agricultural sector contributes more to poverty reduction than growth generated in other sectors, and that growth in a staple sector (e.g. maize) has a greater reduction effect on poverty than growth in an export/cash crop sector.

In this study's context, we investigate how the adoption of PPT would affect maize production, and its potential to affect poverty as a result. Thus, to estimate the impact that PPT adoption would have on aggregate poverty, we followed the approach in Alene et al. (2009), defined as follows:

$$\Delta N = \left(\frac{\Delta TS}{AgGDP} \times \delta \right) \times N \tag{11}$$

where ΔN represents the number of people lifted out of poverty due to changes in economic surplus; ΔTS is the change in total economic surplus due to PPT adoption (also representing the value of additional agricultural production); $AgGDP$ represents the agricultural gross domestic product (GDP); δ is the elasticity of poverty with respect to

AgGDP growth influenced by the growth of staple crops (based on Diao et al., 2010); and *N* is the number of people who are considered poor in western Kenya. Diao et al. (ibid.) find that a 1% annual increase in Kenya's GDP influenced by a growth in staple crops leads to a 1.19% reduction in the country's poverty headcount ratio per year. The data we use to estimate Eq. (11) are presented with their sources in Table 1.

2.3. Study area and data collection

The data for this study is from western Kenya, where PPT was developed and tested and where PPT is promoted to increase maize productivity through controlling *Striga* weed and stemborers and improving soil fertility. *Striga* weed is a major maize production constraint in western Kenya (De Groote et al., 2008, 2010; Khan et al., 2014).

Farmers in western Kenya have two growing seasons, namely the long (March–August) and short (September–December) rainy seasons. Between the 2011 and 2014 growing seasons, western Kenya produced an average of 1.1 million t of maize from 0.6 million ha, representing approximately 30.1% and 26.7% of the country's total maize production and area, respectively (Ministry of Agriculture, Livestock and Fisheries, 2015). Approximately 25% of Kenya's population live in the western part of the country. It is estimated that 77% of western Kenya's population live in rural areas and depend mainly on agriculture for food and income. Western Kenya is a region where 47.3% of the population is estimated to be living below the national poverty line; this figure is close to the national poverty headcount ratio of 45.2% (Kenya National Bureau of Statistics and Society for International Development, 2017).

Data for this study were derived from focus group discussions, household surveys and secondary sources, among others. The focus group discussions were used to inform the design and development of the household survey instrument as well as generate information related to the adoption of PPT and other issues. The household survey data were collected between July and August 2016 through face-to-face interviews and administered by trained enumerators who spoke and understood the respondents' languages.

Due to budget limitations, we selected 8 of the 11 counties where PPT was being used by farmers. The selected counties were Bungoma, Busia, Homa Bay, Kakamega, Kisumu, Migori, Siaya, and Vihiga (Fig. 1). Next, between 3 and 11 villages were randomly selected in each county (Table 2). Within each village, between 2 and 21 households were randomly selected. In total, 56 villages and 642 farmers (i.e. 328 adopters and 314 non-adopters) operating on 4496 plots were surveyed. Table 2 also shows the distribution of villages and sample households by county. *Adopters* are defined as farmers that had been using PPT for more than a year at the time of the survey.

Of the total plots (4496) cultivated by the total sampled farmers, 2374 were planted with maize (i.e. 709 with PPT and 1665 without). After dropping observations that had missing values for some variables and discarding the top and bottom 3% extreme values of maize yield and cost of maize production using Winsorisation, the number of usable sample households was 627 maize farmers (i.e. 309 adopters and 318 non-adopters) operating on 2148 maize plots (i.e. 633 with PPT and 1515 without).

Table 2
Distribution of villages and sample households by county.

County	Number of villages	Sample households		
		Adopters	Non-adopters	Total
Bungoma	6	18	55	73
Busia	3	14	16	30
Homabay	10	32	51	83
Kakamega	4	27	16	43
Kisumu	5	34	40	74
Migori	11	62	66	128
Siaya	10	100	24	124
Vihiga	7	41	46	87
Total	56	328	314	642

Table 3
Descriptive statistics: Plot-level characteristics (mean).

Variable description	PPT adopter	PPT non-adopter	Difference
Outcome variables			
Maize yield (kg/acre)	1572.99	929.51	643.48***
Maize production costs (KSh/acre)	29,486.63	19,902.27	9,584.36 ***
Net maize income (KSh/acre)	40,139.46	25,739.31	14,400.14 ***
Plot characteristics and investment variables			
Soil fertility (1–3: Poor–Average–Good)	1.47	1.76	−0.29***
Plot slope (1–3: Gentle–Medium–Steep)	1.43	1.57	−0.14***
Soil depth (1–3: Shallow–Medium–Deep)	2.48	2.39	0.09***
Plot distance from residence (Walking minutes)	2.20	4.60	−2.39***
Plot shock (= 1 if plot suffered a natural shock such as a pest infestation or drought)	0.29	0.58	−0.29***
Season (1 = Long rainy season, 0 = Short rainy season)	0.50	0.53	−0.03
Plot managed by head of household (1 = Yes)	0.58	0.55	0.04
Plot managed by spouse (1 = Yes)	0.22	0.22	0.00
Plot managed jointly (1 = Yes)	0.19	0.24	−0.04**
Chemical fertiliser use (kg/acre)	73.76	57.46	16.30**
Labour use (Person-day/acre)	68.71	42.13	26.57***
Other input – Seed and pesticides (KSh/acre)	1546.89	1,115.19	431.69***
Wages (KSh/day)	282.26	305.90	−23.63
Fertiliser price (KSh/kg)	54.55	55.88	−1.33
Seed price (KSh/kg)	173.30	142.99	30.31***
Observations	**633**	1515	

Note: *** , **, and * denotes significance level at 1%, 5% and 10%, respectively.

The survey questionnaire captured detailed data at the household, plot, and village levels, including human capital, input and output data, farming practices such as PPT adoption, plot characteristics, productive assets (labour, land, and livestock), and utilisation of crop and livestock products. The questionnaire also captured variables related to household social capital and social networks, such as the number of adopters known by respondents in a village, which was used as a proxy to measure farmers' exposure to PPT; the number of rural institutions in a village; and the number of PPT field days attended by respondent farmers. Social capital and networks play a key role in technology adoption through facilitating the exchange of information and resources and reducing the cost of accessing such information and resources (Bandiera and Rasul, 2006; Di Falco and Bulte, 2013; Isham, 2002). Thus, improved access to information can enhance adoption because PPT is knowledge-intensive (Khan et al., 2014).

Data on farmers' confidence in the skill of extension agents, credit constraints (if a household needed credit but was unable to obtain it), and access to agricultural services, such as distance to input distribution centres or markets, was also collected. In addition, historical data (targeting the six years immediately prior to the survey) were collected on selected variables, including family size, livestock, education, farm

Table 4
Descriptive statistics – Household and village characteristics (mean).

Variable description	PPT adopter	PPT non-adopter	Difference
Household characteristics and assets			
Age of household head (years)	54.71	52.10	2.60***
Average household education (years)	6.98	6.13	0.86***
Family size 6 years ago	6.77	6.21	0.58***
Family size during survey period (in adult equivalent)	5.57	5.41	0.16
Family labour (in person equivalent) during survey period	3.57	3.23	0.31***
Credit-constrained household (1 = Yes)	0.52	0.64	−0.12***
Number of cows owned 6 years ago	1.18	1.27	−0.09
Other livestock owned (Tropical livestock unit – TLU) 6 years ago	1.70	1.95	−0.24***
Livestock owned during survey period (TLU)	1.90	1.78	0.13
Farm size 6 years ago (acres)	2.65	2.72	−0.07
Major furniture and equipment value ('000 KSh)	1198.44	1,471.18	−272.74
Number of PPT field days attended by a respondent	2.55	0.55	2.02***
Confidence in skill of extension officers (1 = Yes)	0.84	0.69	0.15***
Village-level and social network variables			
Distance to nearest input distribution centre (walking minutes)	53.15	48.52	4.63
Number of PPT adopters respondents know in a village	225.07	156.49	68.58***
Number of rural associations respondents know in a village	3.28	2.81	0.47***
Observations	**6333**	1515	–

Note: *** , **, and * denotes significance level at 1%, 5% and 10%, respectively.

size, and age at the time of PPT adoption. These historical data were collected because many farmers had already adopted PPT six years before the study. Tables 3 and 4 list the definitions of all the variables used in the empirical analysis and report the descriptive statistics of the variables employed in this study.

The primary data were augmented with market data to generate parameters for the estimation of the impact of PPT adoption on economic surplus and the impacts of PPT adoption on aggregate poverty impact of PPT adoption. These secondary sources of data were derived from the United Nations Food and Agricultural Organisation (FAOSTAT 2011–2014), the World Bank (2016), and reports by the Kenyan Government.

3. Results and discussion

3.1. Descriptive analysis

On average, sample households allocated approximately 1.15 acres (50%) of their land for maize production. Approximately 14.4% of the total maize area is under PPT. The amount of chemical fertiliser applied to maize plots with PPT was approximately 74 kg per acre, compared with 57 kg per acre applied on plots without PPT (Table 3); this is probably because PPT reduces variability and risk—an aspect that requires further research. Labour use per acre on maize plots was significantly higher among PPT adopters than among non-adopters (Table 3). The unconditional cost of maize production, including the opportunity cost of family labour, was 48% higher for plots planted with PPT than those that did not employ PPT.

The unconditional mean maize yield from plots with PPT was 1573 kg per acre, compared with 930 kg per acre from plots without PPT (Table 3). The PPT system also generated additional benefits from fodder production, either through direct sales of fodder or by increasing livestock products. Notably, these benefits are not captured in the analysis: because of frequent fodder harvesting (five to six times per season), farmers have difficulty estimating exact fodder production.

PPT adoption also appears to stimulate milk productivity, which may be attributable to the increased availability of high-quality fodder for livestock. The annual mean milk production for PPT adopters was approximately 460 ℓ per cow per year, relative to 263 ℓ per cow for the non-adopters. This statistic corroborates the results of the focus group discussions, where farmers reported that push–pull companion plants (*Desmodium* and *Brachiaria* fodders) more than doubled their cows' daily milk production. For example, focus-group farmers from three counties (Kakamega, Kisumu, and Migori) reported an average increase in milk yield from 1.6 ℓ to 4.3 ℓ per day per cow due to PPT.

A similar pattern of increase is observed with respect to per-capita milk and maize consumption and market participation. PPT adopters consumed 56 ℓ of milk per capita during the 2015/16 cropping season, relative to 39 ℓ for non-adopters. PPT adopters consumed 132 kg of maize compared with 113 kg by non-adopters.

Market participation comparisons revealed similar increases. Notably, an average PPT adopter sold approximately 406 ℓ of milk per year, compared with only 161 ℓ sold by non-adopters. Adopters of PPT also sold more maize (378 kg) during the 2015/16 cropping season and purchased smaller quantities of the product (34 kg) than the non-adopters, who sold approximately 298 kg and purchased approximately 82 kg, respectively. In terms of net maize income, adopters achieved a 55% higher return in comparison with their counterparts' returns.

All of these results demonstrate higher productivity and income from PPT adoption, which can translate into improved household food security and reduced poverty.

Regarding household and village-level characteristics, on average, households with PPT adopters had more years of education, attended more field days, and had more access to rural institutions than non-adopters (Table 4). Thus, the unconditional summary statistics and tests in Tables 3 and 4 show systematic differences between adopters and non-adopters that may have implications for adoption decisions and outcomes.

3.2. Econometric results

In this section, we discuss the determinants and impacts of PPT

Table 5
Factors that influence PPT adoption.

Variables	Random effects probit model	Pooled probit model
Ln(distance to input market)	0.13**	0.14***
	(0.052)	(0.038)
Ln(number of adopters in a village)	0.16**	0.11**
	(0.074)	(0.055)
Number of rural institutions in a village	0.04	0.05**
	(0.027)	(0.021)
Number of field days attended	0.15***	0.11***
	(0.021)	(0.015)
Confidence in skill of extension agent	0.33***	0.24***
	(0.107)	(0.083)
Ln(household head age)	−0.02***	−0.01***
	(0.005)	(0.003)
Average household education	0.05***	0.04***
	(0.018)	(0.014)
Credit-constrained household	−0.10	−0.09
	(0.088)	(0.067)
Household size 6 years ago	0.02	0.02
	(0.017)	(0.013)
Number of cows 6 years ago	0.10**	0.08**
	(0.043)	(0.031)
Other livestock 6 years ago	−0.08***	−0.07***
	(0.027)	(0.019)
Ln(farm size 6 years ago)	0.13**	0.08*
	(0.061)	(0.045)
Ln(major furniture and equipment value)	−0.01	−0.01
	(0.037)	(0.029)
Soil fertility	−1.72***	−0.57***
	(0.153)	(0.058)
Plot slope	−0.40**	−0.10*
	(0.175)	(0.062)
Soil depth	0.23	−0.02
	(0.197)	(0.054)
Ln(plot distance to residence)	−0.40***	−0.27***
	(0.064)	(0.036)
Plot managed by spouse	−0.21	−0.00
	(0.269)	(0.083)
Plot managed jointly	−0.61**	−0.08
	(0.294)	(0.084)
County dummy	Yes	Yes
Constant	−1.39*	−0.64
	(0.735)	(0.551)
Wald chi^2	279.38***	338.23***
Log pseudolikelihood	−1072.71	−1089.11
Observations	2148	2148

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

adoption on plot-level maize yield and cost of production using the econometric specification outlined in Section 2.2. The primary objective of this study is to understand the impacts of PPT; thus, we do not discuss the estimates of outcome equations but rather briefly review the determinants of adoption. (The outcome regression estimates are available in Tables A1–A3 of the Appendix A.)

3.2.1. Factors explaining the adoption of PPT

Table 5 reports the results from the pooled probit model (ignoring the panel structure of the data) and the random effects model estimations of the adoption equation. The results show that the probability of adopting PPT appeared to increase according to the number of PPT field days farmers attended, the number of adopters there were in a village, a household's education levels, and the farmers' confidence in the skills of extension workers. These results reveal the knowledge-intensive nature

Table 6
Farm-level impacts of PPT adoption.

Outcome variables	Mean outcome		Average adoption effects (ATT)
	Actual	Counterfactual	
A	B	C	D = (A–B)
Maize yield (kg/acre)	1619.06	999.79	619.27 (49.75)***
Maize production cost (KSh/acre)	24,109.53	20,903.17	3,206.36 (485.13)***
Net maize income (KSh/acre)	40,139.46	28,971.06	11,168.39 (1100.84)***

Note: Standard errors in parenthesis. *** denotes significance level at 1%.

of the technology (Khan et al., 2014) and the role of exposure as measured by the number of PPT adopters and access to information in facilitating PPT adoption. The positive impact of farmers' confidence in the skill of extension workers is consistent with that found by Kassie et al. (2015b), namely that the quality of extension workers enhanced the adoption of minimum tillage, soil and water conservation, and crop diversification in eastern and southern Africa.

The likelihood of adoption also increased with distances to the nearest input distribution centre. This result suggests that farmers might start using PPT as an alternative to purchase external inputs to control insects and weeds.

Another determinant of adoption was ownership of productive resources such as dairy animals, which could take advantage of the fodder production. Similar to the literature on sustainable intensification technologies and practices (Kassie et al., 2015b, and the references therein; Teklewold et al., 2013), this study also found that household and farm characteristics (age of the farmer, plot distance from homestead, and soil fertility) influenced PPT adoption.

A simple correlation analysis (r) between adopting PPT and maize–grain legume intercropping ($r = -0.56$; $p = 0.000$) and adoption of PPT and rotations ($r = -0.04$; $p = 0.055$)shows a negative correlation at the 1% and 10% significance levels (p), respectively. These variables (maize–grain legume intercropping and rotations) were not included in the adoption model because of their perfect collinearity with PPT adoption.

The combined impact of these findings implies that scaling up PPT and reaching poor farmers requires enhancing access to information and that PPT must be adapted to existing farming systems to encourage its wider use in western Kenya.

3.2.2. Impact of adoption of the PPT on farm-level economics

The causal effect of PPT adoption on maize yield using fixed effects models is approximately 619 kg per acre, representing a 61.9% increase in maize yield after controlling for selection bias and other maize yield determinants (Table 6). Adoption is estimated to have increased the cost of maize production by 15.3%, from KSh 20,903 to KSh 24,110 per acre (Table 6). However, average net maize income increased by 38.6%, to KSh 40,139 from KSh 28,971 per acre (Table 6); this increase represents an additional KSh 2034 per capita per year, approximately 11% of the rural poverty line of KSh 18,714 per capita per year (Kenya National Bureau of Statistics and Society for International Development, 2017).[4] De Groote et al. (2010), using long-term researcher-managed trial data and partial budget and marginal analysis, found that PPT was more profitable than other practices used to control *Striga* weed and stemborer. These results, coupled with the descriptive

[4] If the pooled OLS (ordinary least squares) model is used instead, the qualitative results are similar: the changes in maize yield, cost of maize production, and net income are estimated as 48.7%, 25.7%, and 44.8%, respectively. We also tried a random effects model and found the results to be close to the pooled model estimates.

Table 7
Changes in economic surplus estimates and number of people considered poor escaping poverty at different levels of adoption.

Adoption rate	K-shift (%)	Open economy market		Closed economy market			
		Total economic surplus (USD millions)	Number of people considered poor who escape poverty (thousands)	Total economic surplus (USD millions)	Consumer surplus (USD millions)	Producer surplus (USD millions)	Number of people considered poor who escape poverty (thousands)
25%	28.6	142.25	149.86	139.64	65.87	73.77	147.12
30%	34.3	176.93	186.41	172.87	81.54	91.33	182.13
40%	45.7	249.83	263.21	241.19	113.77	127.42	254.11

statistics, imply that policies and programmes aimed at promoting PPT adoption can improve rural households' food security because increasing agricultural yield enhances the availability and accessibility of food.

3.2.3. Potential impacts of adoption of the PPT on aggregate welfare outcomes

The farm-level impact estimates presented in Section 3.2.2 were then used to compute the *K*-shift (i.e. the cost reduction per kilogram of maize output). Next, the *K*-shift was used as an input to calculate, ex ante, what the impact of PPT adoption would be on the overall economic surplus. If the changes in maize yield (61.9%) and cost of maize production (15.3%) due to PPT adoption are combined, the *K*-shift is 16.5% at the current adoption rate of 14.4%.

The aggregate economic surplus change at the 14.4% level of adoption is estimated at USD 72 million under the closed economy assumption (with the total change in consumer surplus at USD 34 million, and a total change in producer surplus of USD 38 million) and USD 73 million under the open economy assumption. This would lead to a decline of 75,077 in the total number of people considered poor for the closed economy scenario and of 76,504 for its open economy counterpart. Moreover, estimates of the extent of potential income gains and poverty reduction could have been higher if the fodder benefits of PPT had been considered in the analysis as well. Future studies could close this gap.

Table 7 presents the results from the sensitivity analysis.[5] With a 25% adoption rate, the change in total economic surplus is USD 140 million in the case of a closed economy and USD 142 million for an open economy. These changes would lead to a decrease of 147,121 in the number of people considered poor in the closed economy and a decrease of 149,864 in the open economy. If the adoption rate increased to 30% of the maize area in western Kenya, the economic surplus is predicted to be USD 173 million in the closed economy and USD 177 million in the open case. In addition, the number of people considered poor in the closed and open economy would decline by approximately 182,128 and 186,405.

4. Conclusions and policy implications

The adoption of agricultural technology is crucial to increasing agricultural productivity, reducing poverty, and sustaining ecosystem services that support livelihoods. Several studies document the microeconomic impacts of adopting agricultural technologies but few analyse the macroeconomic impacts. In this study, we first analysed the impetus for adopting multifunctional PPT and their impacts on farm-level outcomes; next, we estimated the potential macroeconomic impacts of such adoption on aggregate welfare using farm-household survey and secondary data collected in western Kenya. Our analysis relied on a combination of econometric analysis and economic surplus modelling.

Our results imply that adopting PPT generates sizeable farm-level benefits and a substantial economic surplus while reducing poverty. This research also demonstrates that a combination of many variables shapes farmers' decisions to adopt PPT. The probability of adoption is observed to increase as the number of adopters in a village and number of PPT field days farmers attended increases, and with a respondent's confidence in the skills of extension officers. Another major finding was that the household's education levels, input markets, and access to productive assets such as dairy cows were important to farmers in considering whether to adopt the PPT.

While this study confirms that PPT associated with maize production has positive impacts on economic surplus and poverty alleviation in western Kenya, we acknowledge that there are limitations. One is that the study is based on cross-sectional data that does not answer critical policy questions, such as adoption and impact dynamics. Second, the push–pull system provides fodder benefits, but this is not captured in the analysis because farmers find it difficult to provide accurate quantified data on fodder production because of frequent harvests during each season. A third limitation of the study is that the lack of recent human population data and region-specific agricultural GDP data may bias the poverty estimation results. A fourth limitation is that a binary definition of adoption ignores the important impacts of heterogeneity and how a technology is used (e.g. spacing between maize and *Desmodium*). More research is required to close these gaps.

Even with these caveats, the results have important implications. Primary among these is that the evidence presented in this study supports the belief that PPT adoption can increase agricultural productivity, net maize income, and economic surplus and, consequently, reduce food insecurity and poverty. Another significant implication is that effective policy measures to promote PPT adoption should include the improvement of household levels of education and information channels, such as quality extension services, field days, and social networks. Finally, it is crucial not only to adapt the PPT system to existing farming practices (e.g. intercropping and rotation to encourage adoption) but also to engage the private and public sectors to actively promote PPT adoption and ensure that information about the PPT is effectively disseminated and the technology is subsequently adopted. Given the sizeable impacts on potential economic surplus and poverty already achieved with the current low adoption rates, additional widespread adoption should clearly be a policy goal.

Conflict of interest

There is no conflict of interest.

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[5] The potential impact of the adoption of PPT (at a 25%, 30%, and 40% adoption rate) is estimated using the average adoption effects on treated and untreated sample households because we assume that some of the current non-adopters will adopt PPT in the future.

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Appendix A

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Table A1
Determinants of yield function [Dependent variable: ln(maize yield, kg/acre)].

Variables	Endogenous switching regression			
	Fixed effects models		Pooled OLS models	
	Adopters	Non-adopters	Adopters	Non-adopters
Ln(*F*)	0.01	0.01	0.02***	0.03***
	(0.019)	(0.012)	(0.007)	(0.006)
Ln(*KA*)	0.03**	0.03***	0.01***	0.01***
	(0.012)	(0.008)	(0.004)	(0.004)
Ln(*L*)	0.44***	0.19***	0.27***	0.16***
	(0.144)	(0.064)	(0.035)	(0.022)
Soil fertility	−0.81	0.13	0.06	0.03
	(1.505)	(0.498)	(0.054)	(0.040)
Plot slope	−0.39	−0.04	−0.05	−0.02
	(0.404)	(0.149)	(0.052)	(0.033)
Soil depth	−0.30	−0.10	−0.06	0.02
	(0.820)	(0.113)	(0.047)	(0.029)
Ln(plot distance to residence)	−0.36	0.02	0.01	−0.05**
	(0.355)	(0.112)	(0.035)	(0.022)
Plot shock	−0.20***	−0.24***	−0.17***	−0.12***
	(0.063)	(0.067)	(0.053)	(0.041)
Season	0.15***	0.18***	0.14***	0.18***
	(0.031)	(0.032)	(0.045)	(0.028)
Plot managed by spouse	−0.15	−0.16	0.00	0.02
	(0.274)	(0.219)	(0.067)	(0.046)
Plot managed jointly	−0.44	−0.02	0.06	0.02
	(0.613)	(0.246)	(0.069)	(0.047)
Ln(household head age)			0.00	0.00
			(0.002)	(0.002)
Average household education			−0.02*	0.03***
			(0.011)	(0.007)
Livestock owned during survey period			−0.02*	0.01*
			(0.011)	(0.007)
Ln(major furniture and equipment value)			0.04**	−0.02
			(0.018)	(0.017)
Credit-constrained household			−0.16***	−0.02
			(0.046)	(0.041)
Inverse Mills ratio	0.92	−0.17	−0.27**	−0.02
	(1.390)	(0.362)	(0.119)	(0.064)
County dummy	N/A	N/A	YES	YES
Constant	7.26**	6.23***	6.09***	6.01***
	(3.136)	(0.590)	(0.417)	(0.294)
Wald chi^2	61.20***	134.42***	199.51***	613.40***
Observations	633	1,515	633	1,515

Note: Bootstrapped standard errors in parentheses. Inputs include fertiliser (kg/acre, abbreviated as *F*), labour (person-day/acre, abbreviated as *L*), and seed and pesticides (KSh/acre, abbreviated as *KA*). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2
Determinants of cost function [Dependent variable: ln(maize cost of production, KSh/acre)].

Variables	Endogenous switching regression			
	Fixed effects models		Pooled OLS models	
	Adopters	Non-adopters	Adopters	Non-adopters
Ln(*W*)	0.00	0.06	0.04***	0.06***
	(0.111)	(0.038)	(0.015)	(0.011)
Ln(*Ps*)	0.01	0.00	−0.00	0.02***
	(0.007)	(0.006)	(0.005)	(0.004)
Ln(*Pf*)	0.03***	0.01**	0.03***	0.03***
	(0.009)	(0.006)	(0.007)	(0.004)
Ln(*Y*)	0.19***	0.25***	0.43***	0.38***
	(0.058)	(0.033)	(0.036)	(0.024)
Soil fertility	0.24	0.63**	−0.10*	0.11***
	(0.536)	(0.253)	(0.061)	(0.040)
Plot slope	0.14	0.10	0.04	−0.01
	(0.161)	(0.081)	(0.048)	(0.030)
Soil depth	0.29	−0.16*	−0.12***	−0.05*
	(0.231)	(0.088)	(0.037)	(0.029)
Ln(plot distance to residence)	0.12	0.11*	0.10***	0.07***
	(0.121)	(0.060)	(0.035)	(0.017)
Plot shock	0.01	0.01	0.12**	0.21***
	(0.036)	(0.026)	(0.054)	(0.035)
Season	−0.00	0.03	−0.08*	−0.03
	(0.016)	(0.018)	(0.046)	(0.029)
Plot managed by spouse	0.06	0.34	−0.08	−0.03
	(0.118)	(0.247)	(0.062)	(0.037)
Plot managed jointly	−0.02	0.15	−0.05	0.02
	(0.243)	(0.165)	(0.074)	(0.049)
Ln(household head age)			0.00	0.00
			(0.003)	(0.002)
Average household education			0.02*	0.00
			(0.013)	(0.010)
Family size during survey period			0.05**	0.05***
			(0.024)	(0.015)
Family labour during survey period			−0.02	−0.07**
			(0.038)	(0.027)
Livestock owned during survey period			0.00	−0.02**
			(0.012)	(0.006)
Ln(major furniture and equipment value)			0.02	−0.04**
			(0.030)	(0.016)
Credit-constrained households			0.13***	0.08***
			(0.044)	(0.031)
Ln(distance to input distribution centres)			0.01	−0.02
			(0.032)	(0.023)
Inverse Mills ratio	−0.30	−0.45**	0.30**	−0.22***
	(0.486)	(0.185)	(0.118)	(0.061)
County dummy	N/A	N/A	Yes	Yes
Constant	7.52***	7.27***	5.91***	7.25***
	(1.377)	(0.516)	(0.603)	(0.330)
Wald chi^2	39.38***	148.57***	457.26***	1,108.07***
Observations	633	1,515	633	1,515

Note: Bootstrapped standard errors in parentheses. Price vectors include those of Labour (*W*, KSh/day), Fertiliser (*Pf*, Ksh/kg), and Seed (*Ps*, KSh/kg). Yield (kg/acre) is denoted as *Y*. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3
Determinants of net maize income (KSh/acre).

Variables	Endogenous switching regression			
	Fixed effects models		Pooled OLS models	
	Adopters	Non-adopters	Adopters	Non-adopters
Soil fertility	−44,521.39	−5,772.60	2,905.47	1,047.32
	(91,179.915)	(17,167.010)	(2,556.175)	(1,192.866)
Plot slope	−18,815.91	−3,882.91	−167.03	−357.91
	(22,025.303)	(4,949.271)	(2,379.743)	(963.313)
Soil depth	−6,359.97	−1,209.25	1,159.45	219.96
	(43,956.328)	(4,011.527)	(1,925.820)	(765.195)
Ln(plot distance to residence)	−15,319.29	−2,562.70	1,184.42	−856.68
	(16,779.719)	(4,231.364)	(1,675.856)	(689.360)
Plot shock	−11,189.31***	−6,894.36***	−5,410.86**	−3,538.51***
	(4,156.383)	(2,478.729)	(2,603.047)	(939.488)
Season	3,204.49	5,288.42***	3,509.28*	5,296.18***
	(2,244.738)	(976.172)	(2,128.192)	(1,015.982)
Plot managed by spouse	−3,921.38	−6,420.45	2,319.45	−7.17
	(16,656.774)	(5,430.748)	(2,286.550)	(1,271.250)
Plot managed jointly	−8,940.86	−4,924.03	1,473.06	383.48
	(32,044.608)	(7,004.762)	(2,995.846)	(1,226.927)
Ln(household head age)			−202.50*	−6.84
			(105.120)	(47.476)
Average household education			−1,026.73*	476.91
			(531.900)	(293.454)
Livestock owned during survey period			−403.64	242.71
			(612.062)	(187.155)
Ln(major furniture and equipment value)			1,970.61**	−1,059.18*
			(806.807)	(558.328)
Family labour during survey period			−196.99	690.73*
			(774.320)	(402.520)
Credit-constrained households			−201.85	−558.10
			(2,316.145)	(1,116.553)
Inverse Mills ratio	47,285.02	2,789.25	−7,462.82	−2,142.21
	(74,342.906)	(12,548.569)	(5,644.757)	(2,171.238)
County dummy	N/A	N/A	Yes	Yes
Constant	117,335.64	46,697.50**	32,736.25**	43,620.63***
	(188,719.746)	(19,032.577)	(15,772.214)	(8,647.800)
Wald chi^2(10)	11.88	55.88***	52.55***	158.44***
Observations	633	1,515	633	1,515

Note: Bootstrapped standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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