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An act of defiance? Measuring farmer deviation from personalised extension recommendations in Zambia

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Abstract

Given the recognised role of blanket extension advice in the low uptake of productivity-enhancing technologies among developing country farmers, personalised or site-specific extension approaches are gaining attention. Focusing on the case of the plant clinic extension model which provides personalised crop protection services to smallholder farmers, we investigate to what extent and how accurately farmers adopt personalised extension advice, and the implications for agricultural productivity. We combine a unique database of personalised integrated pest management (IPM) recommendations provided to 420 plant clinic attendees in Zambia with survey data on the actual IPM practices implemented by these same clinic attendees. We find that more than 80% of the sample farmers deviated from the personalised IPM recommendations they received from plant clinics. Based on the degree of deviation from the personalised recommendations, we identify five categories of adopters of IPM practices and show their heterogeneous effects on maize productivity. For example, our multi-valued treatment effect estimates suggest an 82% yield penalty for non-adopters compared to full adopters of recommended IPM practices, while the yield gain for full adopters is more than double that of partial adopters, as well as that of those who adopted additional practices beyond what was recommended. Our findings have important implications for the promotion

of personalised extension services and for the measurement of the impact of complex agricultural technologies.

KEYWORDS

integrated pest management, maize productivity, personalised extension services, plant clinics, technology adoption, Zambia

JEL CLASSIFICATION

C21; D13; O13; Q12; Q16

1 | INTRODUCTION

The role of agricultural extension in information and knowledge transfer, technology diffusion and agricultural development has long been recognised (Anderson & Feder, 2007). Several studies have shown that extension services promote the adoption of agricultural technologies and practices, which are in turn associated with increased productivity, higher incomes, improved food and nutrition security, poverty alleviation and environmental benefits (Fabregas et al., 2019; Lambrecht et al., 2016; Pan et al., 2018; Piñeiro et al., 2020; Tambo et al., 2020a; Waddington et al., 2014). Thus, enhancing farmers' access to extension services can contribute to the achievement of several of the sustainable development goals (SDGs), particularly those related to poverty (SDG 1) and hunger (SDG 2).

Unfortunately, the adoption of extension-recommended practices and inputs remains low in many sub-Saharan African countries (Aker, 2011; Sheahan & Barret, 2017). This is especially true for complex and knowledge-intensive technology packages such as conservation agriculture (CA) (Arslan et al., 2014); integrated pest management (IPM) (Parsa et al., 2014); and integrated soil fertility management (ISFM) (Lambrecht et al., 2016). Among the barriers to adopting these practices are top-down extension delivery systems and the provision of general blanket recommendations (Norton & Alwang, 2020). Smallholder farming in sub-Saharan Africa (SSA) is conducted in heterogeneous contexts, requiring customised rather than generalised extension recommendations. Personalised extension services, in which recommendations are tailored to individual farmers or farm-specific conditions, provide a solution to this shortcoming. In the area of plant health, a promising model for providing personalised extension services is the provision of plant clinics, which is the focus of this study.

Plant clinics are a novel approach to providing plant health diagnostic and advisory services to smallholder farmers worldwide. At plant clinics, farmers facing pest problems can bring samples of infested crops and consult plant doctors (specially trained extension agents), who will diagnose the problem and give science-based recommendations following IPM principles.[1] Plant doctors consult the farmer on the extent and severity of pest attack and adapt their recommendations accordingly. For example, they may recommend monitoring and handpicking of pest at low levels of infestation or pesticide use at high levels of infestation; and the recommendations should be effective, safe and practical, as well as reflect the plant doctors' understanding of the farmers' conditions. Thus, plant clinics provide one-on-one personalised advisory services in response to farmers' queries on plant health, similar to the approach of human health clinics. It is expected that the plant clinic model of delivering personalised extension services will promote farmers' adoption of recommended technologies and practices because the plant doctors respond directly to the specific plant health needs of the clinic

[1]IPM aims to minimise reliance on synthetic pesticides by encouraging the use of a combination of sustainable pest control practices, including intensive monitoring, resistant varieties, biological control, cultural control and mechanical control.

attendees. In this article, we examine how accurately plant clinic users in Zambia adopt the personalised extension recommendations provided by plant clinics, and the implications for agricultural productivity. To this end, records on pest management recommendations provided by plant doctors to 420 individual maize farmers are compared with survey data on the pest management practices adopted by the same farmers.

We make several contributions to the agricultural extension and technology adoption literature. First, despite the recognition that technology adoption is a multistage process with heterogeneous adopter groups, adoption is often modelled in the literature as a binary decision (adoption versus non-adoption) (Pannell & Claassen, 2020; Weersink & Fulton, 2020). In this study, we specify a typology of adopters based on the extent to which plant clinic users deviate from personalised extension advice provided by plant doctors. In particular, we distinguish between (1) non-adopters (did not implement any of the recommended practices); (2) 'non-adopters+' (non-adopters who at least applied some non-recommended practices); (3) partial adopters (implemented components of recommended practices); (4) full adopters (implemented the practices exactly as recommended); and (5) innovators (implemented additional practices beyond what was recommended). In addition, we analyse the factors determining these adoption practices.

Second, there is an extensive literature on the impact of agricultural extension recommendations (for reviews, see Birkhaeuser et al., 1991; Anderson & Feder, 2007; Waddington et al., 2014; Pan et al., 2018); however, most of the existing studies rely solely on farmers' self-reported information on whether and to what extent they have adopted recommended practices, without considering how accurately the recommendations were adopted. Failure to align the adopted recommendations with the precise recommendations provided by extension services may mask important information about adoption heterogeneity and could lead to measurement errors (misreporting bias), which is not a trivial issue in self-reported survey data (Abay et al., 2020; Floro IV et al., 2017; Wineman et al., 2020; Wossen et al., 2019). Using matched data on the specific recommendations given by plant doctors to farmers and the farmers' adoption choices present an opportunity to mitigate this potential misreporting bias that may exist in extension impact studies.

Third, we add to the limited empirical evidence on personalised extension services, rather than the often-studied conventional extension services that are usually characterised by blanket recommendations. Previous works in this area include field-specific soil nutrient management advice using decision support tools (Arouna et al., 2020; Oyinbo et al., 2020) and farmer-specific pest diagnostics and recommendations provided by plant clinics (Silvestri et al., 2019; Tambo et al., 2021). We extend the scope of these previous studies by investigating the heterogeneous deviations from personalised extension recommendations.

Finally, we analyse extension advice and farmers' management strategies for fall armyworm (FAW), *Spodoptera frugiperda*, which is a major threat to maize production and food security in Africa and Asia. Native to north and south America, the invasive FAW pest was first detected in West Africa in 2016 and has since spread rapidly across over 60 countries in Africa and Asia (CABI, 2020). According to an estimate by Rwomushana et al. (2018), for 12 maize-producing countries in Africa alone, the pest has the potential to cause annual losses of up to 17.7 million tonnes of maize, if left uncontrolled. Moreover, the severe damage caused by FAW has led to increased use of synthetic pesticides, which can pose a serious risk to human and environmental health (Tambo et al., 2020b). Hence, understanding the extent to which Zambian farmers are adhering to plant doctors' advice on IPM for FAW control is relevant for policies aimed at promoting sustainable pest management in smallholder farming systems.

It should be emphasised that our sample consists of only plant clinic users, as we were particularly interested in measuring the extent of clinic users' deviations from the personalised IPM recommendations they received from plant clinics and the associated implications. Hence, our study cannot examine who uses plant clinic services, the benefits of plant clinics for the communities where they are situated, or how clinic non-users have been managing FAW. This limits the generality of our findings. Nonetheless, our data can be considered representative of Zambian clinic users in major maize-producing provinces with high incidence of FAW, and are useful for evaluating farmer deviations from personalised extension recommendations.

The remainder of the paper proceeds as follows. Section 2 provides a brief discussion on the plant clinic approach to delivering personalised extension services. Section 3 presents the data sources and sample characteristics, and Section 4 describes the empirical models. Section 5 presents and discusses the empirical results. Section 6 concludes and provides some policy implications.

2 | THE PLANT CLINIC MODEL OF PERSONALISED EXTENSION DELIVERY

The use of plant clinics to provide personalised plant health advisory services to smallholder farmers first began in Bolivia in 2003 (Boa, 2009). The introduction of the Plantwise programme in 2011 by the Centre for Agriculture and Biosciences International (CABI) has promoted the application of the plant clinic extension model worldwide. The Plantwise programme aims at helping farmers reduce crop loss from pests and diseases, thereby contributing to increased agricultural productivity and food security. The programme has supported the establishment of over 4500 plant clinics and the training of nearly 11,500 plant doctors in 34 countries across Africa, Asia and the Americas (CABI, 2020). These plant clinics are operated by several institutions, including district local governments, farmer organizations, ministries of agriculture, non-governmental organizations, and academic and research institutions.

The Plantwise programme, in conjunction with national partners, launched the plant clinic extension initiative in Zambia in 2013. So far, around 120 plant clinics have been set up in 40 districts across the country's 10 provinces. Each of these plant clinics are typically manned by two plant doctors, who are local extension workers trained by the Plantwise programme in visual pest diagnosis and how to run a plant clinic and give good plant health advice. The plant clinic sessions are held on a regular basis (weekly or fortnightly) near easily accessible sites such as health posts, village centres, markets, schools and farmers' cooperative offices. A farmer can send a sample of any crop showing any plant health problem to the clinics, where a plant doctor will examine the sample, diagnose the problem and give actionable IPM-based advice free of charge. The plant doctors have access to reference books on pests and diseases, factsheets, diagnostic photosheets and the Plantwise Knowledge Bank (an online repository for pest information), which help them to provide accurate diagnostic and advisory services.[2] Since their establishment, the plant clinics in Zambia have attracted more than 12,000 farmers' queries on roughly 100 crops (POMS, 2020), signifying their importance in delivering plant health advice to farmers in the country.

Given the widespread use of the plant clinic extension model, there is a growing interest in understanding its impact on agricultural and welfare outcomes. For example, evidence from cross-sectional studies show that using plant clinic services is significantly associated with the adoption of clinics' recommendations and improved incomes in Bolivia (Bentley et al., 2011); increased adoption of IPM practices and higher maize productivity in Rwanda (Silvestri et al., 2019); and a reduction in household food insecurity in Rwanda (Tambo et al., 2021). Using a randomised control trial design, AIR (2018) found that plant clinics contribute to increased farmer productivity and incomes, and reduced use of pesticides in Kenya. A recent panel data analysis also suggests positive technology adoption, productivity and poverty reduction effects

[2]Note that, at times, the plant doctors may not be able to diagnose difficult or unfamiliar pest problems on the spot, in which case they refer the problems to other plant health experts, plant diagnosticians or laboratories.

of plant clinic participation in Rwanda (Tambo et al., 2020a). In the present paper, we extend these previous studies by exploring how and why farmers deviate from plant clinic recommendations, and the implications for maize yields and incomes.

3 | DATA

Our empirical analysis is based on data obtained from plant clinic records, plant clinic users and plant doctors for the 2018/2019 agricultural year in Zambia. An important feature of the plant clinic extension model is that the diagnosis and advice given to clinic attendees are documented. The plant doctors record the name, gender, location and contact details of each clinic attendee, sample brought to the clinic, symptoms of pest attack, the diagnosed plant health problem and recommendations on how to manage the problem. These data are captured on a paper or tablet-based prescription sheet, of which a copy is given to the clinic attendee or sent to his/her mobile phone via SMS. The data are instantly or eventually fed into the Plantwise Online Management System (POMS). For our analysis, we extracted from the POMS database information on the diagnosed pest problem, specific recommendations given to a farmer for managing the problem, the year the farmer first noticed the problem, and the farmer's self-reported pest infestation levels prior to visiting the plant clinic.

These POMS data on plant clinic users were supplemented with survey data collected for this study. A multi-level stratified sampling approach was used to select the surveyed plant clinic users. First, given that maize is the primary food crop in Zambia and has by far the highest number of plant clinic queries, the survey concentrated on maize farmers. In particular, we focused on maize farmers who had visited the plant clinics with symptoms of FAW, an important invasive pest that constituted over 80% of the queries on maize during the 2018/2019 agricultural season (POMS, 2020). In the second stage, the plant clinic users were stratified based on the core maize producing agro-ecological zones (AEZs) of Zambia, which are AEZ I, AEZ IIa and AEZ III (Figure A1, Appendix S1).[3,4] Six, twelve and seven plant clinic sites were selected from these three AEZs respectively, based on POMS data on the number of plant clinics that have recorded high incidence of FAW (at least 50 queries on FAW) in each AEZ. Then, in each selected plant clinic site, about 5% of the farmers who had attended the clinic with queries on FAW were randomly selected and interviewed. The POMS database was used to confirm that the selected clinic users had actually visited plant clinics in the past cropping season to seek advice related to FAW. Overall, our survey data comprise 420 clinic users operating 545 maize plots.

The survey data were collected between August and September 2019 by trained enumerators using tablet-based questionnaires. The questionnaires included modules on household demographic and wealth characteristics; maize production and decision-making; FAW incidence and management strategies; participation in plant clinics; and access to infrastructure and institutional support services. An analysis of data from the POMS database revealed that the 420 clinic users in our sample were attended to by 32 plant doctors. These plant doctors were subsequently interviewed via telephone to obtain information about their gender and work experience. Finally, plant clinic-level rainfall data for the 2018/2019 cropping season

[3]Zambia has four AEZs. AEZ I: low-rainfall area (annual rainfall <800 mm), hot and drought-prone region; AEZ IIa: soils and rainfall (800–1000 mm of rain/year) are more favourable for farming; AEZ IIb: sandy soils with 800–1000mm annual rainfall; AEZ III: high rainfall area (> 1000 mm of rain/year).

[4]The data cover seven (Central, Copperbelt, Eastern, Luapula, Lusaka, Muchinga and Northern) out of the country's ten provinces.

were extracted from the Climatology Resource for Agroclimatology database of the National Aeronautics and Space Administration (NASA).

Table 1 provides a list and summary statistics of the study variables. The study sample consists of smallholder farmers who cultivate less than two hectares of maize, on average. The average maize yield is about 1650 kg/ha, which is higher than the reported national average of roughly 1300 kg/ha for the 2018/2019 cropping season in Zambia (MoA, 2019). A typical clinic user in our sample is a middle-aged farmer with low level of education. Besides plant clinics, the majority of the farmers also use media and peers as sources of information on FAW. A clinic user must travel about 17 km to reach agro-dealers. Most of the farmers took FAW-infested samples to the plant clinics when they observed low to medium infestation levels. The mean level of experience of the sample plant doctors is 9 years, and nearly half of the plant doctors had interacted with clinic users of the same gender.

4 | METHOD

As previously mentioned, we propose a typology of plant clinic users on the basis of the extent of deviation from personalised extension advice. We do so by comparing clinic data on the personalised recommendations on FAW offered to a sample of clinic users with survey data on the actual recommendations implemented by these same clinic users. These results are presented descriptively. We then use econometric methods to analyse the determinants and productivity effects of the level of adoption of the personalised recommendations.

To explore the determinants of plant clinic users' adoption of or deviation from personalised IPM recommendations, we specify the following equation:

$$\boldsymbol{AC}_{ip} = \beta_0 + \beta_1 \boldsymbol{CU}_i + \beta_2 FS_i + \beta_3 \boldsymbol{PD}_i + \beta_4 \boldsymbol{A}_i + \mu_{ip} \tag{1}$$

The dependent variable, $\boldsymbol{AC}_{ip}$, measures the adopter category of a plant clinic user i on plot p. The adopter categories (which we present in the next section) are based on the degree of deviation from personalised IPM recommendations. The choice of covariates was guided by literature on the factors affecting IPM and agricultural technology adoption (e.g. Alwang et al., 2019; Midingoyi et al., 2019). $\boldsymbol{CU}$ captures plant clinic user characteristics, such as age, gender, education level, household size, asset wealth, access to off-farm opportunities, risk preference,[5] and access to FAW information through media and peers. FS measures a clinic user's self-assessed severity of FAW infestation (i.e., low, moderate or high infestation) prior to visiting a plant clinic. We hypothesise that high infestation levels may encourage the implementation of plant clinic recommendations. $\boldsymbol{PD}$ is a vector of plant doctor characteristics, which include the number of years of working experience as a plant doctor and as an extension agent. We also test whether farmers are more likely to adopt recommended practices when the advice is provided by extension agents of the same gender (i.e., gender homophily effect). Specifically, we construct a dummy variable that is equal to one if the advisor (plant doctor) and the recipient of the advice (clinic user) share the same gender. The hypothesis is that gender homophily can help build mutual understanding and trust, thereby influencing farmers' adoption choices (Lahai et al., 1999; Lecoutere et al., 2019). $\boldsymbol{A}$ is a vector of agro-climatic variables, which account for differences in growing conditions. It includes rainfall and agro-ecological location of a plant clinic user. The βs are the parameters to be estimated, and μ is the error term. We

[5]Following Dohmen et al. (2011), we applied a survey-based risk preference measure that ranges from 0 (not at all willing to take risks) to 10 (fully prepared to take risks). This measure is hypothetical, but it has been widely validated for the elicitation of an individual's risk preference (for a brief overview, see Roe, 2015). It has also been used by several studies (e.g., Tambo et al., 2020; Sellare et al., 2020) to measure the risk preferences of smallholder farmers in Africa, including Zambia.

TABLE 1 Definitions and summary statistics of study variables.

Variable	Description	Mean	SD
Outcome variables			
Maize yield	Quantity of maize harvested on plot (kg/ha)	1652.23	1734.09
Maize income	Net income from maize production (ZMW/ha)[a]	2833.09	3559.39
Plant doctor characteristics			
Gender homophily	The plant doctor and clinic user share the same gender (1/0)	0.49	0.50
Plant doctor experience	Years of experience as a plant doctor	3.16	1.62
Extension experience	Years of experience as an agricultural extension agent	8.73	4.90
Plant clinic user characteristics			
Age	Age of plant clinic user (years)	49.99	12.84
Gender	Gender of plant clinic user (1=male)	0.53	0.50
Education	Years of schooling of plant clinic user	7.95	3.21
Household size	Number of household members	7.24	2.90
Off-farm activity	Household member has off-farm job (1/0)	0.46	0.50
Asset index	Household asset index[b]	0.10	1.54
Risk attitude	Risk preference of clinic user (0–10)	5.83	3.09
Media information	Clinic user obtained FAW information from media (1/0)	0.62	0.49
Peer information	Clinic user obtained FAW information from peers (1/0)	0.71	0.45
Distance to agro-dealer	Distance from household to the nearest agro-dealer (km)	16.30	13.53
FAW experience	Years since clinic user first observed FAW on maize	1.78	1.05
Plot characteristics			
Maize area	Size of maize plot (ha)	1.42	2.03
Plot distance	Distance of plot from homestead (km)	1.74	3.57
Plot fertility	Soil quality is good (1/0)	0.36	0.48
Seed rate	Quantity of seed applied (kg/ha)	23.74	24.34
Fertiliser rate	Quantity of mineral fertiliser applied (kg/ha)	188.71	198.13
Manure use	Plot received manure (1/0)	0.21	0.41
Herbicide use	Plot received herbicide (1/0)	0.39	0.49
Hired labour use	Use of hired labour (1/0)	0.40	0.49
Low FAW infestation	Low FAW infestation prior to visiting plant clinic (1/0)	0.58	0.49
Moderate FAW infestation	Medium FAW infestation prior to visiting plant clinic (1/0)	0.31	0.46
High FAW infestation	High FAW infestation prior to visiting plant clinic (1/0)	0.11	0.31
Agro-climatic characteristics			

TABLE 1 (Continued)

Variable	Description	Mean	SD
Rainfall	Total rainfall during the past cropping season (mm)	907.22	292.56
AEZ I	Household is located in agro-ecological zone I	0.13	0.33
AEZ IIa	Household is located in agro-ecological zone IIa	0.48	0.50
AEZ III	Household is located in agro-ecological zone III	0.39	0.49
Observations	Number of clinic user (plot) observations	420 (545)	

[a]ZMW =Zambian Kwacha. At the time of the survey, 1 USD =13 ZMW.

[b]We used principal component analysis to construct the asset index, based on household ownership of 11 durable assets.

estimate Equation (1) using the multinomial logit (MNL) regression, given that the dependent variable (plant clinic users' adoption decisions) is an unordered categorical variable.

To examine the productivity outcomes of the clinic users' decisions to deviate from recommended practices, the following equation is used:

$$\boldsymbol{Y}_{ip} = \alpha_0 + \alpha_1 \boldsymbol{AC}_p + \alpha_2 \boldsymbol{P}_p + \alpha_3 \boldsymbol{CU}_i + \alpha_4 \boldsymbol{FS}_i + \alpha_5 \boldsymbol{A}_i + \varepsilon_{ip} \tag{2}$$

where $\boldsymbol{Y}_{ip}$ represents the two productivity outcome measures (maize yield and income). Maize yield is measured by the quantity of maize harvested (expressed in kg/hectare) by plant clinic user i on plot p. Maize income (expressed in ZMW/hectare) consists of gross maize income[6] less production costs, such as costs of seed, fertiliser, herbicide, insecticide and hired labour. $\boldsymbol{AC}$ is the main explanatory variable of interest, and it denotes a vector of adopter categories. It is expected that a plant clinic user will choose the category with the greatest expected outcome or utility. $\boldsymbol{P}$ is a vector of plot-level explanatory variables, including plot size, distance of plot from homestead and plot quality, as well as plot-level input use variables, such as seed, mineral fertiliser, manure, herbicide and hired labour. $\boldsymbol{CU}$, $\boldsymbol{FS}$ and $\boldsymbol{A}$ are as defined in Equation (1). $\boldsymbol{\alpha}$ is a vector of coefficients associated with the covariates, and ε is the error term. The main coefficient of interest is $\boldsymbol{\alpha}_1$, which gives estimates of the average effects of the adoption decision on maize yield and income. A description of the variables included in Equations (1) and (2) is given in Table 1.

While Equation (2) can be estimated using an ordinary least squares (OLS) regression model, we note the possibility that adopters and non-adopters of plant clinic recommendations may differ systematically in observable and unobservable factors that could influence the outcomes of interest, potentially leading to biased results. To attenuate this potential bias, we apply the doubly robust estimator in which the OLS model is weighted by an inverse propensity score to balance the confounding factors between adopters and non-adopters of the personalised extension recommendations.

In the doubly robust procedure, inverse-probability weights are computed from the MNL regression of plant clinic users' adoption decisions (Equation 1). Using the estimated inverse-probability weights, weighted OLS models are fitted to obtain the expected productivity outcomes of the probabilities of adoption and non-adoption of recommended practices. The differences in mean outcomes between adopters and non-adopters of the plant clinic recommendations provide estimates of the average productivity effects of the clinic users' adoption decisions. An attractive property of the doubly robust estimator is that it is robust to

[6]Gross maize income was calculated as total maize yield multiplied by the village-level price of maize for the 2018/2019 cropping season.

TABLE 2 Summary statistics of recommended and adopted practices

Plant doctors' advice	Farmers who received this advice (%)	Farmers who implemented this practice (%)	Mean difference
Monitoring	49.48	42.36	7.12***
Field sanitation	33.33	36.81	−3.48***
Synthetic pesticides	52.43	38.02	14.41***
Biopesticides	43.92	37.67	6.25**
Handpicking	8.68	44.27	−35.59***
Ash or sand	1.91	15.28	−13.37***
Detergent	0.35	10.59	−10.24***
Pheromone trap	0.52	0.00	0.52*
Do nothing	3.47	9.72	−6.08***

Note: *, ** and *** denote that the mean difference between the recommended and adopted practices is statistically significant at the 10%, 5% and 1% significant level, respectively.

misspecification in either the outcome model (OLS model) or the treatment model (MNL model). In other words, even if only one of the two models is correctly specified, our productivity effect estimates will still be consistent (Imbens & Wooldridge, 2009). For comparison purposes, we report results from both the OLS and doubly robust methods.

We recognise that the OLS and doubly robust methods address selection bias due to observable factors but may not correct for potential bias arising from unobserved heterogeneity. While the inclusion of a rich set of covariates in our models may help to reduce unobserved heterogeneity, panel data or instrumental variables techniques would have been more appropriate to address this potential source of bias. However, our analysis is based on cross-sectional data, and finding instruments that satisfy exclusion restriction conditions is challenging, particularly when there are multiple adopter categories, as in our case. This should be taken into consideration when interpreting the estimation results on how the farmers' decisions to deviate from recommended practices affect maize productivity.

5 | RESULTS AND DISCUSSION

5.1 | Deviations from IPM recommendations

Table 2 compares the personalised IPM recommendations made by plant doctors to the sample clinic users for the management of FAW and the observed levels of adoption of these recommendations by the clinic users. We find significant differences between the proportion of farmers who were advised by plant doctors to use a particular FAW management practice and the proportion of farmers who actually used the practice, pointing to high deviations from the recommended practices. For example, plant doctors advised about 44% and 52% of the clinic attendees, respectively, to apply biopesticides and synthetic pesticides for the control of FAW, but only about 38% of the clinic attendees adopted these crop protection strategies. A noticeable finding is that for cost-intensive recommendations such as the spraying of biopesticides and synthetic pesticides, the number of adopters are significantly less than those who received these recommendations, while for relatively simple mechanical and traditional practices such as handpicking of larvae, application of ash or sand into maize whorls and the spraying of detergents, the number of adopters far exceeds the number of clinic users who were encouraged to adopt these practices. Nearly 10% of the clinic users simply did nothing for the management of the pest, as compared to 3% of them who were asked by the plant doctors not to intervene.[6]

Based on the pattern of deviations from the plant doctors' advice in Table 2, we identify five categories of adopters of personalised IPM recommendations: (1) non-adopters, (2) 'non-adopters+', (3) partial adopters, (4) full adopters, and (5) innovators. The non-adopters are the clinic users who did not implement any of the personalised advice they received from plant doctors. The data also show a group of non-adopters who at least implemented non-recommended practices. For lack of a better term, we refer to this group of clinics users as 'non-adopters+'. For instance, if a clinic attendee is advised to apply a certain biopesticide against FAW, but rather applied detergents, he/she is categorised as a 'non-adopter+'.

The third category (partial adopters) comprises those who adopted only components of the recommended practices. Plant doctors tend to recommend multiple complementary pest management methods, in line with the tenets of IPM. Thus, for example, a farmer who adopts only one recommended practice when he/she is advised to combine two or more practices is considered to be a partial adopter. Full adopters consist of the clinic attendees who accurately implemented all the personalised recommendations. Finally, we observe a group of adopters who accurately adopted the recommended practices (just like the full adopters), but also adopted extra practices beyond what was recommended. For instance, if a farmer is advised to scout for FAW and use a particular pesticide (e.g., Azadirachtin), and he/she implemented these practices exactly as recommended but also poured ash and sand into the maize whorls (a traditional practice) or sprayed a non-recommended pesticide (e.g., Dichlorvos) as an additional solution, such a farmer is classified as an innovator, for lack of a better term.

It should be stressed that the classification of the clinic users into the five adopter categories was based on detailed information (beyond the summary in Table 2) on personalised IPM practices recommended to and adopted by the clinic users. For example, a plant doctor's recommendation on the use of synthetic pesticide or biopesticide also includes information on which specific pesticide product to use and the rate of application. Hence, a full adopter should have used the exact recommended product, and not a substitute product. This is important because some of the pesticides used in Africa against FAW are ineffective and pose high risk to humans and the environment (Jepson et al., 2020). Therefore, in situations where pesticide use is inevitable, plant doctors are obliged to recommend only locally registered products, as well as pesticides that both pose minimal risk to human health and the environment, and are not restricted by international agreements (Plantwise, 2020).

Figure 1 shows that over 80% of the plant clinic users adopted at least one IPM recommendation, with about half of them (42%) implementing all the recommended practices. This is compelling, given previous reports of limited adoption of IPM practices by smallholders in developing countries (Alwang et al., 2019; Parsa et al., 2014). This may suggest that greater uptake of IPM practices or composite technologies is encouraged if they are promoted through personalised extension advice. These results also complement previous studies that have shown that plant clinics stimulate the adoption of crop protection technologies (Silvestri et al., 2019; Tambo et al., 2020a). Figure 1 also indicates that nearly 40% of the clinic users adopted components of the recommended practices, confirming previous evidence that partial adoption of IPM is prevalent among developing country farmers (Norton et al., 2019). We also find that among the 20% non-adopters of plant clinic recommendations, about half of them at least took non-recommended actions in attempts to curb the effects of FAW. Overall, Figure 1 suggests that more than 80% of the clinic attendees in our sample deviated from the personalised IPM recommendations they received from plant clinics. We examine the correlates and implications of these farmer deviation decisions below.

[6]Given the intensity of infestation or economic threshold, a plant doctor may advise a clinic attendee not to adopt any control measure as it would not be cost-effective to do so.

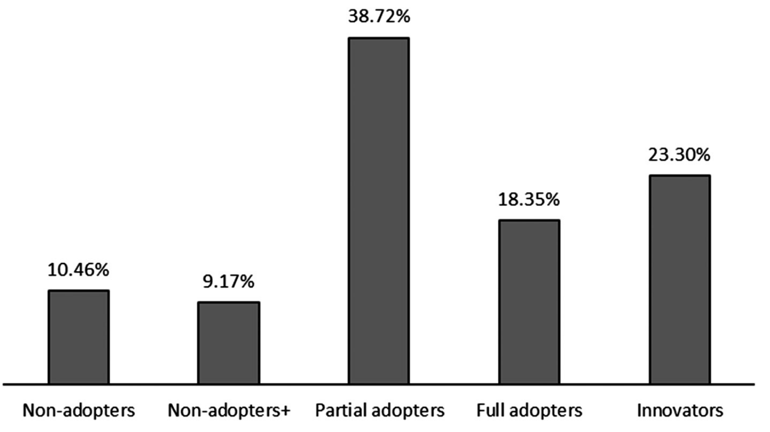

FIGURE 1 Percentage of adopter categories of plant clinic recommendations

TABLE 3 Summary statistics of maize outcomes by adopter categories

	Maize yield (kg/ha)		Maize income (ZMW/ha)	
	Mean	**SD**	**Mean**	**SD**
Non-adopters	1199.2	1553.8	1873.4	2967.5
Non-adopters+	1431.3	965.2	2567.8	2451.3
Partial adopters	1481.2	1622.1	2580.9	3447.4
Full adopters	2102.5***	2100.3	3684.1***	3841.0
Innovators	1671.7	1887.1	2741.8	3936.1

Note: *** denotes that the mean difference in maize yield and income between full adopters and non-adopters are statistically significant at the 1% significant level.

Table 3 displays the summary statistics of the outcome variables according to the adopter categories of plant clinic advice.[7] The results show that all the clinic users who implemented a FAW control practice (whether recommended or not) achieved higher maize productivity than those who did not apply any control measure (non-adopters). Notable are the statistically significant differences in outcomes between the full adopters and non-adopters. In particular, the yield and income of full adopters are almost twice those of the non-adopters, suggesting improved outcomes when the personalised recommendations are fully implemented. However, the results in Table 3 do not control for important confounding factors, such as farmer, input use and plot characteristics, and thus cannot be interpreted as necessarily causal effects of the adoption decisions.

Note that given the small proportion of farmers in the 'non-adopters' and 'non-adopters+' categories (see Figure 1), and to overcome problems of insufficient statistical power (and thus imprecise parameter estimates) as well as poor overlap in the doubly robust estimation, these two adopter categories are merged into one category (non-adopters) in the following regression analysis.

[7]A disaggregation of the covariates by the adopter categories are presented in Table A1 in the Online Appendix.

5.2 | Correlates of adoption decisions

Table 4 shows the results from the first-stage MNL model on the factors influencing plant clinic users' decisions to adopt the personalised advice received from plant doctors. We find that male clinic users are significantly more likely than their female counterparts to adopt the complete personalised IPM package. This may reflect the well-known problem of gender disparity in access to productive resources (FAO, 2011). The probability of adopting the full recommendations of plant doctors increases with clinic users' age, which may be related to farming experience or risk-taking propensity. The coefficients on maize area are positive and statistically significantly for all the three adopter categories, suggesting that clinic users with more hectares of maize are more likely to follow the personalised recommendations. A plausible explanation is that a larger area under maize may signify the economic importance of the crop to the household and thus interest in limiting yield loss by adopting recommended practices. It is also possible that larger maize plots are exposed to higher FAW infestation levels; hence, such farmers may be more willing to follow recommendations to limit the spread of the pest. Participating in off-farm income earning activities, which may relax household liquidity constraints, is significantly associated with the adoption of personalised crop protection recommendations.

We also find that risk averse clinic users have a lower probability of adopting any of the plant clinic recommendations. This lends credence to the hypothesis that risk and uncertainty are among the main factors contributing to the slow adoption of IPM in developing countries (Parsa et al., 2014; Alwang et al., 2019). Seeking FAW information from peers is significantly correlated with a higher likelihood of adopting plant clinic recommendations, either partially, fully or beyond what was recommended. Perhaps peer information may reinforce farmers' confidence in applying a practice recommended by plant doctors. Additionally, FAW-related media information significantly increases the probability of implementing the recommendations of plant doctors, beyond what was recommended. Taken together, these results underscore the importance of information in the adoption of IPM practices, particularly when the pest in question (FAW) is a new invasive species that causes serious crop damage within a short period of time. The crucial role of information in IPM adoption has also been highlighted in previous research (Alwang et al., 2019; Carrión Yaguana et al., 2016; Midingoyi et al., 2019).

The coefficient on the gender homophily variable is not statistically significant, suggesting that a farmer's decision to adopt recommended practices is not influenced by whether or not the advice is provided by a plant doctor who is of the same gender as the farmer. This is in contrast to Lahal et al. (1999) who found evidence of gender homophily effect in the adoption of extension-recommended technologies and practices in Nigeria. Plant clinic recommendations provided by experienced extension agents are more likely to be completely followed than those by less experienced agents. This is intuitive, as several years of working with farmers may help the plant doctors to understand farmers' technology adoption behaviour and recommend measures that are most likely to be adopted, while more experienced advisors are, perhaps, seen as more trustworthy. The number of years of experience with FAW is a significant determinant of the adoption of plant clinic recommendations, probably because previous experience with the pest allows a farmer to appreciate its potential damage in case no action is taken. Farmers who observed a high level of FAW infestation prior to visiting the plant clinics are less likely to adopt the recommended management practices. This somewhat unexpected result might be because plant doctors' recommendations against severe pest infestation tend to include the use of pesticides, which may be too costly for risk-averse smallholders to implement. Finally, the results show that farmer adoption of personalised IPM recommendations is also related to differences in agro-climatic conditions.

TABLE 4 Correlates of clinic users' IPM adoption decisions

	Partial adopters[a]	Full adopters[a]	Innovators[a]
Age	0.001	0.028**	0.007
	(0.011)	(0.013)	(0.012)
Gender (1 = Male)	0.266	0.621*	0.346
	(0.300)	(0.374)	(0.342)
Education	0.009	0.050	−0.004
	(0.047)	(0.054)	(0.052)
Household size	−0.061	−0.134**	−0.097*
	(0.048)	(0.056)	(0.054)
Maize area	0.278*	0.365**	0.295*
	(0.152)	(0.157)	(0.158)
Off-farm activity	0.725**	0.539	1.028***
	(0.287)	(0.340)	(0.319)
Asset index	0.036	0.107	0.094
	(0.110)	(0.128)	(0.120)
Risk attitude	0.127***	0.197***	0.183***
	(0.048)	(0.056)	(0.053)
Media information	0.424	−0.065	0.631**
	(0.281)	(0.333)	(0.321)
Peer information	0.862***	0.889***	1.106***
	(0.285)	(0.343)	(0.334)
Distance to agro-dealer	−0.004	−0.004	−0.003
	(0.012)	(0.014)	(0.013)
Gender homophily	−0.037	−0.076	0.055
	(0.296)	(0.364)	(0.337)
Plant doctor experience	0.167	0.085	0.048
	(0.134)	(0.160)	(0.145)
Extension experience	0.022	0.118***	0.099***
	(0.038)	(0.037)	(0.037)
FAW experience	0.253*	0.400**	0.287*
	(0.134)	(0.158)	(0.150)
Moderate FAW infestation	−0.997**	−0.469	−0.592
	(0.444)	(0.507)	(0.491)
High FAW infestation	−1.626***	−1.448***	−1.448***
	(0.434)	(0.500)	(0.480)
Rainfall	0.002**	0.003**	0.001
	(0.001)	(0.001)	(0.001)
AEZ IIa	−1.324*	−0.174	−0.808
	(0.700)	(0.864)	(0.756)
AEZ III	−2.750***	−1.793*	−2.289**
	(0.830)	(1.019)	(0.927)
Observations =545 $Prob > Chi^2 = 0.000$			

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

[a]Base category is non-adopters.

TABLE 5 Treatment effect on maize yield (kg/ha)

	OLS		Doubly robust	
	Coefficient	Percentage effect	Treatment effect	Percentage effect
Partial adopters[a]	394.79***	30.17	307.30**	26.18
	(150.20)		(137.92)	
Full adopters[a]	870.99***	66.56	948.80***	82.24
	(228.53)		(242.32)	
Innovators[a]	522.62***	39.94	413.83**	32.90
	(118.78)		(202.88)	
Control variables	Yes		Yes	
Observations	545		545	
R-squared	0.34			

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

[a]Base category is non-adopters.

5.3 | Treatment effects on maize yield and income

Table 5 presents the OLS and doubly robust estimates of how farmers' deviations from plant clinic recommendations affect maize yield. The signs and statistical significances of the yield effect estimates are generally similar across the two estimators. We focus on the results from the doubly robust model, which is our preferred estimator. Given that the doubly robust method relies on the assumption of common support (Imbens, 2004), we first examine whether or not this assumption is violated by visually checking the extent of propensity score overlap and by checking for covariate balancing using the overidentification test suggested by Imai and Ratkovic (2014). Figure A2 in the Appendix S1 shows sufficient overlaps in the distribution of the propensity scores between adopters and non-adopters of the plant clinic recommendations, confirming satisfaction of the common support condition. Moreover, the balance diagnostic test results (Table A2, Appendix S1) show insignificant chi-squared statistics, implying that the first-stage MNL model successfully balanced the covariates by weighting.

We find evidence that the adoption of personalised extension recommendations increases maize yield significantly, but the effect is disproportionally greater for plant clinic users who fully adopt the recommended practices (Table 5). In particular, after controlling for plant clinic user and plot characteristics, input use and other determinants of maize yield, the full adopters obtain an increase in maize yields by 949 kg/ha, which represents an 82% gain over maize yields for non-adopters. The innovators achieve about 414 kg/ha (33%) significantly more maize yield than the non-adopters. Thus, the plant clinic users who modify recommended practices by adding additional practices obtain higher yields compared to non-adopters, but the yield gain is lower when compared with those of their full adopter counterparts. This suggests that some of the non-recommended practices are counterproductive when implemented in combination with the recommended practices. Finally, we find a yield advantage of about 26% for the partial adopters relative to the non-adopters, implying that it is worthwhile to encourage the plant clinic participants to implement components of the personalised IPM recommendations even if full adoption is not possible. This may also partly explain why partial adoption of IPM and other composite technologies is very common in developing country settings (Midingoyi et al., 2019; Norton et al., 2019).

Table 6 reports the treatment effect estimates of the implications of the varied adoption of the personalised IPM recommendations on maize income. We find positive and significant

TABLE 6 Treatment effect on maize income (ZMW/ha)

	OLS		Doubly robust	
	Coefficient	**Percentage effect**	**Treatment effect**	**Percentage effect**
Partial adopters[a]	917.54***	41.90	826.97***	47.32
	(317.75)		(308.93)	
Full adopters[a]	1827.15***	83.45	1553.05***	72.88
	(418.50)		(472.33)	
Innovators[a]	1128.05***	51.52	824.68**	43.02
	(393.76)		(369.54)	
Control variables	Yes		Yes	
Observations	545		545	
R-squared	0.35			

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses.
[a]Base category is non-adopters.

income gains from adopting personalised IPM recommendations, but the size of the gains depends on the extent of deviation from the recommendations. The results show an increase in maize income ranging from 43% for innovators to 73% for full adopters, compared to the non-adopters of the recommended practices. As with the results for maize yields, we find that the treatment effect is greater for plant clinic users who adopt the full set of recommendations provided by plant doctors. These results suggest that the extra production costs incurred by the three categories of adopters of plant clinic recommendations are less than the gain in maize yield. Our results also confirm previous findings that plant clinics stimulate the adoption of crop protection technologies, which translate into increased crop yield and income (Bentley et al., 2011; Silvestri et al., 2019; Tambo et al., 2020a). Complementarily, our findings show that there are varied categories of adopters of plant clinic recommendations, and this matters for the level of productivity gains achieved.

6 | CONCLUSION

In many developing countries, the provision of blanket extension advice to farmers is widely recognised as one of the major reasons for the low adoption of agricultural innovations, particularly complex technologies such as integrated pest management (IPM). This recognition has spurred the promotion of personalised or site-specific extension services in which extension recommendations are tailored to the needs of individual farms or farmers. While there are few empirical studies on the uptake and impact of personalised extension advice, little is known about to what extent or how accurately farmers implement personalised extension advice, or about the implications for yields and incomes. This paper aimed to fill this knowledge gap by measuring the degree to which farmers deviate from personalised extension recommendations and the effect on maize productivity. We also examined the factors influencing the decisions of farmers to follow or deviate from personalised extension recommendations. Our analysis is based on data from the plant clinic extension model in which trained plant doctors provide personalised diagnostic services and IPM-based recommendations to smallholder farmers.

By matching clinic data on personalised IPM recommendations offered to 420 clinic users in Zambia with survey data on the actual IPM practices implemented by these same clinic users, we differentiated five adopter categories, based on the degree of deviation from the personalised recommendations. The categories include: (1) non-adopters (ignored the personalised IPM recommendations); (2) 'non-adopters+' (ignored the recommendations but implemented some non-recommended practices); (3) partial adopters (implemented components of the recommended practices); (4) full adopters (implemented the practices exactly as recommended); and (5) innovators (implemented additional practices beyond what was recommended). We found that more than 80% of the clinic users deviated from the personalised IPM recommendations they received from plant clinics. Regression results showed that risk aversion (at least as measured here), farm size, access to alternative sources of pest information, severity of pest infestation and agro-climatic conditions are the key factors explaining the heterogeneity in farmers' deviations from the personalised extension recommendations.

Results further showed that 80% of the plant clinic users adopted at least one of the recommended IPM practices, while 42% implemented the full package of recommendations. These results imply that the plant clinic method of providing personalised extension services to smallholder farmers could be used to foster the adoption of IPM recommendations. This is particularly salient, given the low rate of IPM adoption in developing countries, and the recognition that failure of extension systems is a major obstacle to widespread adoption (Norton et al., 2019; Orr, 2003; Parsa et al., 2014).

We found clear evidence that the adoption of personalised extension advice increases maize productivity, with significant effects even for partial adopters. However, the effect is much larger for the plant clinic users who accurately followed the recommendations of their plant doctors (i.e., full adopters). For example, our multi-valued treatment effect estimates suggest an 82% yield penalty for non-adopters compared to full adopters of recommended IPM practices, while the yield gain for full adopters is more than double that of partial adopters or innovators. These results emphasise the need to encourage farmers to accurately adopt a complete set of recommended IPM strategies. However, in situations where full adoption is challenging, it would still be worthwhile to encourage farmers to implement certain components of an IPM package. Our findings also imply that in the context of farmers' management of the invasive fall armyworm pest, the adoption of additional unrecommended practices offers no added advantage (in terms of productivity gains) when combined with accurate implementation of the plant doctors' recommendations.

Overall, we show that farmers deviate considerably from personalised extension recommendations, resulting in significant implications for agricultural productivity. Hence, failure to account for farmer deviation decisions when assessing the adoption and impact of extension recommendations (as is often the case in the literature) can obscure important insights. Further research on this topic could include the use of panel data to explore the dynamics of deviations from personalised extension advice and to reduce unobserved heterogeneity bias that may be present when examining the effects of the deviations. Moreover, we only examined the economic implications of farmer deviations from IPM recommendations. Given that IPM is also promoted for its potential health and environmental benefits (Midingoyi et al., 2019; Norton et al., 2019), it would be interesting for future research to investigate the health and environmental consequences of the decisions of farmers to deviate from personalised IPM recommendations.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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