



Research article

Rural non-farm income diversification: implications on smallholder farmers' welfare and agricultural technology adoption in Ghana

Gideon Danso-Abbeam^{*}, Gilbert Dagunga, Dennis Sedem Ehiakpor

Department of Agricultural and Resource Economics, University for Development Studies, Tamale, Ghana

ARTICLE INFO

Keywords:

Ghana
 Non-farm diversification
 Propensity score matching
 Inverse-probability weighted regression adjustment
Zai-technology
 Agricultural economics
 Agricultural policy
 Agricultural technology
 Economics
 Environmental economics

ABSTRACT

This study explored the potential impact of rural non-farm income diversification on households' welfare and adoption of *Zai-technology* (a proxy for agricultural technology adoption) using primary data collected from agricultural households in the Upper East region of Ghana. We used Propensity Score Matching (PSM) and Inverse-Probability-weighted Regression Adjustment (IPWRA) techniques to estimate welfare and *Zai-technology* impacts of non-farm income diversification. After controlling for differences in covariates, the results show that non-farm income diversification increases the likelihood of *Zai-technology* adoption and contributes to significant household welfare gains. We therefore suggest that the activities of agricultural extension services and farmer-based organizations (FBOs) be enhanced as they facilitate the diversification of non-farm incomes, thereby increasing investment in productivity-enhancing technologies (*Zai*) and household welfare.

1. Introduction

Smallholder farmers living in rural communities in low-income countries make up more than 70% of the world's impoverished and food-insecure population (FAO, 2014). Ironically, they contribute about 80% of the Africa's total food supply, and 70% of world's food supply (FAO, 2015). Dittoh (1981) argued that the smallholder farmer is the primary productive force of the agricultural sector and only a consistent policy based on evolving from a highly productive smallholder farmer can solve the food production problems in the African continent. Altieri et al. (2012) revealed that smallholder farmers feed almost all the hungry people living in rural areas and about one-third of the food insecure people living in urban areas.

In the Ghanaian context, although agriculture is a prominent income generating industry for many households and contributes significantly to the Gross Domestic Product (GDP), the sector is plagued with numerous challenges. Key among these challenges is low adoption of productivity-enhancing inputs, access to financial credit, issues of climate change, missing and incomplete market (Asravor, 2017).

Therefore, the search for alternative ways of generating income to overcome liquidity constraint and to smoothing income is critical to the rural-poor households. In this regard, households allocate part of their labour outside of crop production, such as livestock rearing, salaried work, and other non-farm enterprises. This allocation of labour constitutes income diversification. The term "income diversification" can be described using four distinct but related concepts (Minot et al., 2006). First, Minot et al. (2006) defined income diversification as a means of increasing the number of sources of income or stabilizing the different sources of income for households. Second, the change from small-scale or subsistence crop production to industrial production also constitutes income diversification (Delgado and Siamwalla, 1997). Reardon (1997) indicates an extension in the prominence of income from non-farm economic activities in the third concepts of income diversification. Finally, income diversification can also be characterized as the transition from low-value crop production to high-value crop production, livestock production or non-farm production (Minot et al., 2006). This study adopted the diversification concept suggested by Reardon (1997).

^{*} Corresponding author.

E-mail address: dansoabbeam@uds.edu.gh (G. Danso-Abbeam).

Thus, a farm household is said to participate in income diversification if he or she generates income from non-farm sources such as trading, salaried employment, self-employment, and other non-farm vocations or enterprises.¹²

Diversification of income is seen as a thoughtful technique used by households to mitigate risks and respond to opportunities to improve their wellbeing (Ellis, 2010). Income diversification acts as a risk management and coping method intended to cushion the consequences of crop failures and economic hardship. In addition, households are engaged in income diversification during the off-farm season to escape idleness and to recognize their maximum capacity for labour (Ellis, 2000). As a result, income diversification helps to combat poverty, hunger and boost the welfare of smallholder families. Diversification into non-farm sources acts as a way of accumulating income to expand farm lands and purchase additional inputs (Lay and Schüler, 2008). As indicated by Asmah (2011), agricultural households have diversified their income as a result of either a pull factor (opportunity-led diversification) or a push factor (survival-led diversification). The pull factors are favourable factors that push households to participate in other non-farm economic activities, while the push factors are harsh conditions, such as changes in climate parameters that cause (survival-led) households to diversify.

Extant literature has documented that participation in income diversification is perceived to be one of the ways to escape the poverty trap. Ellis (2000) found that income diversification helps to enhance the welfare and livelihoods of farmers. A study by Chirwa et al. (2017) further explained that income diversification has a positive impact on the welfare of households by increasing total household income in Malawi. Moreover, income diversification strategies have been widely established in order to address the credit constraints of smallholder farmers and improve productivity by increasing the intensity of agricultural technology adoption (Reardon et al., 2007). Available evidence in Ghana (Agyeman et al., 2014; Asravor, 2017; Dagunga et al., 2018) suggests an increase in income diversification among smallholder farmers. Though rural households in Northern Ghana are considered vulnerable to climate change challenges and have a high level of poverty and food insecurity, they are fairly diverse (Ghana Statistical Service, 2014). In addition, northern Ghana has a single rainy season, with the lowest average rainfall between 800 and 1100 mm per year and a maximum temperature of 43 °C. Consequently, the inadequacy of rainfall adversely affects the livelihoods of smallholder farmers and plunges them deeper into poverty. As a result, many households work part-time in non-farm sectors during agricultural or off-farm seasons to offset these impacts.

Despite the empirical work on diversification in Ghana, there is little empirical literature on the impact of income diversification on the adoption of agricultural technology and household welfare. The study therefore takes yet another significant step towards enhancing Ghana's empirical work by analysing the impact of non-farm income diversification not only on the welfare of households, but also its impact on the adoption of high productivity-enhancing technologies, *Zai*, disseminated in the areas under study. *Zai* is a traditional land-restoration technique 'invented' by Burkinabe farmers to rehabilitate degraded drylands and increase soil productivity for dryland crops. *Zai* pits are small dug-outs of around 20–30 cm deep where organic manure is buried in the soil to boost the nutritional condition of the soil as well as to maintain the moisture content of the soil. Motis et al. (2013) indicated that *Zai-technology* increases farm yield and productivity. The technology was

introduced in Northern Ghana in 2010 by the Presbyterian Agricultural Station, a non-governmental organization providing agricultural extension services in Northern Ghana, and has since been adopted by many households in the districts of Garu and Tempene in the Upper east region of Ghana. Thus, while the adoption of *Zai-technology* was used as a proxy for agricultural technology, household income per capita and total household consumption expenditure per capita were used as welfare indicators in our analysis. The study thus provides realistic evidence of the impact of rural income diversification on the adoption of farm technology and welfare outcomes, which will serve as a guideline for agricultural policy and planning aimed at developing the rural sector.

2. Methodology

2.1. Conceptual framework

Many studies, including Diiro and Sam (2015) and Chirwa et al. (2017), have shown that the degree to which income diversification contributes to the empirical adoption hypothesis can be modelled using a random utility framework. According to the random utility model, farmers will only diversify if the net diversification gain is positive. Thus, a farm household will diversify his/her income if and only if $U_j^* = U_{Dj} - U_{NDj} > 0$, where U_j^* is the net utility or benefit for diversification, U_{Dj} and U_{NDj} are utilities from diversification and non-diversification, respectively. As discussed above, farm households engaged in some non-farm activities (trading, vocation, salaried jobs, self-employment) are considered to be a participant in income diversification (or a diversified household) and those not engaged in any non-farm income generation activity are called non-participants in income diversification (non-diversified households).³

From the descriptive statistics, a significant difference in the outcome variables (*Zai-technology* and welfare indicators) between participants and non-participants in income diversification can be used to evaluate the effect of income diversification on technology adoption and welfare. However, determining the effect of the treatment variable (diversification of income) encounters the problem of sample selection bias that may occur as a result of observed and unobserved covariates (Baker, 2000). In most cases, farmers make voluntary decisions to diversify their income on the basis of access to productive resources, knowledge, information, etc., leading to self-selection bias. The role of farmers in diversifying their sources of income is therefore non-random. Simple differences in outcomes between participants and non-participants in income diversification should not, however, be considered as possible differences in characteristics between these groups. In order to better determine the impact of income diversification on the adoption of *Zai* and welfare, diversification must be randomly assigned in such a way that the impact of covariate between the treated and the control groups are the same, such that diversification remains the only distinction between the two. If we do not randomly assign households to treatment, their participation in income diversification may be influenced by differences in their characteristics, which could be correlated with the outcome variables of interest. Another major econometric difficulty in the estimation of the impact of any treatment (e.g., program, adoption of innovation, non-farm income diversification) is the lack of data for the counterfactuals. There is missing data since both the outcomes and the counterfactuals for each group cannot be observed at the same time (Wooldridge, 2003).

Consider that Y_{1i} is the outcome variable for households who diversified their income and Y_{0i} is the outcome variable for households who did not diversify their income. Following Heckman et al. (1997) and Smith and Todd (2001), the impact of income diversification is the

¹ The study classified all farmers that make income from non-farm sources as participants of non-farm income diversification or diversified farm households. Those that do not generate income from any non-farm economic activities are classified as non-participants of non-farm income diversification or non-diversified farm households.

² Moreover, the study used non-farm income diversification and income diversification interchangeably.

³ In this study, participants (non-participants) of non-farm income diversification, and diversified household (non-diversified) are used interchangeably.

difference in outcome that can be ascribed to income diversification and be expressed as:

$$\Delta Y = Y_{1i} - Y_{0i} \tag{1}$$

where ΔY denotes the impact of diversification for a sampled household.

The mean difference stated in Eq. (1) can only be possible if an individual household is involved in both situations (treatment and control group) concurrently. However, since households can only be in one group at a time, measuring treatment effect on households who have participated in income diversification has serious limitations, as only one of the potential outcomes can be observed at a time. Thus, either Y_1 or Y_0 for each household can be observed, suggesting that potential outcomes Y_1 and Y_0 cannot be observed simultaneously. This is the problem of missing data for the counterfactuals, as indicated by Smith and Todd (2005). In order to overcome the problem of missing data, an analysis of what would have been the outcome of the participants had they not participated in income diversification can be employed to estimate the impact of income diversification (Becker and Ichino, 2002). In this case, the average impact of the treatment (income diversification) on the treated (participants of income diversification), which focuses on the effect of farmers who diversified their incomes is applied (Chirwa et al., 2017). The average treatment effect on the treated (ATT) is the difference between the potential outcomes of households who diversified their incomes with and without diversification (Heckman et al., 1997).

$$\Delta Y_{ATT} = ATT(Y / X, D = 1) = E(Y_1 - Y_0 / X, D = 1) = E(Y_1 / X, D = 1) - E(Y_0 / X, D = 1) \tag{2}$$

In Eq. (2), Y is the potential outcome, X is a vector of covariates, and D denotes income diversification, where $D = 1$ if households engage in non-farm diversification (in addition to farm operations and $D = 0$, otherwise (only farm operations).

2.2. Empirical estimation techniques

In order to address the issues of sample selection bias and the missing data, instrumental variable (IV) and propensity scores (PS) are the most widely used methods. IV approaches, such as endogenous switching regression, provide a solution to hidden heterogeneity in treatment and control groups. However, one big drawback to the IV strategy is how to identify the suitable technique for applying a more rigid linear functional form inference compared with the PS approach, which is invariant to the functional form assumption (Heckman and Vytlačil, 2007; Takahashi and Barrett, 2014). Contrary to the above-mentioned parametric approaches, PS needs no inference as to the role of determining the interaction between the control variable and the treated variable, and the endogeneity of covariates in estimating the causal effects of the outcome variable.

The study used the methodology of propensity score matching (PSM) (within the PS framework) as its primary strategy for estimating the impact of income diversification on smallholder farm households, considering the cross-sectional structure of the data and the difficulties in identifying the correct and solely exogenous methods to justify the IV procedure. Meanwhile, an Inverse-Probability-Weighted Regression Adjustment (IPWRA), which is a doubly robust estimator was used as a robustness measure of PSM estimates.

2.2.1. Propensity score matching (PSM)

PSM is described as obtaining the likelihood of conditional treatment (Rosenbaum and Rubin, 1983). PSM creates a statistical contrast system where the unit being treated is compared by measurable covariates with unit in the control group, so that treatment is assigned randomly. This

helps to establish a causal relation between the income diversification variable and the outcome variables.

We follow two steps to operationalize PSM. First, income diversification is modelled by means of probit models as a choice-dependent variable, following the determination of propensity score for each observation. The following equations specified diversification:

$$p(X_i) = \Pr[D = 1 / X_i] = E[D / X_i]; \quad p(X_i) = F\{h(X_i)\} \tag{3}$$

$$p(X_i) = \Pr(p = 1) / X_i \tag{4}$$

where $F\{\cdot\}$ is a binary probit model, D and X_i as previously defined. Eq. (4) is the propensity score according to Rosenbaum and Rubin (1983). After the propensity score is determined, the overall impact on the individual (ATT), which is the second step, may be measured by comparing the participants with non-participants conditioned on similar attributes. The ATT is the net impact of income diversification on the likelihood of *Zai-technology* adoption and welfare of the sampled households, who diversified their income. ATT is the difference in the potential outcomes of the treatment group as defined in the above Eq. (2) with and without treatment. Thus, ATT estimates the net impact of income diversification on households with diversified incomes, and can be specified as:

$$ATT = E(Y^D - Y^C / D = 1) = \frac{1}{N_D} \left[\sum_{i \in D} Y_i^D - \sum_{j \in C} \omega(i, j) Y_j^C \right] \tag{5}$$

where N_D denote the treated households, Y^D and Y^C represent *Zai-technology* adoption and welfare for the treated and reference groups, respectively, and $\omega(i, j)$ is the relevant load factor used in the matching process. Since PSM is so sensitive to exact parameters and matching procedures, we used three matching algorithms most seen in literature (Imbens, 2004; Gebrehiwot, 2015), namely nearest-neighbor matching, kernel-based matching and radius matching to serve as robustness check. Nearest-neighbor matching involved comparing of sample in the treated group with a control group with the closest propensity score (Becker and Ichino, 2002). One factor or one closest neighbor matching compares each sample in the treated group with a sample in the control group on a one-to-one basis with the closest propensity value. In Kernel-based matching, all treated subjects are paired with a weighted average of all reference groups using weights that are inversely proportional to the gap between participants' and non-participants' propensity score (Caliendo and Kopeinig, 2008). The default Kernel bandwidth of 0.06 was used. For radius matching, all reference samples available with a given radius are used, and 0.06 radius was used.

However, PSM estimates rely on two simple assumptions, the Conditional Independence Assumption (CIA) and Common Support Assumption (CSA). The CIA states that the likelihood of treatment with a particular range of measurable features, the potential outcome without treatment Y_i , and income diversification D_i , are statistically independent (Takahashi and Barrett, 2014). This assumption of independence between treatment variable and the outcome variable is referred to as unconfoundedness and is based on observed rather than unobserved variables such that variables that strongly affect income diversification status, but not outcome variables, are included in the model (Chirwa et al., 2017). The common support assumption ensures that households with the same characteristics have a positive probability of belonging to

both treated and control group (Takahashi and Barrett 2014). Thus, there should be substantial overlap in covariates between the two comparing groups (Becerril and Abdulai, 2010). When these two assumptions are satisfied, then the PSM estimators can be used to estimate the ATT for the treated group.

2.2.2. Balancing tests and sensitivity analysis

The study performs two critical diagnostic tests: covariate balancing test and sensitivity analysis, to further validate the results from the PSM estimations. Balancing test is vital to ensure that plausible counterfactual information is created to measure the ATT. The notion of balancing test is to check whether households with the similar propensity scores have similar characteristics, independent of the treatment assignment (income diversification). The analysis ensures that the dispersion of variables among participants and non-participants in income diversification is well matched by measuring an equivalent mean of covariate across groups using *t*-test as suggested by Rosenbaum and Rubin (1985). Following Caliendo and Kopeinig (2008), the *Pseudo-R*² before and after matching was also used for a further covariate balancing test. The *Pseudo-R*² after matching should be relatively small with insignificant joint probability (Ali and Abdulai, 2010). The matched reference category may be called counterfactual after removing the covariate variations between the two groups (Heckman and Vytlacil, 2007; Ali and Abdulai, 2010).

The assumption of conditional independence or unconfoundedness allows the researcher to consider all factors affecting both the non-farm job decision and the outcome variables. If there are unobserved covariates that potentially affect participation in non-farm jobs, and welfare and adoption outcome variables, then there is a risk of a latent bias that may hinder the robustness of the matching estimators (Rosenbaum, 2002). Hence, examining the degree to which the magnitudes of the effects generated from the PSM process is sensitive to hidden bias is crucial. Becker and Caliendo (2007) noted that "checking the sensitivity of the estimated results with respect to deviations from this identifying assumption has become an increasingly important in the applied evaluation literature." Therefore, this diagnostic test is to examine the extent of latent biases arising from unobserved variables that are most likely to affect income diversification variable and outcome concurrently. In this study, we used Rosenbaum bounding approach (Rosenbaum, 2002) for welfare indicators, and Mantel and Haenszel approach (MH 1959) suggested by Aakvik (2001),⁴ for *Zai-technology* adoption. Following Rosenbaum (2002), the odds ratio for the bounding method can be expressed as:

$$\frac{1}{\tau} \leq \frac{P_i(1 - P_i)}{P_j(1 - P_j)} \leq \tau \quad (6)$$

where $\tau = 1$ suggests that the odds of treatment is the same and there is an absence of hidden biases, while every increase in the value of τ would also indicate non-existence of hidden bias. DiPrete and Gangl (2004) noted that if τ is smaller (less than 2), then the likelihood of having some unobserved covariates affecting the outcome variable is high and the estimated results are therefore associated with unobserved characteristics of the respondents. Thus, τ is a measure of the extent of departure of an estimate that is free from hidden bias (Rosenbaum, 2002).

2.2.3. Inverse-probability-weighted regression adjustment - IPWRA

IPWRA acts as an appropriate solution for intrinsically bias estimates (ATTs) arising from propensity score models in the presence of misspecification (Robins et al., 2007; Wooldridge, 2007). According to Wooldridge (2003), IPWRA estimates would be consistent even if the treatment or outcome were not specified correctly, but not both. Thus, due to its dual-robust structure, the IPWRA can ensure accurate results as

it allows the treatment and the outcome models to compensate for the misspecification. Therefore, a chosen estimator used to check the robustness of the estimates obtained from the PSM. According to Imbens and Wooldridge (2009), calculating ATT using IPWRA is a two-step method. Consider that outcome indicator, as usual, is Y_i which can be represented by a linear function specified as:

$$Y_i = \delta_i + \varphi_i X_i + \varepsilon_i \quad \text{for } i = [0, 1] \quad (7)$$

The propensity score generated from the selection equation can be represented as:

$$ps = p(X; \gamma) \quad (8)$$

First, the propensity score is estimated as $p(X; \hat{\gamma})$. Second, it employs linear OLS to estimate (δ_0, φ_0) and (δ_1, φ_1) using inverse probability weighted least square.

The inverse probability weighted least squares can be specified as follows:

$$\min_{\delta_0, \varphi_0} \sum_{i=0}^N (Y_i - \delta_0 - \varphi_0 X_i) / p(X, \hat{\gamma}) \quad \text{if } k_i = 1 \quad (9)$$

The ATT can then be computed as the difference between Eqs. (7) and (8),

$$ATT = \frac{1}{N_w} \sum_i^{N_w} [(\hat{\delta}_1 - \hat{\delta}_0) - (\hat{\varphi}_1 - \hat{\varphi}_0) X_i] \quad (10)$$

where $(\hat{\delta}_1, \hat{\varphi}_1)$ are the inverse probability weighted estimates for the treated households and $(\hat{\delta}_0, \hat{\varphi}_0)$ are the estimated inverse probability weighted estimates for the control households. Finally, N_w denote the treated households. Nonetheless, propensity score procedures can only deal with observed heterogeneity regardless of adjustment for biases emanating from misspecification of the model (Wosen et al., 2017).

3. Sampling techniques, data sources, and summary statistics

Data for this study were collected from households residing in Garu and Tempane districts in the Upper East region, Ghana. A household refers to a group of people living together, eating from the same pot and sharing the same resources (Yaro, 2006). Following these criteria, the study followed a multi-stage random household survey. First, Upper East region was predefined, the reasons being that it is where *Zai-technology* was implemented and one of the poorest regions in Ghana. Second, Garu and Tempane districts⁵ were purposively selected from the three administrative districts in the Upper East region where *Zai-technology* was diffused. Third, with the assistance of the extension agents in the districts, we randomly selected 10 villages from the list of villages where *Zai-technology* is practiced. Finally, 40 households were selected through simple random sampling and interviewed via a well-structured questionnaire. In total, 400 households where 240 households engaged in income diversification and 160 were not engaged in income diversification as defined in sections 1 and 2.1.

3.1. Definition of variables and summary statistics

The study followed many pieces of empirical literature (Agyeman et al., 2014; Danso-Abbeam and Baiyegunhi, 2017) to select the indicators of welfare and independent variables hypothesized to influence income diversification. Table 1 summarizes welfare indicators and

⁴ Readers are referred to Becker and Caliendo (2007) for further information on MH sensitivity analysis for treatment effects.

⁵ The *Zai-technology* was first piloted in the Garu and Tempane districts. The third district was added after 2 years hence the selection of the two districts for the study.

Table 1. Definition of variables and summary statistics of the respondents.

Variables	Full sample	DIV	Non-DIV	t-test
<i>Treatment Variable</i>				
Diversified farm households (dummy, = 1)	0.631	-	-	-
<i>Outcome Variables</i>				
Household consumption expenditure per capita (Ln)	2.418	2.445	2.373	2.26 ^b
Household income per capita (Ln)	3.662	3.684	3.626	1.71 ^c
Zai-technology adoption (dummy, = 1)	0.545	0.543	0.340	3.02 ^a
<i>Farmers' Characteristics</i>				
Sex of the household head (1 if male, 0 otherwise)	0.679	0.695	0.653	0.62
Age of the household head (years)	43.463	42.008	45.947	-1.96 ^c
Household size (Number)	9.768	9.273	10.613	-1.85 ^c
No formal education (dummy, = 1)	0.315	0.328	0.293	0.51
Primary education (dummy, = 1)	0.332	0.305	0.373	-1.00
Junior high education (dummy, = 1)	0.148	0.158	0.133	0.44
Senior high education (dummy, = 1)	0.123	0.125	0.120	0.10
National diploma education (dummy, = 1)	0.015	0.008	0.027	-1.07
Tertiary education (dummy, = 1)	0.064	0.070	0.053	0.47
Number of years in crop farming (years)	23.502	21.82	26.373	-3.19 ^a
<i>Household assets</i>				
Farm size allocated to maize production (ha)	1.249	1.232	1.279	0.62
Active family labour force (person-hours)	350.891	342.52	365.19	-0.62
Amount of labour hired (person-hours)	177.195	202.43	134.13	2.22 ^b
<i>Institutional and social capital variables</i>				
Access to extension services (dummy, = 1)	0.527	0.679	0.267	6.17 ^a
Membership of Farmer-based Organization (dummy, = 1)	0.256	0.367	0.067	4.99 ^a
Membership of Village savings group (dummy, = 1)	0.414	0.539	0.200	4.99 ^a
Access to agricultural credit facility (dummy, = 1)	0.399	0.508	0.213	4.30 ^a

a, b, and c represent significance level at 1%, 5%, and 10%, respectively.

Zai-technology adoption (outcome variables), and socioeconomic, field-specific and institutional variables of the sampled households.

3.1.1. Treatment and outcome variables

The treatment variable here is income diversification, dummied one (1) if household participates in non-farm income diversification, otherwise zero (0). Two variables were used as proxies for welfare: household consumption expenditure and income, adjusted for adult equivalents to get household consumption expenditure per capita and household income per capita. Zai was used as an indicator for agricultural technology adoption. A household is assigned a value of one (1) if Zai is applied on his maize farm and 0 otherwise. From Table 1, the welfare indicators and Zai adoption suggest that participants of income diversification were better-off than non-participants as indicated by the *t-test* statistic. However, variations in these magnitudes do not indicate causality since they are unable to account for systemic differences in observable characteristics amongst treated and untreated households.

3.1.2. Independent variables

Table 1 provides descriptive household statistics in the study area. From the table, the proportion of male-headed households in the diversified and non-diversified group are 0.70 and 0.65, respectively. The average age of farmers was 44, which is within the economic working population. The mean age for the diversified and non-diversified households was about 42 and 46 years, respectively. Age of the household has been hypothesized to have an indeterminate (Ibekwe, 2010) effect on diversification. The average size of the households in the study was nine people per household whereas the average experience in farming was 24, 25 and 22 for the entire sample, the diversified groups and the non-diversified groups, respectively. Larger household is expected to

increase income diversification regarding labour supply both on and off the farm as suggested by Agyeman et al. (2014).

The descriptive statistics further indicate that about 32% had no formal education, while about 33% and 27% had primary and high school (junior and senior) education. Additionally, 1.5% and 6% of the sampled farmers had attained diploma and university degrees, respectively. This suggest a low level of education by households in the northern part of the country. The average number of years in crop farming was found to be about 23 years, while the average age of a farmer in the diversified category was marginally lower (21 years) compared to the non-diversified farmer (26 years). An average farm area allocated to maize production is 1.25 ha. The inclusion of this variable was significant because it is the predominant crop of the people in these districts and the Zai-Technology was mainly used for maize cultivation. The average family labour, used during the farming season, was about 350 person-hours, while that of the hired labor was about 177 person-hours. However, hired labour used was significantly higher in the diversified group than the non-diversified group. Institutional or policy variables including extension services and participation of social organizations were among the ways in which information was conveyed to the rural people. In comparison, the table reveals that about 53% of respondents had access to extension services where the greater proportion of diversified households (68%) had access to agricultural extension services compared with the non-diversified households (27%). Also, 26% of the sampled farmers were members of a Farmer-based Organization (FBOs) with a higher percentage for the diversified groups (37%) relative to the non-diversified groups (6%). On average, most (54%) of the farmers that were members of Village Savings group diversified their sources of income relative to those who were not (20%). The estimated proportion of the population with access to agricultural credit was

Table 2. Probit model of the determinants of rural non-farm income diversification.

Variables	Coefficient	Std. Err.	Marginal effects	Std. Err.
<i>Farmers' characteristics</i>				
Sex of the household head	0.0240	0.2344	0.0067	0.0655
Age of the household head	-0.0120***	0.0020	-0.0034***	0.0006
Household size	-0.0535**	0.0241	-0.0149***	0.00645
Primary Education (dummy, = 1)	0.4886*	0.2758	0.1366*	0.0751
Junior high education (dummy, = 1)	0.3678**	0.1893	0.1028**	0.0514
Senior high education (dummy, = 1)	0.1478	0.1337	0.0413	0.0370
National Diploma education (dummy, = 1)	0.9577***	0.3141	0.2677***	0.0820
Tertiary education (dummy, = 1)	0.1130***	0.0109	0.0315***	0.0308
Number of years in crop farming	-0.0347**	0.0161	0.0096**	0.0043
<i>Household assets</i>				
Total farm size allocated to maize cultivation	0.0235	0.0442	0.0065	0.0123
Active family labour force	0.0002	0.0004	0.0004	0.0001
Income from main crop farm (maize)	0.0013*	0.0007	0.0004**	0.0002
<i>Institutional and social capital variables</i>				
Access to extension services	0.7896***	0.2431	0.2208***	0.0621
Membership of farmer-based organization	0.7457*	0.3950	0.2084*	0.1080
Membership of village savings group	0.2792	0.3952	0.0781	0.1103
Access to agricultural credit facility	0.0419	0.3585	0.0117	0.1001
Constant	0.9486	0.5872		
<i>LR Chi2 (16) [16; p > 0.000]</i>				
<i>Wald Chi2 (16) [37.07; p > 0.000]</i>				
<i>Sensitivity (% correctly classified among diversified group)</i>	80.47			
<i>Specificity (% correctly classified among non-diversified group)</i>	64.00			
<i>Total correctly classified (%)</i>	74.38			

Note: ***, **, and * denote 1%, 5% and 10% levels of significance. No-formal education was used as a base category for educational attainment.

roughly 51% in the diversified group, compared to 21% in the non-diversified group.

4. Empirical results and discussions

4.1. Determinants of rural non-farm income diversification

Table 2 reports the estimated probit model, in which the model is statistically significant at one percent level of significance as indicated by the likelihood ratio value ($LR\ Chi^2 = 66.97; p = 0.000$). The value of the Wald Chi^2 (37.07; $p > 0.000$) suggests that the estimates of all the variables included in the model are significantly different from zero. Furthermore, the model correctly classified about 80% of the sampled households among those who engage in non-farm activities, while 64% were classified among the non-diversified group.

Following Ellis (1998), socioeconomic and institutional factors influence farmers' decision to diversify their income into non-farm economic activities.

Since the coefficients of parameters do not have precise explanations of the magnitudes of regression estimate, we used the value of marginal effect to explain our results. The magnitude of marginal effects indicates the degree to which covariates affect the dependent variable. The results obtained indicate that the age of the respondents is significant and negatively correlated with non-farm income diversification. Thus, the age of the household head reduces the possibility of diversification into non-farm economic activities by about 0.3%. The probable reason is that age has a negative relationship with physical strength. Hence, as the household head gets older, his or her working capacity decreases and is thus less likely to engage in non-farm income activities. These results are in line with studies by Sallawu et al. (2016) who found that age of farmers reduces the probability of participation in non-farm income activities. The results further indicate that farmer characteristics such as

household size, educational attainment, and the number of years in crop cultivation (a proxy for experience) significantly influence non-farm diversification. The results imply that larger households have about 1.5% less probability of diversification than smaller households. This could be attributed to the fact that larger households tend to weaken household income as it increases consumption expenditure, thereby leaving little or no funds available for further activities outside the farm operations. This result is consistent with the one reported by Awotide et al. (2012) but invariance with the study of Diirro and Sam (2015) who found in Nigeria that larger households tend to have multiple sources of non-farm income activities compared with smaller-sized households. Asravor (2017) also reported that large farm households suggest more family labour supply, which tends to increase the likelihood of non-farm diversification.

Education is a powerful tool that boosts the productivity of human capital, making people aware of the various opportunities for generating incomes. Many empirical studies such as Dagunga et al. (2018) have operationalized education as the number of years in school. Another aspect that this study focuses on is the level of education. Farm households with a higher level of education is expected to have a greater chance of engaging in different sources of income than those with low level or no formal education. The results imply that household heads who have had a diploma and university degree, respectively are about 27% and 3.2% most likely to participate in non-farm income than their counterparts with no formal education (base category). This implies that education is a critical pull factor when it comes to non-farm income diversification. Contrary to the expected notion, household heads with lower level of education, specifically at the primary and junior high school was found to also have a higher probability of diversification. The results suggest that households who did not advance into senior high school probably started other non-farm business enterprises early in their career. Also, those who made it to the diploma

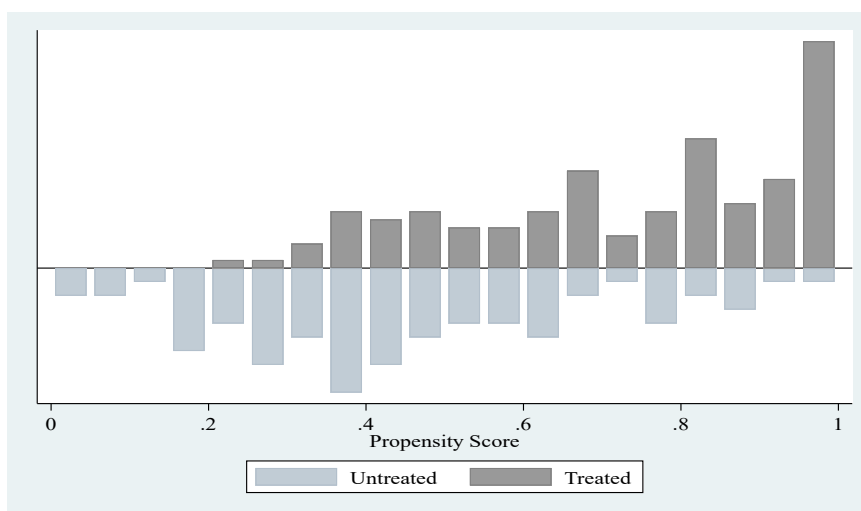


Figure 1. Propensity score distribution and common support by participation in non-farm income diversification.

and tertiary levels might have been formally employed, but those who got to senior high schools and did not continue do not show significant probability of diversification. Many empirical studies (Ibekwe, 2010; Sallawu et al., 2016) have established a positive relationship between education and participation in non-farm income. Additionally, in Ghana, Asravor (2017) have reported a positive influence of educational attainment on income diversification, confirming the results of this study. Similarly, the coefficient of the number of years farmers have worked in crop farm is significant and positively signed suggesting that farmers with long-term experience in their farm have higher propensity to engage in non-farm activities compared with those who have short-term experience.

Studies such as Awotide et al. (2012) suggests that farmers' possession of assets like crop farm and its returns enhances diversification into non-farm economic activities. This is particularly because, in a situation where farmers are liquidity or credit constrained, income from the farm can be used to support non-farm diversification strategies. Other households' assets such as the number of household members actively involve in farming operations (active labour force) and farm size allocated to cultivation of maize, are positively related to non-farm diversification though not significant.

Much empirical evidence (Agyeman et al., 2014; Dagunga et al., 2018) have documented that institutional factors including demonstration plots, extension services, among others have positive influence on the likelihood of farmers' engagement in income diversification. Farmers that have access to extension services are exposed to several opportunities. Modern days extension services do not only focus on adoption of agricultural technology but also how farmers can diversify their source of livelihoods, particularly in developing economies like Ghana where the majority of farmers have to depend on the weather for agricultural productivity. It is therefore not surprising that farm households with access to extension services are more likely to diversify their income than their peers without access to extension services. The membership of FBOs is another main institutional variable that influences the probability of farmers diversifying their incomes. Social networks such as FBOs improve farmers' access to information on other business opportunities in their environment. In addition, several non-governmental organizations working in rural farming communities train farmer groups on alternative livelihood programs such as livestock farming, apiculture and other micro-enterprises. This suggests that the distribution of households belonging to groups of farmers will have a large base of alternative sources of income relative to those not belonging to any farmer group.

4.2. Impact of non-farm income diversification on household welfare and Zai-technology adoption

In order to estimate the causal effects of income diversification for farm households that diversified their income, we compare the outcome indicators of the diversified population with the same population (their counterfactual situations) had they not diversified their incomes. As mentioned earlier, the study carried out a triangulation or robustness check for estimation methods using both PSM and IPWRA.

4.2.1. Propensity score matching approach

The study carried out a diagnostic test to determine the reliability of the matching process in estimating the impact of income diversification on welfare, following predictions of propensity scores for diversified and non-diversified groups. The two diagnostic tests conducted are the assumption of a common support condition and the covariate balance test as shown in Figure 1 and Table 3.⁶ Figure 1 is a graph showing the density distribution of the diversified and non-diversified propensity scores. The propensity score for the full sample varies from almost zero (0.00002) to close to one (0.99972) with a mean value of about 0.628 and a standard deviation of about 0.260.

For non-farm diversification participants, the propensity score ranges from a minimum of 0.23937 to a maximum of 0.99972 with a mean value of 0.735 and a standard deviation of 0.214. However, for the non-participants, the propensity score ranges from approximately 0.00002 to 0.95264 with an average value of 0.444 and a standard deviation of approximately 0.230. No farm observation had been dropped because all of them had their match (on-support). It is evident from the figure that the distribution of propensity scores for the diversified group converges with the non-diversified group, thereby satisfying the general criterion of common support.

In addition, a balance test was conducted on covariates so as to ensure that non-farm diversification is the only distinction between diversified and non-diversified households with the same or identical characteristics. The balancing test of the mean equality across the covariates is illustrated in Table 3. Thus, both diversified and non-diversified households have identical characteristics, since their mean covariates show no statistical differences. In addition, the mean standard test as proposed by

⁶ Note: All the three algorithms of PSM provided similar results with all the outcome variables. Hence, the nearest neighbour matching using consumption expenditure per capita is presented here.

Table 3. Test of equality of means of each variable before and after matching.

Variables	Unmatched			Matched		
	DIV	Non-DIV	t-test	DIV	Non-DIV	t-test
<i>Farmers' Characteristics</i>						
Sex of the household head	0.695	0.653	0.62	0.646	0.708	-0.85
Age of the household head	42.008	45.947	-1.96 ^c	42.253	40.342	0.89
Household size	9.273	10.613	-1.85 ^c	10.278	11.557	-1.37
Primary Education	0.305	0.373	-1.00	0.286	0.286	0.00
Junior high education	0.156	0.133	0.44	0.190	0.179	0.20
Senior high education	0.125	0.120	0.10	0.155	0.274	-1.89 ^c
National Diploma education	0.008	0.027	-1.07	0.000	0.006	-0.70
Tertiary education	0.070	0.053	0.47	0.048	0.029	0.60
Number of years in crop farming	21.82	26.373	-3.19 ^a	22.684	21.81	1.15
<i>Household assets</i>						
Farm size allocated to maize production	6.953	6.415	1.16	6.221	6.699	-1.08
Active labour family force	342.52	365.19	-0.62	353.64	295.09	1.60
Amount of labour hired	202.43	134.13	2.22 ^b	164.95	124.45	1.47
<i>Institutional and social capital variables</i>						
Access to extension services	0.679	0.267	6.17 ^a	0.569	0.632	-0.81
Membership of farmer-based organization	0.367	0.067	4.99 ^a	0.228	0.215	0.19
Membership of village savings group	0.539	0.200	4.99 ^a	0.392	0.379	0.16
Access to agricultural credit facility	0.508	0.213	4.30 ^a	0.379	0.379	-0.00

Note: DIV, and Non-DIV denote non-farm income diversification and non-farm income non-diversification farm households. a, b and c represent significant level at 1%, 5% and 10%, respectively.

Table 4. Overall matching quality indicators before and after matching.

Sample	Pseudo R ²	LR chi ²	p > chi ²	Mean Bias	Total % bias reduction
Unmatched	0.236	61.05	0.000 ^a	40.3	
Matched	0.064	14.46	0.272	4.6	76.18

^a indicates significance level at 1%.

Table 5. Impact of income diversification on households' welfare and adoption of Zai.

Outcome Variable	Matching on PS		
	Single-NNM	KM (Bandwidth = 0.06)	Radius (Calliper = 0.06)
	ATT	ATT	ATT
Consumption expenditure per capita	0.216 (0.031) ^a	0.229 (0.055) ^a	0.192 (0.003) ^a
Household income per capita	0.194 (0.052) ^a	0.188 (0.036) ^a	0.182 (0.038) ^a
Zai-technology	0.361 (0.119) ^a	0.314 (0.045) ^a	0.309 (0.110) ^b

Note: NNM and KM denote Nearest neighbour matching and Kernel matching, respectively. a, b, and c denote significance levels at 1%, 5%, and 10%, respectively.

Rosenbaum and Rubin (1983) was used to validate the consistency of the matching technique. Results from Table 4 reveal that the standardized mean covariate variance decreased from 40.3% before matching to 4.6% after matching.

This leads to a cumulative total bias reduction of about 76.18%. This finding supports the comparison's statistical significance as the standardized mean is not greater than 5% after matching (Rosenbaum and Rubin, 1983). Accordingly, the estimated average impact for farm households with comparable propensity from non-farm diversification may be calculated by estimated using Eq. (2) above.

Table 5 illustrates the extent of the impact of income diversification on welfare and Zai-technology adoption using three distinct PSM algorithms. Income diversification was found to have a significant impact on welfare and Zai-technology adoption in all three algorithms. The results revealed that income diversification improves the welfare of households

through consumption expenditure per capita. The estimated impacts are 0.19, 0.22, and 0.23 for radius, nearest-neighbor, and Kernel-based matching, respectively. Thus, income diversification has increased the welfare of the diversified group by 19–23 percentage points. These findings are consistent with the results of Martin and Lorenzen (2016), who indicated that income diversification in rural areas leads to the accumulation of wealth and thus makes farmers better-off. Blundell and Preston (1996) noted that consumption expenditure per capita is a better measure of one's standard of living and will better reflect expected lifetime resources.

Moreover, income diversification has a positive and significant effect on the household income per capita of the treated households. As a result, households that diversified their sources of income increased their household income per capita by approximately 19%. The two welfare indicators confirm that diversification of income has a statistically

Table 6. Sensitivity analysis with Rosenbaum test with Nearest Neighbor matching.

Critical values (τ)	Consumption expenditure/capita				Household income per capita			
	Sig+	Sig-	t-hat+	t-hat-	sig+	Sig-	t-hat+	t-hat-
1	0	0	0.772449	0.772449	0	0	2.41999	2.41999
1.5	2.2e-11	0	0.543095	0.955012	0.008714	0	2.13392	2.70671
2	8.1e-07	0	0.403238	1.04475	0.009779	0	2.13106	2.70833
2.5	0.000133	0	0.313004	1.0997	0.010892	0	2.12854	2.71121
3	0.002484	0	0.247661	1.13816	0.01205	0	2.12564	2.71432
3.5	0.01573	0	0.188647	1.16491	0.58327	0	2.06861	2.76805
4	0.053794	0	0.143841	1.19387	0.62719	0	2.06386	2.77192
5	0.125605	0	0.10382	1.21018	0.67041	0	2.06088	2.77614

Note: Sig+ and sig- denote upper and lower bound significance levels, respectively.

Table 7. Mantle-Haenzsel sensitivity test for *Zai-technology* adoption.

Critical values (τ)	Q_mh+	Q_mh-	p_mh+	p_mh-
1	4.42507	4.42507	4.8e-06	4.1e-08
2	4.1134	5.04663	.000019	2.2e-07
3	3.77639	4.70285	.00008	1.3e-06
4	3.40794	4.32593	.000327	7.6e-06
5	2.99941	3.90705	.001353	.000047
6	2.53802	3.43324	.005574	.000298
7	2.00362	2.88433	.022555	.001961
8	1.36188	2.22632	.086617	.012996
9	0.546933	1.39477	.292212	.081543
10	0.241064	.241064	.404753	.404753

Note: τ : denotes odds of differential assignment due to unobserved factors.

significant positive impact on the welfare of households. This confirms the results of several empirical studies (Awotide et al., 2012; Martin and Lorenzen, 2016; Chirwa et al., 2017) that income diversification has a positive effect on the well-being of households and should therefore be supported in policy formulations. Alaba and Kayode (2011) concluded that farming households engaged in non-farm income diversification have increased welfare compared to farming households that do not diversify their income.

Finally, income diversification had a positive impact on the adoption of *Zai-technology* in the Garu and Tempene districts of Ghana. This means that farmers who diversified their income are between 0.31 and 0.36 likely to adopt *Zai* compared with those who did not. Thus, the adoption of *Zai* in the study area can be stimulated by diversification of income. This may be because, as households gain more income through diversification, they may employ labour to dig *Zai* pits for planting relative to non-diversified households as the process is said to be labour-intensive (Koome, 2017). The positive and significant impact of the diversification of income estimated in this study is corroborated with the results of recent study (Diro and Sam, 2015).

4.2.1.1. Sensitivity test - PSM. The empirical findings provided in Table 5 assumes that all covariates have been matched and therefore, no unmeasured or unobserved confounder may account for difference across both diversified and non-diversified households. If there is an unobserved characteristic that affects both non-farm income diversification and the outcome variables simultaneously, then the magnitude of the measured impact could be influenced by unobserved heterogeneity (Rosenbaum and Rubin, 1983; Rosenbaum, 2002; Becker and Caliendo, 2007). The Rosenbaum and Mantel-Haenzsel sensitivity tests allow the validity of this assumption to be tested. Tables 6 and 7 present the results of the Rosenbaum (welfare indicators) and Haenzsel-Mantel (*Zai* adoption), respectively.

As indicated in Table 6 (robust critical value: τ), in both cases of welfare indicators, the estimates are found to be robust or insensitive to

an unobserved bias that would at least triple the odds of participation in non-farm income diversification. For consumption expenditure per capita, an increase in the critical value to 4 produces an upper bound significance level of 0.054, while a critical value of 5 produces an upper bound significance value of 0.126 which are above the usual threshold of 0.05. Similarly, the critical value of 3.5 provides upper bound significant level of 0.583 for household income per capita. These results imply that our inferences on the welfare impact of non-farm diversification remain the same for unobservable covariates that would increase the likelihood of non-farm income diversification among the diversified group by about at least three and a half folds compared to the non-diversified group. With regards to *Zai-technology* adoption, if the results are free from hidden bias, where $\tau = 1$ the QMH test statistic value is 4.43, and that would suggest evidence of a strong causal effect of non-farm diversification on *Zai-technology* adoption.

Since the study hypothesized positive (unobserved) selection such that household who engage in non-farm income diversification have a greater probability of adopting *Zai*, then the estimated treatment effects overestimate the true treatment effects (Becker and Caliendo, 2007). The reported estimates are too high and should, therefore, be adjusted downwards. Hence, the focus of analysis is on Q_{mh+} and p_{mh+} . The results reported in Table 7 indicate that the upper bounds on significant levels for critical value (τ) = 8, 9, 10 are 0.087, 0.292, and 0.404, respectively. These suggest that the results are insensitive to hidden bias that would increase the odds of participating in non-farm income diversification by at least eight folds. From the sensitivity tests, the study can confidently conclude that the strength of the hidden bias must be sufficiently high to negate the inferences drawn.

4.2.2. Inverse-probability-weighted regression adjustment (IPWRA)

Table 8 shows the ex-post welfare and *Zai-technology* estimates of the impact of income diversification provided by IPWRA. The estimated results confirm that income diversification makes substantial improvements in the welfare of households and encourages the adoption of *Zai-*

Table 8. Impact of diversification on household welfare and adoption of *Zai-technology*.

Outcome variables	Treatment effects (IPWRA)	
	ATT	POM
Consumption expenditure per capita	0.194 (0.029) ^a	0.426 (0.027) ^a
Household income per capita	0.172 (0.048) ^a	0.293 (0.047) ^a
<i>Zai-technology</i> adoption	0.296 (0.086) ^a	0.349 (0.079) ^a

Note: The standard errors are in parentheses. ^adenotes significant levels at 1%.

technology. The estimated causal effects on consumption and household income per capita are 19% and 17%, respectively. Thus, households engaged in non-farm economic activities had a per capita consumption of 19% higher than non-diversified households. Similarly, the diversification of non-farm incomes raised the household income per capita of diversified households by 17% relative to non-diversified households. Likewise, the rate of adoption of *Zai* is around 30 % higher with non-farm income diversification.

The results of the average impact of income diversification on welfare and *Zai-technology* adoption reported in Tables 5 and 8 show significant benefits of non-farm diversification in promoting sustainable farm practices such as *Zai* and improving the welfare of rural households.

5. Conclusions and recommendations

This study analyzed how non-farm income diversification affect rural households' welfare and the adoption of *Zai-technology*. We used the probit model to identify factors that affect the decision of the respondents to participate in non-farm income diversification. Results from the probit model indicate that household demographic factors, including age of respondent, household size, educational achievement, and farmers' experience in crop production, have influenced non-farm income diversification. In addition, extension programs and FBOs are important policy or institutional variables to stimulate income diversification. The PSM and IPWRA techniques were used to estimate the effect of income diversification on the welfare of smallholder farmers and the adoption of *Zai-technology*. After controlling for differences in covariates, the results of the two estimation techniques suggested that non-farm income diversification produced substantial welfare benefits and a higher likelihood of inspiring the adoption of farm technology such as *Zai*. Thus, diversification of non-farm income activities led to an increase in the welfare of diversified farm households by about 17%–23% and the likelihood of *Zai-technology* being adopted by about 30%–36%.

The study therefore recommends that extension services and the establishment and promotion of FBOs should be strengthened by government and development partners as they facilitate non-farm income diversification, which in turn enhances investment in farm inputs and the welfare of farmers. As Northern Ghana has a one-year cropping season from May to September, the remaining non-farm season may contain a lot of idle rural labour force. A plan for agricultural growth that involves non-agricultural income-generating activities during the off-season is strongly recommended. This income diversification strategy would enable farm households to actively employ their labour force throughout the year. Revenues from the non-farm sector can be returned to farm operations, which would increase productivity-enhancing technologies such as *Zai*, while at the same time increasing overall farm productivity and rural welfare. In addition, income diversification techniques could be integrated into existing programs, such as extension services and farmer-based organisations. These projects should also be comprehensively designed so that, while farmers learn about improved farm management practices, they also learn how to reduce their risk through diversification.

Declarations

Author contribution statement

Gideon Danso-Abbeam: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Gilbert Dagunga: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Dennis Sedem Ehiakpor: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

The authors are grateful to the farmers who sat hours to answer all the questions and the enumerators who collected the data used for this study.

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