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Do Agricultural stakeholder panels enhance post-harvest loss reduction? Evidence from Malawi

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Abstract

Post-harvest loss significantly affects food security in sub-Saharan Africa (SSA) and elsewhere across developing countries. Weak institutional factors like ineffective agricultural extension services in rural communities can exacerbate such problems among smallholder farmers in SSA and other developing countries. Therefore, international development policies have prioritized strengthening rural extension systems to enhance access to effective extension services and thereby enhance food security outcomes like ineffective agriculturalpost-harvest loss reduction among rural households. As such, the US-Agency for International Development supported the *Strengthening Agricultural and Nutrition Extension* program in Malawi from 2015 to 2021 to improve access to rural extension services by promoting Agricultural Stakeholder Panels (ASPs)—platforms designed to enhance farmer interaction with local extension agents in rural communities and thereby enhance improved access to quality extension services in rural areas. The ASP approach can reduce post-harvest losses for major crops, such as maize. However, rigorous analyses of the effects of ASPs on post-harvest loss reduction remain limited. To address this knowledge gap, we apply recursive bivariate probit regression to primary survey data from 2134 households in Malawi to estimate the effects of the ASP approach on post-harvest loss reduction in 2018. The results show that ASPs reduced post-harvest losses among households by 53%, and a crucial outcome that can improve household food security. The result demonstrates that policies that strengthen rural extension systems can contribute to the achievement of the Sustainable Development Goals on hunger and food security in rural Malawi and similar contexts.

Keywords Agricultural extension, Farmer voice, Food security, Post-harvest loss

Introduction

Post-harvest loss constitutes a major challenge in rural communities across sub-Saharan Africa (SSA) and other developing regions due to binding resource constraints and weak institutions such as agricultural extension[1] services to help rural households adopt crucial technologies, like post-harvest management practices like improved storage and processing of crops [1–3]. To reduce such constraints, therefore, many innovative agricultural policies are increasingly implemented to boost agricultural extension services in rural communities in SSA. One such approach is the use of Agricultural Stakeholder

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[1] In this study, the terms extension, agricultural extension, agricultural and nutritional extension, and rural extension services are used synonymously.

Panels (ASPs)[2]—extension governance platforms that can enhance farmer voice and thereby improve efficient delivery of agricultural and nutritional extension services in rural areas of developing countries, such as Malawi [6].

In 2015, the US Agency for International Development (USAID) in Malawi supported the *Strengthening Agricultural and Nutrition Extension* (SANE) project—a $10 million investment under its *Feed the Future* program to establish new ASPs and strengthen existing ones in the USAID *Feed the Future* Zone of Influence (ZOI)[3] from 2015 to 2021. The ASP approach was a core strategy in the SANE project and was implemented in the USAID Feed the Future ZOI across Malawi. ASPs provide a forum for farmers to have vigorous discussions about their priorities and how their lead farmers and local extension agents can provide services to meet such priorities [4]. As such, farmers and extension agents can equally demand accountability from other farmers regarding their implementation of the extension and advisory services they receive. Moreover, ASPs serve as a linkage between government representatives (such as extension officers at the Ministry of Agriculture) and other extension service providers in the private sector. In so doing, ASPs can induce the adoption of Green Revolution technologies, such as improved seeds and fertilizers [7–9], climate smart agriculture practices [10–12], and sustainable land management practices, like agroforestry [13, 14], as well as the adoption of post-harvest technologies. Thus, ASPs can invigorate the rural economy toward food security [15, 16].

Post-harvest loss is a vital aspect of food security through sustainable consumption or utilization in Malawi [17–20]. A prior analysis shows that ASPs enhanced the resilience of rural communities to climate related shocks [4]. However, analyses of the effects of ASPs on crucial outcomes like reduction of post-harvest losses for major crops like maize remain lacking. Therefore, an important question is, can ASPs reduce post-harvest loss among rural households?

To answer this question, we apply recursive bivariate probit (RBP) regression to survey data from 2,134 rural households in 22 districts in Malawi in 2021 to estimate the effects of the ASP approach on post-harvest loss reduction in Malawi. The RBP model is a suitable analytical technique that estimates the effects of a binary variable such as participation in a program like farmer interaction with an ASP (measured as a binary outcome (yes = 1, 0 otherwise), on the effect of another binary outcome such as reported experience of post-harvest losses (yes = 1, 0 otherwise). The RBP approach is a maximum likelihood estimation technique that accounts for endogeneity arising from unobservable factors and selection bias in impact assessment [21]. Other methods such as ordinary probit regression and propensity score matching (PSM) do not account for unobservable factors and endogeneity, which can lead to bias estimates of the effects of farmer interaction with ASPs on post-harvest loss reduction. As such, the RBP approach has been used extensively in similar studies across Malawi (e.g. [10, 11, 22]) and other developing countries (e.g., [23, 24]).

We posit that the ASP approach can enhance post-harvest loss reduction in Malawi and elsewhere. A crucial pathway through which ASPs can reduce post-harvest losses among rural farmers is by inducing the adoption of post-harvest management practices [25, 26].

This study contributes to the literature on agriculture and food security by shedding lights on the role of the ASP approach as an innovative extension system that can induce food security outcomes such as post-harvest loss reduction, and thereby provide a pathway for rural transformation in SSA and elsewhere [27–30]. It also contributes to international development policy by shedding light on the effectiveness of the SANE project in enhancing the effective operations of ASPs in rural Malawi. Moreover, the study contributes to agricultural extension by highlighting the ASP approach as an exemplary rural extension system for achieving sustainable extension service delivery in rural areas of developing countries like Malawi and similar contexts where access to rural extension services remain lacking [31]. Furthermore, this study contributes empirically by being among the first set of studies to apply an RBP regression technique to analyze primary survey data on the ASP approach as a demand-side extension system in rural Malawi. Most prior studies on post-harvest loss reduction associated with smallholder farmer interactions with extension agents in rural contexts of developing countries do not account for the endogeneity of farmer interaction and unobservable factors associated with crucial outcomes like post-harvest loss reduction stemming from such interactions. Studies that have utilized the RBP model in agricultural extension-related programs do not focus on post-harvest loss reduction (e.g., [10, 24]). This study, therefore, can be useful in scaling up rigorous analyses of the effects ASPs and other conduits of rural extension services in developing countries. Such analyses can enhance an achievement of the Sustainable Development Goals (SDGs) in Malawi and similar contexts elsewhere [27, 32–34].

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[2] Also known as Agricultural Stakeholder Platforms generally and our usage here is different from that of "Area Stakeholder Panels" that are subsets of Agricultural Stakeholder Platforms at Extension Planning Area levels across districts [4, 5].

[3] A list of districts with high level of food and nutrition insecurity compounded by weak institutional factors like ineffective extension services. They include Balaka, Blantyre, Chikwawa, Dedza, Lilongwe, Machinga, Mangochi, Mchinji, Nsanje, Ntcheu.

Agricultural stakeholder panels in Malawi

The ASP approach has been widely implemented in Malawi to improve rural development through the provision of effective demand-driven and community-led extension services in rural communities [4]. However, there are diverse problems ranging from governance to cost and lack of efficiency in their operations across different rural communities, which limits their effectiveness in responding to farmer priorities [4, 6]. Thus, USAID supported the SANE[4] project to improve the functionality of ASPs in various areas of the country especially across the USAID Feed the Future ZOI.

An important objective of SANE was to provide technical assistance to improving the national extension system in Malawi by strengthening the District Agricultural Extension Services System (DAESS) of the Government of Malawi to enhance effective extension services through resource mobilization and better coordination among service providers [4]. The SANE project empowered the DAESS to deliver high-quality extension services in rural communities using the ASP approach both as a vehicle of efficient extension services and as a source of mutual accountability between farmers and local extension workers.

SANE was operational in the USAID Feed the Future ZOI in Malawi from 2015 to 2021 to enhance the operations of ASPs and thereby enhance their outreach to smallholder farmers in the project area (Fig. 1). SANE sought to improve the policy environment for efficient agricultural and nutrition extension service delivery in Malawi through activities led by various ASPs in collaboration with Ministry of Agriculture personnel. Prior to SANE, many ASPs were not effectively meeting the needs of the farmers. The SANE project sought to reverse this trend by empowering ASPs to serve as effective platforms, where the varying needs of farmers can be discussed through interactions with local extension agents and experts while also meeting the needs of extension workers by equipping them with vital training and feedback toward their effectiveness in their daily operations. The operations of SANE aligned with the core principles of Malawi's National Agricultural Extension Policy through DAESS such as demand-driven and decentralized extension services, accountability to stakeholders, and sustainable resource management through a stakeholder-driven framework.

Following Álvarez-Mingote et al. [4], this study operationalizes ASP functionality as the ability of an ASP to effectively respond to the needs of their clientele in a spirit of inclusivity, diversity, and equity. ASPs improve the delivery of rural extension services in Malawi. Accordingly, ASP functionality is measured in three ways. First, the use of standard operating procedures (SOPs) like adherence to regular meeting schedules, having a well-prepared agenda for meetings, well-organized meetings, minutes for each meeting, and follow-up action points and feedback for meetings. Second, inclusive farmer representation in terms of small-scale farmers comprising 50 percent of membership disaggregated by gender and youths. And third, diversity of stakeholder participation in meetings—in terms of local farmers, state, and non-state actors as well as the private sector [4].

Functional ASPs can facilitate robust stakeholder engagement, enhance community participation and expression of felt needs, and thereby ensure that service providers can efficiently address such needs. They also enhance accountability to farmers and their representatives for extension service providers through the communication of feedback. Thus, the ASP framework considers farmers and extension workers as consumers and providers, respectively, co-existing along a knowledge value chain [4].

In this study, however, we implicitly assume that ASPs were largely functional in the SANE area. Therefore, although the terms "functional ASPs" or "functioning ASPs" are used interchangeably throughout the paper, the focus of analysis is not on ASP functionality per se, but rather on the effects of the ASP approach on post-harvest loss reduction in Malawi. The findings can be potentially applicable in similar contexts elsewhere in SSA and beyond.

Theoretical framework and expectations

The literature on agricultural extension has evolved in diverse ways in the past several decades in terms of the various approaches and principles of extension service delivery [27, 35–38]. These approaches include (1) "top-down", (2) Training and Visit, (3) bottom-up or more participatory system, and (4) one-to-one information exchange and advice systems [39–41]. However, advances in agricultural extension have led to the concept of pluralistic extension systems that emphasize a "best-fit" approach to extension delivery across context, because the effectiveness of extension services often vary across context [40, 42, 43]. Therefore, context-specific extension service delivery is increasingly useful in developing countries such as Malawi, where access to extension services remain low [5, 31].

This study utilized several theoretical concepts such as the diffusion of innovations [44], social learning—a process or mechanism that can enhance the transfer of knowledge and foster learning through social interaction

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[4] The SANE project was implemented by the University of Illinois at Urbana-Champaign in partnership with Catholic Relief Services (CRS) in Malawi and Michigan State University.

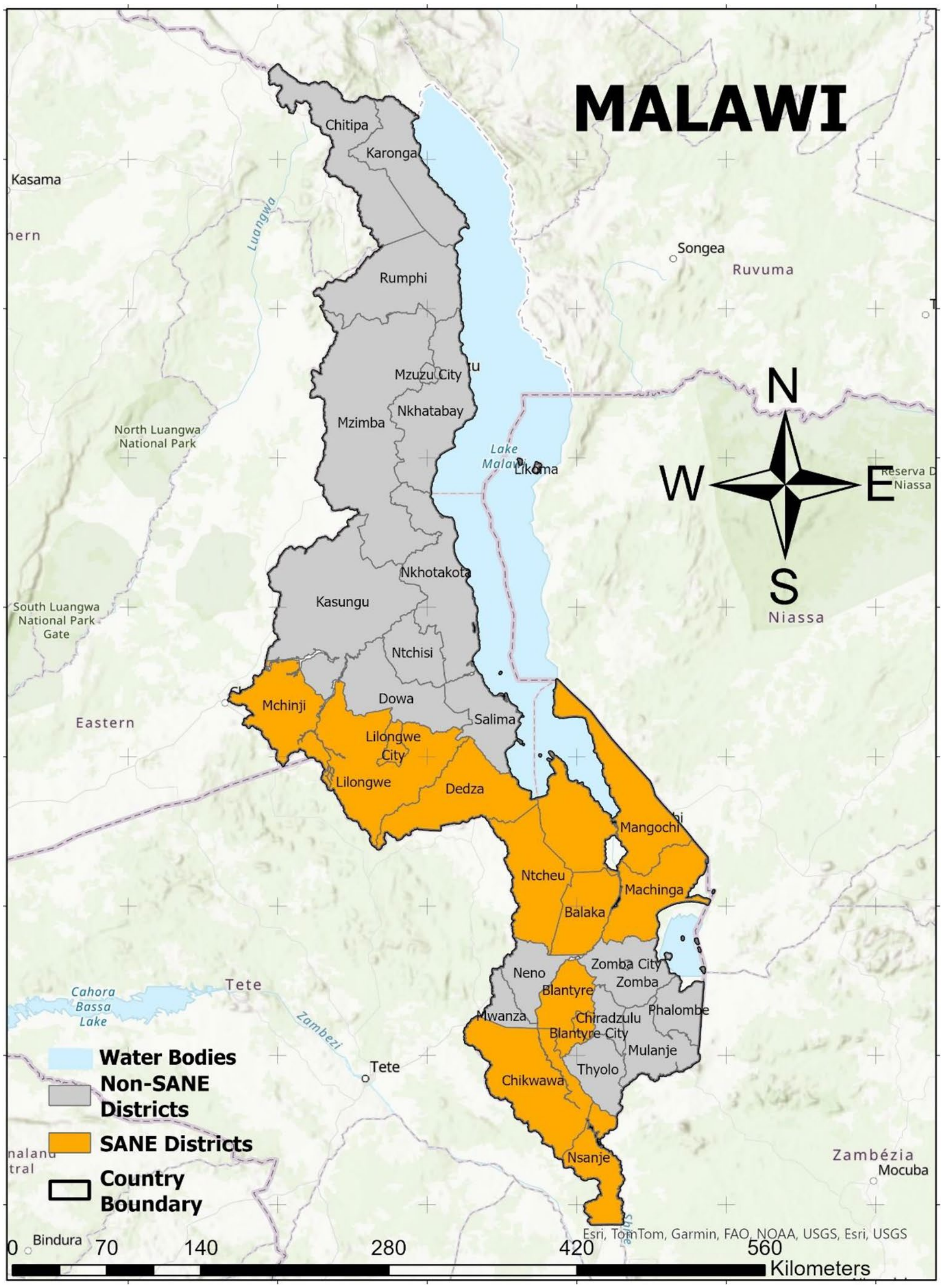

Fig. 1 Map of the study area

across context [10, 45–47], the concept of learning by doing [48, 49], as well as the theory of innovation systems [50]. ASP functionality can enhance access to improved extension services especially regarding quality nutritional information for farmers [4, 6]. Functional ASPs can enhance agricultural productivity and related outcomes such as adoption of post-harvest management practices that can reduce post-harvest loss among rural households. They do so by serving as conduits of crucial extension messages at the community level by linking local farmers and extension agents with resources beyond the immediate community, such as district level and national actors in the supply chain. As such, ASPs can improve extension services through a form of information cascade

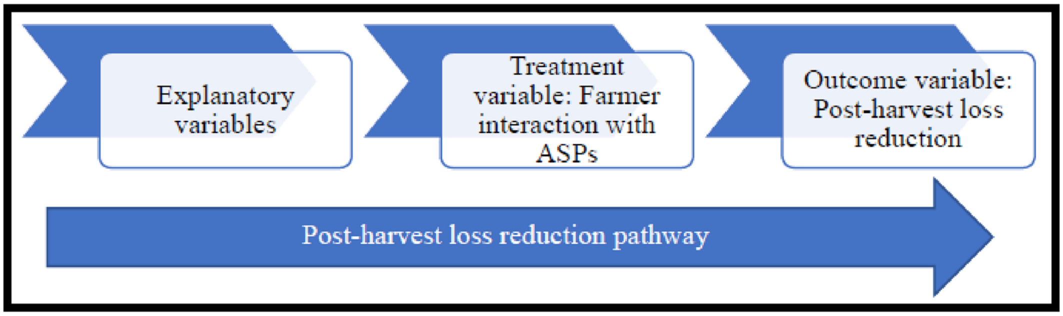

Fig. 2 Relationship between explanatory variables, agricultural stakeholder panels, and post-harvest loss reduction

wherein local extension agents can better interact with farmers and thereby yield an indirect effect through improved farmer attention to services and feedback from their local extension agents.

Post-harvest loss prevention, like many development priorities, is complex, and requires substantial knowledge and training to enhance the transmission of crucial information among smallholder farmers in the developing world [1, 2, 51–53]. Without adequate training and information on post-harvest loss techniques such as drying and appropriate storage, can reduce post-harvest loss many food commodities are subject to post-harvest losses [1, 2, 51, 52]. Thus, when farmers interact with other farmers and local extension agents through functioning ASPs in their communities, they can learn about critical agricultural information such as those pertaining to post harvest losses by improving their capacity to understand the value and benefits of such practices. This, in turn, can enable them to adopt better practices that can reduce post-harvest losses as demonstrated by previous studies in similar contexts elsewhere in Malawi [54, 55] Kenya [12, 56], and Ghana [26].

Therefore, from the forgoing discussion, this study tests the hypothesis that ASPs can significantly reduce post-harvest losses among smallholder farmers in Malawi. As discussed in this section, farmer interaction with extension agents associated with functional ASPs[5] can reduce post-harvest losses in rural Malawi. For instance, by enhancing farmer voice in the supply of critical agricultural extension services in their communities [4, 57–59] and through linkages with other stakeholders beyond their immediate village [17, 60, 61].

Moreover, functional ASPs provide critical information that can influence household adoption of post-harvest management practices, which can reduce post-harvest losses at the household level [17, 20, 62] and other benefits such as dietary diversity by helping farmers make proper utilization of food crops [63–66], and thereby enhance the Sustainable Development Goals (SDGs) on hunger and food security in such contexts.

Furthermore, interaction with functional ASPs can enhance farmer voice, better collaboration, and improved peer interaction among stakeholders including local farmers and NGO staff associated with such ASPs. Thus, ASPs can enhance the capacity of farm households to demand higher performance standards from local extension agents [4, 6]. Therefore, household interactions with extension agents associated with ASPs receive quality extension services by holding such extension agents accountable through their awareness of improved techniques. Equally, extension agents associated with such ASPs can hold their constituent farmers accountable by ensuring that they apply the information they received, which can result in improved outcomes, such as post-harvest loss reduction.

Conceptual framework

Following the afore-mentioned literature and concepts, such as diffusion of innovations [44], innovation systems [50], and social learning [45, 46, 48, 49], we present a conceptual framework that illustrates the relationship between explanatory variables, the treatment variable—interaction with ASPs, and the outcome variable—post-harvest loss reduction. According to this framework, our treatment variable is farmer interaction with ASPs, which can reduce post-harvest losses (Fig. 2). Thus, we expect ASPs to have a negative effect on post-harvest losses, because they help to reduce constraints and barriers and thereby reduce the transaction costs faced by smallholder farmers in the adoption of post-harvest management technologies [67, 68].

Explanatory variables such as age and gender of household heads, their level of education, and the distance

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[5] Throughout this paper, our reference to the effects of ASPs implicitly refers to functional ASPs—i.e., those that demonstrate the three principles of inclusivity, farmer representation, and standard operating procedures (see [4]).

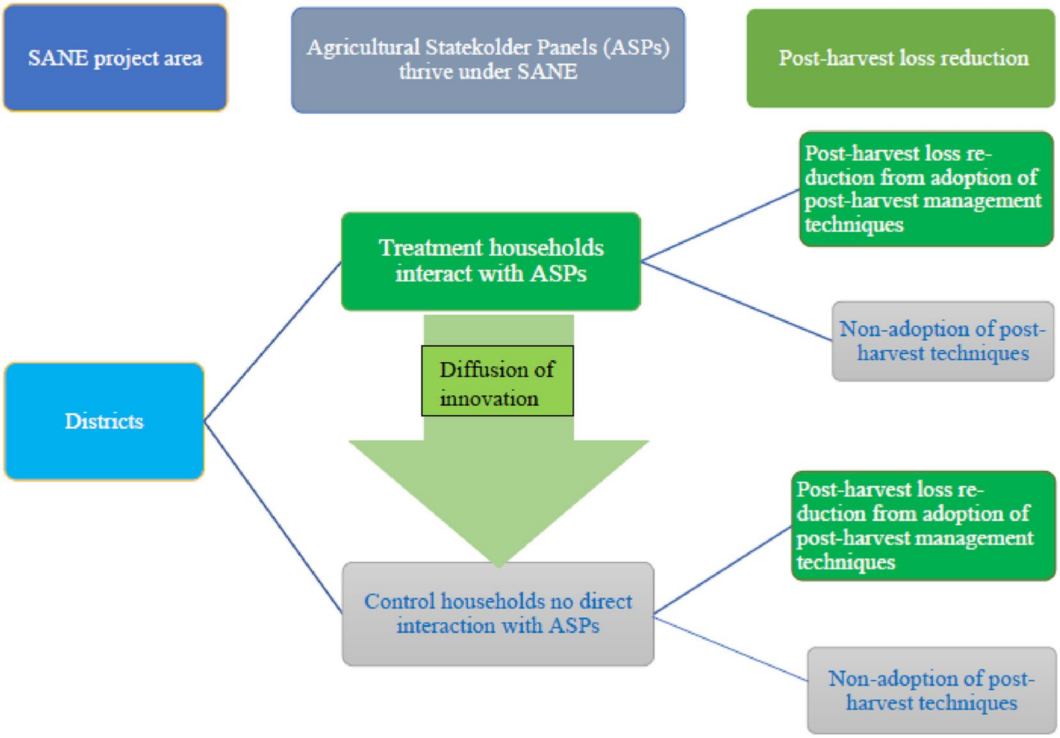

Fig. 3 Analytical framework for how ASPs can enhance post-harvest loss reduction (Adapted from Amadu [10])

from markets can affect farmers interaction with formal extension agents such as those associated with the Ministry of Agriculture due to proximity and other constraints as noted in recent studies from Malawi [31] and elsewhere [67, 68]. These variables can shape the participation decision of farmers in ASPs, which can affect post-harvest loss reduction. Specifically, communities that are farthest away from paved roads are more likely to participate in ASPs to receive viable extension services through such platforms, which in turn, can enhance their adoption of post-harvest management techniques and consequently reduce post-harvest losses.

Analytical approach

In Fig. 3, we provide a stylized analytical framework for how the ASP approach can enhance post-harvest loss reduction. Farmer interaction with functional ASPs can enhance their adoption of post-harvest management techniques that can help reduce post-harvest losses normal distribution expressed as. Specifically, households in the SANE project area (i.e., the treatment area) can have more access to viable extension services through functional ASPs. However, due to the diffusion of innovation [44], households in non-SANE districts can also benefit from high quality extension services associated with ASPs, which can inform their adoption of viable post-harvest management techniques, and thereby enhance their probability of post-harvest loss reduction.

Moreover, because the SANE project that enhanced ASP functionality and the interaction of farmers with such ASPs was not random across the study area, selection bias from unobservable factors can affect the extent to which ASPs affected post-harvest loss reduction. Thus, we utilized appropriate analytical techniques (discussed below) to account for such factors and thereby enhance rigorous estimates of the effects of the ASP approach on post-harvest loss reduction in the study area.

Empirical strategy

Using random utility theory, we assume that households interact with ASPs if their perceived utility of interaction (U^I) is greater than the utility of non-interaction (U^{NI}). Because we cannot observe the interaction utility as we do with the interaction decision (I^*), we can express I^* as a binary variable, such that:

$$I^* = 1 \text{ if } U^I > U^{\mathrm{NI}} > 0; \text{ and } I^* = 0 \text{ if } U^{\mathrm{NI}} > U^I > 0 \tag{1}$$

From Eq. (1), we express the interaction decision as a latent variable, such that:

$$I_i^* = \boldsymbol{\Theta}\mathbf{Z}_i + \lambda_i, \text{ for } I = 1, \text{ if } I_i^* > 0, \tag{2}$$

where I^{*}_{i} represents interaction decision. $\mathbf{Z}_i$ is a vector of determinants of interaction, $\boldsymbol{\Theta}$ is a vector of parameters to be estimated, and λ is a normally distributed error term with a zero mean and constant variance. By imposing linearity on the expected effects of interaction such as post-harvest loss reduction along with a dummy variable for interaction and other covariates, we can express the effects of ASPs as follows:

$$y_i^* = \alpha'\mathbf{X}_i + \boldsymbol{\beta}\mathrm{Pi} + \phi_i, \tag{3}$$

where y^{*}_{i} is the impacts of ASPs on post-harvest loss reduction, $\mathbf{X}_i$ is a vector of covariates accounting for the effects of ASPs including household, biophysical, and institutional factors (such as credit constraints), I_i is farmer interaction as defined in this section, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are vectors of parameters to be estimated, and ϕ is an error term.

Identification strategy

As noted in "Analytical approach" section, the establishment of ASPs under SANE and the subsequent interactions of farmers with extension workers associated with such ASPs were not random. Thus, there are two potential sources of endogeneity that can affect our analysis of the effects of ASPs on post-harvest loss reduction in this study. The first source of endogeneity is placement endogeneity, which can arise, because the ASPs were not randomly established and supported. Instead, their establishment and support were determined by specific community attributes—such as being in the ZOE of the *Feed-the-Future* (*FtF*) area of USAID in Malawi. Such communities may be strategically different from other communities. Therefore, to enhance a rigorous analysis, we should consider such potential placement endogeneity.

The second source of endogeneity is selection bias, which arises, because farmers self-select to interact with extension workers associated with functional ASPs over and beyond other extension agents in their communities. Selection bias can be serious if such interactions are driven by unobservable factors, such as motivation and experience, which can affect both the interaction decision and the outcome of such interactions on post-harvest losses. Such farmers, therefore, may be systematically different from other farmers, and can lead to bias estimates of the effects the ASP approach on post-harvest loss reduction. Therefore, to provide rigorous estimates, we need to account for both sources of potential endogeneity.

Our identification strategy utilized an RBP regression model in the spirit of Amadu [10], Amadu et al. [11], and Sitko et al. [22]. The RBP model is suitable in this context, because the interaction of farmers with extension agents in functional ASPs, and the outcome variable (post-harvest loss reduction) are both binary. The RBP model accounts for the endogeneity of our treatment variable and the potential selectivity bias in post-harvest loss reduction by controlling for potential endogeneity bias related to unobservable characteristics in the treatment variable, which we cannot efficiently account for using ordinary probit or ordinary least square (OLS) regression or other analytical techniques, such as propensity score matching (PSM).

We used an RBP model with full information maximum likelihood algorithm to estimate the determinants of the treatment and the impact of ASP functionality (conditional on other covariates), while accounting for endogeneity and selectivity bias. The RBP model estimates both the determinants of the treatment variable and the effects on post-harvest loss reduction. From Eq. (3), we specify the following participation and outcome equations jointly:

$$P_i^* = \delta'\mathbf{Z}_\mathrm{i} + \vartheta_\mathrm{i},\ \text{for}\ P = 1,\ \text{if}\ P_i^* > 0 \tag{4}$$

$$y_i = \tau'\mathbf{X}_i + \boldsymbol{\psi}P^* + \xi_i, \tag{5}$$

where P^{*}_{i} denotes a latent variable for the treatment, y_i denotes the effects of ASPs on the reduction of post-harvest losses, $\mathbf{Z}_i$ and $\mathbf{X}_i$ are, respectively, vectors of determinants of farmer interaction with ASPs and the effects of ASPs on post-harvest loss reduction, $\boldsymbol{\delta}$, $\boldsymbol{\tau}$, and $\boldsymbol{\psi}$ are vectors of parameters to be estimated, while ϑ_i and ξ_i are error terms. The joint error term (Ω) follows a bivariate normal distribution expressed as

$$\Omega = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}, \tag{6}$$

where ρ denotes the correlation coefficient of unobservable factors.

Application of the RBP model requires the use of at least one instrumental variable (IV)—a concept of exclusion restriction, wherein the vector $\mathbf{Z}_i$ in Eq. (2) include at least one variable that is not in the vector $\mathbf{X}_i$. To be valid, such an IV (or a set of IVs) should affect the treatment variable conditional on other covariates, but they should not directly affect post-harvest loss reduction except through the treatment. Instrument validity is a major challenge in empirical studies including the present study, because variables that affected the treatment can also affect the crucial outcomes, such as post-harvest losses [11, 24]. We use a set of binary dummy variables (yes = 1, 0 otherwise) as our exclusion restriction. First, we ask whether there was any *farmer-to-farmer extension* program in the village prior to the ASP approach, and second, whether the district was in a *feed-the-future area* before the ASP approach under SANE intervention in 2015. In Malawi, the categorization of districts and communities within the USAID ZOI is well-pronounced [69].

We argue that farmers in the FtF areas that had prior exposure to farmer-to-farmer extension agents are more likely to be aware of, and interact with lead farmers and extension agents associated with functional ASPs through pathways such as group interactions, farmer social networks, as well as prior rural infrastructures arising from previous projects. Such factors can enhance the effectiveness of ASPs to provide better services to households in their locality. However, merely being in an FtF area or living in a community that had prior exposure to an extension program may not necessarily affect post-harvest loss reduction except through interactions with lead farmers and extension agents associated with functional ASPs, which were pivotal in influencing the adoption of post-harvest loss prevention technologies in such communities.

We used falsification tests to establish the validity of these two potential IVs as done in relevant studies (e.g., [10, 11]). They affected the interaction decision with extension workers associated with ASPs, but they did not affect post-harvest loss reduction among non-participants (Table 4). From Eqs. (4) and (5) we estimate marginal effects (ME) and average treatment effects of the ASP approach (i.e., average treatment effects on the treated (ATT)) as follows:

$$ME = \operatorname{Exp}\left[\left(y_i\right)|P_i > 1\right] \tag{7}$$

$$\text{ATT} = E\left\{\left[\left(y_i = 1\right)|P_i = 1\right] - \left[\left(y_i = 0\right)|P_i = 1\right]\right\}. \tag{8}$$

In Eqs. (7) and (8), $\operatorname{Exp}\left[\left(y_i\right)|P_i > 1\right]$ is the conditional effect of the ASP approach, $E\left[\left(y_i = 1\right)|P_i = 1\right]$ denotes the effect of ASPs on beneficiary farmers, and $E\left[\left(y_i = 0\right)|P_i = 1\right]$ is the effects of ASPs among the control group.

Data

Data were collected in 2018 from 2134 rural households across 20 Malawian districts—including all ten districts in the ZOI where SANE was operational (i.e., Balaka, Blantyre, Chikwawa, Dedza, Lilongwe, Machinga, Mangochi, Mchinji, Nsanje, and Ntcheu), and ten other districts[6] beyond the ZOI to serve as an artificial control in our analysis We used a set of structured survey questionnaires designed mainly for this study. The sampled households were purposely selected from rural communities across the ten USAID ZOI districts and the other districts beyond. The outcome variable is post-harvest loss in the previous season immediately before the survey period. We used households' self-reported measure of post-harvest losses in terms of a binary dummy variable equal to one if household experienced post-harvest losses in the preceding season, and zero otherwise. The treatment variable—farmer interaction with extension workers associated with functional ASPs in their communities—was also used as a binary dummy variable (yes = 1, 0 otherwise).

Questionnaires were administered by trained local enumerators experienced in the local languages. Moreover, key informant interviews were conducted with lead farmers and community leaders about their perceptions of ASPs in their communities, and the average agricultural activities per community. The key informant responses were used to complement the household data. Data were analyzed using STATA statistical package version 17.

Description and measurement of variables and summary statistics

Table 1 provides definition and descriptions of the main variables. As noted in "Data" section, the outcome variable—post-harvest loss—is a binary variable that equals one if a household experienced post-harvest loss in the previous harvest season immediately before the survey, and zero, otherwise. Likewise, interaction with ASPs—the main policy (treatment) variable—was measured as a binary dummy variable equal to one if the household had interactions with an ASP under the SANE project and zero otherwise.

We controlled for several demographic, socioeconomics and institutional, as well as biophysical factors to ensure reliability of our estimates. Demographic factors include the age, gender, and educational status of the household head (a binary variable equal to one if the household head attained secondary education, and zero otherwise), household size, and the number of adults in the households. These variables are important determinants of program participation such as interaction with extension workers like those associated with ASPs as noted in literature from Malawi (e.g., [10, 11]) and elsewhere (e.g., [27, 70, 71]).

Socioeconomic and institutional factors were measured as dummy variables (yes = 1, 0 otherwise) for livestock ownership, whether the household experienced credit constraints, market constraint, and fertilizer constraints, transportation constraints, and storage constraints, if the household participated in any farmer field day program in the community, and whether the household received extension services from multiple sources. These

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[6] Dowa, Karonga, Kasungu, Mwanza, Nkhatabay, Nkhotakota, Phalombe, rumphi, Thyolo, and Zomba district.

Table 1 Variable definition and summary statistics

Variable	Definition	Mean	Std. dev	Min	Max
Post-harvest loss (1/0)	If the household experienced post-harvest losses	0.55	0.50	0	1
Interaction with an ASP	If the household had interaction with an extension agent associated with an ASP through the SANE project (yes = 1)	0.69	0.30	0	1
Age	Age of household head (years)	42.40	15.71	18	81
Male-headed household	If the household head is a male	0.83	0.38	0	1
High school plus	If the household Head completed high school education	0.15	0.36	0	1
Married	If the respondent is married	0.65	0.48	0	1
Household size	Number of persons in the household	5.34	2.04	3	13
Number of adults per household	Number of adults in the household	2.19	0.94	1	6
Credit constraint	If the household is credit constrained (1 = yes, 0 otherwise)	0.49	0.50	0	1
Livestock ownership	If the household owned livestock (yes = 1)	0.08	0.27	0	1
Market constraints	If the household experienced market constraint (yes = 1)	0.69	0.46	0	1
Fertilizer constraint	If the household had fertilizer constraint (yes = 1)	0.39	0.49	0	1
Off-farm income	If household has other sources of income	0.03	0.17	0	1
Distance to markets	Distance to the nearest market	233.31	611.71	1	2016
Transportation constraint	If household experienced transportation constraints	0.19	0.39	0	1
Storage constraint	If household experienced storage constraints	0.30	0.46	0	1
Farmer field day	If there was a farmer field day in the community	0.64	0.48	0	1
Multiple EAS sources	If household received extension services from multiple sources	0.01	0.10	0	1
Districts					
Balaka	If household is in Balaka district (1 = yes, 0 otherwise)	0.05	0.22	0	1
Blantyre	If household is in Blantyre district (1 = yes, 0 otherwise)	0.08	0.27	0	1
Chikwawa	If household is in Chikwawa district (1 = yes, 0 otherwise)	0.06	0.23	0	1
Dedza	If household is in Dedza district (1 = yes, 0 otherwise)	0.08	0.27	0	1
Lilongwe	If household is in Lilongwe district (1 = yes, 0 otherwise)	0.16	0.36	0	1
Machinga	If household is in Machinga district (1 = yes, 0 otherwise)	0.12	0.32	0	1
Mangochi	If household is in Mangochi district (1 = yes, 0 otherwise)	0.08	0.27	0	1
Mchinji	If household is respondent is in Mchinji district (1 = yes, 0 otherwise)	0.07	0.26	0	1
Nsanje	If household is in Nsanje district (1 = yes, 0 otherwise)	0.03	0.17	0	1
Ntcheu	If household is in Ntcheu district (1 = yes, 0 otherwise)	0.06	0.23	0	1
Dowa	If household is in Dowa district (1 = yes, 0 otherwise)	0.04	0.19	0	1
Karonga	If household is in Karonga district (1 = yes, 0 otherwise)	0.02	0.13	0	1
Kasungu	If household is in Kasungu district (1 = yes, 0 otherwise)	0.03	0.18	0	1
Mwanza	If household is in Mwanza district (1 = yes, 0 otherwise)	0.01	0.08	0	1
Nkhatabay	If household is in Nkhatabay district (1 = yes, 0 otherwise)	0.02	0.13	0	1
Nkhotakota	If household is in Nkhotakota district (1 = yes, 0 otherwise)	0.01	0.09	0	1
Phalombe	If household is in Phalombe district (1 = yes, 0 otherwise)	0.02	0.16	0	1
Rumphi	If household is in Rumphi district (1 = yes, 0 otherwise)	0.01	0.11	0	1
Thyolo	If household is in Thyolo district (1 = yes, 0 otherwise)	0.03	0.18	0	1
Zomba	If household is in Zomba district (1 = yes, 0 otherwise)	0.03	0.18	0	1
Instrumental variable dummy					
Feed the Future Area dummy	If ASP was in a FtF district before the SANE project (1 = yes, 0 otherwise)	0.79	0.41	0	1
Farmer-to-farmer extension	If there was a farmer-to-farmer extension program in the area before SANE	0.15	0.36	0	1

ASP, Agricultural Stakeholder Panel, *EAS* Extension and Advisory Services, *NGO* Non-governmental Organization, Dummy variables; yes = 1

variables were selected, because they are important factors for rural extension services in Malawi [4, 6, 10, 17] and elsewhere in SSA [15, 27, 52, 70, 72]. Biophysical factors include distance to markets, measured in terms of proximity to motorable roads—a major determinant of services delivery and access to extension in Malawi [10, 31] as well as district dummy variables to account

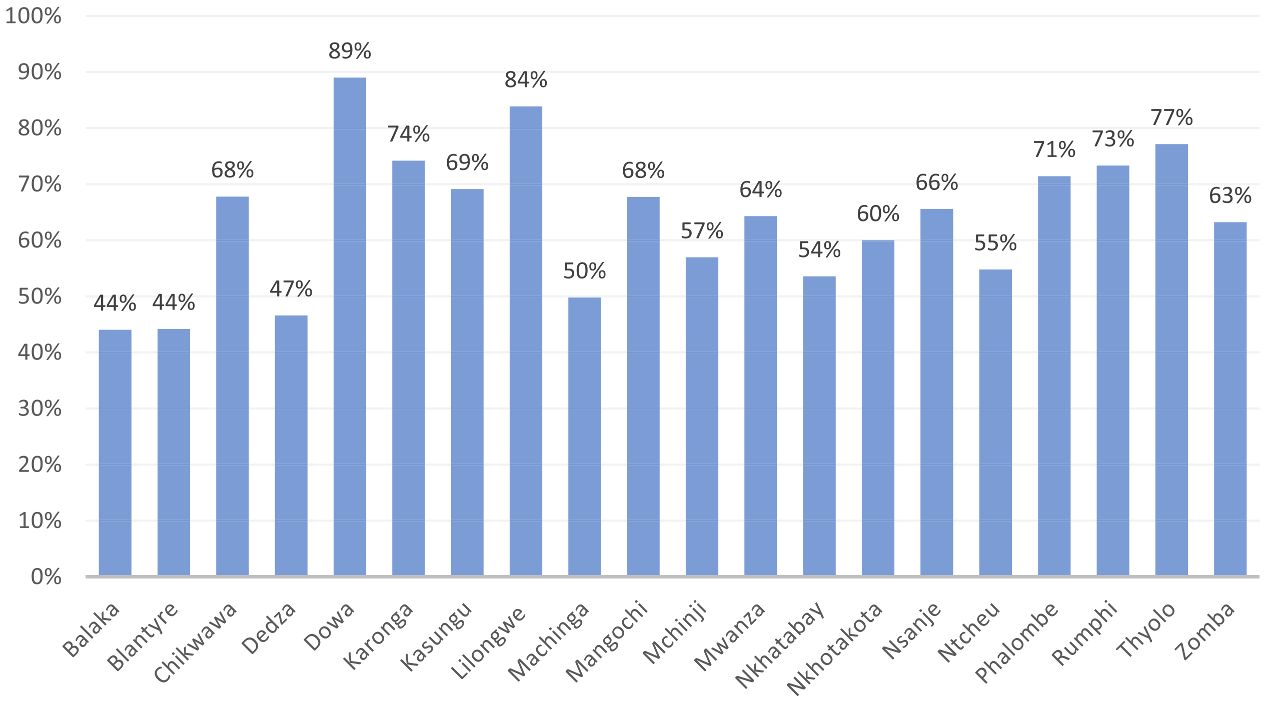

Fig. 4 Average post-harvest loss across districts

district-level heterogeneity of the effectiveness of ASPs and household interaction of such ASPs.

On average, 55% of households reported post-harvest losses across the study area, while 69% had interactions with ASPs through the SANE project. The average age of respondents was 42 years, while 83% of households are headed by males. Only 15% of household heads attained high school education, and 65% of respondents were married. The average household size was five.

Figure 4 shows district-level heterogeneities in terms of post-harvest losses, with Dowa, Lilongwe, Thyolo, and Karonga districts having the highest rates at 89%, 84%, 77% and 74%, respectively, while Balaka and Blantyre had the lowest rates at 44% each (Fig. 4). Such differences show that post-harvest loss constitutes a serious problem in Malawi and further reinforces the need for an analysis of post-harvest loss reduction as a function of extension programs like the ASP approach that was targeted to address such problems in Malawi.

Summary statistics conditional on farmer interaction with ASPs

Table 2 provides summary statistics, conditional on farmer interaction with functional ASPs through the SANE project. There are statistically significant differences between our treatment and control group in terms of the outcome variable (post-harvest losses). Households that had interactions with ASPs had lower post-harvest losses than other households (with a statistically difference of 18%). This indicates that the ASP approach helped to reduce post-harvest losses in the project area. There are also statistically significant differences between the treatment and control households in terms of other important variables like the average educational level of the household head (in terms of high school completion rates), household size, market constraints, fertilizer constraints, and off-farm income. For instance, the average level of education was slightly lower for households that had interactions with the project ASPs than other households with a difference of 6%. Likewise, households in the control area had higher constraints in terms of access to markets and fertilizer. These differences may have shaped the program targeting and participation across the country, and, therefore, requires the use of rigorous analytical techniques for understanding the effects of the ASP approach.

Failure to account for those differences can bias our estimates of the effects of the ASP approach on post-harvest loss in this context. Thus, we apply an RBP model as our main analytical technique to account for such differences, and thereby, enhance credible estimates of the effects of functional ASPs on post-harvest loss reduction in rural Malawi.

Table 2 Summary statistics, conditional on farmer interaction with ASPs

Variable	**Control**		**Treatment**		
	Mean	**SD**	**Mean**	**SD**	**Difference**
Post-harvest loss (1/0)	0.714	0.453	0.536	0.499	0.179***
Age	41.908	14.521	42.448	15.835	−0.54
Male-headed household	0.816	0.388	0.826	0.379	−0.01
High school plus	0.204	0.404	0.147	0.354	0.057**
Married	0.634	0.483	0.647	0.478	−0.01
Household size	5.648	2.113	5.307	2.025	0.341**
Number of adults per household	2.296	0.974	2.182	0.933	0.11
Credit constraint	0.474	0.501	0.490	0.500	−0.02
Livestock ownership	0.066	0.249	0.077	0.267	−0.01
Market constraints	0.791	0.408	0.675	0.469	0.116***
Fertilizer constraint	0.474	0.501	0.381	0.486	0.093**
Off-farm income	0.066	0.249	0.027	0.162	0.039***
Distance to markets	180.186	540.393	239.165	618.960	−58.98
Transportation constraint	0.184	0.388	0.190	0.393	−0.01
Storage constraint	0.352	0.479	0.290	0.454	0.062*
Farmer field day	0.698	0.461	0.638	0.481	0.06
Multiple EAS sources	0.010	0.101	0.010	0.101	0.00
Feed the Future Area dummy	0.148	0.356	0.858	0.350	−0.710***
Farmer-to-farmer extension	0.216	0.413	0.145	0.352	0.071**
Districts					
Balaka	0.000	0.000	0.058	0.235	−0.058***
Blantyre	0.000	0.000	0.090	0.287	−0.090***
Chikwawa	0.000	0.000	0.063	0.242	−0.063***
Dedza	0.000	0.000	0.085	0.279	−0.085***
Lilongwe	0.000	0.000	0.173	0.378	−0.173***
Machinga	0.000	0.000	0.129	0.336	−0.129***
Mangochi	0.000	0.000	0.086	0.280	−0.086***
Mchinji	0.134	0.342	0.066	0.249	0.068***
Nsanje	0.000	0.000	0.033	0.180	−0.033***
Ntcheu	0.000	0.000	0.062	0.241	−0.062***
Dowa	0.273	0.447	0.011	0.104	0.262***
Karonga	0.060	0.238	0.011	0.107	0.049***
Kasungu	0.185	0.389	0.018	0.132	0.167***
Mwanza	0.005	0.068	0.007	0.085	0.00
Nkhatabay	0.083	0.277	0.011	0.104	0.072***
Nkhotakota	0.000	0.000	0.009	0.094	−0.01
Phalombe	0.046	0.211	0.022	0.148	0.024**
Rumphi	0.051	0.220	0.007	0.085	0.044***
Thyolo	0.162	0.369	0.019	0.136	0.143***
Zomba	0.000	0.000	0.038	0.191	−0.038***

ASP Agricultural Stakeholder Panel, *EAS* Extension and Advisory Services, *SD* Standard Deviation, Number of observations for all variables, 2050

Table 3 Main estimates of the effects of ASPs and covariates on post-harvest loss reduction in Malawi

Variable	Coef	SE	*P* value	ME	Std. Err	*P* value
Interaction with ASPs	−1.654**	0.750	0.027	−0.525**	0.249	0.035
Age	0.004	0.003	0.199	0.001	0.001	0.196
Male-headed household	0.103	0.162	0.523	0.033	0.051	0.521
High school plus	0.072	0.130	0.579	0.023	0.041	0.579
Married	−0.076	0.109	0.485	−0.024	0.035	0.485
Household size	−0.027	0.026	0.304	−0.009	0.008	0.308
Number of adults per household	0.074	0.056	0.189	0.024	0.018	0.190
Farmer field day	−0.267***	0.099	0.007	−0.085***	0.031	0.006
Multiple EAS sources	0.238	0.456	0.602	0.075	0.145	0.602
Credit constraint	0.124	0.090	0.170	0.039	0.029	0.171
Livestock ownership	0.070	0.145	0.627	0.022	0.046	0.627
Market constraints	0.580***	0.105	0.000	0.184***	0.031	0.000
Fertilizer constraint	0.407***	0.114	0.000	0.129***	0.034	0.000
Off-farm income	0.141	0.276	0.610	0.045	0.087	0.607
Distance to markets	0.000	0.000	0.128	0.000	0.000	0.126
Transportation constraint	0.310***	0.099	0.002	0.098***	0.031	0.001
Storage constraint	0.156*	0.091	0.088	0.049*	0.029	0.086
Balaka	−0.512*	0.286	0.074	−0.162*	0.091	0.073
Blantyre	−0.215**	0.120	0.038	−0.068***	0.006	0.001
Chikwawa	−0.393***	0.116	0.002	−0.125**	0.062	0.037
Dedza	−0.404	0.260	0.120	−0.128	0.082	0.118
Lilongwe	−0.482**	0.246	0.050	−0.153**	0.078	0.050
Machinga	−0.286**	0.142	0.041	−0.091***	0.017	0.004
Mangochi	0.461	0.281	0.101	0.146	0.089	0.100
Mchinji	−0.191***	0.038	0.006	−0.061***	0.021	0.009
Nsanje	−0.420**	0.205	0.032	−0.133**	0.064	0.032
Ntcheu	−0.078**	0.043	0.049	−0.025*	0.013	0.071
Dowa	−1.337*	0.739	0.070	−0.424**	0.215	0.041
Karonga	−1.374***	0.760	0.000	−0.388***	0.220	0.000
Kasungu	−0.056	1.191	0.962	−0.018	0.379	0.962
Mwanza	0.319	0.579	0.582	0.101	0.183	0.580
Nkhatabay	−0.874*	0.497	0.079	−0.278*	0.160	0.082
Nkhotakota	−0.519	0.644	0.420	−0.165	0.204	0.420
Phalombe	−0.200	0.392	0.611	−0.063	0.125	0.613
Rumphi	−0.550**	2.239	0.042	−0.444**	0.680	0.034
Thyolo	−0.389	0.772	0.615	−0.123	0.248	0.618
Constant	1.093	0.971	0.260			
Wald Chi-Square	549.76***		0.000			
Log Pseudoliklihood	−989.58***		0.000			
rho	0.438**	0.151	0.021			
Wald test of rho = 0	6.318***		0.012			

Zomba is the base category district; SE, Standard Error; Asterisks ***, **, *, significance at the 1%, 5%, and 10% levels, respectively

Results and discussion

Main results: impact of ASP functionality on post-harvest losses

We present the main findings of our empirical analysis of the effects of ASP approach on the reduction of post-harvest losses in Malawi. The fifth column of Table 3 shows the marginal effects of our treatment variable—ASPs along with a set of control variables including household demographic, socioeconomic and institutional variables such as farmer field days and contacts with multiple extension and advisory services (EAS) as well as biophysical factors such as distance to a market, transportation constraints, and district dummy variables to account for time-invariant heterogeneity across districts in the study area.

We found a negative and statistically significant effect of ASPs on post-harvest losses, with effects of 53% (Table 3). This result implies that households that are associated with functional ASPs through the SANE project experienced a 53% reduction in self-reported post-harvest losses compared to other households. Our result supports our hypothesis that ASPs can reduce post-harvest losses in Malawi.

In addition to interaction with ASPs, we also found that participation in farmer field days (a forum where farmers are often organized to view demonstrations from local extension agents) had a significant effect on post-harvest loss reduction by 9%. While more research would be needed to unpack the actual effects of participation in farmer field days across Malawi and other context, our results suggests that improving participatory extension services in rural communities can significantly improve food security outcomes, such as reduction of post-harvest losses.

As expected, we found that weak socioeconomic and institutional factors such as credit constraints, market constraints, fertilizer constraints, transportation constraints, and storage constraints worsened the problem of post-harvest losses among households in the study area. Specifically, credit constraints, market constraints, fertilizer constraints, transportation constraints, and storage constraints increased post-harvest losses by 4%, 18%, 13%, 10%, and 5%, respectively.

These results underscore the relevance of addressing resource constraints not only to enhance agricultural productivity in rural communities but also to minimize food security outcomes like post-harvest losses at the household level. Our results imply that to sustainably improve food security outcomes associated with ASPs in Malawi, the government of Malawi and its development partners should reduce those factors that increase post-harvest losses such as credit constraint, market constraints, and transportation constraints in the farming systems of the rural communities. This result is consistent with previous studies in Malawi [4, 10, 17, 31] and elsewhere [1, 2, 52, 67, 68].

We also found significant district-level effects on post-harvest loss reduction across the ZOI districts (i.e., Balaka, Blantyre, Chikwawa, Dedza, Lilongwe, Machinga, Mangochi, Mchinji, Nsanje, Ntcheu) with all of them having statistically significant negative effects on post-harvest losses compared to other districts. This implies that households in the ZOI districts experienced significant reduction of post-harvest lasses as a result of their interaction with ASPs across their communities—a result that is consistent with Álvarez-Mingote et al. [4] in support of the role of the agricultural platforms in improving crucial development outcomes in Malawi.

At the lower end of Table 3, there are statistically significant results for the various diagnostics tests such as the Wald Chi-square test, Log Pseudolikelihood, and rho (the measure of correlation between unobservable factors associated with ASP and post-harvest losses). These results indicate both a good model fit and the presence of unobservable factors in the determinant of ASP functionality and post-harvest loss reduction in this context. Specifically, the statistically significant Wald-Chi-squared estimate suggests that the model fits the data very well, while the statistically significant rho value, which is statistically significant at the 5% level, shows that unobservable factors influenced ASP functionality, which could have biased our impact assessment estimates if we had relied on our other methods, such as OLS or PSM. Likewise, the statistically significant estimates and the Wald test of rho overwhelmingly rejects the null hypothesis that farmer interaction with functional ASPs and the effects of the ASPs on post-harvest loss reduction are uncorrelated, further justifying our use of the RBP model as our main analytical approach.

Discussion and implications

There are several implications of our results. First, our results show that improving agricultural and nutrition extension systems at the local and national levels in Malawi can significantly enhance the reduction of post-harvest losses—a critical constraint to food security in Malawi and elsewhere in SSA [17, 20, 73, 74]. Being a drought and flood prone country, any policy that reduces Malawi's post-harvest loss situation is especially vital for stimulating rural development in terms of food and nutrition security, which are crucial aspects of development policy implementation in the country [17, 20].

Moreover, studies show that addressing such a critical constraint requires broader efforts beyond the farm-level of smallholder agricultural households [74–76]. Therefore, improving rural extension systems using ASPs (and similar demand-side extension governance efforts) that empower farmers with better access to improved extension systems is a crucial first step in the right direction towards food and nutrition security in low-income countries like Malawi [77, 78].

Furthermore, our results show that innovative extension policies such as the ASP approach can serve as vital channels through which rural households can be empowered with the right tools to aid their recovery from chronic food insecurity conditions through food waste due to post-harvest losses [77, 79–81]. Strengthening the rural extension systems can, therefore, can have significant effects on the productive capacities of rural households in Malawi and elsewhere [66, 82–84]. For example, ASPs can serve as platforms for farmer-to-farmer and farmer-extension agents' interaction, which can yield benefits like information on the adoption of critical agricultural productivity techniques, such as climate smart and resilient agriculture [11, 70, 85, 86], crop and dietary diversity [66, 87], and better food storage systems [20, 60, 88], thereby increasing households' nutritional outcomes [4, 64, 81, 89]. Therefore, this study is crucial for stimulating significant food policy debates around the development of sustainable pathways that can help empower rural households to tackle the critical issues of food and nutritional deficiency in their communities.

The statistically significant findings of market and credit constraints underscore the persistent problem of resource constraints in rural areas not just in Malawi but elsewhere in SSA and beyond. As such, the use of innovative extension programs such as the ASP approach can help to ameliorate such development constraints and thereby enhance food security in Malawi and similar contexts elsewhere [86, 90]. Improving rural extension systems through innovative approaches such as ASPs can help shed light on such important issues and contribute to vital institutional development as well as food and nutrition security policies in rural Malawi and beyond. Further, local extension agents in rural communities can use the ASP approach to scale up rural extension outreach to poor farmers in diverse areas of Malawi and thereby enhance the sustainability of development programs such as post-harvest loss reduction in the country.

Robustness checks

To check the robustness of our main estimates, we ran several robustness checks. First, we reran the main RBP model with only one IV, to determine if the results would be significantly different. The result shows that ASP functionality reduced post-harvest losses by 49% (Table 5), and thereby supports our main estimate. Moreover, we re-ran the main RBP model without district dummy variables to determine if a lack of variation across districts variation can adversely affect our main estimates. The results have the expected sign for the effect of ASPs on post-harvest loss reduction in supports of our main estimates, albeit at lower magnitudes (Table 6).

Furthermore, we ran an ordinary probit regression, which does not account for unobserved heterogeneity and endogeneity to determine the extent at which we might have underestimated the effect of the ASP approach on post-harvest loss reduction. The result shows that ASP functionality reduced post-harvest losses—in support of our main estimates (Table 7). The lower probit estimates, suggest that unobserved factors influenced ASP functionality, which would have significantly biased our results, and therefore, justify our use of an RBP regression, which captures such unobservable factors in estimating the effects of a treatment such as ASPs on outcomes such as post-harvest losses.

Limitation and recommendations for future research

Although our analytical techniques and our robustness suggests that our estimation result are quite robust, we are careful to note that our study may have some limitations, which we herein discuss and provide potential recommendations for improvement. First, the study utilized cross-sectional data, which limits our ability to adequately address all potential endogeneity-related issues in our study. Future research using panel data from Malawi or similar contexts elsewhere can provide more rigorous estimates of the impacts of the ASP approach on post-harvest losses in Malawi and elsewhere. Another limitation of this study is its reliance on households' self-reported measure of post-harvest loses and their interaction with extension agents associated with ASPs. Self-reported data is often fraught with errors, which can be overcome by the use of more nuanced measurements of core variables associated with post-harvest losses and ASPs in Malawi. Therefore, future research on the effectiveness of the ASP approach on post-harvest loss reduction should conduct more detailed measurements of the key socioeconomic and institutional variables credit constraints, transportation constraints, market constraints, and storage constraints to obtain more rigorous estimates.

Conclusion

We have estimated the effects of agricultural stakeholder panels (ASPs) on post-harvest loss reduction in Malawi. The ASP approach was implemented through the Strengthening Agricultural and Nutrition Extension (SANE) activity, a $10 million investment by the US Agency for International Development in Malawi from 2015 to 2021. The goal of SANE was to improve smallholder farmer access to effective extension services, to improve accountability of extension agents, and thereby enhance agricultural productivity, incomes, and nutritional outcomes such as post-harvest loss reduction in the country. SANE provided technical assistance to the Government of Malawi's District Agricultural Extension Services System (DAESS) to enhance effective resource mobilization and better coordination among service providers, and thereby help to achieve efficient extension service delivery in the country.

SANE worked in alignment with the core principles of Malawi's national agricultural extension policy through DAESS to enhance demand-driven and decentralized extension services, accountability to stakeholders, and sustainable resource management through a stakeholder-driven framework. In so doing, SANE helped improve the national extension system in Malawi by strengthening the DAESS to be effective and efficient in its functionality through the establishment and operations of ASPs across the rural communities in specific districts. Yet, there was a gap in terms of rigorous analysis that determine the effectiveness of the ASP approach in achieving critical outcomes, such as post-harvest loss reduction. To address this gap, we used primary survey data collected from 2134 households in 20 districts across Malawi in 2018 to estimate the impacts of the ASP approach on post-harvest loss reduction—a crucial food security outcome in Malawi and elsewhere in developing countries. We utilized recursive bivariate probit regression to account for the endogeneity of farmers' interaction with extension agents associated with ASPs under the SANE project and the potential selection bias in the effects ASPs on post-harvest reduction in the study area.

We found that the ASP approach reduced post-harvest losses by 53%: a significant indicator of the potential for the approach to enhance food security in Malawi. We contribute to the literature on agriculture and food security by highlighting the important role of the ASP approach as an innovative extension program that can induce agricultural development in Malawi. Our study also provides empirical evidence of the importance of such funding streams towards rural extension systems, which can provide a pathway for rural transformation in Malawi and elsewhere in SSA. Additionally, we contribute to food and nutrition security debates in SSA and other developing regions by highlighting the continued existence of institutional factors such as credit constraints, market constraints, and transportation constraints as crucial impediments to food security outcomes, such as post-harvest loss reduction in Malawi.

Further research using panel data from the SANE area in Malawi and elsewhere can provide better insights on the long-term impacts of the ASP approach on post-harvest loss reduction and other food security outcomes in Malawi. Moreover, nuanced measurements of post-harvest loss reduction beyond household self-reported data can provide rigorous estimates of post-harvest loss reduction attributable to the ASP approach and thereby, enhance food security and rural development in Malawi, similar contexts elsewhere, and beyond.

Appendix

See Tables 4, 5, 6, 7.

Table 4 Falsification test for the validity of the instrumental variables

	ASP functionality index				Post-harvest (outcome)			
Variable	Coefficient	SE	*Z*-stats	*P* > *z*	Coef	SE	*Z*-stats	*P* > *z*
Farmer-to-farmer extension	− 0.243*	0.146	− 1.660	0.096	0.167	0.340	0.490	0.623
Feed the Future Area dummy	1.578***	0.117	13.470	0.000	0.326	0.364	0.900	0.370
Constant	0.466***	0.083	5.630	0.000	0.757***	0.159	4.770	0.000

SE Standard error; Asterisks ***, *, Significance at the 1% and 10% levels, respectively

Table 5 Main RBP model with only one instrumental variable

Variable	Coef	Std. Err	*P*-value	ME	Std. Err	*P*-value
Interaction with ASPs	−1.555**	0.738	0.035	−0.492**	0.242	0.042
Age	0.004	0.003	0.193	0.001	0.001	0.191
Male-headed household	0.112	0.157	0.475	0.036	0.049	0.473
High school plus	0.068	0.131	0.605	0.021	0.041	0.605
Married	−0.077	0.110	0.483	−0.024	0.035	0.483
Household size	−0.026	0.026	0.321	−0.008	0.008	0.323
Number of adults per household	0.073	0.057	0.196	0.023	0.018	0.196
Farmer field day	−0.265***	0.099	0.008	−0.08***	0.031	0.007
Multiple EAS sources	0.222	0.459	0.629	0.070	0.145	0.628
Credit constraint	0.122**	0.061	0.043	0.039**	0.013	0.027
Livestock ownership	0.072	0.145	0.618	0.023	0.046	0.618
Market constraints	0.586***	0.105	0.000	0.186***	0.031	0.000
Fertilizer constraint	0.415***	0.105	0.000	0.131***	0.031	0.000
Off-farm income	0.158	0.263	0.548	0.050	0.083	0.545
Distance to markets	0.000	0.000	0.122	0.000	0.000	0.120
Transportation constraint	0.312***	0.099	0.002	0.099***	0.031	0.001
Storage constraint	0.156*	0.092	0.088	0.050*	0.029	0.086
Balaka	−0.505*	0.287	0.078	−0.160*	0.091	0.077
Blantyre	−0.214**	0.170	0.029	−0.068**	0.035	0.048
Chikwawa	−0.394**	0.196	0.047	−0.125**	0.064	0.039
Dedza	−0.404	0.260	0.120	−0.128	0.082	0.119
Lilongwe	−0.482**	0.246	0.050	−0.153**	0.078	0.050
Machinga	−0.280**	0.148	0.048	−0.089**	0.038	0.043
Mangochi	−0.469*	0.282	0.096	−0.149*	0.089	0.095
Mchinji	−0.166***	0.039	0.010	−0.052**	0.025	0.038
Nsanje	−0.418***	0.061	0.006	−0.132**	0.064	0.043
Ntcheu	−0.079*	0.053	0.787	−0.025**	0.012	0.047
Dowa	−1.244*	0.714	0.081	−0.394*	0.232	0.090
Karonga	4.374**	1.853	0.018	1.385**	0.563	0.014
Kasungu	0.069	1.051	0.948	0.022	0.332	0.948
Mwanza	0.362	0.575	0.529	0.115	0.181	0.527
Nkhatabay	−0.848	0.520	0.103	−0.268	0.167	0.107
Nkhotakota	−0.522	0.644	0.417	−0.165	0.204	0.417
Phalombe	−0.172	0.393	0.662	−0.054	0.125	0.664
Rumphi	4.550	3.217	0.157	1.441	0.993	0.147
Thyolo	−0.310	0.683	0.650	−0.098	0.218	0.652
Constant	0.969	0.931	0.298			
Wald Chi-Square	7294.9***		0.000			
Log Pseudolikelihood	−989.58***		0.000			
rho	−715.81**	0.151	0.021			
Wald test of rho = 0	0.798***		0.010			

Zomba is the base district category; *SE* Standard Error, *ME* Marginal Effects; Asterisks ***, **, *, Significance at 1%, 5%, and 10% levels, respectively

Table 6 RBP estimates of the without district dummy variables

Variable	Main estimate with both IVs			Main estimate with one IV		
	Coef	Std. Err	*P*-value	Marginal effects	Std. Err	*P*-value
Interaction with ASPs	−0.235**	0.101	0.020	−0.230**	0.101	0.023
Age of household head	0.001	0.001	0.234	0.001	0.001	0.236
Male-headed households	0.046	0.050	0.367	0.046	0.051	0.366
High school plus	0.026	0.043	0.540	0.026	0.043	0.545
Married	−0.024	0.036	0.498	−0.025	0.036	0.497
Household size	−0.004	0.008	0.601	−0.004	0.008	0.602
Number of adults per household	0.028	0.019	0.126	0.029	0.019	0.125
Farmer filed days	−0.105***	0.031	0.001	−0.105***	0.031	0.001
Multiple EAS sources	0.106	0.169	0.529	0.106	0.169	0.531
Credit constraint	0.031	0.029	0.290	0.031	0.029	0.292
Livestock ownership	0.011	0.046	0.805	0.011	0.046	0.807
Market constraints	0.209***	0.032	0.000	0.210***	0.032	0.000
Fertilizer constraints	0.161***	0.028	0.000	0.161***	0.028	0.000
Off-farm income	0.083	0.075	0.267	0.084	0.075	0.264
Distance to the nearest market	0.000	0.000	0.310	0.000	0.000	0.312
Transportation constraint	0.084***	0.032	0.008	0.084***	0.032	0.008
Storage constraints	0.053*	0.030	0.071	0.054*	0.030	0.069
Regression diagnostics						
Number of observations	1044			1044		
Wald Chi-Square	368.91***		0.000	367.27***		0.000
Log Pseudolikelihood	−826.431			−825.934		
rho	0.812***	0.101		0.788***	0.121	
Wald test of rho = 0	1.952***		0.000	1.452***		0.000

SE Standard Error, *ME* Marginal Effects; Asterisks ***, **, *, Significance at 1%, 5%, and 10% levels, respectively

Table 7 Ordinary probit regression model

Variable	Coef	Std. Err	*P*-value	ME	SE	*P*>*z*
Interaction with ASPs	−0.419**	0.158	0.008	−0.140***	0.053	0.008
Age of household head	0.003	0.003	0.259	0.001	0.001	0.259
Male-headed households	0.139	0.155	0.371	0.047	0.052	0.370
High school plus	0.064	0.128	0.614	0.022	0.043	0.614
Married	−0.071	0.109	0.512	−0.024	0.036	0.512
Household size	−0.011	0.024	0.657	−0.004	0.008	0.657
Number of adults per household	0.087	0.055	0.113	0.029	0.018	0.112
Farmer filed days	−0.309***	0.094	0.001	−0.104***	0.031	0.001
Multiple EAS sources	0.302	0.466	0.517	0.101	0.156	0.517
Credit constraint	0.086	0.089	0.333	0.029	0.030	0.333
Livestock ownership	0.031	0.138	0.820	0.011	0.046	0.820
Market constraints	0.639***	0.098	0.000	0.214***	0.031	0.000
Fertilizer constraints	0.492***	0.085	0.000	0.165***	0.027	0.000
Off-farm income	0.280	0.228	0.220	0.094	0.076	0.219
Distance to the nearest market	0.000	0.000	0.347	0.000	0.000	0.347
Transportation constraint	0.251***	0.095	0.008	0.084***	0.031	0.008
Storage constraints	0.176**	0.089	0.047	0.059**	0.030	0.045
Constant	−0.401	0.265	0.131			
Regression diagnostics						
Number of observations	1044					
Likelihood ratio	147.53***		0.000			
Log Likelihood	−616.138					
Pseudo R2	0.1069					

SE Standard Error, *ME* Marginal Effects; Asterisks ***, **, Significance at 1% and 5%, levels, respectively. No of obs., 2050

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Author contributions
Paul McNamara received the funding and directed the research conceptualization and reviewed the data and manuscript. Festus Amadu managed data cleaning and analysis and wrote manuscript drafts and incorporated comments from co-author and other sources to produce a revised version of the manuscript for submission.

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Availability of data and materials
Data will be available upon request.

Declarations

Ethics approval and consent to participate
Note applicable.

Consent for publication
Both authors agree to publish this work in the Journal Agriculture and Food Security

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None. The authors declare that they have no conflicts of interests.

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