

Does intensive adoption of improved agricultural practices enhance vegetable household welfare in southern Benin? A Panel Data Analysis

Senouwa Hector Valère KPANGON

kpangonhector@gmail.com

Université d'Abomey-Calavi

Ygué Patrice Adegbola

Institut National des Recherches Agricoles du Bénin

Tèko Augustin Kouévi

Université d'Abomey-Calavi

Kossi Nounagnon Augustin AOUDJI

Université d'Abomey-Calavi

Segla Roch Cedrique Zossou

Université d'Abomey-Calavi

Research Article

Keywords: Vegetable interventions, Welfare, unbalanced panel data, continuous endogenous variable, correlated random coefficients model, southern Benin

Posted Date: September 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11054028/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Does intensive adoption of improved agricultural practices enhance vegetable household welfare in southern Benin? A Panel Data Analysis

Senouwa Hector Valère Kpangon^{1*}, Ygué Patrice Adegbola², Tèko Augustin Kouévi¹, Augustin Kossi Nounagnon Aoudji¹, Segla Roch Cedrique Zossou¹

¹ Department of Economics, Socio-Anthropology and Communication for rural development, Faculty of Agricultural Sciences, University of Abomey-Calavi, Abomey-Calavi, Republic of Benin.

² Laboratory for Analysis and Research of Agricultural Policies, National Agricultural Research Institute of Benin, Abomey-Calavi, Republic of Benin.

***Corresponding author email address:** Department of Economics, Socio-Anthropology and Communication for rural development, University of Abomey-Calavi, Abomey-Calavi.

e-mail address: kpangonhector@gmail.com

Abstract

Food security remains a persistent challenge in sub-Saharan Africa, and sustainable agricultural intensification has been proposed as a promising strategy to improve both agricultural productivity and household welfare. However, there is limited empirical evidence on the heterogeneous welfare effects of the intensity of adopting multiple sustainable agricultural practices, particularly when these technologies are implemented individually or in combination. This study addresses this gap by examining the welfare impacts of certified seeds (CS), improved technical itineraries (ITK), and irrigation systems on annual per capita expenditure and the Food Consumption Score (FCS) among vegetable farm households in southern Benin. The analysis uses an unbalanced three-round panel dataset collected in 2018, 2020, and 2022. It estimates heterogeneous effects of multiple treatments in the presence of the endogeneity with respect to both time-constant and time-varying unobserved heterogeneity and selection on idiosyncratic gains. Accordingly, a panel-data fixed-effects endogeneity-corrected correlated random coefficients model combined with a latent factor approach is used. The main findings are that the largest effects on per capita expenditure (an average partial effect of 82%) were obtained with an increase in the area covered by the adoption of the three technologies combined, especially in the presence of an irrigation system. Similarly, an increase of area under the three combined technologies increases the probability of achieving an acceptable FCS by 0.45 points, specifically among male-headed farm households. The findings have important policy implications for designing targeted agricultural programs that promote complementary technology packages and account for household heterogeneity to maximize welfare.

Keywords: Vegetable interventions; Welfare; unbalanced panel data; continuous endogenous variable; correlated random coefficients model; southern Benin.

1 Introduction

In recent decades, agricultural interventions in West African countries have focused primarily on staple and cash crops such as maize, rice, cassava and cotton [1], [2]. In contrast, the vegetable farming subsector has comparatively received limited attention, despite its significant potential to enhance food and nutritional security, stimulate economic growth, and generate employment, particularly for young people and women in Benin [3].

In Benin, the vegetable sector has experienced sustained growth in recent years. It accounted for approximately 15.11% of agricultural gross domestic product (GDP) in 2024[4], with more than 333,734 farmers engaged in vegetable production as of 2019. Total production reached 717,365 tons during the 2023–2024 season, representing a 6.2% increase over that of the previous year [4]. Despite this expansion, the sector continues to face structural constraints, including limited access to quality inputs such as certified seeds (CS), inadequate irrigation infrastructure, insufficient technical knowledge and weak value chain integration [1], [3]. In response, the government of Benin, supported by development partners and nongovernmental organizations, has prioritized investments in vegetable farming [1], [5]. These interventions promote the adoption of key agricultural technologies, including CS, improved technical itinerary knowledge (ITK) (mineral/organic fertilization and certified biopesticides) and irrigation technology (IrrT) (tube wells, boreholes, and raised boards). These innovations are expected to enhance vegetable farmers' welfare through two main pathways: (i) increasing productivity and market participation, leading to higher incomes and employment opportunities along the value chain, and (ii) improving household food availability and dietary diversity, contributing to better nutritional outcomes and long-term human capital development [6].

Despite these efforts, rigorous empirical evidence on the welfare impacts of such interventions remains limited, particularly interventions targeting irrigation systems, CS access and improved technical itineraries. This study addresses several critical gaps in the literature in four main ways.

The first limitation is that the literature predominantly evaluates single technologies in isolation, despite the fact that vegetable farmers typically combine complementary innovations such as certified seeds, improved technical practices, and irrigation [7]. As a result, little is known about whether these technologies generate complementary

or synergistic welfare effects when adopted jointly or whether their impacts depend on the intensity of adoption.

A second limitation concerns the measurement of welfare, previous studies on vegetable production in developing countries have mainly focused on yield and marketing efficiency [8], [9], income, poverty and food security using cross-sectional data [2], [10], [11], [12], [13]. While these studies report positive outcomes, these indicators conventionally used do not fully capture broader dimensions of household well-being, such as food consumption, education, and living conditions. Moreover, yield-based measures are difficult to standardize in diversified vegetable systems involving multiple crops (e.g., onion, tomato, pepper, lettuce, amaranth, and carrot) [2]. Consequently, there is limited evidence on how technology adoption simultaneously affects both the economic and nutritional dimensions of household welfare though annual per capita consumption expenditure and the food consumption score (FCS) indicators as recommended by [2] and [14]. Third, very few studies explicitly consider the intensity of adoption in the vegetable sector, which is typically proxied by the share of cultivated areas allocated to specific technologies. This study advances the literature by analyzing the welfare effects of both single and combined technologies while explicitly accounting for adoption intensity in the vegetable sector. Fourth, unlike most prior studies relying on cross-sectional data, this analysis exploits a multiwave panel dataset, thus allowing for a more robust identification of causal effects over time [2], [15]. Cross-sectional designs are prone to selection bias and fail to adequately control for unobserved heterogeneity, thereby potentially leading to biased estimates [16], [17]. Panel data offer a critical advantage by enabling the control of both time-invariant and time-varying unobserved heterogeneity, particularly in contexts where farmers self-select into technology adoption based on latent characteristics such as ability, motivation, and expectations of future gains [18]. This dynamic selection process induces endogeneity, as adoption decisions are correlated with anticipated welfare improvements. To control time-invariant unobserved heterogeneity, the correlated random effects (CRE) or fixed effects approach is typically used, mainly in the context of panel data [19], [20], [21]. However, the CRE commonly used in nonlinear models is considered complementary to fixed effects and has limitations since it is applicable to situations with short panels and small samples, implying arbitrary time heterogeneity and dependence [21]. Thus, we apply a combination of econometric techniques, specifically fixed effects models for controlling

time-invariant unobserved heterogeneity commonly used in linear models addressing the linear nature of the intensity of adoption variable, and control function / latent factor models that control time-varying unobserved heterogeneity and address potential endogeneity and selection bias following the recommendations of [18], [19], [20], [22]. In fact, control function and latent factor approaches are more efficient than traditional instrumental variable (IV) methods when dealing with heterogeneous and multiple endogenous treatment effects, as demonstrated by [23] and [24]. The remainder of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 details the methodology. Section 4 presents the empirical results, and Section 5 discusses them. Finally, Section 6 concludes the paper and offers policy recommendations.

2 Nexus between vegetable-focused interventions and farmers' welfare: Household-level pathways

This study builds on a conceptual impact pathway that provides a comprehensive understanding of how vegetable-based interventions influence household welfare through food production, income generation, and women empowerment pathways [25]. The model emphasizes the role of farm-household access to integrated vegetables intervention packages, which include the provision of certified seeds of improved varieties, irrigation systems and training in optimal agronomic practices, such as the use of biopesticides, biofertilizers, and organic manure.

The analysis focuses on vegetable-producing households, as they serve as both production and consumption units within the rural economy. Due to the presence of imperfect markets for food commodities and production inputs, particularly labor, production and consumption decisions are interlinked. Thus, a non-separable agricultural household model is adopted to reflect the dual roles and constraints faced by these households.

Our theoretical framework is grounded in the agriculture-nutrition impact pathway described by [6], [26], [27]. Households' welfare is proxied by two key outcomes: food security status and household consumption expenditure [28]. The conceptual model integrates three primary pathways: 1) food production pathway, 2) income generation pathway and 3) women's empowerment pathway [26].

These pathways provide a structured lens through which the behavioural changes induced by vegetable interventions can be linked to improvements in household welfare outcomes. The sustainability of these impacts depends on the extent to which farmers adopt improved practices. A visual illustration of the adapted framework is provided in Figure 1, derived from [26], emphasizing its relevance to food security and consumption dynamics.

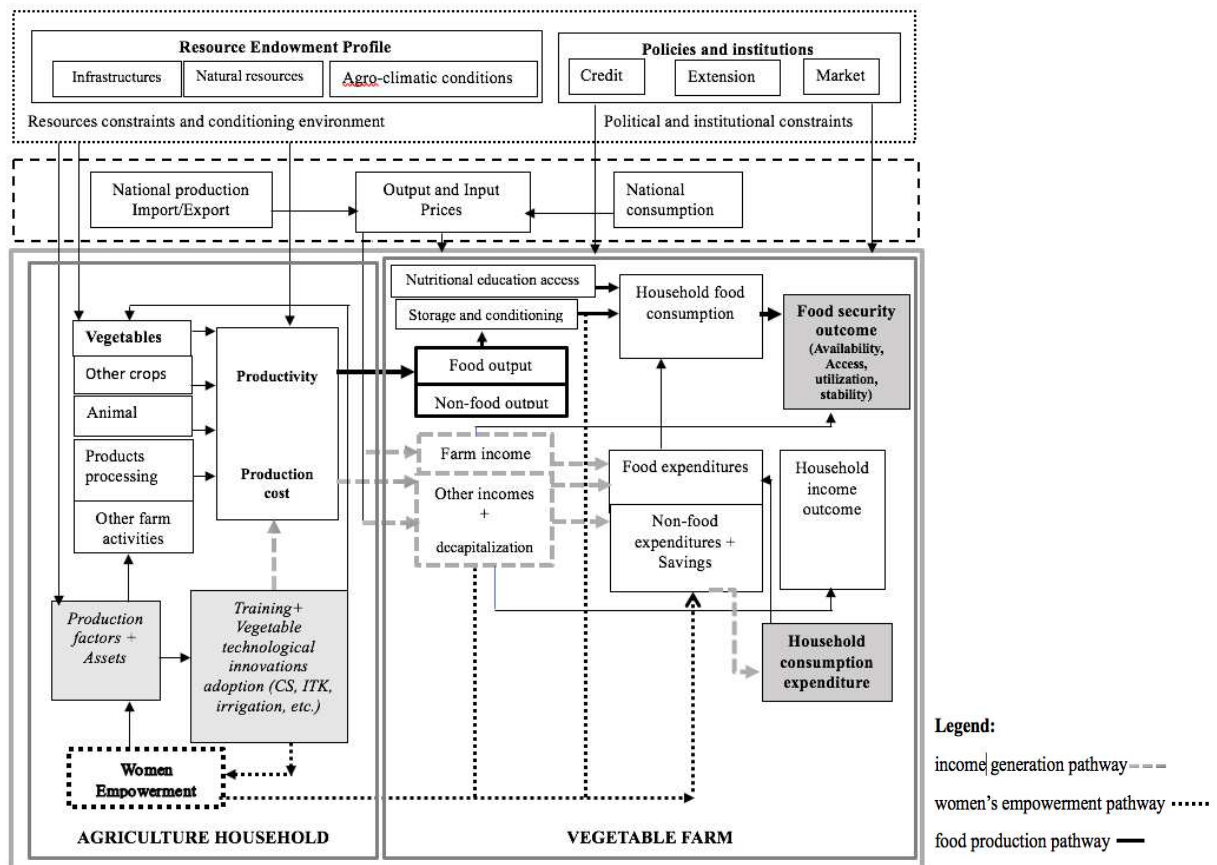
The model assumes that targeted farmers receive a comprehensive vegetable intervention package. Enhanced access to modern production inputs (fertilizers, pesticides, and improved seeds), along with training on their optimal use, is expected to reduce production costs and boost yields. Adoption of improved agronomic practices further augment vegetable productivity [6]. Higher productivity leads to surplus production, enabling farmers to sell excess output and generate farm income. The income pathway posits that increases in net farm income enhance the households' purchase power, enabling access to more diverse and nutritious food. Income may also be reinvested in other food crops enterprises, fostering diversified and resilient household diets. Thus, improved food availability and access translate into greater household food security. The direct cultivation of staple and nutrient-rich crops remains a central strategy to increase food availability at the household level. Moreover, net farm income positively influences both food and non-food consumption expenditures, reflecting its broader effect on household well-being [6], [14], [26].

The women's empowerment pathway constitutes a critical mediating mechanism within this framework. Women are actively engaged across all segments of the vegetable value chain, from production to marketing, and control over resources and income significantly shapes household expenditure patterns. Evidence indicates that women-controlled income is more likely to be allocated toward food and health-related expenses [26]. Furthermore, vegetable production interventions may reduce women's time burdens by improving efficiency in farm and household tasks. Time saving enable investment in caregiving and food preparation activities, thereby enhancing the nutritional well-being of women and children. Empowering women thus emerges as a critical leverage point for advancing food security and household welfare [6].

At the meso- and macro-levels, these three pathways are shaped by enabling environment, which includes factors such as the food market system, natural resource base, infrastructure, cultural norms, and knowledge systems[26]. Agricultural policies and development interventions can either reinforce or constrain these pathways,

179 underlining the importance of a multisectoral approach in the design and
180 implementation of vegetable-based development programs [26].

Fig. 1



Description: Causal pathways from vegetable interventions to both household food security and consumption expenditures

3 Materials and Methods

3.1. Identification strategy of bias

In this study, the evaluation of the effects of multiple vegetable-related interventions on household consumption outcomes is grounded in a latent variable discrete choice framework—specifically, the index function formulation and the generalized Roy model [7]. Based on the generalized Roy model [29], adoption decisions of vegetable interventions $m(m = 0, \dots, 5)$ are made under partial or complete knowledge of potential returns [30]. Thus, the probability that the adoption decision D equals a specific alternative m is expressed as follows:

$$P_m = Pr(D_{mit}^* = m) = F_j(x_{it}\delta_m), m = 0, \dots, 5 \quad (1)$$

where $F_j(\cdot)$ is the cumulative distribution function of the error term and observed variables x_{it} .

Various specifications for F_j correspond to specific models, namely the multinomial logit, nested logit, multinomial probit, ordered, sequential, and multivariate models for the polychotomous endogenous treatment case [31].

Under the generalized Roy model and assuming linearity, at time t , the welfare outcome Y equation for alternative combinations of multiple vegetable interventions m is given [18], [22] as follows:

$$Y_{0it} = \alpha_{0t} + x_{it}\beta_0 + c_{i0} + u_{0i}$$

$$Y_{mit} = \alpha_{mt} + x_{it}\beta_m + c_{im} + u_{mi} \quad \forall i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (2)$$

where Y_{0it} is the potential outcome that economic agent i would obtain at time t if he is not assigned to any alternative combination of vegetable intervention ($m = 0$), Y_{mit} is the potential outcome that person i would obtain at time t if assigned to an alternative combination of vegetable intervention, $m(m = 1, \dots, 5)$, α_{0t} and α_{mt} are the time-specific intercepts common in panel data applications [32], and x_{it1} is a vector of various explanatory variables[18]. The time-constant unobserved heterogeneity across units in the six regimes is captured by c_{i10} and c_{i1m} . The idiosyncratic errors are captured by u_{0i} and u_{mi} .

In this study, we also assume heterogeneous treatment effects and selection on the gain [33]. To take this hypothesis into account, some interaction terms of a subset of demeaned explanatory variables x_{it} with the dummy adoption variable D_{jit} are included in the model. The impact of adopting vegetable interventions on welfare (γ_k) is accordingly expressed in equation (2) as a function of an intercept (λ), the demeaned explanatory variables of x_{it} , such as socioeconomic demographic characteristics, the deflated consumer price index and unobserved heterogeneity (c_i), and the ability and motivation of the vegetable farmers included in the idiosyncratic error (ε_{it}) [34]. Accordingly, the expected impact is expressed following Imbens and Wooldridge [18]:

$$Y_{jit} = \beta_{t0} + x_{it}\beta_m + D_{mit} \lambda + D_{mit}(x_{it} - \bar{x}_{it})\delta + \alpha_i + c_i + D_{mit}\varepsilon_{it} + u_{mi} \quad (3)$$

The model in Eq. (3) with Roy selection is commonly referred to as a correlated random-coefficient model because the coefficient on D_{mit} is an unobserved random variable that is permitted to be arbitrarily dependent on D_{mit} itself [33]. The most important assumption for Eq. (3) to determine a consistent causal effect of the

vegetable intervention adoption variable D_{mit} on household welfare outcomes is that of the strict exogeneity of the covariates. Therefore, any correlation between the explanatory variables and the composite error term of Eq. (3) is ruled out [33], [34]. The difficulty in identifying Eq. (3) arises in the presence of unobserved constant heterogeneity, endogenous variables and selection into treatment. If the noncorrelation assumption is invalid, then the variable D_{mit} is said to be endogenous. The endogeneity of the regressors makes the estimators inconsistent and results in inappropriate inferences.

This study considers the endogeneity problem derived from omitted variables that vary across both farm households and time and are included in the error term of Eq. (3). The omission of these variables in Eq. (3) means that they will be incorporated into the error term ($D_{mit}\varepsilon_{it} + u_{i0}$). As a result, the error term is correlated with the adoption of vegetable interventions variable (D_{mit}), hence violating the exogeneity assumption [33], [34]. For instance, some farm households have an inherent ability to adopt more vegetable interventions and to invest more in welfare. This ability might be neither specifically reported in the data nor proxied by any of the reported variables. Afterward, the adoption status of vegetable interventions will be correlated with the unobserved ability component of the error term. This situation results in an upward bias in the estimated coefficient of the adoption status, as it captures both the direct effect of adoption and the indirect effect of capability on gains. This example of the effects of unobserved factors indicates the potential endogeneity of the adoption decisions variable in the outcome equation, which introduces bias in all the estimated coefficients. Consequently, in light of the aforementioned biases, a bias-corrected estimator is necessary.

3.2. Selection of corrected panel data models

Several methods have been developed to control selection bias and endogeneity stemming from selection on unobservables, including instrument variables (IVs) with estimators such as the two-stage least squares (2SLS) method and the two-stage residual inclusion approach, also known as control function approaches, and latent factor models [15], [23], [35], [36]. Among these, control function methods and latent factor models are often more efficient than traditional IV techniques are, especially in the presence of multiple treatments, heterogeneous effects, and self-selection

[24], [31]. Furthermore, Drukker [35] and Heckman [23] demonstrate that latent factor models can consistently identify treatment effects even in the absence of valid instruments. Furthermore, they show that the latent factor can be used regardless of whether the endogenous variables and outcomes are linear or nonlinear. In this case, we estimate the control function and the latent factor approach separately to select the appropriate one in this study.

With respect to the control of time-constant and variant unobserved heterogeneity in the context of panel data, three major approaches are conventionally used depending on the case, such as fixed effects, CRE and random effects models. Fixed effects models assume the control of time-invariant unobserved heterogeneity that is correlated with explanatory variables, while random effects models assume uncorrelated and potentially time-varying unobserved effects [18]. Unlike CRE models, fixed effects models are particularly useful when continuous variables are endogenous and correlated with unobserved heterogeneity in technology use, as is the case in our study [19].

In light of these considerations, the present study applies a correlated random coefficient model with fixed effects to control for unobserved heterogeneity, incorporating a control function on the one hand and a latent factor approach on the other hand to account for time-varying unobserved heterogeneity, endogeneity and heterogeneity with multiple continuous endogenous treatments.

3.3. Specification of a fixed effects panel data endogeneity corrected correlated random-coefficients model

Drawing from the proposed theoretical framework, this study specifies two-system equations as a joint distribution of a multiple continuous endogenous treatments D_{it} equation and a welfare outcome Y_{jit} equation. Following Imbens et al. [34], the main equation is specified as a correlated random-coefficient model accounting for Roy-type selection[29], [31], [32], [37], [38], [39] and can be expressed as follows:

$$\begin{cases} D_{jit} = x_{it}\gamma + \eta_{it} \\ Y_{jit} = \beta_0 + x_{it1}\beta_1 + D_{mit}\lambda_{mi} + D_{mit}(x_{it1} - \bar{x}_{it1})\delta + c_{it} + v_{jit} + u_{it} \end{cases} \quad (4)$$

Fixed effects are applied to correct for the bias resulting from the correlation between the time constant unobserved heterogeneity c_{it} and the continuous endogenous variables D_{mit} [29], [33], [38], [40], [41]. However, neither the bias from the omitted

time-varying unobserved heterogeneity v_{jit} nor that from the selection on gain is eliminated via fixed-effects-style transformations [24].

Moreover, we applied a control function approach to address the time-varying endogeneity issue of D_{mit} , the selection on the gain bias, while accommodating the linear functional form [34].

The estimation is a two-step process. We first estimate the reduced-form treatment equation using a pooled linear model [42], [43].

Next, we construct the control function (τ_{imt}) for each endogenous treatment. In the second step, following Kawatkar et al. [24] Imbens et al. [34], we rewrite the main equation's welfare outcome in the system equation (eq. 4) as follows:

$$Y_{jit} = \beta_0 + x_{1it}\beta_1 + D_{mit}\lambda_{im} + D_{mit}(x_{1it} - \bar{x}_{1i})\delta_{im} + (h(\tau_{imt}))\rho + D_{mit} * ((h(\tau_{imt})))\xi_m + c_i + u_{it} \quad (5)$$

where $\bar{x}_{1i}$ is the expected value of x_{1it} and $(x_{1it} - \bar{x}_{1i})$ is thus the individual demeaned exogenous variables vector. The last two terms are the generalized residual function and the interaction of the generalized residual with the endogenous multiple treatment variable. Fixed effects consistent estimation of λ_{mi} requires that we ignore c_i from the main equation of the system equation (5). Accordingly, we make the following assumption[34]:

$$E(a_i|D_{i1}, \dots, D_{iT}) = E(a_i|\bar{D}_{mi}) = D_{mit}(\bar{D}_{mi} - \bar{D}_m) \quad (6)$$

where other covariates have been suppressed.

The final and complete outcome equation in the case of control function approach is as follows:

$$Y_{jit} = \beta_0 + x_{1it}\beta_1 + D_{mit}\lambda_{im} + D_{mit}(x_{1it} - \bar{x}_{1i})\delta_{im} + \theta D_{mit}(\bar{D}_{mi} - \bar{D}_m) + (h(\tau_{imt}))\rho + D_{mit} * ((h(\tau_{imt})))\xi_m + u_{it} \quad (7)$$

Concerning the case of implementing the latent factor approach, we use generalized structural equation modeling (GSEM) estimator that involves the latent factor. GSEMs involving latent factors l_t have been seen as a more advanced estimator of multiple outcomes (expenditure and level of food security) simultaneously [15]. Unlike the SEM, the GSEM can accommodate not only continuous data but also binary, ordinal, counted, or categorical data. The work of Chaoying et al. [15] confirms the effectiveness of the GSEM compared with the traditional SEM. This model was applied in the panel context following [36], [44] and [36] showed that the GSEM estimator

involving latent factors performs well in resolving the endogeneity problem. The final equation in the case of latent factor approach is as follows:

$$Y_{jit} = \beta_0 + x_{1it}\beta_1 + D_{mit}\lambda_{im} + D_{mit}(x_{1it} - \bar{x}_{1i})\delta_{im} + \theta D_{mit}(\bar{D}_{mi} - \bar{D}_m) + \iota_{it}l + u_{it} \quad (8)$$

In models where the treatment effects depend on unobserved heterogeneity, attention usually turns to population-averaged effects, also called average partial effects (APEs) for continuous endogenous variables [21], [30]. Therefore, in this study, we estimated the APEs of the vegetable interventions on the welfare outcome from the parameters estimated.

3.4. Empirical estimation

This section presents the two approaches adopted (control function and latent factor approaches) to select the best one for correcting bias and estimating the average treatment effect related to each technology package used. First, to account for the unbalanced nature of the panel data, we introduced a selection indicator, also known as a complete case indicator, s_{it} , and rejected the hypothesis of nonrandomness of systematic attrition rate test ($p < 0.05$) after that there is no significant difference in the regression analysis (with attrition and without attrition).

- **Control function approach**

With respect to the approach involving control functions, we follow a two-step procedure to estimate the model. In the first step, we estimate a linear regression simultaneously of the continuous endogenous variables, which represent the intensity of adoption of each of the five technologies (surface area covered by technology), with a linear model to define the control function. In the second step, we save the fitted values and construct a bias correction term from each estimated endogenous equation for the complete cases, as we use a linear specification. Then, we estimate the two outcomes equation (7) separately following Biru et al. [7], Kawatkar et al. [24], Papke and Wooldridge [37], Chamberlain [45], and Mundlak [46].

Estimation of total annual expenditure per capita outcome

In this step, fixed effects correlated random coefficient linear regression is used to estimate the outcome equation related to the total annual expenditure¹ per capita in FCFA, which is a continuous variable and log transformed.

¹ Total annual household expenditure is defined as the aggregate value of both food and nonfood items consumed or purchased by a household[16].

Estimation of the FCS outcome

With respect to the estimation of the FCS², a fixed effects endogenous ordered logit regression is used given the ordered categorical nature (1 = *poor diet*, 2 = *borderline diet*, 3 = *acceptable diet*). Furthermore, we included the mean of time-varying explanatory variables $\bar{Z}_{it}$ to avoid the problem of incidental parameters in nonlinear models given that the number of parameters β increases with the number of individuals [7].

Note that given the difficulty in interpreting the coefficients of the ordered logit model, we present only the elasticities of the significant explanatory variables. Elasticities are calculated as $\partial \log_{y.t} / \partial \log_{Xm.t}$ evaluated at the mean value of the m^{th} component of the x vector using the `eyex` command in Stata 17.

• Latent factor approach

With respect to the latent factor approach, the equations were estimated simultaneously in one step with the GSEM.

Estimation of total annual expenditure per capita outcome

The estimation of total annual expenditure per capita outcome is done following equation (8), the outcome model related to the expenditure is expressed as follows:

$$\ln Y_{expenditure.t} = \beta_{t0} + X_{it}\beta + g(\lambda_1 CS_{it} + \lambda_2 ITK_{it} + \lambda_3 CS \times ITK_{it} + \lambda_4 ITK \times IrrT_{it} + \lambda_5 CS \times ITK \times IrrT_{it} + \iota_1 l_{CS_{it}} + \iota_2 l_{ITK_{it}} + \iota_3 l_{CS \times ITK_{it}} + \iota_4 l_{ITK \times IrrT_{it}} + \iota_5 l_{CS \times ITK \times IrrT_{it}}) + \delta_1 CS_{it} * (X_{it} - \bar{X}_i) + \delta_2 ITK_{it} * (X_{it} - \bar{X}_i) + \delta_3 CS \times ITK_{it} * (X_{it} - \bar{X}_i) + \delta_4 ITK \times IrrT_{it} * (X_{it} - \bar{X}_i) + \delta_5 CS \times ITK \times IrrT_{it} * (X_{it} - \bar{X}_i) + u_{it} \quad (9)$$

X_{it} covariates are often used in the literature (Table 2). The estimation with the GSEM includes five latent factors (l) to five types of potential improved practices and a reference alternative following the procedures of Deb et al. [47], Drukker [35] and [20] by simulating a large number of Halton sequences. Terms $l_{CS_{i,t}}, l_{ITK_{i,t}}, l_{CS_ITK_{i,t}}, l_{ITK_IrrT_{i,t}}, l_{CS_ITK_ITrr_{i,t}}$ and their covariance are unobserved latent utility factors for the treatments, which serve to control for endogeneity in the equation, with $\iota_1, \iota_2, \iota_3, \iota_4$ and $\iota_5 \neq 0$ [47], [48]. The Stata *margins* command is used to systematically estimate the means of each predicted potential outcome. This command accounts for the two-step estimation problem using the standard method

² The ordinal classification of food security levels is estimated following FCS method based on predefined thresholds established by the World Food Program (WFP) [14], [68].

discussed by [49]. Next, we estimate the total marginal effects of technology adoption following [35] and [50].

Estimation of the FCS outcome

The model related to the FCS is as follows:

$$Y_{FCS\ level\ .t} = \beta_{t0} + X_{it}\beta + \bar{Z}_{it}\psi + g(\lambda_1 CS_{it} + \lambda_2 ITK_{it} + \lambda_3 CS \times ITK_{it} + \lambda_4 ITK \times IrrT_{it} + \lambda_5 CS \times ITK \times IrrT_{it} + \iota_1 l_{CS_{it}} + \iota_2 l_{ITK_{it}} + \iota_3 l_{CS \times ITK_{it}} + \iota_4 l_{ITK \times IrrT_{it}} + \iota_5 l_{CS \times ITK \times IrrT_{it}}) + \delta_1 CS_{it} * (X_{it} - \bar{X}_i) + \delta_2 ITK_{it} * (X_{it} - \bar{X}_i) + \delta_3 CS \times ITK_{it} * (X_{it} - \bar{X}_i) + \delta_4 ITK \times IrrT_{it} * (X_{it} - \bar{X}_i) + \delta_5 CS \times ITK \times IrrT_{it} * (X_{it} - \bar{X}_i) + u_{it} \quad (10)$$

The parameters APE and average partial effect for treated (APET) are postestimated following [21], [30], [31], [47], [51], given that the parameter of interest in this study, adoption intensity, is a continuous variable. In contrast, when the program variable is a dummy, the parameter of interest can be the average treatment effect (ATE) or the average treatment effect on the treated (ATT). Thus, we can define a parameter of the APE that measures the change in the expected outcome due to a small change in the program level. Similarly, the APET measures the change in the expected outcome of the program participants due to a small change in the program level. In reality, the adoption of technology provides farmers with different technology coverage levels D . D is a continuous variable, which is higher than zero for the adopter. Furthermore, let $Y_{(D)}$ denote the potential outcome corresponding to the value of D . We can be interested in the technology effect when the technology changes by an intensity, denoted by δ . More specifically, we want to measure the change in the technology impact due to a change in the adoption intensity from d to $d + \delta$.

Following Nguyen [52], the parameters APE and APET are expressed as follows:

$$APE_{(d+\delta)} = \frac{E[Y_{(D=d+\delta)} - Y_{(D=d)}]}{\delta} = \frac{1}{n} \sum_{i=1}^n \frac{\partial F(D_i, X_i, \hat{\epsilon}_i, \hat{\beta})}{\partial D_i} \quad (11)$$

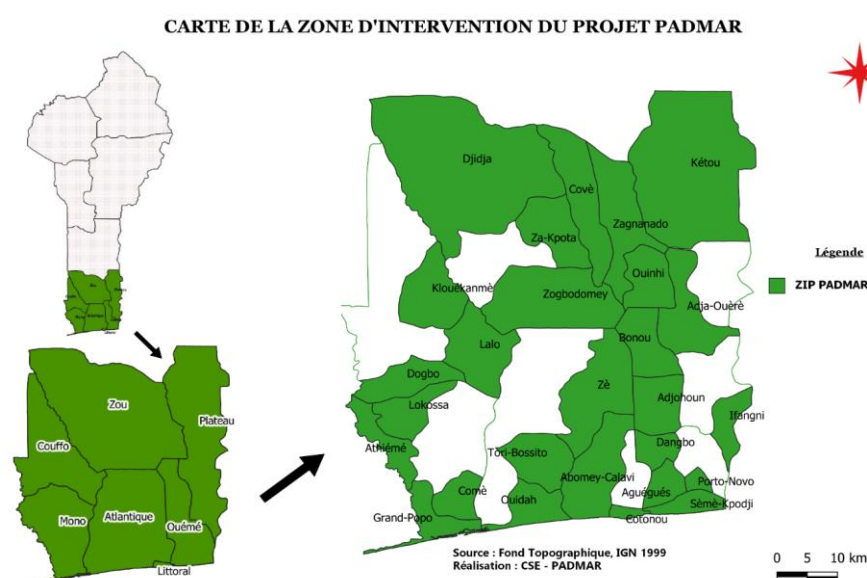
$$APET_{(d+\delta)} = \frac{E[Y_{(D=d+\delta)} - Y_{(D=d)}]^{D>0}}{\delta} = \frac{1}{n_h} \sum_{i=1}^{n_h} \frac{\partial F(D_i, X_i, \hat{\epsilon}_i, \hat{\beta})}{\partial D_i} \quad (12)$$

where n_h is the number of adopters h , ϵ are observed and unobserved variables, β are model parameters estimated from the estimated outcome equations 9 and 10, and $\partial F(\cdot)$ is a known derivative function and is continuously differential.

3.5. Data and descriptive statistics

This study relies on unbalanced panel data collected over three survey rounds conducted in 2018, 2020 and 2022 in southern Benin (Fig. 2), a West African country where vegetable farming represents a major economic sector.

Fig.2.



Description: Area zone

The sample includes 331 vegetable-producing households surveyed in 2018, 2020 and 2022. The total sample size was determined using the formula developed by Rea [53], employing a two-stage stratified random sampling design. In the first stage, three villages were selected per municipality using probability proportional to size (PPS) sampling, resulting in a total of 81 sampled villages. In the second stage, the number of producers selected within each village was proportionate to the number of vegetable producers in that village.

The final panel dataset comprises 1,200 household-level observations, among which 662 correspond to households that benefited directly from the interventions of government and private projects through technical, organizational, financial (subsidies and donations) or institutional advisory support; or those who learned about the technology through their peer's producer, and adopted at least one improved vegetable production technology on the plots. 538 households served as a control group with no adoption. A household was classified as a technology adopter if the

producer both knew the technology and had applied at least twice within the past three years following the criteria used by Mugwe et al. [54].

The technologies considered in this study include CS, technical ITK, and IrrT, as well as their combinations: CS – ITK, CS – IT, ITK – IT, and CS – ITK – IrrT. Less frequently adopted combinations, such as IrrT only (n=13) and CS – IrrT (n=10), were excluded from the data analysis because of insufficient sample size, resulting in a final analytical sample of 1,200 observations.

Table 1 provides a summary of the distribution of technology adoption across the sample. Notably, adoption patterns varied over time, with some household specific technologies adoption or disadoption across survey rounds.

Table 1. Number of vegetable household treated and untreated

	Technology	Observations
Treated	Certified Seed (CS)	95
	ITK	188
	CS x ITK	195
	ITK x IrrT	83
	CS x ITK x IrrT	101
	Total	662
	Untreated	538
	TOTAL	1200

The dataset contains detailed information on the socioeconomic and demographic characteristics of vegetable-producing households, as well as their living conditions, dietary patterns, and price-related characteristics. Summary statistics of the variables used in the impact estimation equations, particularly those capturing household expenditure and food security status, are presented in Table 2. These descriptive statistics include a comparison of the mean values for each variable between the treatment and control groups, i.e., households that adopted improved agricultural practices and those that did not.

Table 2. Mean and standard deviation of the variables included in the models.

Variables	Description	Without treatment	CS	ITK	CS x ITK	ITK x IrrT	CS x ITK x IrrT	Statistical test (comparison of means)				
								CS vs. without treatment	TKI vs. without treatment	CS x TKI vs. without treatment	TKI x IrrT vs. without treatment	1CS x ITK x IrrT vs. without treatment
Household expenditure per capita	FCFA/year (per capita per equivalent adult)	285691.4	326012.3	366244	371100.1	396429.1	454175.9	1.08**	1.55***	0.91***	5.56***	9.57***
FCS	1= poor 2= borderline 3= acceptable diet	1.45	1.56	1.77	1.89	2.23	2.32	27.56***	1.41***	11.90***	4.72***	9.66***
Man-headed household	1 if the head of household is a man; 0 otherwise	0.76	0.79	0.72	0.72	0.81	0.85	1.54	-0.97	-6.58***	0.94	-5.12***
Age of household head	Years	39.04	39.70	39.83	39.88	39.94	40.06	1.15***	3.57***	1.28**	-4.64***	-6.12***
Family Household size	per capita adult	5.31	5.38	5.19	5.44	5.76	5.66	3.20***	-13.55**	-5.94***	1.00*	3.21***
Education	1 if the producer is educated; 0 otherwise	0.50	0.55	0.61	0.70	0.64	0.74	5.32***	5.62***	2.29**	5.02***	5.02***
Contact extension	1 if the producer has contact with extension	0.36	0.57	0.68	0.77	0.90	0.91	8.10***	12.86***	8.88***	23.33***	27.90***

Variables	Description	Without treatment	CS	ITK	CS x ITK	ITK x IrrT	CS x ITK x IrrT	Statistical test (comparison of means)				
								CS vs. without treatment	TKI vs without treatment	CS x TKI vs. without treatment	TKI x IrrT vs without treatment	1CS x ITK x IrrT vs without treatment
Membership of a group	structures; 0 otherwise 1 if the producer is in a group; 0 otherwise	0.16	0.19	0.45	0.49	0.72	0.71	12.09***	1.56***	9.15***	32.37***	28.64***
Access to credit	1 if the producer has access to credit; 0 otherwise	0.31	0.38	0.49	0.51	0.51	0.54	10.85***	9.19***	3.80***	7.57***	2.659***
Area for vegetable garden farms	hectare	0.05	0.03	0.07	0.04	0.08	0.07	-1.05**	4.50***	-3.69***	7.40**	4.50***
Extra activity	1 if yes ; 0 otherwise	0.35	0.37	0.52	0.56	0.64	0.76	7.97**	5.60***	7.04***	6.41**	2.94***
Distance market	kilometer	4.15	3.47	4.23	4.01	3.03	2.83	-7.40	6.37***	-4.07**	-5.14	-5.77***
Livestock	1 if yes ; 0 otherwise	0.17	0.14	0.17	0.23	0.28	0.41	-8.14***	-7.79***	17.53***	2.06***	24.91
Plot ownership	1 if yes ; 0 otherwise	0.24	0.21	0.23	0.22	0.47	0.42	-13.61**	0.72***	-8.52***	1.66*	0.04***
Participation to Project	1 if yes ; 0 otherwise	0.23	0.49	0.57	0.59	0.63	0.69	0.44***	1.96**	5.97***	0.09***	0.86***
Price FCFA	Tomato per kg	843.44	867.41	889.43	911.34	852.99	845.89	6.09**	-0.88***	9.97***	6.14***	2.22***
Price Chili pepper per kg	FCFA	574.08	577.01	589.42	592.65	579.06	603.20	1.33***	2.76*	-2.83***	0.02***	1.56*

Variables	Description	Without treatment	CS	ITK	CS x ITK	ITK x IrrT	CS x ITK x IrrT	Statistical test (comparison of means)				
								CS vs. without treatment	TKI vs without treatment	CS x TKI vs. without treatment	TKI x IrrT vs without treatment	1CS x ITK x IrrT vs without treatment
Price Onion per kg	FCFA	351.20	354.82	353.98	355.46	370.30	371.06	0.52*	3.13***	1.62**	0.12*	5.47***

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

4 Empirical Results

This section addresses the goodness-of-fit of the models and the estimation results.

4.1. Goodness-of-fit of models

Model fit was assessed using standard information pseudo R-squared, the Akaike information criterion (AIC) and the Bayes information criterion (BIC). AIC and BIC can be calculated as follows:

$$AIC = -2 \ln(L) + 2p \text{ and } BIC = -2 \ln(L) + p \ln(n) \quad (13)$$

where L is the likelihood function, p is the number of estimated parameters, and n is the sample size [55].

Among the models estimated, the specification incorporating five latent factors using the GSEM approach outperforms the others, as evidenced by the lowest AIC and BIC values (Table 3) [55]. This result suggests a better overall fit than that of the control function model. Nonetheless, for comparison purposes, the results from the control function specification are also reported in table 3.

Table 3. AIC and BIC

Control function Approach		Latent factor Approach
Expenditure outcome		
AIC	1662.73	1553.77
BIC	1673.02	1576.09
Food security outcome		
AIC	2126.39	2007.94
BIC	2144.75	2053.66

4.2. Estimation of Impact models of improved agricultural technologies and their combinations on household expenditure and food security

The empirical results provide valuable insights into the role of improved agricultural technologies and their combinations in enhancing household welfare, particularly in terms of per capita expenditure and food security. Both modeling approaches, the control function and the latent factor model, yield broadly consistent findings (Table 4 and 5). However, the coefficients obtained from the latent factor approach tend to be larger in magnitude and more statistically significant. Given its superior fit, the latent

factor (GSEM) specification is retained as the reference model, and the discussion and policy implications that follow are based on its estimates.

The goodness-of-fit indicators support the quality of adjustment of the estimated models. The Hosmer–Lemeshow test is not significant, indicating adequate model specification. The Hausman test confirms that the five latent factors are jointly significant at the 1% level, suggesting that unobserved heterogeneity is effectively captured. Moreover, the Wald test rejects the null hypothesis of no interaction effects ($p < 0.01$), highlighting the heterogeneous impact of technology.

To address potential time-varying endogeneity in treatment assignment, the statistical significance of the control function terms was assessed, confirming the presence of endogeneity. In addition, the significance of the interaction between the control function and treatment variables indicates heterogeneity in the treatment effects, further supporting the use of flexible, interaction-rich specifications.

The intercept parameters in Table 5 differ significantly across technology groups, confirming that the five treatment categories should be modeled separately. The Hausman specification test rejects the random effects assumption in favor of the fixed effects model for the outcome equation.

The direction of the estimated coefficients suggests that the intensity of technology adoption has a positive and significant effect ($p < 0.05$) on both household expenditure and food security. Notably, an increase of area covered by the adoption of CS alone increases the likelihood of higher expenditures by 4% compared with 18% for the adoption of technical ITK alone (Table 4). Similarly, the probability of belonging to the borderline diet food consumption group increases by 0.35 and 0.55 with an intensity of adoption, mainly on plots under CS and ITK, respectively (Table 5).

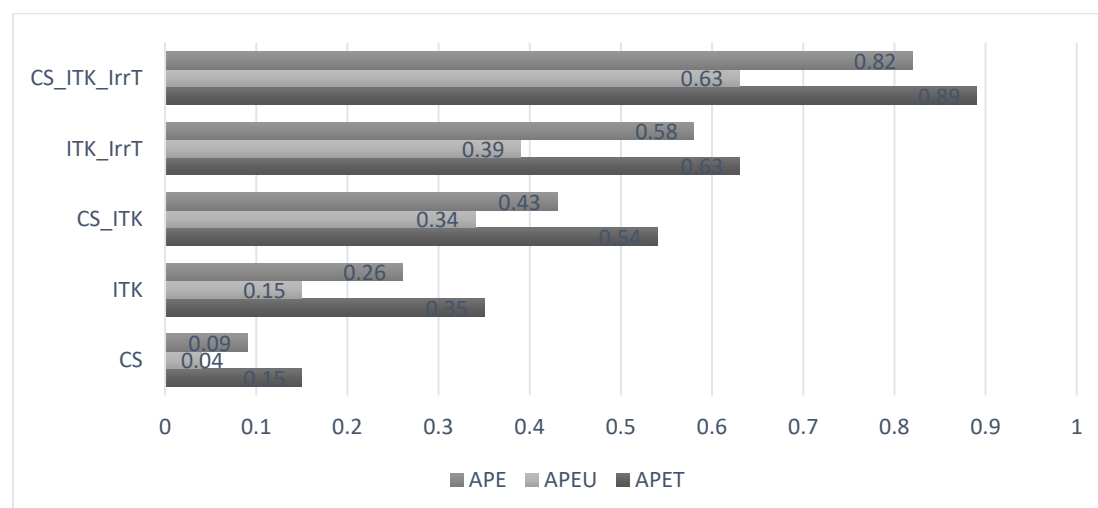
The adoption of multiple technologies yields even stronger effects. For instance, an increase of area covered by the *ITK x IrrT* combination increases the probability of higher expenditure by 53% compared with 46% for *CS x ITK* (Table 4). An intensity of adoption of the full package (*CS x ITK x IrrT*) leads to the highest observed gains: a 58% probability of increased expenditure and an increase of 0.45 points in the probability of belonging to the acceptable food consumption group (Tables 4 and 5).

Gender-based heterogeneity is also evident. Compared with women, male-headed households experience greater improvements in both outcomes, particularly for combinations involving irrigation technologies. In contrast, women benefit more from

ITK *only* and CS × ITK but are more likely to remain in the borderline food consumption categories. Indeed, an increase of 1 ha with adoption of ITK only and CS × ITK by women implies an increase in the probability of expenditures of 20% and 31% (table 4), respectively, and a 57% and 76% increase in the probability of belonging to the borderline food consumption categories (table 5), respectively.

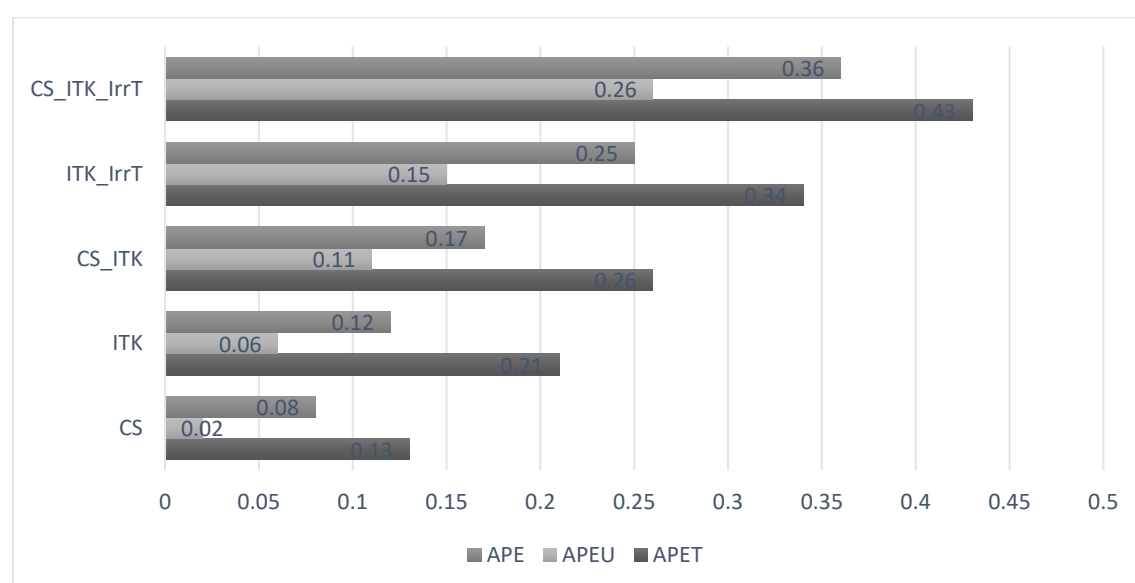
The average treatment effect (ATE) illustrates the increasing marginal gains from adopting more complex technological packages. Compared with nonadopters, the adoption of CS, ITK, CS × ITK, ITK × IrrT and CS × ITK × IrrT increases per capita expenditures by 9%, 26%, 43%, 58% and 82%, respectively (Figure 3). Similarly, the food security impact—as measured by improvements in the consumption categories—increases with the intensity of technology adoption: an additional area under adoption increases food security by 8% (CS), 12% (ITK), 17% (CS × ITK), 25% (ITK × IrrT), and 36% (CS × ITK × IrrT) (Figure 4).

Fig. 3



Description: Average partial effect (APE), for Treated (APET), for Untreated (APEU) (household expenditure outcome)

Fig. 4



Average partial effect (APE), APET, APEU (household on food security outcome)

Several household-level characteristics significantly influence both per capita expenditure and food security status.

The age of the head of household has a positive and statistically significant effect on per capita expenditure. As age increases, so does the likelihood of higher expenditure, with an estimated marginal increase of 33% ($p < 0.10$) (Table 4). Age also positively affects food security outcomes: the probability of being in the acceptable food consumption group increases by 0.43 with age, while that of being in the borderline group increases marginally by 0.10 (Table 5). These results suggest that older household heads are more likely to engage in behaviors or strategies that enhance welfare.

An increase in household size is also associated with a higher risk of poor dietary outcomes with the probability of being classified in the poor food consumption group increases by 0.73 (Table 5), which is likely due to resource dilution effects in larger households.

The education level of the household head plays a positive role in welfare outcomes. Education is associated with a 33% increase in the probability of higher expenditure (Table 4) and a 0.71 increase in the probability of belonging to the acceptable food consumption group (Table 5). However, it also slightly increases the probability of

falling into the borderline group by 0.21, possibly reflecting transitional consumption behaviors among newly educated farmers.

Access to extension services and group membership significantly improve welfare outcomes, increasing the probability both of higher expenditures and of being in the acceptable consumption category. These results underscore the importance of social capital and information diffusion.

Access to credit positively influences welfare indicators: it increases per capita expenditure by 52% (Table 4) and the probability of being in the acceptable food security group by 0.43 (Table 5).

Engagement in nonagricultural income-generating activities significantly improves both dimensions of welfare. It increases the probability of increased expenditure by 52% and the likelihood of being in the acceptable food group by 0.41 (Tables 4 and 5), reflecting income diversification benefits.

The size of the cultivated vegetable plot and proximity to markets are both positively and significantly associated with higher per capita expenditure and food security. Larger farm areas and better market access increase household income and diet quality (Tables 4 and 5).

Practices such as livestock keeping and land ownership are also positively associated with improved outcomes, suggesting asset-based resilience.

Participation in the project intervention is strongly correlated with a 57% increase in the probability of higher expenditure (table 4). Furthermore, price variations in key vegetables significantly influence household welfare: an increase in the price of tomatoes, chili peppers, and onions increases the probability of higher expenditures by 57%, 33%, and 21%, respectively (Table 5). These findings reflect the income effect of favorable output prices on producer welfare.

Table 4. Fixed effect correlated random coefficient (household expenditure outcome).

Control function Approach			Latent factor Approach		
Variable	Coef.	ME	Variable	Coef.	ME
CS	0.06***	0.03***	CS	0.08 ***	0.04 ***
ITK	0.26***	0.15***	ITK	0.29***	0.18 ***
CS x ITK	0.44***	0.28***	CS x ITK	0.43 ***	0.46 ***
ITK x IrrT	0.57***	0.51***	ITK x IrrT	0.59 ***	0.53 ***
CS x ITK x IrrT	0.77***	0.53***	CS x ITK x IrrT	0.81***	0.58***
Interaction terms D # characteristics			Interaction terms D # characteristics		

Control function Approach			Latent factor Approach		
Variable	Coef.	ME	Variable	Coef.	ME
(CS)# Man-headed household	0.05*	0.12*	(CS)x Man-headed household	0.08*	0.16*
(ITK)# Man-headed household	-0.15**	-0.21**	(ITK) x Man-headed household	-0.17*	-0.20*
(CS x ITK) # Man-headed household	-0.27	-0.22	(CS x ITK) x Man-headed household	-0.32*	-0.31*
(ITK x IrrT) # Man-headed household	0.62	0.49	(ITK x IrrT) x Man-headed household	0.59**	0.52**
(CS x ITK x IrrT) # Man-headed household	0.64	0.58	(CS x ITK x IrrT) x Man-headed household	0.65**	0.76**
t_{2022}	0.42**	0.22**	t_{2022}	0.44*	0.33*
Man-headed household	0.42***	0.15***	Man-headed household	0.54*	0.21*
Age of household head	0.09	0.32	Age of household head	0.14*	0.33*
Family Household size	0.14	0.52	Family Household size	0.11	0.79
Education	0.56	0.21	Education	0.62*	0.33*
Contact extension structure	0.36***	0.42***	Contact extension structure	0.38***	0.63***
Membership of a group	0.27**	0.54**	Membership of a group	0.31**	0.63**
Access to credit	0.04*	0.33*	Access to credit	0.09**	0.52**
Area for vegetable garden farms	0.11*	0.12*	Area for vegetable garden farms	0.17*	0.23*
Extra activity	0.88**	0.44**	Extra activity	0.84*	0.52*
Distance market	-0.31	-0.15	Distance market	-0.33***	-0.15***
Livestock	0.10	0.25	Livestock	0.13*	0.33*
Plot ownership	0.66	0.21	Plot ownership	0.66***	0.35***
Participation to Project	0.61***	0.33***	Participation to Project	0.62***	0.57***
Price Tomato	0.42*	0.29 *	Price Tomato	0.46**	0.36**
Price Chili pepper	0.25***	0.22***	Price Chili pepper	0.24***	0.33***
Price Onion	0.15	0.16	Price Onion	0.19*	0.21*
Interaction terms					
$D \# \bar{D}$					
θ (CS)	0.03*				
θ (ITK)	0.05				
θ (CS x ITK)	0.05**				
θ (ITK x IrrT)	0.13***				

Control function Approach			Latent factor Approach		
Variable	Coef.	ME	Variable	Coef.	ME
θ (CS x ITK x IrrT)	0.17				
Control function			Latent factors		
			L		
$h(\gamma_{it})_{(CS)}$	0.12***		L2	0.06***	
$h(\gamma_{it})_{(ITK)}$	0.09***		L3	0.07***	
$h(\gamma_{it})_{(CS \times ITK)}$	0.31***		L4	0.22*	
$h(\gamma_{it})_{(ITK \times IrrT)}$	0.15***		L5	0.18**	
$h(\gamma_{it})_{(CS \times ITK \times IrrT)}$	0.21***		L6	0.06***	
Interaction terms			Interaction		
D # control			terms D #		
function			latent factors L		
$h(\gamma_{it})_{(CS)} \# (CS)$	0.17***		L2L3#CS	0.24*	
$h(\gamma_{it})_{(ITK)} \# (ITK)$	0.16		L2L4#CS	-0.07**	
$h(\gamma_{it})_{(CS \times ITK)} \# (CS \times ITK)$	0.08		L2L5#CS	0.03	
$h(\gamma_{it})_{(ITK \times IrrT)} \# (ITK \times IrrT)$	0.27***		L2L6#CS	0.01	
$h(\gamma_{it})_{(CS \times ITK \times IrrT)} \# (CS \times ITK \times IrrT)$	0.12***		L3L4#CS	0.08	
			L3L5#CS	-0.11	
			L3L6 #CS	0.14***	
			L4L5#CS	0.09	
			L4L6 #CS	-0.02*	
			L5L6 #CS	0.00	
			L2L3#ITK	0.01	
			L2L4#ITK	0.04*	
			L2L5#ITK	0.01	
			L2L6#ITK	0.00	
			L3L4#ITK	0.02	
			L3L5#ITK	0.12	
			L3L6#ITK	0.03	
			L4L5#ITK	0.33***	
			L4L6#ITK	0.05	
			L5L6#ITK	-0.03	
			L2L3#CS x ITK	0.13	
			L2L4#CS x ITK	-0.00	
			L2L5#CS x ITK	0.18**	
			L2L6#CS x ITK	0.06	
			L3L4#CS x ITK	0.28**	
			L3L5#CSxITK	0.51**	
			L3L6#CSxITK	-0.14	
			L4L5#CS x ITK	0.00	
			L4L6#CSxITK	0.01	
			L5L6#CSxITK	0.06***	
			L2L3# ITK x IrrT	-0.15**	
			L2L4# ITK x IrrT	0.00	
			L2L5# ITK x IrrT	0.04	
			L2L6# ITK x IrrT	0.00	
			L3L4# ITK x IrrT	0.73**	
			L3L5# ITK x IrrT	0.06	
			L3L6# ITK x IrrT	0.23*	
			L4L5# ITK x IrrT	-0.01	
			L4L6# ITK x IrrT	0.22	

Control function Approach			Latent factor Approach		
Variable	Coef.	ME	Variable	Coef.	ME
			L5L6 # ITK x IrrT	0.08*	
			L2L3# CS x ITK x IrrT	0.09	
			L2L4# CS x ITK x IrrT	0.12**	
			L2L5 # CS x ITK x IrrT	0.19	
			L2L6#CS x ITK x IrrT	-0.05	
			L3L4# CS x ITK x IrrT	0.02*	
			L3L5 # CS x ITK x IrrT	-0.00	
			L3L6 # CS x ITK x IrrT	0.14**	
			L4L5 # CS x ITK x IrrT	0.28***	
			L4L6 # CS x ITK x IrrT	0.04	
			L5L6 # CS x ITK x IrrT	0.05	
Constant	0.64***		Constant	0.73***	
N observation	1200		N observation	1200	
Log pseudolikelihood	-706.85		Log pseudolikelihood	-795.14	
Pseudo R ²	0.51		Pseudo R ²	0.62	
Wald test for joint significance of coefficients of interaction terms: (all interaction terms = 0)	Chi2 (61)=12.96**		Wald test for joint significance of coefficients of interaction terms: (all interaction terms = 0)	Chi2 (103)=85.33***	
			Hausman test z statistic of H0: no endogeneity	CS: 0.08 ITK: 0.64 CS x ITK: -2.77 ITK x IrrT : 0.86 CS x ITK x IrrT : -1.17	
			z statistic: H0: (variance of over-dispersion term)	5.71	
Goodness-of-fit test (Hosmer-Lemeshov test)	Chi2(61)= 5.02		Goodness-of-fit test (Hosmer-Lemeshov test)	Chi2(103)= 3.15	

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

604 **Table 5. Fixed effect random correlated coefficient (household on food security outcome).**

Variables	Control function				Latent factor				
	Coef.	Elasticity			Coef.	Elasticity			
		Poor diet	Borderline diet	Acceptable diet		Poor diet	Borderline diet	Acceptable diet	
CS	0.07***	0.21	0.26*	0.07	CS	0.07**	0.19**	0.35*	0.06
ITK	0.11***	0.07	0.31**	0.08*	ITK	0.12***	0.13	0.55**	0.10***
CS x ITK	0.13***	0.09	0.39**	0.13	CS x ITK	0.19***	0.18	-0.13	0.15***
ITK x IrrT	0.21***	-0.26	0.36	0.24***	ITK x IrrT	0.25**	-0.13**	0.11	0.36**
CS x ITK x IrrT	0.33***	0.11	0.27	0.38***	CS x ITK x IrrT	0.36***	0.12	0.45	0.45***
Interaction terms D # characteristics					Interaction terms D # characteristics				
(CS)x Man-headed household	0.03**	0.25	0.09	0.09*	(CS)x Man-headed household	0.04	0.33	-0.15***	-0.83
(ITK) x Man-headed household	0.17	0.22	0.44	0.05*	(ITK) x Man-headed household	-0.11	0.12	-0.57**	0.03***
(CS x ITK) x Man-headed household	0.15	-0.15	0.32**	0.31**	(CS x ITK) x Man-headed household	0.17***	-0.05*	-0.76***	0.07
(ITK x IrrT) x Man-headed household	0.24***	-0.09	0.19	0.43***	(ITK x IrrT) x Man-headed household	0.29*	0.61	0.25**	0.56*
(CS x ITK x IrrT) x Man-headed household	0.28*	0.28	0.21	0.46***	(CS x ITK x IrrT) x Man-headed household	0.31**	-0.48	0.06	0.65**
<i>t</i> ₂₀₂₂	0.27	0.05**	0.12	0.51*	<i>t</i> ₂₀₂₂	0.29***	0.26	0.49	0.43***
Man-headed household	0.19	0.05	0.17	0.09	Man-headed household	0.26***	-0.14	0.08	0.34**
Age of household head	-0.07	0.10	0.16***	0.32**	Age of household head	-0.07	0.25	0.10*	0.43*
Income	0.38**	0.05	0.24***	0.57**	Income	0.39*	0.08 (0.06)	0.37	0.44**
Education	0.08	0.12	0.26***	0.57**	Education	0.12	0.03	0.21**	0.71*
Family Household size	-0.10	0.53	0.59	0.04	Family Household size	-0.13***	0.73**	-0.08	0.07
Contact extension structure	0.58**	0.12	0.18	0.71***	Contact extension structure	0.56***	0.18	0.01	0.93**
Membership of a group	0.52**	0.22	0.62***	0.76***	Membership of a group	0.58**	0.01	0.04	0.81**
Access to credit	0.33	0.07	0.08***	0.35***	Access to credit	0.32	-0.97	0.09**	0.43**

Variables	Control function				Latent factor				
	Coef.	Elasticity			Coef.	Elasticity			
		Poor diet	Borderline diet	Acceptable diet		Poor diet	Borderline diet	Acceptable diet	
Area for vegetable garden farms	0.26*	0.04	0.73	0.41***	Area for vegetable garden farms	0.33*	0.41	0.04	0.74***
Extra activity	0.15**	0.14	0.05	0.32**	Extra activity	0.17**	0.04	0.12	0.41**
Distance to market	-0.54	0.20	0.04	-0.38*	distance to market	-0.61***	-0.98	0.08	-0.50*
Livestock	0.06	0.05	0.07	0.13	Livestock	0.09**	0.27	0.58**	0.19
Participation to Project	0.39**	0.07	0.17*	0.39***	Participation to Project	0.46**	0.05	0.03	0.50**
Interaction terms D # $\bar{D}$									
$\theta(\text{CS})$	0.27***								
$\theta(\text{ITK})$	0.13								
$\theta(\text{CS} \times \text{ITK})$	0.34*								
$\theta(\text{ITK} \times \text{IrrT})$	0.28**								
$\theta(\text{CS} \times \text{ITK} \times \text{IrrT})$	0.09*								
Control function					Latent factors L				
$h(\gamma_{it})_{(\text{CS})}$	0.43**				L2L3_CS	0.15			
$h(\gamma_{it})_{(\text{ITK})}$	0.09***				L2L4_CS	0.15***			
$h(\gamma_{it})_{(\text{CS} \times \text{ITK})}$	0.06**				L2L5_CS	-0.09*			
$h(\gamma_{it})_{(\text{ITK} \times \text{IrrT})}$	0.09***				L2L6_CS	-0.41			
$h(\gamma_{it})_{(\text{CS} \times \text{ITK} \times \text{IrrT})}$	0.12*				L3L4_CS	0.09*			
Interaction terms D # control function					Interaction terms D # latent factors L				
$h(\gamma_{it})_{(\text{CS})} \times (\text{CS})$	-0.33				L3L5_CS	0.16			
$h(\gamma_{it})_{(\text{ITK})} \times (\text{ITK})$	0.16**				L3L6_CS	0.07*			
$h(\gamma_{it})_{(\text{CS} \times \text{ITK})} \times (\text{CS} \times \text{ITK})$	0.06**				L4L5_CS	0.58*			
$h(\gamma_{it})_{(\text{ITK} \times \text{IrrT})} \times (\text{ITK} \times \text{IrrT})$	0.14**				L4L6_CS	0.12			
$h(\gamma_{it})_{(\text{CS} \times \text{ITK} \times \text{IrrT})} \times (\text{CS} \times \text{ITK} \times \text{IrrT})$	-0.08***				L5L6_CS	0.03*			

Variables	Control function				Latent factor			
	Coef.	Elasticity			Coef.	Elasticity		
		Poor diet	Borderline diet	Acceptable diet		Poor diet	Borderline diet	Acceptable diet

Variables	Control function				Latent factor			
	Coef.	Elasticity			Coef.	Elasticity		
		Poor diet	Borderline diet	Acceptable diet		Poor diet	Borderline diet	Acceptable diet
					L2L5_ CS x ITK x IrrT	-0.13*		
					L2L6_ CS x ITK x IrrT	0.02		
					L3L4_ CS x ITK x IrrT	0.08**		
					L3L5_ CS x ITK x IrrT	0.06		
					L3L6_ CS x ITK x IrrT	0.17*		
					L4L5_ CS x ITK x IrrT	0.03*		
					L4L6_ CS x ITK x IrrT	0.09		
					L5L6_ CS x ITK x IrrT	-0.41***		
Constant	0.24***				Constant	0.41***		
Cut1	0.23					0.36		
Cut2	0.55					0.45		
N observation	1200				N observation	1200		
Log pseudolikelihood	-883.46				Log pseudolikelihood	-807.55		
Pseudo R ²	0.44				Pseudo R ²	0.62		
Wald test for joint significance of coefficients of interaction terms: (all interaction terms = 0)	Chi2 (61)=23.04**				Wald test for joint significance of coefficients of interaction terms: (all interaction terms = 0)	Chi2 (103)=6.08*		
	*				Hausman test z statistic of H0: no endogeneity	CS:2.62 ITK: 1.63 CS x ITK: -0.27		

5 Discussion

The empirical findings reveal that compared with nonadopters, the intensity of adoption of improved agricultural practices, either individually or in combination, significantly enhances annual per capita expenditure and food security outcomes over time. The temporal effects captured by the models suggest that production and marketing conditions were generally favorable during the study period, partly because of the implementation of various programs aimed at improving physical access to markets and installing postharvest infrastructure[3].

• Effectiveness of technology adoption

Among standalone technologies, the intensity of adoption of technical ITK generates greater welfare gains than that of CS alone. This finding indicates that failing to follow appropriate agricultural practices undermines the performance potential of improved seed varieties—despite their proven resistance to climatic variability and pests[12]. When CS is applied without ITK, the benefits in term of production are marginal. Consequently, the probability of increased expenditures and improved food consumption remains low.

The APEs are notably higher for bundled interventions, especially those involving irrigation (ITK x IrrT; CS x ITK x IrrT). Irrigation emerges as a critical mechanism for buffering households against climatic shocks, thereby improving food security. These results are consistent with previous evidence from [56], [57] and [13], which highlights the complementarities among technologies and the resilience-enhancing role of irrigation.

• Gender-differentiated impacts

The impact of the technology adoption intensity varies by gender. Male-headed households consistently exhibit higher levels of food expenditure, particularly in zones characterized by better access to irrigation infrastructure and high agricultural productivity [3]. In contrast, female-headed households benefit more from adopting ITK or CS × ITK but are less likely to access irrigation technologies because of persistent gender disparities in resource access, including land, credit, and extension services. These disparities are rooted in structural barriers and traditional norms, which limit women's participation in and benefits from agricultural innovation. Similar

findings are reported by Abdullah et al. [58], who underscore the vulnerability of women-headed households to food insecurity.

- **Socioeconomic determinants of welfare**

The results indicate that age is positively associated with both per capita expenditure and food security. Older household heads are more likely to possess diverse skills, accumulated [59], [60] experience, and access to productive networks, enabling them to diversify their income sources. However, these findings contrast with those of the studies using cross-sectional data, namely [61] and [11] which report that older heads are more prone to poverty because of declining productivity. In our panel framework, age likely captures a cumulative advantage effect [62].

Similarly, household size is associated with higher expenditures but is also linked to a higher probability of food insecurity, supporting the view that larger households face resource constraints despite higher overall spending [59], [60].

Education, group membership, and contact with extension services significantly improve both outcomes. Education enhances awareness and the uptake of good agricultural practices and high-quality inputs [63]. Furthermore, group membership and extension access facilitate knowledge sharing and reduce transaction costs in accessing technologies [64]. These findings support stronger investment in agricultural advisory services, particularly for smallholder farmers.

- **Financial and market access**

Access to credit is strongly associated with improved welfare. It enables investment in both agricultural and nonagricultural income-generating activities, which is consistent with the findings of [65] and [66]. Similarly, the expansion of nonfarm economic activities increases household resilience and expenditure.

The size of the vegetable plot and proximity to markets are also positively correlated with household welfare. Increased land under cultivation allows for economies of scale, while market access facilitates better price realization and reduces postharvest losses. This result reinforces the findings of [16], who demonstrate the importance of spatial and scale variables in smallholder outcomes.

- **Land tenure and livestock ownership**

Secure land tenure plays a crucial role in stimulating investment and productivity. Households with plot ownership are more likely to engage in long-term planning and adopt yield-enhancing technologies [56]. Similarly, livestock ownership enhances

household resilience through asset diversification, acting as a buffer against food insecurity. These findings support the promotion of integrated crop–livestock systems as a pathway toward sustainable intensification.

- **Price effects**

Finally, rising output prices for key vegetables (tomato, chili pepper, and onion) significantly improve producers' welfare through increased margins. However, as [67] note, smallholders are both producers and consumers, making price volatility a double-edged sword with important implications for food security at the global scale.

6 Conclusion and Policy Implications

In recent years, national and international institutions have implemented diverse policy interventions to strengthen

productivity and market participation, increasing incomes and employment opportunities throughout the value chain, as well as welfare. This study contributes to the literature by using panel data to rigorously assess the heterogeneous effects of the intensity of adoption of CS, ITKs, IrrTs and their combinations on household welfare and food security in vegetable-producing regions of Benin.

The results provide strong empirical evidence that these technologies, particularly when adopted in combination, generate significant improvements in per capita and food consumption outcomes. Unlike many previous studies based on cross-sectional data, our panel approach captures dynamic effects over time and thereby better accounts for unobserved heterogeneity and selection bias.

The findings have several key implications:

- Respecting technical itineraries is essential for maximizing the benefits of improved seeds. ITK should be disseminated through farmer field schools, extension services, and community-based learning mechanisms.
- Technology alone is not sufficient. Access to quality inputs (fertilizers, seeds), diversification into livestock and nonfarm activities, and respect for technical guidance are all necessary for sustained improvements. The synergistic effect of adopting CS × ITK × IrrT yields the largest gains, suggesting that programs should encourage integrated technology packages rather than isolated interventions.

- Policy should promote enabling conditions. Measures that enhance education, facilitate access to credit, support the formation of producer cooperatives, and strengthen extension services are essential for widespread adoption. Particular attention must be given to vulnerable groups—especially women and young people—through targeted support schemes.
- Secure land tenure is a cornerstone of agricultural investment. Consistent with prior studies, our findings suggest that land ownership increases household welfare and food security. This insight highlights the need to formalize land rights—through the expansion of rural land certification—and support tenure systems that empower farmers to invest in long-term productivity-enhancing technologies.
- Structural transformation of the vegetable sector is needed. Strengthening value chain linkages and promoting price stabilization mechanisms—such as minimum support prices or buffer stocks—can encourage smallholder investments and shield them from market volatility.
- Nutrition education must accompany income gains to ensure that increased resources translate into improved diet quality. Programs that integrate nutritional messaging with agricultural extension may increase the adoption of diverse and nutrient-rich food baskets.
- Study limitations and future research. Future research should explore the temporal dynamics of impact, the role of fertilizer combinations (organic vs. inorganic), and potential environmental externalities—such as improvements in soil health and ecosystem resilience—associated with sustainable technology adoption.

Overall, this study reinforces the central role of context-specific and inclusive agricultural innovations in enhancing rural welfare and food security. Scaling such interventions while addressing gender, institutional, and agro-ecological constraints remain a critical priority for policymakers across sub-Saharan Africa.

Statements and Declarations

None of the coauthors has relevant material or financial interests in the subject of the research.

Conflict of interest

The authors declared that they have no conflict of interest.

Funding statement

This study was supported by a Vegetable Development Support Programme (PADMAR) of International Fund for Agricultural Development (IFAD) N° 2000000882 Grant

Author's contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by **Senouwa Hector Valère Kpangon, Ygué Patrice Adegbola, Tèko Augustin Kouévi**, and **Segla Roch Cedrique Zossou**. The first draft of the manuscript was written by **Senouwa Hector Valère Kpangon, Ygué Patrice Adegbola, Augustin Kossi Nounagnon Aoudji** and **Segla Roch Cedrique Zossou** and all authors commented on previous versions of the manuscript. All authors read, amended, and approved the final manuscript.

Acknowledgements

We acknowledge the funding and scientific contribution of the International Fund for Agricultural Development (IFAD) through Vegetable development support project (PADMAR). The authors would also like to thank Déwanou Kant David AHOYA for his valuable contribution. Thanks to the International Center of Research and Training in Social Science (CIRFOSS) for data collection, processing and contribution to data analysis.

References

- [1] P. N. Assogba *et al.*, "Determinants of credit access by smallholder farmers in North-East Benin," *J. Dev. Agric. Econ.*, vol. 9, no. 8, 2017, doi: 10.5897/JDAE2017.0814.
- [2] I. F. Akpo, F. T. Zakari, F. O. Agani, K. Issaka, and J. A. Yabi, "Effects of sustainable land management practices on food security of beneficiary households in a context of adaptation to climate change in the communes of Malanville and Kouandé in Northern Benin," *International Journal of Agricultural Policy and Research*, vol. 11, no. 1, Dec. 2022, doi: 10.15739/IJAPR.23.002.

- [3] ACDD, “Etude de Faisabilité du Programme de développement de la filière des cultures maraichère au Benin,” Cotonou, Benin, 2017. Accessed: Dec. 01, 2025. [Online]. Available: <https://apidpp.agriculture.gouv.bj/public/storage/uploads/Stl4PaqG6H99l6V2Ncmg6B0ApC9T5Vzr6F8A6Tlg.pdf>
- [4] DSA, “Les chiffres définitifs de la campagne agricole 2023-2024 au Bénin,” Cotonou, Bénin, 2024. Accessed: Dec. 01, 2025. [Online]. Available: https://instad.bj/images/docs/insae-statistiques/agricoles/production-agricole/Evolution_de_la_production_agricole_2023/R%C3%A9sultat_d%C3%A9finitif%20de%20la%20campagne_VERSION_FINALE.pdf
- [5] PADMAR, “Projet d’appui au développement du maraîchage (PADMAR). Rapport de conception de projet – Version finale,” Cotonou, Benin, 2015. Accessed: Dec. 01, 2025. [Online]. Available: <https://www.ifad.org/fr/-/document/rapport-de-conception-de-projet-version-finale>.
- [6] J. Choufani, E. Bryan, D. K. Mekonnen, and C. Ringler, “Exploring small scale irrigation-nutrition linkages,” 2021. doi: 10.2499/p15738coll2.134911.
- [7] W. D. Biru, M. Zeller, and T. K. Loos, “The Impact of Agricultural Technologies on Poverty and Vulnerability of Smallholders in Ethiopia: A Panel Data Analysis,” *Soc. Indic. Res.*, vol. 147, no. 2, pp. 517–544, Jan. 2020, doi: 10.1007/s11205-019-02166-0.
- [8] A. G. Singbo, “Analyzing efficiency of vegetable production in Benin,” Wageningen University, Wageningen, , the Netherlands, 2012. doi: 10.18174/212094.
- [9] A. Alinsato and U. Yagbedo, “Analyse d’offre des produits maraîchers au Bénin,” 2018.
- [10] ACED, “Les impacts du maraîchage agro écologique dans la vie d’un homme maraîcher. Centre d’Actions pour l’Environnement et le Développement Durable,” Cotonou, Benin, 2017. Accessed: Dec. 01, 2025. [Online]. Available: <https://www.acedafrica.org/wp-content/uploads/2021/10/Impact-maraichage-agroecol-sur-homme.pdf>
- [11] A. Alinsato and F. Saliga, “Analyse de la sécurité alimentaire des ménages agricoles dans le département du Borgou en République du Bénin,” *Revue Repères et Perspectives Economiques*, vol. 5, no. 1, 2021, Accessed: Dec. 01, 2025. [Online]. Available: <https://doi.org/10.34874/IMIST.PRSM/RPE/25756>
- [12] A. Avadi, R. Hodomihou, and F. Feder, “Maraîchage raisonné versus conventionnel au sud-Bénin: comparaison des impacts environnementaux, nutritionnels et socio-économiques,” 2020. Accessed: Dec. 01, 2025. [Online]. Available: <http://www.glofoods.inra.fr>
- [13] G. M. A. Nonvide, “Beyond productivity, does the adoption of agricultural technologies improve food consumption and reduce poverty? Empirical evidence from Benin,” *Economics of Innovation and New Technology*, vol. 33, no. 1, pp. 124–141, Jan. 2024, doi: 10.1080/10438599.2022.2144846.
- [14] G. Baliki, M. Al Daccache, H. Ghattas, and T. Brück, “Short- and medium-term impacts of small-scale vegetable support on food security: evidence from Syria,”

- Food Secur.*, vol. 16, no. 4, pp. 921–932, Aug. 2024, doi: 10.1007/s12571-024-01460-1.
- [15] C. Yin, J. Zhang, and C. Shao, “Relationships of the multi-scale built environment with active commuting, body mass index, and life satisfaction in China: A GSEM-based analysis,” *Travel Behav. Soc.*, vol. 21, pp. 69–78, Oct. 2020, doi: 10.1016/j.tbs.2020.05.010.
- [16] G. Berhane and C. Gardebroek, “Does Microfinance Reduce Rural Poverty? Evidence Based on Household Panel Data from Northern Ethiopia,” *Am. J. Agric. Econ.*, vol. 93, no. 1, pp. 43–55, Jan. 2011, doi: 10.1093/ajae/aaq126.
- [17] M. M. Pitt and S. R. Khandker, “The impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?,” *Journal of Political Economy*, vol. 106, no. 5, pp. 958–996, Oct. 1998, doi: 10.1086/250037.
- [18] J. Wooldridge, “What’s New in Econometrics? Difference-in-Differences Estimation. Lecture Notes 10,” 2007. Accessed: Dec. 01, 2025. [Online]. Available: https://www.nber.org/sites/default/files/2021-03/slides_10_diffindiffs.pdf
- [19] B. H. Baltagi, *Econometric Analysis of Panel Data 3rd Edition*. New York: John Wiley & Sons Inc., 2005.
- [20] R. E. Mújica-Mota, P. Landa, M. Pitt, M. Allen, and A. Spencer, “The heterogeneous causal effects of neonatal care: a model of endogenous demand for multiple treatment options based on geographical access to care,” *Health Econ.*, vol. 29, no. 1, pp. 46–60, Jan. 2020, doi: 10.1002/hec.3970.
- [21] J. M. Wooldridge, “Correlated random effects models with unbalanced panels,” *J. Econom.*, vol. 211, no. 1, pp. 137–150, Jul. 2019, doi: 10.1016/j.jeconom.2018.12.010.
- [22] J. J. Heckman and E. Vytlacil, “Structural Equations, Treatment Effects, and Econometric Policy Evaluation1,” *Econometrica*, vol. 73, no. 3, pp. 669–738, May 2005, doi: 10.1111/j.1468-0262.2005.00594.x.
- [23] J. Heckman and S. Navarro-Lozano, “Using Matching, Instrumental Variables, and Control Functions to Estimate Economic Choice Models,” *Rev. Econ. Stat.*, vol. 86, 2004.
- [24] A. A. Kawatkar, J. W. Hay, W. Stohl, and M. B. Nichol, “Consistent estimation of polychotomous treatment effects with selection-bias and unobserved heterogeneity using panel data correlated random coefficients model,” *Health Serv. Outcomes Res. Methodol.*, vol. 18, no. 2, pp. 75–95, Jun. 2018, doi: 10.1007/s10742-018-0177-4.
- [25] A. Springer-Heinze, F. Hartwich, J. S. Henderson, D. Horton, and I. Minde, “Impact pathway analysis: an approach to strengthening the impact orientation of agricultural research,” *Agric. Syst.*, vol. 78, no. 2, pp. 267–285, Nov. 2003, doi: 10.1016/S0308-521X(03)00129-X.
- [26] A. Herforth and Jody. Harris, “Understanding and applying primary pathways and principles. Arlington, VA: USAID/Strengthening Partnerships, Results, and Innovations in Nutrition Globally (SPRING) Project,” KRCTF-01425, 2014.

- Accessed: Dec. 01, 2025. [Online]. Available: <https://spring-nutrition.org/publications/briefs/understanding-and-applying-primary-pathways-and-principles>
- [27] S. Dury, A. Alpha, and A. Bichard, "The Negative Side of the Agricultural-Nutrition Impact Pathways: A Literature Review," *World Food Policy*, vol. 2, no. 1, pp. 78–100, Mar. 2015, doi: 10.18278/wfp.2.1.5.
- [28] R. Kousar, T. Sadaf, M. S. A. Makhdum, and A. Ijaz, "Determinants of household's education and nutrition spending," *Humanomics*, vol. 33, no. 4, pp. 470–483, Nov. 2017, doi: 10.1108/H-06-2016-0050.
- [29] A. D. Roy, "Some Thoughts on the Distribution of Earnings," *Oxf. Econ. Pap.*, vol. 3, no. 2, pp. 135–146, 1951, Accessed: Nov. 19, 2025. [Online]. Available: <http://www.jstor.org/stable/2662082>
- [30] J. M. Wooldridge, *Econometric analysis of cross section and panel data*. London, England: The MIT Press, Cambridge, Massachusetts, 2002. Accessed: Nov. 19, 2025. [Online]. Available: <https://ipcid.org/evaluation/apoio/Wooldridge%20-%20Cross-section%20and%20Panel%20Data.pdf>
- [31] J. J. Heckman and S. Urzúa, "Comparing IV with structural models: What simple IV can and cannot identify," *J. Econom.*, vol. 156, no. 1, pp. 27–37, May 2010, doi: 10.1016/j.jeconom.2009.09.006.
- [32] S. Auci, N. Barbieri, M. Coromaldi, and M. Michetti, "Innovation and Weather Change Adaptation: A Panel Endogenous Switching Regression Analysis," 2019, Accessed: Dec. 01, 2025. [Online]. Available: https://www.siecon.org/sites/default/files/media_wysiwyg/87-aucci-barbieri-coromaldi-michetti.pdf
- [33] D. Benson, M. A. Masten, and A. Torgovitsky, "ivcrc: An instrumental-variables estimator for the correlated random-coefficients model," *The Stata Journal: Promoting communications on statistics and Stata*, vol. 22, no. 3, pp. 469–495, Sep. 2022, doi: 10.1177/1536867X221124449.
- [34] G. W. Imbens and J. M. Wooldridge, "Recent Developments in the Econometrics of Program Evaluation," *J. Econ. Lit.*, vol. 47, no. 1, pp. 5–86, Mar. 2009, doi: 10.1257/jel.47.1.5.
- [35] D. M. Drukker, "A Generalized Regression-adjustment Estimator for Average Treatment Effects from Panel Data," *The Stata Journal: Promoting communications on statistics and Stata*, vol. 16, no. 4, pp. 826–836, Dec. 2016, doi: 10.1177/1536867X1601600402.
- [36] H. T. Vu and N. M. Ha, "A Study on the Relationship Between Diversification and Firm Performance Using the GSEM Method," *Emerging Markets Finance and Trade*, vol. 57, no. 1, pp. 85–107, Jan. 2021, doi: 10.1080/1540496X.2019.1582413.
- [37] L. E. Papke and J. M. Wooldridge, "Panel data methods for fractional response variables with an application to test pass rates," *J. Econom.*, vol. 145, no. 1–2, pp. 121–133, Jul. 2008, doi: 10.1016/j.jeconom.2008.05.009.

- [38] J. J. Heckman, S. Urzua, and E. Vytlacil, "Understanding Instrumental Variables in Models with Essential Heterogeneity," *Review of Economics and Statistics*, vol. 88, no. 3, pp. 389–432, Aug. 2006, doi: 10.1162/rest.88.3.389.
- [39] D. Läpple and F. Thorne, "The Role of Innovation in Farm Economic Sustainability: Generalised Propensity Score Evidence from Irish Dairy Farms," *J. Agric. Econ.*, vol. 70, no. 1, pp. 178–197, Feb. 2019, doi: 10.1111/1477-9552.12282.
- [40] J. J. Heckman, "Sample Selection Bias as a Specification Error," *Econometrica*, vol. 47, no. 1, p. 153, Jan. 1979, doi: 10.2307/1912352.
- [41] T. Suri, "Selection and Comparative Advantage in Technology Adoption," *Econometrica*, vol. 79, no. 1, pp. 159–209, 2011, doi: 10.3982/ECTA7749.
- [42] I. Fernández-Val and F. Vella, "Bias corrections for two-step fixed effects panel data estimators," *Journal of Econometrics, Elsevier*, vol. 163, no. 2, pp. 144–162, 2007.
- [43] V. Verdier, "Average treatment effects for stayers with correlated random coefficient models of panel data," *Journal of Applied Econometrics*, vol. 35, no. 7, pp. 917–939, Nov. 2020, doi: 10.1002/jae.2789.
- [44] Y. Jiang and W. Ni, "Association Between Supplemental Private Health Insurance and Burden of Out-of-Pocket Healthcare Expenditure in China: A Novel Approach to Estimate Two-Part Model with Random Effects Using Panel Data," *Risk Manag. Healthc. Policy*, vol. 13, pp. 323–334, Apr. 2020, doi: 10.2147/RMHP.S223045.
- [45] G. Chamberlain, "Efficiency Bounds for Semiparametric Regression," *Econometrica*, vol. 60, no. 3, p. 567, May 1992, doi: 10.2307/2951584.
- [46] Y. Mundlak, "On the Pooling of Time Series and Cross Section Data," *Econometrica*, vol. 46, no. 1, p. 69, Jan. 1978, doi: 10.2307/1913646.
- [47] P. Deb and P. K. Trivedi, "Maximum Simulated Likelihood Estimation of a Negative Binomial Regression Model with Multinomial Endogenous Treatment," *The Stata Journal: Promoting communications on statistics and Stata*, vol. 6, no. 2, pp. 246–255, Jun. 2006, doi: 10.1177/1536867X0600600206.
- [48] A. Aakvik, T. H. Holmås, and E. Kjerstad, "A Low-key Social Insurance Reform - Treatment Effects for Back Pain Patients in Norway," Working Papers in Economics 07/02, 2002.
- [49] J. M. Wooldridge, *Econometric Analysis of Cross Section and Panel Data. Second Edition*. Cambridge, MA: MIT Press Massachusetts Institute of Technology Press, 2010.
- [50] T. Bartus, "Estimation of Marginal Effects using Margeff," *The Stata Journal: Promoting communications on statistics and Stata*, vol. 5, no. 3, pp. 309–329, Sep. 2005, doi: 10.1177/1536867X0500500303.
- [51] T. Cornelissen, C. Dustmann, A. Raute, and U. Schönberg, "From LATE to MTE: Alternative methods for the evaluation of policy interventions," *Labour Econ.*, vol. 41, pp. 47–60, Aug. 2016, doi: 10.1016/j.labeco.2016.06.004.
- [52] V. C. Nguyen, *The average treatment effect and average partial effect in nonlinear models*. Munich, Germany: MPRA Paper 44483, University Library of

- Munich, 2007. Accessed: Dec. 21, 2025. [Online]. Available: <https://mpra.ub.uni-muenchen.de/44483/>
- [53] L. M. Rea and R. A. Parker, *Designing and Conducting Survey Research: A Comprehensive Guide*, 3rd Edition. San Francisco: Josey-Bass Publishers, 1997.
- [54] J. Mugwe, D. Mugendi, M. Mucheru-Muna, R. Merckx, J. Chianu, and B. Vanlauwe, "DETERMINANTS OF THE DECISION TO ADOPT INTEGRATED SOIL FERTILITY MANAGEMENT PRACTICES BY SMALLHOLDER FARMERS IN THE CENTRAL HIGHLANDS OF KENYA," *Exp. Agric.*, vol. 45, no. 1, pp. 61–75, Jan. 2009, doi: 10.1017/S0014479708007072.
- [55] F. J. Fabozzi, S. M. Focardi, S. T. Rachev, and B. G. Arshanapalli, *The Basics of Financial Econometrics*. Wiley, 2014. doi: 10.1002/9781118856406.
- [56] J. B. Ajefu and O. Abiona, "L'Impact Atténuant de la Sécurité Foncière sur l'Insécurité Alimentaire Induite par la Sécheresse : Preuves Provenant des Zones Rurales du Malawi," Document de Politique Générale No.741, 2021. Accessed: Dec. 01, 2025. [Online]. Available: <https://ideas.repec.org/p/aer/wpaper/560889b9-9048-4f4f-9657-3e6121105fd8.html>
- [57] A. S. Adekambi, V. D. Agbotridja, C. L. Hinnou, and O. C. D. Kossoko, "Impact de l'adoption des technologies résilientes sur le bien-etre des menages producteurs de maïs au Nord du Benin: Impact of resilience technologies adoption on maize farmers livelihood in the Northern Benin," *Journal De La Recherche Scientifique De l'Université De Lomé*, vol. 22, no. 3, pp. 21–39, 2021.
- [58] Abdullah *et al.*, "Factors affecting household food security in rural northern hinterland of Pakistan," *Journal of the Saudi Society of Agricultural Sciences*, vol. 18, no. 2, pp. 201–210, Apr. 2019, doi: 10.1016/j.jssas.2017.05.003.
- [59] K. B. Dankwa, H. J. Sartorius von Bach, J. Van Zyl, and J. F. Kirsten, "Expenditure patterns of agricultural households in Lebowa and Venda : effects of the Farmer Support Programme on food security," *Agrekon*, vol. 31, no. 4, pp. 222–223, 1992, Accessed: Dec. 01, 2025. [Online]. Available: <http://hdl.handle.net/2263/2368>
- [60] L. O. Bello, B. A. Awotide, Gideon-Danso-Abbeam, and T. Sakurai, "Impact of climate-smart agricultural technologies adoption on food security in the West African Sahel: evidence from Mali and Niger," *Food Secur.*, vol. 18, no. 3, pp. 715–739, Jun. 2026, doi: 10.1007/s12571-026-01654-9.
- [61] I. Kostakis, "The determinants of households' food consumption in greece," *Agricultural and Food Sciences, Economics International Journal of Food and Agricultural Economics*, vol. 2, no. 2, 2014.
- [62] W. Awoke, K. Eniyew, G. Agitew, and B. Meseret, "Determinants of food security status of household in Central and North Gondar Zone, Ethiopia," *Cogent Soc. Sci.*, vol. 8, no. 1, Dec. 2022, doi: 10.1080/23311886.2022.2040138.
- [63] M. Ndiaye, "Déterminants du revenu agricole des ménages au delta du fleuve Sénégal," *Rev. Ivoir. Sci. Technol.*, vol. 30, pp. 281–290, 2017.

- [64] S. Nurudeen Afolabi and Y. Olumuyiwa Ganiyu, "Impact of Cooperative Membership on Rural Income Generation in Southwest, Nigeria," *REVESCO. Revista de Estudios Cooperativos*, vol. 138, p. e75563, May 2021, doi: 10.5209/reve.75563.
- [65] A. Maniriho, E. Musabanganji, F. Nkikabahizi, C. Ruranga, and P. Lebailly, "An Analysis of the Determinants of Household Expenditures in Rwanda," *UKH Journal of Social Sciences*, vol. 5, no. 1, pp. 8–17, Jun. 2021, doi: 10.25079/ukhjss.v5n1y2021.pp8-17.
- [66] A. D. Kehinde and M. A. Kehinde, "The impact of credit access and cooperative membership on food security of rural households in southwestern Nigeria," *Journal of Agribusiness and Rural Development*, vol. 57, no. 3, 2020.
- [67] J. A. Matz, M. Kalkuhl, and G. A. Abegaz, "The short-term impact of price shocks on food security-Evidence from urban and rural Ethiopia," *Food Secur.*, vol. 7, no. 3, pp. 657–679, Jun. 2015, doi: 10.1007/s12571-015-0467-4.
- [68] G. Kennedy *et al.*, "Proxy measures of household food consumption for food security assessment and surveillance: comparison of the household dietary diversity and food consumption scores," *Public Health Nutr.*, vol. 13, no. 12, pp. 2010–2018, Dec. 2010, doi: 10.1017/S136898001000145X.