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Assessing the adoption rates of improved technology in traditional poultry farming: Evidence from rural Togo

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Abstract

The adoption of improved agricultural technologies is known to significantly improve incomes, create more wealth, alleviate poverty and contribute to rural development in many developing countries. The Government of Togo, through the National Programme for Agricultural Investment and Food Security (PNIASAN) and the Agricultural Sector Support Project (PASA), and with financial support from the World Bank and help from the Food and Agriculture Organization of the United Nations (FAO), provides assistance to smallholder farmers in improved technology adoption in traditional poultry farming (ITTPF) for wealth creation, food security and poverty alleviation. However, for any technology or emerging agricultural practices, awareness and exposure are necessary conditions for their adoption. And because these two factors are not distributed randomly in the population of potential adopters, not taking them into account will lead to estimates of population adoption rates that are not informative of the true demand for the technology, and to inconsistent estimates of the parameters of the adoption model. In this study, we evaluate the adoption rates of ITTPF among farmers in Togo. Data was collected from 400 farmers in 2014, prior to the introduction of ITTPF, and again five years later. This data was then analysed using inverse propensity score weighting and parametric estimation of adoption regression models. The results of the estimates indicate that the average treatment effect (ATE), which represents the mean potential adoption rate of the population, is 57%, the average treatment effect on the treated ($ATET$), which represents the mean potential adoption rate in the exposed subpopulation, is 60%, the population mean joint exposure and adoption rate (JEA) is 13%, and the population selection bias (PSB) is 3%. The sample adoption rate (JEA)

implies a population adoption gap of -47% due to a lack of exposure and adoption by a sufficient size of the population. The PSB is insignificant and indicates that all the sampled farmers had an almost equal opportunity of adopting ITTPF. The study reveals that the sample adoption rate does not consistently estimate the true population adoption rate. Hence, controlling for non-exposure and selection biases is a perquisite to acquiring consistent estimates of ITTPF adoption rates. The findings indicate a relatively high supply-demand gap for ITTPF that justifies investment in its further dissemination and adoption in Togo for optimal positive impact on potential outcomes and the welfare of farmers.

Key words: traditional poultry farming, improved technology adoption, adoption rate assessment, average treatment effect (ATE), average treatment effect on the treated (ATET), parametric and semiparametric estimations

1. Introduction

Agriculture is crucial to the economy of Sub-Saharan Africa (SSA) because it accounts for a large portion of the gross domestic product (GDP) and involves approximately two thirds of the active population (Djoumessi *et al*. 2020). This notwithstanding, concerns about poverty, food (in)security and welfare, particularly in rural areas, remain an imperative agenda in SSA and worldwide (Alem 2015; Sisha 2020). Previous empirical studies support the basic premise that agricultural production, particularly crop production and productivity, has significantly declined in recent years due to adverse weather conditions, a decrease in soil fertility and exponential population pressure, resulting in overexploitation of arable land, and land-use constraints (Afolayan 2021; Mng'ong'o *et al*. 2021; Ortiz-Bobea *et al*. 2021). To date, the literature has mainly addressed barriers to sustainable agricultural production and productivity (Hübel & Schaltegger 2021; Laurett *et al*. 2021; Liu *et al*. 2021). However, only a few studies have focused on leveraging farmers' inherent know-how within the process of resilience building through the adoption of agricultural technologies. For their livelihood, farmers engage in both crop and livestock farming (Boote *et al*. 2021; Gauthier & Langlois 2010; Giller 2020). Livestock farming is increasingly becoming recognised as an important sector that has the potential to be one of the most effective means of strengthening farmer resilience through income diversification, wealth creation, food security and poverty reduction (FAO 2014a). Poultry, pigs, cattle and small ruminants are among the most common types of livestock farming practised by smallholder farmers in rural areas (Devendra & Chantalakhana 2002; Gauthier & Langlois 2010). Previous studies reported that poultry rearing is one of the most environmentally friendly forms of livestock farming, producing the tiniest amount of greenhouse gas compared to other types of livestock production, such as cattle and other ruminants, which not only emit large amounts of greenhouse gases, but their production is extremely reliant on vegetation cover (Menghistu *et al*. 2021; NDC 2021; Zubir *et al*. 2021).

Poultry farming in Togo helps livestock production to contribute 14% to agricultural GDP (Gauthier & Langlois 2010). Poultry farming is basically characterised by two types of production, namely traditional poultry rearing based on the breeding of local birds, and modern poultry farming based on the breeding of imported, exotic bird species with different levels of intensification. In traditional poultry farming, local birds are mainly short-cycle species such as chickens, ducks, guinea fowls, pigeons, turkeys, etc. (Dao 2010). Poultry commodities and by-products are consumed by the vast majority of the population. The purchasing prices of poultry commodities are within reach of the majority of the population. In terms of environmental preservation through best practices in sustainable agriculture, poultry excreta could be transformed into compost for natural farmland fertilisation and integrated management of soil fertility, resulting in improving crop yields (Toldrá *et al*. 2016; Tesfaye *et al*. 2017a, 2017b).

In Togo, the predominant method of poultry farming is traditional poultry production, since the purchasing prices of traditional poultry commodities are affordable compared to modern commercial poultry commodities or other types of livestock products. Due to low entry barriers, traditional poultry farming is established extensively amongst smallholder farmers in developing nations, particularly in pastoral communities. It is an economic activity easily accessible and manageable, even by the most vulnerable social strata of the population, including low-income, landless and female farmers. In this regard, traditional poultry rearing can be classified among the most promising sources of income diversification for the poorest social strata (FAO 2014b). Nevertheless, it experiences huge constraints that considerably limit its productivity and profitability (Kondombo *et al*. 2003), including high poultry mortality rates. That notwithstanding, traditional poultry rearing appears to serve diverse purposes, including income diversification, wealth creation, food security, improved livelihoods and employment creation (FAO 2014a). It is necessary to bear in mind, however, that the success of poultry rearing, like any livelihood farming venture, relies to a large extent upon the availability and accessibility of inputs.

In order to strengthen the livelihoods of smallholder farmers, alleviate poverty and build the resilience of farmers who have experienced a decline in their incomes from crop production in recent years (UNDP 2011; Ouédraogo 2012), the Government of Togo has implemented several initiatives and programmes in response to the objectives of boosting sustainable rural development. In this context, the government, through the National Programme for Agricultural Investment and Food Security (PNIASAN) and the Agricultural Sector Support Project (PASA), has offered subventions to smallholder farmers for the adoption of improved technology in traditional poultry farming (ITTPF) in order to improve poultry farming, create more wealth, enhance food security and alleviate poverty (Gauthier & Langlois 2010). It is worth highlighting that ITTPF is a semi-intensive type of traditional poultry farming that differs from free-range traditional poultry rearing in terms of improving farm management, farm equipment, poultry housing, poultry feeding and diseases control.

Currently, ITTPF is being implemented in all agricultural regions of the country. Since its introduction in Togo through the implementation of PNIASAN and PASA, however, the adoption rates of ITTPF among smallholder farmers in rural areas has not been evaluated until now.

The objective of this paper was to present estimates of actual and potential adoption rates of ITTPF, based on findings from a country-wide survey. To the best of our knowledge, we are the first to fill this knowledge gap. The research findings provide leverage points that will guide policymakers in scaling up decisions on ITTPF adoption within the framework of PNIASAN, PASA and beyond. Finally, the findings make a significant contribution to the adoption of knowledge of agricultural technologies, with a particular emphasis on animal technologies.

The remainder of the paper is structured as follows. Section 2 presents the introduction and implementation of ITTPF in Togo through PNIASAN and PASA. Section 3 covers the materials and methods for this study. Descriptive statistics and econometrics results are presented and discussed in Section 4. The conclusion and policy implications are highlighted in Section 5.

2. Introduction and implementation of ITTPF in Togo through PNIASAN and PASA

Since the commitments made at Maputo in 2003 (Benin & Yu 2012), the Comprehensive Africa Agriculture Development Programme (CAADP) has formed the core of many African governments' efforts to boost growth and alleviate poverty and hunger in African countries. The African Union (AU) and the New Partnership for Africa's Development (NEPAD) have served as vehicles to achieve these goals. Following the implementation of CAADP in 2005, the Economic Community of West African States (ECOWAS) developed its Regional Agricultural Policy, referred to as ECOWAP

(Kolavalli 2010; Kolavalli & Birner 2012). Togo established the National Programme of Agricultural Investment for Food and Nutritional Security (PNIASAN) in the framework of its 2010 to 2015 investment plan, with financial support from the World Bank and help from the Food and Agriculture Organization of the United Nations (FAO) (Gauthier & Langlois, 2010). The objective of PNIASAN is to enhance farmers' incomes and contribute to improving the trade balances, as well as the living conditions of rural populations, through sustainable agricultural development, with special attention to the poorest and the most vulnerable groups (ROPPA 2013).

PNIASAN is structured into five sub-programmes, one of which is focused on improving the coverage of national livestock commodities through intensive traditional livestock production and the enhancement of small and medium firms in this subsector. To achieve the objectives of this specific PNIASAN sub-programme, the government developed the Agricultural Sector Support Project (PASA), which aims to improve the productivity and competitiveness of strategic food crops, export crops and livestock production, as well as promoting an environment conducive to sustainable agricultural development. As such, a sub-component of PASA is aimed at boosting the livestock subsector, with the specific objective of providing short-term emergency assistance to revive poultry and small ruminant farming, and to assist small-scale livestock farmers to develop and strengthen livestock farming for wealth creation and poverty alleviation (Gauthier & Langlois 2010; World Bank 2017; Togolese Republic 2018).

The government, through this PASA sub-component, made available to all farmers a technical package to enable ITTPF adoption. This technical package comprises the building of semi-modern poultry housing (improved poultry housing), the supply of technical poultry breeding equipment, training in the formulation of balanced and quality feeds at minimum cost, prophylaxis, poultry vaccination, health care, etc. The technical package is worth US$ 6 364. Through PNIASAN and PASA, and with financial support from the World Bank and assistance from FAO, the government has subsidised 90% of the costs from the technical package acquisition cost. Any farmer who wishes to participate in PNIASAN and PASA for improved technology adoption in traditional poultry farming must contribute his or her share of the remaining 10%, totalling US$ 636. This complement or individual contribution from smallholder farmers interested in PNIASAN and PASA has to be paid in cash or in kind.[1] Most smallholder farmers choose an in-kind contribution, by way of land used as a site for the implementation of an improved poultry farm. Smallholder farmers who are aware and have realised the benefits of PNIASAN and PASA in terms of income diversification, wealth creation and poverty reduction, but who do not have both financial capacity and land to cover their 10%, take out loans from financial enterprises to participate in PNIASAN and PASA for ITTPF adoption.

3. Material and methods

3.1 Empirical literature

The development of novel agricultural technologies or emerging agricultural practices remains important to increase agricultural production and productivity. Several factors and various socio-economic characteristics could explain the decision by farmers whether or not to participate in agricultural development programmes and projects for the adoption of agricultural technologies and innovations. In addition, awareness and the availability of the required means are indispensable for the adoption. Once the farmer has decided to adopt an emerging agricultural practice, exposure to the technology is indispensable for its adoption (Feder *et al*. 1985; Besley & Case 1993; Mariano *et al*. 2012).

[1] Any form of payment that does not involve the exchange of actual cash is referred to as payment in kind.

While awareness and exposure are both indispensable elements in the adoption of a new agricultural technology, the assessment of the adoption rates is also necessary because it would allow agricultural policymakers to decide whether or not to invest more in the improvement of the technology's dissemination programmes in order to make it accessible to the entire target population. Adoption, according to Rogers (1967), is the mental process that an individual goes through from first hearing about an innovation to final adoption. The diffusion process can be defined in the context of aggregate adoption behaviour as the process of spreading a new technology within a region. The adoption of technological innovations in agriculture has drawn significant attention from agricultural and development economists because most of the population in developing countries depend on agricultural production for their livelihoods, and because emerging agricultural technologies are likely to substantially increase agricultural production and incomes (Feder *et al*. 1985; Krishna *et al*. 2020).

The separation of adoption and diffusion continues to be a problem. According to Besley and Case (1993), the coefficients of adoption models are difficult to interpret when technology diffusion is incomplete. In this context, this study addresses the problem of evaluating adoption rates from the standpoint of modern theories of assessing the effects of interventions, as highlighted in the treatment effects estimation literature (Heckman *et al*. 1999; Wooldridge 2002; Imbens 2004; Heckman & Vytlacil 2007a, 2007b). As demonstrated by Diagne and Demont (2007), the widely used adoption rate estimators suffer from either a 'non-exposure' bias or a selection bias. As a result, even when based on a randomly selected sample, they generally result in biased and unreliable estimates of population adoption rates. The non-exposure bias occurs when farmers who have not been exposed to a new technology are unable to adopt it, even if they could if they were aware of it. As a result, the adoption rate in the general population is underestimated (Diagne & Demont 2007).

Besley and Case (1993), Atanu *et al*. (1994) and Dimara and Skuras (2003) emphasise the difficulty in interpreting the coefficients of the simple logit, probit or tobit adoption models when technology diffusion in the population is incomplete. Diagne and Demont (2007) demonstrated that the more well-known, classical model of the correction of latent variables, used to solve the problem of non-exposure and selection bias by Atanu *et al*. (1994) and Dimara and Skuras (2003), cannot identify the adoption rate in the entire population, despite the most restrictive parametric functional form and distribution assumptions embedded in this model. Only the adoption rate in the exposed subpopulation can be determined using the classical model for correcting selection bias.

The population adoption rate corresponds to what is known in the treatment effect literature as the average treatment effect, abbreviated as ATE. The average treatment effect (ATE) parameter, first proposed by Rubin (1974), assesses the effect or impact of a 'treatment' on a randomly selected individual in the population (Wooldridge 2002). A 'treatment' in the context of adoption is exposure to a new technology, and the average treatment effect is the population's mean potential adoption rate. This is the rate of adoption after the entire population has been exposed to the technology or emerging agricultural practice. The population non-exposure bias is the difference between the population adoption rate and the actual adoption rate, which occurs due to the incomplete diffusion of the technology or emerging agricultural practice in the population. It is indeed a measure of the population's unmet demand for this technology or emerging agricultural practice, which is referred to as the 'adoption gap'. The average treatment effect on the treated, abbreviated as ATET, ATT or ATE1, and the average treatment effect on the untreated, abbreviated as ATEU, ATU or ATE0, are other parameters that receive special attention in the treatment effect literature. In the context of adoption, ATET is the adoption rate among exposed individuals and is a measure of the average treatment effect in the treated subpopulation. Diagne and Demont (2007) used counterfactual outcomes and the average treatment effect framework to non-parametrically identify population adoption rates and derived consistent nonparametric and parametric estimators. The authors demonstrated why the more familiar classical model of selection bias/latent variables cannot be used to identify and estimate the adoption rate in the entire population.

Thus, in this paper, and drawing on the research work of Diagne and Demont (2007), we apply the inverse propensity score weighting (IPSW) and the average treatment effect (ATE) parametric models to consistently estimate the population adoption rates of ITTPF among farmers, as well as estimate the population adoption gap and selection biases created by the presently limited dissemination of ITTPF in Togo.

3.2 Empirical specifications

3.2.1 Average treatment effects estimations of adoption rates

In the adoption context, a 'treatment' corresponds to exposure to the technology. To correct for self-selection into adoption and to reduce exposure bias, one might employ the counterfactual average treatment effect (ATE) framework, suggested by Diagne and Demont (2007). The ATE framework dates back to the work of Rubin (1974) and simply measures the effect of any treatment on an individual drawn from a target population (Imbens & Woodridge 2009). The counterfactual outcome framework can be applied in situations where each farmer in the population comes up with two possible outcomes, such as with and without being exposed to a new agricultural technology (Diagne & Demont 2007). In our case, treatment is the exposure to ITTPF, and the ATE will thus measure the mean potential adoption rate when all members in a population are exposed to ITTPF. However, information flow is not always symmetrical, and some farmers may be exposed while others are not exposed.

Assuming we have a population of N households, with a binary variable a indicating the observed status of adoption ($a = 1$), which can be regarded as a treated household, and the observed status of non-adoption ($a = 0$), which can be regarded as the control. From the above, we are interested in three different estimations – the exposure rates (N_e/N), the adoption rates (N_a/N) assuming all farmers are exposed to ITTPF, and the adoption rates among farmers who are exposed to ITTPF (N_a/N_e) when we observe partial exposure.

3.2.2 Identification of treatment effects

Representing the adoption as Y, we can similarly observe two potential outcomes, Y_1 and Y_O, which represent the adoption outcomes for farmers who are exposed and not exposed to ITTPF respectively. This is formally represented as:

$$Y = Y_0(1-a) + Y_1 a = \begin{cases} Y_1 & \text{if } a = 1 \\ Y_O & \text{if } a = 0 \end{cases} \tag{1}$$

Under partial/incomplete exposure, the treatment effect for a given farmer, i, is $Y_{1i} - Y_{0i}$, or simply $E(Y_1 - Y_0)$ when aggregated to the population level, which is the ATE of exposure. Similar to the impact evaluation literature, we cannot observe adoption with and without exposure for a particular farmer. This makes the estimation of $Y_{1i} - Y_{0i}$ somewhat impossible. That notwithstanding, as exposure is a necessary precondition for adoption, Y_0 will likely be zero, giving a farmer's adoption impact of Y_1 with $Y = aY_1$, and an accompanying $ATE = E(Y_1)$ representing the average of the adoption impact. Unfortunately, we only see Y_1 for farmers who have been exposed to the treatment. As a result, the sample average of a randomly drawn sample is unlikely to estimate the required value of Y_1, because some of the Y_1 in the sample are missing. If we consider the dichotomous variable, w, as a proxy for treatment exposure, where $w = 1$ indicates exposure and $w = 0$ indicates non-exposure, the mean adoption impact among the subpopulation exposed is yielded by the conditional expected value, $E(Y_1|w = 1)$. This, by definition, is the ATE on the treated, commonly denoted by $ATET$. Given that we observe Y_1 across all the exposed farmers, the sample mean of Y_1 drawn from the exposed farmer subsample will consistently estimate ATET, assuming that the sampling is done randomly.

The awaited adoption impact for the non-exposed subgroup or subpopulation can be decomposed into a weighted sum of ATET and ATEU $= E(Y_1|w = 0)$ (Diagne & Demont 2007):

$$ATE = EY_1 = P(w = 1) \times ATET + \big(1 - P(w = 1)\big) \times ATEU \tag{2}$$

The probability of being exposed is denoted by $P(w = 1)$. As a result, once we have consistently estimated ATE, ATET and the exposure probability $P(w = 1)$, we can use equation (2) to calculate the expected non-exposure bias or adoption gap ($NEB = GAP = P(w = 1) \times ATE$T $- ATE$); the expected bias from using the sampling average rate of adoption in the exposed subpopulation or the population selection bias ($PSB = ATE$T $- ATE$); and the intended adoption impact on the non-exposed subgroup or subpopulation (ATEU):

$$ATEU = \frac{ATE - P(w=1) \times ATET}{P(w=0)} \tag{3}$$

As is customary, we can calculate the identified outcome, Y, as just a component of the potential results Y_1 and Y_0, with the treatment status parameter being:

$$Y = wY_1 + (1 - w)Y_0 = wY_1 \tag{4}$$

Second, equality stems from the following fact: Y_0, in the particular case of adoption results, is still nil.

3.2.3 Non-parametric estimation of adoption rates

When compared to the general case, the fact that, in the adoption context, the potential outcome $Y_0 = 0$ for both the treated and untreated subpopulations brings several simplifying results. As previously stated, the primary illustrative result is that the rate of adoption between those who have been exposed can be systematically identified and consistently based on a random sample of both observed adoption results as well as exposure status $(Y_i; w_i), i = 1, \cdots, n$, without any additional data and assumptions. Conditional independence is not required. In more formal terms, the population mean rate of adoption by those who have been exposed is given by:

$$ATET = E(Y_1|w = 1) = \frac{E(Y)}{P(w=1)}, \tag{5}$$

which is identified non-parametrically from the joint distribution of (Y, w), as well as estimated robustly through the observed random sample, $(Y_i, w_i), i = 1, \dots, n$, by:

$$\widehat{ATET} = \frac{\frac{1}{n}\sum_{i=1}^{n} Y_i}{\frac{1}{n}\sum_{i=1}^{n} w_i} = \frac{1}{n_e}\sum_{i=1}^{n_e} Y_i, \tag{6}$$

where n_e is the sample number of farmers exposed to ITTPF. Under the conditional independence assumption, the second illustrative result yields a simplified formulation of the non-parametric evaluator of the adoption rate in the population (ATE). If, in addition to the assumption of conditional independence, we assume that

(i) Potential adoption is independent of z conditional on x: $P(Y_1 = 1|x, z) = P(Y_1 = 1|x)$,
(ii) Exposure is independent of x conditional on z: $P(w = 1|x, z) = P(w = 1|z)$, and
(iii) the propensity score, $P(z) \equiv P(w = 1 \mid z)$, satisfies the condition $P(z) > 0$ for all z, then the mean population adoption function, $ATE(x) = E\,(Y_1 \mid x)$, and the mean population adoption rate, $ATE = E(Y_1)$, are non-parametrically identified from the joint distribution of (Y, w, x, z) and are given by (Diagne & Demont 2007):

$$ATE(x) = \frac{E(Y|x,z)}{P(z)} = E\left(\frac{Y}{P(z)}\middle|x,z\right), \tag{7}$$

and the population adoption rate is given by

$$ATE = E(Y_1) = E\left(\frac{Y}{P(z)}\right) \tag{8}$$

Furthermore, ATE and ATEU are consistently estimated from a random sample of observed $(Y_i, w_i, x_i, z_i), i = 1, \ldots, n$, by

$$\widehat{ATE} = \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i}{\hat{P}(z_i)} \tag{9}$$

$$ATEU = \frac{1}{n-n_e}\sum_{i=1}^{n}\frac{\left(1-\hat{P}(Z_i)\right)}{\hat{P}(Z_i)}Y_i, \tag{10}$$

where Y_i is the adoption outcome of a farmer i, n is the sample of farmers surveyed, $n_e = \sum_{i=1}^{n} w_i$ is the sample number of exposed farmers, x and z are covariates, $\hat{P}(z)$ is a consistent estimate of the propensity score evaluated at z (Heckman *et al*. 1999; Wooldridge 2002; Imbens 2004; Heckman & Vytlacil 2007a, 2007b; Diagne & Demont 2007).

3.2.4 Parametric estimation of adoption rates

A potential caveat in the treatment effect literature is the identification of the treatment effect, especially when treatment is not assigned randomly. In our case, identification is somewhat easier, since our adoption outcome is binary. Moreover, the potential outcome is Y_0 for both the treated and untreated subsamples, $E(Y_0|w = 1) = E(Y_0|w = 0)$.

Under these conditions, identification through the unconfoundedness/ignorability assumption holds (Imbens & Wooldridge 2009).

The parametric estimation approach consists, first of all, of specifying the parametric model. This method uses only the subpopulation of exposed farmers to estimate the adoption rates. This is also known as the conditional independence assumption, which states that, conditional on a set of observables, the treatment variable, adoption, is independent of the potential outcomes, Y_1 and Y_0. From this assumption, we estimate the ATE, ATET and ATEU employing parametric procedures in a regression framework. We specify a model for the conditional expectations of the observed variables, Y, x and w, as (Diagne & Demont 2007; Dibba *et al*. 2012):

$$E(Y|x, w = 1) = g(x, \beta), \tag{11}$$

where x is a vector of observed farmers' characteristics, g is a function of a set of variables (covariates x) driving adoption and the unknown parameter, vector β, which is to be estimated using standard least squares (LS) or maximum likelihood estimation (MLE) procedures. This is performed by using the observations (Y_i, x_i) from the sub-sample of exposed farmers only, with Y as the dependent variable and x the vector of explanatory variables. With an estimated parameter β, the predicted values, $g(x_i, \beta)$, are computed for all the observations i in the sample (including the observations in the non-exposed sub-sample), and ATE, ATET and ATEU are estimated by taking the average of the predicted $g(x_i, \beta), i = 1, \ldots, n$ across the full sample (for ATE), and across the respective sub-samples (for ATET and ATEU):

$$\widehat{ATE} = \frac{1}{n}\sum_{i=1}^{n} g\left(x_i, \hat{\beta}\right) \tag{12}$$

$$\widehat{ATET} = \frac{1}{n_e}\sum_{i=1}^{n_e} w_i\, g\left(x_i, \hat{\beta}\right) \tag{13}$$

$$\widehat{ATEU} = \frac{1}{n-n_e}\sum_{i=1}^{n}(1 - w_i)\, g\left(x_i, \hat{\beta}\right), \tag{14}$$

where Y_i is the adoption outcome of a farmer i, w_i is the exposure status of a farmer i, n is the sample of farmers surveyed, $n_e = \sum_{i=1}^{n} w_i$ is the sample size of exposed farmers, $\hat{P}(z)$ is a robust estimate of the probability or propensity score evaluated at z; and β must be estimated with standard least squares (LS) as well as maximum likelihood estimation (MLE) methods (Heckman *et al*. 1999; Blundell & Dias 2002; Wooldrige 2002; Imbens 2004; Diagne & Demont 2007; Diagne *et al*. 2007).

An interesting feature of the conditional independence assumption is its non-requirement of variable exogeneity (Diagne & Demont 2007), enabling us to obtain causal impacts of exposure and adoption. It only requires the variables to be pre-treatment variables, or in other words variables that are determined outside the model (Heckman & Vytlacil 2005). In our case, this means that our variables should not be determined by exposure. This assumption of exogeneity can be passed safely for most of our variables, as they were not determined by exposure. Our membership in cooperative groups can be thought of as an endogenous variable. However, membership of these groups was determined prior to learning about the new poultry scheme. One other concern here is the fact that adopting households can group themselves into local groups for better communication and access to improved poultry farming technology. This is not considered in the membership dummy and was excluded from the analysis.

Based on these empirical specification, the adoption rates estimation approach used in this study to assess the adoption rates of ITTPF by smallholder farmers in Togo was built on modern theories of assessing intervention impacts (Heckman *et al*. 1999; Blundell & Dias 2002; Wooldridge 2002; Imbens 2004; Diagne & Demont 2007; Heckman & Vytlacil 2007a, 2007b). This method corrects both non-knowledge bias due to the incomplete diffusion of ITTPF in the population, and the selection bias of the beneficiary population. Following the same procedures developed by Diagne and Demont (2007), we used both semi-parametric weighting estimators (equations 6, 9 and 10) and parametric regression-based estimators (equations 12, 13 and 14) in this study to estimate ATE, ATET, ATEU, the population adoption gap, and the population selection bias. All the estimations were done in Stata using the Stata add-on adoption command developed by Diagne in 2006. The following adoption rate parameters were estimated: ATE = mean potential adoption rate in the population; ATET = mean potential adoption rate in the exposed subpopulation; ATEU = mean potential adoption rate in the unexposed subpopulation; JEA = population mean joint exposure and adoption rate; GAP = population adoption gap; and PSB = population selection bias.

3.3 Data collection

A farm household survey was conducted in the five regions (Savannah, Kara, Central, Plateaux and Maritime) of Togo in late 2020 (see the map in Figure 1). From a rural population of 3 738 430 farmers, 400 smallholder farmers were sampled as the core sample for this study, using Fellegi's (2003) sampling technique with a 95% confidence level. Baseline data obtained from the Ministry of Agriculture, Livestock and Rural Development helped in the identification of 86 smallholder farmers who received government subsidies for ITTPF adoption in 2014. These grants were awarded to them as a result of their voluntary participation in PNIASAN and PASA, which were implemented by the government in Togo with the financial support of the World Bank and help from the FAO. The total sample of 400 responding smallholder farmers was stratified by region according to each region's weight in the country. The 86 smallholder farmers exposed to ITTPF were distributed by district in the five regions of the country. As a result, they were considered beneficiaries and were included in the total sample. Respondents not benefiting from government subsidies, who were selected randomly from the general population using baseline data, made up the remainder of the sample and were also stratified based on the weight and distribution of subsidised smallholder farmers by district in the five regions. Key socioeconomic characteristics, institutional variables, and information on livestock ownership, potential outcomes and expenditure were all collected. The core variables in the analyses are presented in Tables 1, 2 and 3.

4. Results and discussions

It should be remembered that, in the case of the adoption evaluation study, the treatment corresponds to exposure and, in our context, the exposure reflects the functional status[2] of a traditional poultry farm five years after the introduction of ITTPF. Estimates were made using the inverse propensity score-weighting (IPSW) method, or the so-called semi-parametric method, and the parametric method (ATE logit). SPSS and Stata software were used for data processing and analysis. The results of the analysis are indicated in Tables 1, 2 and 3.

4.1 Descriptive statistics

The descriptive statistics are indicated in Table 1. We categorise farmers according to ITTPF exposure and adoption status and compare several variables of interest. Overall, 86 farmers out of 400 respondents were exposed to ITTPF in 2014.

[2] Farmer's participation in PNIASAN and PASA and implementation of improved poultry farm for ITTPF adoption – Improved poultry farms in good conditions five years after the introduction of ITTPF: Continuous adoption; and improved poultry farms in poor conditions five years after the introduction of ITTPF: Partial adoption.

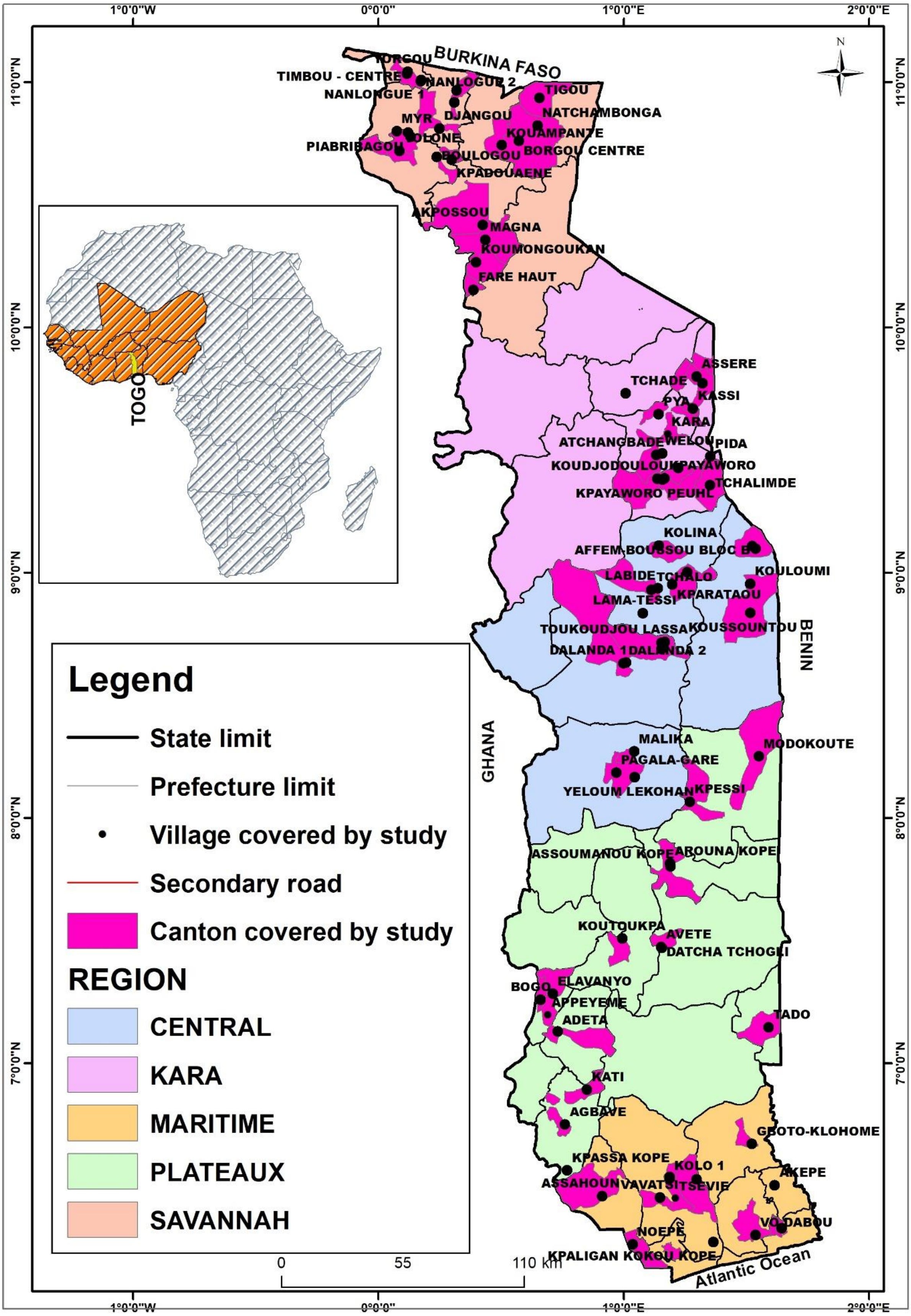

Figure 1: Map of the study area (Togo)
Source: Authors' conceptualisation

The findings in Table 1 show a significant difference between the two groups in terms of level of study, household size, farm size, average annual sale of poultry, poultry loss rate and self-financing capacity. These variables could be related to the participation of farmers in PNIASAN and PASA for ITTPF adoption. We used network membership, defined as a dummy that takes a value of one if the farmer is a member in any agricultural cooperative, and zero otherwise. We considered both formal associations, such as inputs or marketing cooperatives, and informal associations, such as savings and credit groups. Table 1 indicates that such agricultural cooperative or network membership is higher among smallholder farmers who were exposed to ITTPF. Membership of agricultural cooperative societies could be related to the participation of smallholder farmers in PASA for the adoption of ITTPF. Of 86 farmers aware of and exposed to ITTPF in 2014, 60% were full adopters in 2019/2020 on a continuous adoption basis, and 40% were partial adopters. Only full adopters five years after the introduction of ITTPF were counted as reals adopters in our analysis.

Table 1: Comparative table of socioeconomic characteristics of participants and non-participants in PNIASAN and PASA within the framework of ITTPF adoption in Togo

	Project participants	Project non-participants	t/chi^2	Statistical significance
Household size	10 (0.58)	7 (0.18)	-4.91	***
Farm size	188 (21.68)	42 (2.08)	-12.12	***
Annual sale of poultry	283 (33.00)	31 (1.27)	-14.47	***
Poultry loss rate	0.14 (0.02)	0.76 0.00	22.83	***
Level of study	2 (0.09)	1 (0.05)	-6.24	***
Membership of cooperative	-	-	324.85	***
Self-financing capacity	-	-	296.20	***
Adoption status	60% (0.05)	0% (0)	-21.85	***

Notes: Asterisks (***) indicate that mean values are significantly different at the 1% level (t-test for continuous variables and chi-square test for non-continuous variables); mean values are shown, with standard errors in parentheses.
Source: Authors' computation based on field data from 2014 and 2020

4.2 Econometrics results

Based on the study objective and in line with the empirical literature and specifications, a two-stage regression framework was employed. In the first stage (Table 2), we analysed factors associated with farmers' participation in PNIASAN and PASA for ITTPF adoption, since adoption depends to a large extent on the information acquired about the improved traditional poultry scheme. The findings in Table 2 indicate that different socio-economic and contextual factors matter in the participation of farmers in PASA. Key among these are level of study, household size, membership of cooperative, farm size and self-financing capacity, which showed a positive and significant relationship with participation in PASA for the adoption of ITTPF.

We then assessed the adoption rates of ITTPF among farmers in the second stage (Table 3). The results of the estimates in Table 3 indicate that the semiparametric and parametric models estimated the population mean potential adoption rate (ATE), which is dependent on farmer demand for ITTPF, to be 54% and 57% respectively. This means that the ITTPF adoption rate could have been 54% or 57% five years after the implementation of PASA if the whole population of farmers was exposed to ITTPF at the beginning of PNIASAN and PASA in 2014, instead of the observed 13% sample adoption rate (JEA).

Table 2: Factors related to participation of farmers in the agricultural sector support project for the adoption of improved technology in traditional poultry farming in Togo

Variables	Coefficient	Standard error	z
Sex (male = 1, female = 0)	0.005	0.004	1.031
Age (years)	0.0002	0.0003	0.568
Marital status (categorical)	-0.007	0.006	−1.166
Level of study (categorical)	0.0025**	0.0022	1.136
Household size (number of members)	0.0002**	0.0004	0.447
Membership of cooperative (yes = 1, no = 0)	0.957***	0.040	23.699
Self-financing capacity (US$)	0.024***	0.027	0.892
Farm size (number of poultry)	0.008**	0.012	0.689
Average annual sale of poultry (NPS)	0.005*	0.008	0.571
Hatching rate of eggs (%)	0.055	0.040	1.353
Loss rate of poultry (%)	0.006	0.027	0.221
Diagnostic statistics			
Number of observations	400		
Log-likelihood	502.3723		
P-value (F)	0.0000		
R-squared	97.16%		
Adjusted R-squared	97.08%		

Notes: * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
NPS = number of poultry sold
Source: Authors' computation based on field data from 2014 and 2020

Table 3: Estimation of adoption rates showing the rates of adoption of improved technology in traditional poultry farming (ITTPF) among farmers in Togo

	ATE adoption rate (IPSW) (semi-parametric estimation)	ATE adoption rate (parametric estimation)
ATE	0.540 (0.072)***	0.570 (0.066)***
$ATET$	0.604 (0.089)***	0.604 (0.052)***
$ATEU$	0.522 (0.076)***	0.560 (0.073)***
JEA	0.130 (0.020)***	0.130 (0.011)***
GAP	-0.410 (0.059)***	-0.440 (0.057)***
PSB	0.064 (0.060)	0.034 (0.040)
$ATET_S$	0.809 (0.078)***	0.809 (0.078)***
$ATET_K$	0.352 (0.078)***	0.352 (0.078)***
$ATET_C$	0.470 (0.078)***	0.470 (0.078)***
$ATET_P$	0.500 (0.078)***	0.500 (0.078)***
$ATET_M$	0.923 (0.078)***	0.923 (0.078)***
N_e/N	0.215 (0.021)***	0.215 (0.021)***
N_a/N	0.130 (0.017)***	0.130 (0.017)***
N_a/N_e	0.604 (0.078)***	0.604 (0.078)***
Number of observations	$N = 400$	
Number exposed	$N_e = 86$	
Number of adopters:	$N_a = 52$	

Notes: Robust z-statistics in parentheses
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level; ATE = mean potential adoption rate in the population; ATET = mean potential adoption rate in the exposed subpopulation; ATEU = mean potential adoption rate in the unexposed subpopulation; JEA = mean joint exposure and adoption rate in the population; GAP = population adoption gap; PSB = population selection bias
$ATET_S$ = ATET in the Savanah Region, $ATET_K$ = ATET in the Kara Region, $ATET_C$ = ATET in the Central Region, $ATET_P$ = ATET in the Plateaux Region, $ATET_M$ = ATET in the Maritime Region
Source: Authors' computation based on field data from 2014 and 2020

When a sample estimation based on incomplete diffusion was used to represent the true adoption rates in the population, the 13% sample adoption rate or the population mean joint exposure adoption rate (JEA) implies a very negative non-exposure bias of -41% (population adoption gap (GAP) estimated by the ATE semiparametric) or -44% (population adoption gap (GAP) estimated by the ATE parametric). These findings are in line with those of Diagne and Demont (2007), Diagne *et al*. (2019), Ouédraogo *et al*. (2019), Owusu (2019) and Adekambi *et al*. (2020), who found significant population adoption gaps due to a lack of exposure by a sufficient size of the population.

Moreover, it is important to note that the 60% mean potential adoption rate in the subpopulation of farmers exposed to ITTPF (ATET) is much closer to the mean potential adoption rate (ATE) of the population. This indicates an insignificant population selection bias, which the data analysis confirmed. The insignificant population selection biases of the semiparametric and parametric models, of 0.064 and 0.034 respectively, indicate that all of the farmers in the sample have nearly equal chances of adopting ITTPF. Ouédraogo and Dakouo (2017), Amengor *et al*. (2018), Ndiaye *et al*. (2018) and Diagne *et al*. (2019) had similar results regarding the insignificant population selection bias. In contrast, Diagne and Demont (2007), DioufSarr *et al*. (2018), Muthini (2018), Ouédraogo *et al*. (2019), Owusu (2019) and Adekambi *et al*. (2020) found significant population selection bias in their studies evaluating adoption rates, which means that a farmer selected in the exposed subpopulation had a higher probability of adoption than a farmer randomly picked from the general population. Furthermore, the mean potential adoption rate in the unexposed subpopulation of farmers (ATEU) is estimated by the semiparametric and parametric models to be 52.25% and 56%, respectively. This shows that about 52.25% or 56% of those farmers would have adopted the ITTPF if all farmers were given an equal opportunity of being exposed to PNIASAN and PASA at the beginning. This estimate shows a very high supply-demand gap for ITTPF in Togo. Similar to the findings of most previous studies (Ouédraogo & Dakouo 2017; Amengor *et al*. 2018; Ndiaye *et al*. 2018; Diagne *et al*. 2019), the potential adoption rate of ITTPF is equally high among exposed and unexposed farmers. Furthermore, the population selection bias is insignificant because ITTPF is a new technology introduced in the rural world by the government through PASA, which justifies the fact that its adoption demand by farmers is very high. In addition to the above, since ITTPF is made up of several technical components, its full adoption will only be enabled through both awareness and exposure.

The potential adoption rates among the regional subpopulations of exposed farmers are, in decreasing order, 92.30%, 80.95%, 50%, 47.05% and 35.29% in the Maritime, Savannah, Plateaux, Central and Kara regions respectively. These results imply that the adoption rate of ITTPF among exposed farmers differs from one region to another. The high adoption rates could be explained by the fact that, in certain regions (especially in the Savannah region), some farmers have acquired experience in traditional poultry farming and have developed an inherent know-how that enables them to easily adopt ITTPF. During the fieldwork, it was discovered that there were abandoned and non-functioning poultry farms in the programme for the simple reason that some farmers, after receiving funding (for the adoption of ITTPF), abandoned the programme to invest in other economic activities. These non-objective behaviours of certain beneficiary smallholder farmers could explain the low adoption rates in some regions.

Furthermore, while some potential adopters understood the importance of technological innovations and were willing to take advantage of the available opportunities to improve their traditional poultry farm and make it more profitable, others lacked dynamism and did not make enough of a continuous effort to adopt ITTPF. The low adoption rates could also be the consequence of the lack of continuous technical capacity-building and the lack of periodic monitoring and technical support to beneficiary farmers by the animal production actors (experts and agricultural structures) involved in PNIASAN and PASA.

5. Conclusion and policy implications

The objective of this paper was to assess the adoption rates of improved technology in traditional poultry farming (ITTPF) among smallholder farmers in Togo. Even though the sample was selected randomly, the study found that the sample adoption rate does not reflect the true population adoption rate due to incomplete diffusion of ITTPF. As a result, the population adoption rate is underestimated. The rate of adoption within the exposed subpopulation of farmers could be used as a possible solution to this problem. However, because of selection bias, the rate of adoption among farmers exposed to the technology might not be a better measurement of the true adoption rate in the population. It has the potential to either overestimate or underestimate the true adoption. As a result, accounting for non-exposure as well as selection biases is essential for obtaining accurate estimations of the adoption rates of new technologies/emerging agricultural practices that are not widely recognised in the population. The adoption evaluation approach developed in this paper has significant policy implications in terms of judging the intrinsic merit of ITTPF, in terms of its potential demand by farmers independent of issues related to its accessibility, and in terms of the decision to invest or not to invest in its wide-scale dissemination.

The research findings provide leverage points that should guide policymakers in scaling up decisions on ITTPF adoption within the framework of PNIASAN and PASA and beyond. Agricultural policies should promote networking by agricultural cooperative societies, coupled with effective extension services to boost the adoption of improved agricultural technologies that are indispensable for sustainable agricultural development. Furthermore, in response to the very high gap in the supply and demand for ITTPF in Togo, agricultural policymakers should invest more in the improvement of the dissemination programmes for ITTPF in order to make it accessible to the entire target population. Ongoing training in the different components of improved agricultural technologies, and regular technical capacity-building of potential adopters, are essential for optimal positive impacts on farmers' potential outcomes and well-being.

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