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Role of Agricultural Diversification in Improving Resilience to Climate Change: An Empirical Analysis with Gaussian Paradigm

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Abstract: Agricultural diversification efforts towards sustainable agriculture generates environmental and economic benefits. Climate change and agricultural production are characterized by a complex cause-effect relationship. In the present study, the primary dataset is collected through an interview-based survey from 410 farmers in 3 districts located in different agro-ecological zones of Punjab, Pakistan. Detailed analysis is conducted by employing the Gaussian treatment effects approach. Results of the study show that the farmers who adopted agricultural diversification to mitigate the impact of climate change were less and insignificantly benefited e.g., on an average of RS 95,260 (US $635) per annum whereas non-adopted farmers lost their farm income on an average of RS 115,750 (US $772) per annum if they had practiced the agricultural diversification. Moreover, determinants of agricultural diversification such as demographic and institutional indicators were significant and larger effects to adopt as compared to social indicators. This study suggests that policies should be designed in the regional context particularly related to the improvement in demographic characteristics and institutional factors such as providing subsidies, training, and awareness to the farmers, particularly to those who practice agricultural diversification. These measures will help to raise the farmers' adaptive capacity for the adoption of agricultural diversification, and it will enable them to generate tangible benefits by increasing income through adopting sustainable agricultural livelihood.

Keywords: agricultural diversification; climate change; agro-ecological zones; Gaussian treatment effects; adaptive sustainability

1. Introduction

Climate is a key driver for the agricultural system that poses additional uncertainty and vulnerability to the environment. The agricultural systems have a complex relationship with climate change. On the one hand, it is directly affected by climate change due to more frequent and extreme uneven precipitation patterns, a rise in average temperature, and changes in cropping seasons. The impact of these climate changes has serious biophysical effects specifically, on the agriculture sector by the decrease in crop productivity, invasions

of pathogens and pests, shifts in crop planting dates, and reduced resilience of agro-ecosystems. On the other hand, the agriculture sector and different land-use practices are responsible for emitting anthropogenic greenhouse gases (GHGs) and carbon (CO_2) emissions [1–3]. It is observed that climate change has a larger impact in developing countries than in developed countries. This hypothesis states that the consequences of climate variability and extreme events have a more severe impact on poor countries than rich countries. This could be due to the differences in the adaptive capacity that comprise the vulnerability of the populations in hazardous zones, the lack of institutional support, and farm household demographic and socio-economic characteristics [4].

Studies have found that Pakistan is a developing country and contributes less than one percent to the total greenhouse gas (GHG) emissions in the world, but unfortunately, it is highly affected due to the adverse impacts of climate change [5,6]. Pakistan's economy is primarily based on the agriculture sector, which is highly sensitive to climate change. However, agriculture contribution to the gross domestic product (GDP) has been decreased by 53% to around 20% over the last 70 years (1949 to 2019), respectively. However, agriculture share is still the predominant contributor to its GDP.

As the agriculture sector is affected by pests, diseases, and weather variability affecting crop and livestock production, climate change and environmental shocks amplify risks that affect the farm livelihoods in different ways. While it directly reduces agricultural productivity and livestock production, it indirectly reduces labour demand, raises prices, and ultimately has negative effects on the infrastructure [6].

There are many livelihood diversification strategies and agricultural practices that are used to mitigate the impact of climate change. Studies described that agricultural diversification is used as an alternative strategy to increase food security and to shape resilience against environmental shocks and climate change [7,8]. Agricultural diversification is defined as the development of conventional crops and livestock income-earning activities associated with sustainable agriculture. Diversification can be interpreted as a livelihood strategy derived for logical development to conserve natural resources and cope with the downside of environmental variability [9]. On the other hand, agricultural diversification is the addition of activities to the existing crops and livestock farming [10]. It is meaningful if the farmers allocated timely and significant resources to the new activity. Therefore, diversification accounts for the number of socio-economic characteristics and the resources that farm households hold. By adopting new technology and innovative measures for crops and livestock production, farmers are more inclined to adapt their sustainable livelihoods to mitigate the impact of precipitation deficits and climate shocks. It ensures the farmers' income becomes more resilient, not only from the short-term climate shocks but also in the long run by producing crops that are resilient to drought and weather variability [11,12]. Diversification in the context of specialization is very important particularly for seasonal crop production and extensive livestock farming as a suited combination for sustainable livelihood. On the other hand, studies such as [13–15] have emphasized that the adoption of agricultural diversification is highly correlated with the socioeconomic and institutional-level characteristics of households. Therefore, it is extremely important for a developing country such as Pakistan to uncover the impact of agricultural diversification applied at the farming level. While such factors are broken down by demographic, social, institutional, and environmental indicators, the literature suggests that farmers better equipped with socioeconomic characteristics are more likely to adopt the highest degree of livelihood diversification [16,17]. In Pakistan, the main reason for the low adoption rate of technologies and innovative practices, particularly for small landholding and marginalized farmers, is the limited access to financial resources and institutional services [18,19]. It may include market infrastructure, other institutional aspects, and the interactions between public and private sectors, which can help in shaping the context in which farming takes place (e.g., easy access to the credit market and agricultural extension services, advisory services on climate change, availability of resources) [20–22].

In today's world, there is a strong belief that the effects of climate change on agriculture will be tackled with an integrated approach that covers the progress in the agricultural sector, the tremendous progress in mobile information networks such as social media, meteorology, and the practices used by farmers before and after climate change. In light of this information, producers take a set of adaptation measures to cope with prevailing climate change, depending on the severity of hedging, their knowledge of local weather, and their use of resource assets to adopt agricultural diversity. Anticipating the impact of a shock and avoiding this potential risk, farmers often rely on advanced risk management strategies such as saving, creating a rich non-farming portfolio business, and choosing a portfolio of less risky crops to maintain a liveable income level [22,23]. In addition to knowing how the resources used in agricultural production are distributed more efficiently and rationally, it is also extremely important to know how much income is generated by adopting agricultural diversification under different scenarios in the fight against climate change. Therefore, this study identifies factors that can play a vital role in the adoption of agricultural diversity in coping with climate change, while also revealing the impact of diversification adoption on income, which is perceived as a livelihood indicator for the farmer. In this context, the objectives described above were achieved using very different methodological arguments, such as average treatment effect (ATE) and average treatment effects on both treated (ATT) and untreated (ATU). To reveal these average treatment effects in different intensities and directions, the Gaussian treatment effect model (TEM) was preferred [24–27]. The average treatment effect will measure the causal impact of the agricultural diversification on the potential outcome variable, such as income, while the remaining two average effects (e.g., ATT and ATU) will measure the counterfactual causal impact of the diversification if it had not been accepted when the ATT is the case, or if it had been accepted when the ATU is the case. In addition, the impact of different characteristics of farms and farmers on both the probability of adopting the agricultural diversification decision and income levels are also calculated, providing robust and reliable insights for policymakers.

The remaining part of the paper is as follows. Section 2 elaborates econometric methodology and specification. Section 3 presents the variable description and study site. Section 4 provides descriptive and empirical results. Sections 5 and 6 demonstrate the discussion and the conclusion of the study.

2. Econometric Framework and Estimation Strategy

The empirical challenge in observational studies to estimate the impact assessment is required to establish a suitable counterfactual argument against the outcome variable to avoid self-selection problems. Basically, two different treatment scenarios are possible depending on whether the treatment is exogenous to the decision-maker or not [20,21]. First, after controlling the factors that can be observed by the researcher, the treatment with respect to the output (e.g., hourly wages, home values, health status, income, production amount, yield, etc.) can be ignored. This is often called selection over observable. The key point here is that if people choose to be treated or are randomly assigned, it directs the assignment to a particular treatment situation that is fully observed and thus can be included in the econometric technique for modeling its impact on the outcome. In the second case, the appointment of people or the economic unit to a particular treatment situation can be guided by observable and unobservable factors. This situation is also related to the output variable (for example, there may be an unobserved factor such as a farmer's 'talent' or 'courage', which relates the treatment variable such as 'participation in agricultural diversification' and the output variable, which reflects 'the level of income'). This is often referred to as the choice or treatment endogeneity of those who cannot be observed. In such a case, there is a relationship between the set of unobserved factors (e.g., residuals of the treatment) that determine the treatment and the unobserved factors (e.g., the residuals of the output) that determine the level of output. The effects of the

treatment on the output variable can be handled after such a relationship is statistically controlled.

The literature for the first situation described that there are some econometric approaches that deal with selection bias problems in cross-sectional data such as instrumental variable (IV) approaches, propensity score matching (PSM), and generalized propensity score (GPS) matching approaches [22], while, the Gaussian treatment effect (GTE) and switching regression (SR) models were proposed to handle the second situation [23–27]. In this study, we applied the GTE model because it can be contemporaneously associated with unobservable factors (such as farmers' motivation, perception ability, and management skills in the participation of agricultural diversification) and heterogeneity in the outcome variable (e.g., the income variable). In this context, we built two equations to estimate the determinants of agricultural diversification and their impact on the farmers' income, respectively. As agricultural diversification is one of the determinants of agricultural income, we, therefore, incorporated the characteristics of the farm and the farmers rather than income for the adoption of agricultural diversification. For example, technological use and the existence of extension services to farmers are considered key factors that expedite adoption in agricultural diversification. In this perspective, the application of GTE is also helpful to account for the main problem of endogeneity bias rather than simultaneous bias. It is worth mentioning another issue in treatment effect models. It is not possible to simultaneously observe both states of a farmer (adopting and non-adopting positions). In other words, since those who accept agricultural diversity do not have a counterfactual situation, information about the counterfactual situation is obtained by including farmers, who do not support agricultural diversity, with the same characteristics on average in the sample.

Consider a rational farm household that faces a decision whether or not to adopt agricultural diversification to mitigate the impact of climate change and to improve the farm income. Suppose U_1 represents the gains or benefits received by a farm household from the adoption of agricultural diversification and U_0 shows the gains or benefits received in the case of non-adoption. The farm household chooses to adopt agricultural diversification if $d_i = U_1 - U_0 > 0$. The net benefit (d_i) is received by the farm household from the adoption of agricultural diversification. It is a latent variable that derives from the observed characteristics z_i' and the error term ε_i [23,28].

$$\begin{array}{l} d_i = 1 \; if \; z_i'\alpha + \varepsilon_{1i} > 0 \\ d_i = 0 \; if \; z_i'\alpha + \varepsilon_{1i} \leq 0 \end{array} \tag{1}$$

where α is a set of parameters corresponding to z variables. The outcome equation (y_i) is affected by the treatment variable (d_i) in the following way:

$$\log y_i = x_i'\beta + \gamma d_i + \varepsilon_{2i} \tag{2}$$

where $\log y_i$ is the natural logarithm of the income level of farmers, while x' is a set of farm and farmer characteristics affecting the income of households and β is a set of parameters to be computed for their corresponding x' regressors. While the error terms (ε_{1i}, ε_{2i}) are assumed as normally distributed with zero means, standard deviations, correlation, and the covariance are given as follows [23–27].

$$\begin{bmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix} \right) \tag{3}$$

Now define a dichotomous indicator $\kappa_i = 2d_i - 1$ such that $\kappa_i = 1$ if $d_i = 1$ and $\kappa_i = -1$ if $d_i = 0$. The sample likelihood function for n sampled farmers is gives the following.

$$\begin{aligned} L &= \prod_{d_i=0} y_i^{-1}\sigma^{-1}\phi\left(\frac{\log y_i - x_i'\beta - \gamma d_i}{\sigma}\right)\Phi\left(\frac{z_i'\alpha + \rho\sigma^{-1}\left(\log y_i - x_i'\beta - \gamma d_i\right)}{\left(1-\rho^2\right)^{1/2}}\right) \\ &\quad x \prod_{d_i=1} y_i^{-1}\sigma^{-1}\phi\left(\frac{\log y_i - x_i'\beta - \gamma d_i}{\sigma}\right)\Phi\left(\frac{z_i'\alpha + \rho\sigma^{-1}\left(\log y_i - x_i'\beta - \gamma d_i\right)}{\left(1-\rho^2\right)^{1/2}}\right) \\ &= \prod_{i=1}^{n} y_i^{-1}\sigma^{-1}\phi\left(\frac{\log y_i - x_i'\beta - \gamma d_i}{\sigma}\right)\Phi\left(\kappa_i\frac{z_i'\alpha + \rho\sigma^{-1}\left(\log y_i - x_i'\beta - \gamma d_i\right)}{\left(1-\rho^2\right)^{1/2}}\right) \end{aligned} \tag{4}$$

In the above equation, y_i^{-1} represents the Jacobian of transformation from $\log y_i$ to y_i. The probability of adoption of agricultural diversification, the conditional means for treated and untreated income levels, and the unconditional mean levels of income are as follows.

$$\begin{aligned} &\Pr(d_i = 1) = \Phi\left(z_i'\alpha\right) \\ &E(y_i|d_i = 1) = \exp\left(x_i'\beta + \gamma d_i + \sigma^2/2\right)\left(\frac{\Phi\left(z_i'\alpha + \rho\sigma\right)}{\Phi\left(z_i'\alpha\right)}\right) \\ &E(y_i|d_i = 0) = \exp\left(x_i'\beta + \sigma^2/2\right)\left(\frac{\Phi\left(-z_i'\alpha - \rho\sigma\right)}{\Phi\left(-z_i'\alpha\right)}\right) \\ &E(y_i) = \Pr(d_i = 1) * E(y_i|d_i = 1) \end{aligned} \tag{5}$$

The marginal effects of the exogenous variables on the probability of agricultural diversification and conditional mean levels of income can be obtained by differentiating each Equation in (5) with respect to regressors in question. The delta method can be utilized to obtain the standard errors of the marginal effects. The treatment effect (TE) is equal to the difference between the two-conditional means, and the average treatment effect (ATE) is the average value of this equation:

$$\begin{aligned} TE_i &= E(y_i|d_i = 1) - E(y_i|d_i = 0) \\ ATE &= n^{-1}\sum_{i=1}^{n} TE_i \end{aligned} \tag{6}$$

We have also calculated the average treatment effect on the treated (ATT) and untreated (ATU) for adopters and nonadopters in actual and counterfactual scenarios by comparing the following equations, respectively:

$$ATT = n_1^{-1}\sum_{i=1}^{n_1} TE_i(d_i = 1) \tag{7}$$

$$ATU = n_0^{-1}\sum_{i=1}^{n_0}(E(y_i|d_i = 1) - \exp(\log y_{0i})) \tag{8}$$

where n, n_1, and n_0 are the total sample and subsamples for treated and untreated farmers, respectively. The magnitude and the sign of the treatment effect cannot be determined because they depend on γ, σ, and ρ [23–27]. It is noticed that the average treatment effect on treated farmers (e.g., Equation (7)) is the average value of the difference between the expected values of their current income levels and the expected income levels if they had not chosen the agricultural diversification. On the other hand, the average treatment effects on un-treated farmers (e.g., ATU) are the average values of the difference between their expected income levels if they had chosen the agricultural diversification and their current actual income levels. Since the outcome variable (e.g., income) is estimated on a logarithmic scale, we took the anti-log to get the outcome variable back in its plain level (e.g., Rupees) in Equation (8). Meanwhile, as with all sample selection models, it requires the application of exclusion constraints to identify our parameters in the model. When the random utility theory is taken as a reference [29], sociodemographic factors are more preferred in the

decision or treatment equation, while more economic factors are used in the outcome equation. In this context, some explanatory variables such as farm size and climate shocks are only included in the level equation, allowing the identification of parameters.

3. Data, Variable Construction, and Study Site

We have measured the impact of agricultural diversification on farmers' income using its determinants. We have categorized these determinants into demographic and social characteristics, institutional support to the farmers, and vulnerability to weather-related shocks [30,31]. Agricultural diversification is considered a tool of climate risk management. Agricultural diversification includes re-allocation of the farm's productive resources from low-value to high-value crops, adding plant varieties, changing cropping dates and patterns, and the adoption of new technology. We considered those farmers who adopted diversification to reduce the risk of the changes in climate during the last 10 years.

We have measured the farmers' demographic characteristics by using labour force, education attainment, farming experience, and the size of farmland owned or rented that farm households hold. We have examined the institutional role using the indicators of physical infrastructure such as the distance of extension centre from farmland, agriculture technology assets that households hold, access to the market information, weather information, and access to the credit services. Whereas we assessed the social characteristics of the farmers using indicators of the strength of collective action of the farmers [32]. Plot disturbance index was calculated by simple count, and it was reported in terms of the self-reported experience of disturbances faced by the farmers, as the result of climatic shocks or weather variabilities such as floods, droughts, severe crop pests attack, and human diseases. All proxy variables used for measuring the demographic, social, and institutional characteristics are assumed to have a positive impact to improve the farmers' adaptive capacity, except for the social dependency variable because it is assumed to be undetermined in the local context, while the distance of the extension centre from the farmland and climate shocks are expected to have a negative impact. A detail of the variables used in the study is given in Table 1.

Table 1. Variables descriptions.

Variable Name	Definition
Dependent Variables	
Farm income	Net income earned from the production of the crops and livestock-related activities (in '0000' Rupees per year)
Agricultural diversification	1, if a farmer adopted crops or livestock diversification, 0 otherwise
Independent Variables	
Demographic characteristics	
Working members	Working family members in a household (in numbers)
Labour force	Number of persons living in a household (1 if the number of individuals in a household is greater than 10, 0 otherwise)
No Schooling	Illiterate (1 if a farmer did not attend the school, 0 otherwise)
Elementary	1 if a farmer finished elementary school education, 0 otherwise
Secondary	1 if a farm household finished secondary school education, 0 otherwise
College	1 if a farmer has at least two years of college-level or above education, 0 otherwise
Experience	Farming experience (in years)
Farm size	Size of farmland (area) owned or rented for cultivation (in hectares)

Table 1. *Cont.*

Variable Name	Definition
Social characteristics (strength of the collective action)	
Social dependency	Dependency of a farmer on the family system (i.e., to be the head of the family) or to the head of the village for taking decision-related to agricultural production (1 = yes, 0 = no)
Relative assistance	Availability of relatives and friends for assistance such as seeking money or equipment sharing (1 = yes, 0 = no)
Institutional support/characteristics	
Market information	Market information (1 if a farmer had access, 0 otherwise)
Weather information	Weather forecasting information (1 if a farmer had access, 0 otherwise)
Distance $\leq$ 20	1 if the distance from farmland to the nearest the extension centre is less than or equal to 20 km, 0 otherwise
Distance 21–50	1 if the distance from farmland to the nearest the extension centre is greater than 20 and less than 51 km, 0 otherwise
Distance 51–80	1 if the distance from farmland to the nearest the extension centre is greater than 50 and less than 81 km, 0 otherwise
Distance 80	1 if the distance from farmland to the nearest the extension centre is greater than 80 km, 0 otherwise
Technology assets	Availability of agricultural technology assets such as tractors and machinery to the farmer (in numbers)
Credit access	Availability of credit access (1 = yes; 0 = no)
Climate shocks	Plot-disturbance-index
Jhang district	1 if the farmland is located in Jhang district, 0 otherwise.
Rahim Yar Khan district	1 if the farmland is located in Rahim Yar Khan district, 0 otherwise.
Sailkot district	1 if the farmland is located in Sailkot district, 0 otherwise

The survey data were collected in three districts based on different agro-ecological zones (AEZs) prepared by the Pakistan Agricultural Research Council (PARC) [33]. We have interviewed 420 farmers, consisting of about 140 farmers from each district including Jhang, Sialkot, and Rahim Yar Khan of Punjab province during August and September 2018 using a multi-stage sampling technique. We reduced our sample size to 410 farmers after deleting some missing information. This multi-stage sampling procedure consists of six stages. First, we selected the Punjab province as the main study area. Second, we included three AEZs out of four AEZs in our study based on diverse characteristics of climate, geography, and cropping patterns. Third, we randomly selected three districts from the three AEZs such as Jhang, Rahim Yar Khan, and Sialkot. Fourth, we randomly choose two sub-districts (tehsils) from each district. Fifth, we randomly selected five to six villages from each tehsil. Sixth, in the last stage, we randomly selected 10–12 farmers from each village based on the list of farmers collected from the agriculture department. Our first study district, Jhang, is located in between Jhelum and Chenab rivers. It falls in the central mixed cropping sub-zone and lies in the irrigated plains agro-ecological zones (AEZs) [34]. The second study district is Rahim Yar Khan. It partly falls in the alluvium plain and some part lies in the irrigated plains AEZs (Cotton subzone and Cholistan sub-zone) [35]. The third district, Sialkot, is partly located in the Barani (rain-fed) AEZ and some part into irrigated plains AEZ [36]. All three selected AEZs have different attributes of environment, geography, and socioeconomic conditions.

Before the beginning of the survey, off-field and in-field training were given to the enumerators about the data collection methods and for the structured questionnaire to improve the quality of the survey. The enumerators were graduated and well trained for collecting the survey data about the objectives of the study. A pre-tested questionnaire was used to collect all the necessary information related to assets, demographic characteristics, and institutional support for adopting agricultural diversification.

4. Results

4.1. Descriptive Statistics of the Sample Data

Table 2 presents the descriptive statistics of the sample farmers used in the study. Around 86% of the sample farm households had adopted agricultural diversification. However, the conditional and combined effect of adoption of agricultural diversification on farmers' income might be ambiguous. It may be differed by the type of livelihood diversification, size of farmland, and income earned from the diversification.

Table 2. Descriptive statistics of the sample data used in the study.

Variable	Mean	Std. dev.	Min	Max
Dependent Variables				
Farm income	91.834	100.617	7.066	500.163
Agricultural diversification	0.859	0.349	0	1
Explanatory Variables				
Working members	1.927	1.189	1.000	6.000
No Schooling (reference)	0.215	0.411	0	1
Elementary	0.210	0.408	0	1
Secondary	0.410	0.492	0	1
College	0.166	0.372	0	1
Labour force	0.127	0.333	0	1
Experience	22.288	11.606	0	50
Credit access	0.400	0.490	0	1
Weather forecasting	0.671	0.471	0	1
Market information	0.580	0.494	0	1
Working members	1.927	1.189	1	6
Technology assets	1.239	0.828	0	3
Relative assistance	0.690	0.463	0	1
Social dependency	0.483	0.500	0	1
Distance $\leq$ 20	0.693	0.462	0	1
Distance 21–50	0.144	0.351	0	1
Distance 51–80	0.110	0.313	0	1
Distance >80 (Reference)	0.054	0.226	0	1
Farm size	4.546	5.523	0.400	32.370
Index	1.612	1.326	0	4
Jhang district	0.334	0.472	0	1
Numbers of observations		410		

We have estimated demographic characteristics of the farm household level by using labour force, farmers' experience, and education indicators. Our sample data shows that around 21% of the farmers were illiterate and only 16% of the sample farmers were qualified from college and a higher level of education. Only around 12% of the sample farmers had more than 10 family members. The size of household members was used as a proxy for the availability of the labours [37]. Therefore, we have captured the impact of the labour force by using the proxy variable of household size.

Social characteristics can be one of the pulling factors that can encourage the farmers to adopt agricultural diversification. Statistics show that 69% and 48% of sample farmers were dependent on the relative assistance and for the head of the households or the village head for taking agricultural production-related decisions. Further, the roles of institutions related to providing information, training, guidance, and helping the farmers are very important for deriving the agricultural diversification outcome. We have also incorporated the impact of the farmland distance to the relevant institutions e.g., distance from extension centres to the farmland. We have divided this distance into groups to identify the comprehensive impact. Around 70% of the sample farmers have extension centres within 20 km from their farmland while only 5% of the farmers have their farmland away from the 80 km.

4.2. Empirical Results for the Adoption of Agricultural Diversification and Its Impact on Households' Farm Income

Results of the Maximum Likelihood GTE estimates, and their marginal effects are shown in Tables 3 and 4, respectively. The computed Wald test statistic for the hypothesis independence (H_0: $\rho = 0$) between the probability of agricultural diversification and the income of farm households was rejected (Wald statistic = 9.6, d.f. = 1, $p < 0.05$). It shows that the errors computed between the decision in agricultural diversification and the agricultural income of farmer households are dependent after controlling exogenous regressors in the GTE model.

Table 3. Gaussian maximum likelihood treatment effect estimates of agricultural diversification determinants and farm income models.

Variable	Agricultural Diversification Determinants Model	Farm Income Model
Constant	−0.136 (0.627)	3.707 *** (0.166)
Elementary	0.322 (0.235)	0.085 (0.122)
Secondary	0.272 (0.227)	0.392 *** (0.119)
College	0.824 *** (0.362)	0.616 *** (0.138)
Labour force	0.079 (0.286)	0.284 ** (0.121)
Experience	0.036 *** (0.007)	0.014 *** (0.003)
Credit access	0.011 (0.273)	0.002 (0.115)
Weather forecasting	0.474 ** (0.213)	0.057 (0.111)
Market information	0.197 (0.218)	0.002 (0.111)
Technology assets	0.215 ** (0.108)	0.039 * (0.021)
Relative assistance	0.284 (0.183)	0.017 (0.091)
Social dependency	0.097 (0.221)	−0.081 (0.093)
Working members	0.124 (0.091)	—
Distance ≤20	0.827 ** (0.401)	—
Distance 21–50	0.269 (0.679)	—
Distance 51–80	0.266 (0.645)	—
Jhang district	0.147 (0.185)	0.181 ** (0.084)
Farm size	—	0.084 *** (0.005)
Climate shocks	—	0.034 (0.038)
Agri. diversification	—	−0.891 *** (0.231)

Table 3. *Cont.*

Variable	Agricultural Diversification Determinants Model	Farm Income Model
Sigma (σ)	0.749 *** (0.038)	
Correlation coefficient (ρ)	0.553 *** (0.139)	
Log-likelihood value	−2248.146	

Note: ***, ** and * indicates the significance of probability levels at 1%, 5% and 10%, respectively. Standard errors in parenthesis.

Table 4. Marginal estimates for the adoption of diversification determinants and its impact on farm income models.

Variable	Probability of Adaptation	Conditional Level	Unconditional Level
Elementary	4.024 (4.828)	7.254 (14.402)	5.409 (14.195)
Secondary	4.682 (3.910)	6.443 *** (2.768)	4.360 *** (1.108)
College	7.940 *** (3.347)	8.924 *** (3.108)	6.305 *** (2.302)
Labour force	1.350 (4.829)	3.063 ** (1.379)	3.432 ** (1.385)
Experience	0.638 *** (0.129)	1.099 *** (0.402)	1.645 *** (0.420)
Credit access	0.185 (4.798)	0.378 (11.921)	0.127 (12.447)
Weather forecasting	8.725 ** (4.192)	1.230 (11.292)	10.329 (11.372)
Market information	3.448 (3.941)	1.656 (11.805)	2.260 (11.689)
Technology assets	3.743 ** (1.848)	2.074 * (1.058)	0.857 * (0.445)
Relative assistance	5.180 (3.461)	4.866 (9.683)	1.414 (9.668)
Social dependency	1.686 (3.895)	−9.710 (9.674)	−6.666 (10.175)
Working members	2.166 (1.601)	1.247 (1.136)	1.265 (0.977)
Distance ≤20	12.566 * (6.528)	6.849 (6.194)	6.791 (5.373)
Distance 21–50	5.039 (13.192)	3.013 (11.294)	3.081 (9.714)
Distance 51–80	5.043 (12.712)	3.005 (10.916)	3.075 (9.262)
Jhang district	−2.627 (3.361)	2.703 ** (1.323)	5.775 * (3.463)
Farm size	——	9.084 *** (1.057)	7.883 *** (0.905)
Climate shocks	——	3.771 (4.365)	3.272 (3.742)
Agri. diversification	——	−137.391 ** (57.818)	−122.433 ** (51.321)

Note: ***, ** and * indicates the significance of probability levels at 1%, 5% and 10%, respectively. Standard errors in parenthesis.

We only describe the direction of the relationship between the dependent and independent variables in Table 3 because it only displays the direction of the coefficients, whereas

the results in Table 4 present the marginal effects of regressors on dependent variables that were previously described in detail.

We assessed the farmers' demographic characteristics by using the indicators of farming experience, labour force, education attainment, and size of landholding by the farmers. Results show that farmers' demographic characteristics, specifically education and experience indicators, were positively associated with the probability for the adoption of agricultural diversification and the farm income earned by the farmers (Table 4).

The farming experience coefficient shows that a year increase in experience of the farmers was likely to increase in the probability of adoption (0.6%) and was also likely to rise in farm income by around 1% (Table 4). We have estimated the land size owned or rented cultivated by the farmers using the indicators of farm size (i.e., area). It is indicated that a one-hectare increase in farmland cultivated area could increase the probability of the farm income among the treated farmers by 9%, which is around 1% more in the case of untreated farmers.

We have also estimated the institutional characteristics by using the indicators of access to extension centres, market information, weather information, and agricultural technology assets that farm households hold. Agricultural technology assets had a positive and significant impact to determine the probability of adopting agricultural diversification and its impact on farm income. Distance to extension centres had a positive and significant impact on the probability to adopt if the extension institutions were located within 20 km, and it was likely to increase by 12.5% for the probability of the adoption of diversification decision.

We have measured social characteristics using the indicators of social dependency, and relative assistance. Results show that social dependency and relative assistance have a positive but insignificant impact on the probability of adopting agricultural diversification, which is consistent in the local context and with previous findings [38].

We have examined the impact of agricultural diversification on the farm income of the farm households using a dummy variable. We have both types of farmers in the overall estimation sample who adopted agricultural diversification and who did not adopt. The significant and negative coefficient sign shows that treated farmers (ATT) are gaining less income than the untreated framers (ATU), who are losing more income (Table 4). We estimated the conditional and unconditional impact on farm income between the treated and untreated groups. In the treated group we examined the conditional impact in terms of probabilities on the farm income concerning those farmers who adopted agricultural diversification (Table 5).

Table 5. Treatment effect estimates.

Average treatment effect (ATE)	6.818 (12.114)
Average treatment effect on the treated (ATT)	9.526 (13.120)
Average treatment effect on the untreated (ATU)	−11.575 *** (3.929)

Note: We calculated the treatment effect in the figures '0000' in Rupees.

Results of the Maximum Likelihood GTE model show that the farmers who adopted agricultural diversification to mitigate the impact of climate change had less and an insignificant income on an average of RS 95,260 (US $635) per annum than non-adopted farmers, who are significantly losing a farm income on an average of RS 115,750 (US $772) per annum if they had practised the agricultural diversification.

5. Discussions

Descriptive findings show that the labour force has a positive impact on the probability for the adoption of agricultural diversification. In this study, we have used family size as a proxy of the labour force. This could be explained by the availability of labour for working

in the farmland, which will allow for earning more income than farm households with a smaller size [32]. The relative assistance variable shows the positive association with the probability for the adoption of diversification, as relative assistance at the time of need and for raising the moral motivation can be a helpful indicator. The distance of the extension centre from the farmland is very importantbecause these institutions are the key source to providing important information regarding agricultural productions, climate vulnerability, and fertilizer usages [39].

Results of the Maximum Likelihood GTE estimates, and their marginal effects are shown, where the correlation coefficient (ρ) between the agricultural diversification decision and the agricultural income of the farmer households was found to be positive and statistically significant. It would increase (or decrease) the agricultural income of the farmer when the variables other than the factors controlled in the system increased (or decreased) the agricultural diversification decision or vice versa. The farmers' demographic characteristics, such as education, indicate that a one-unit increase in the farmers who have a college degree and higher level of education may be likely to adopt 7.9% more agricultural diversification. It could be pointed out that receiving higher education contributes positively to the probability for the adoption of agricultural diversification and its conditional impact on the farmer income (Table 4). Such as, the increase in one-unit college and the higher level of education may likely increase the farm income from 6.3% to 8.9% among the untreated to treated farmers. This could be explained that the higher education, and experience of the farm households better-off the farmers' adaptive capacity, which makes them more able to adopt a sustainable livelihood [40]. A positive association of the land size (i.e., area) indicates that large farm size holding farmers were more likely to adopt than small landholding farmers. Distance to the extension centre had a positive and significant impact on the probability to adopt if the extension institutions were located within 20 km. Findings suggested that easy and near access to the institutional services was more important and beneficial to the framers for proving timely knowledge, training, and awareness about climate change and mitigating the impact of extreme events, enabling them to adopt a sustainable practice [3,41].

We have examined the impact of agricultural diversification on the farm income earned by farm households using a Gaussian treatment effect model. The significant and negative coefficient sign of the agricultural diversification on the income variable shows that treated farmers are gaining less income than the untreated framers, who are losing more income (Table 3). Therefore, the net impact is negative. It is indicated that farmers who do not prefer agricultural diversification will face further loss of income if they abandon their current situation and prefer agricultural diversification. On the other hand, farmers who are prone to agricultural diversification lose about 15% more income than untreated farmers. The negative coefficient sign of the diversification in the GTE model coincides with this finding. With these results, it can be assumed that the farmers who do not diversify have specialized in the production of ordinary products and thus have achieved resource efficiency in production. On the other hand, it can be said that farmers who choose to diversify to cope with climate change are most likely not accustomed to the production pattern of new products or they are experiencing income losses as a result of their wrong choices of production patterns [42]. We verify this argument by calculating the average treatment effect for the adoption of agricultural diversification on the households' farm income. We calculated the average treatment effect on the treated and on the untreated, which are shown in Table 5.

Results reveal that the farmers who adopted agricultural diversification to mitigate the impact of climate change had less and insignificant income amount on average, while the non-adopter farmers start losing significantly more income per annum if they chose to adopt diversification (US $772). Thus, the sustainable livelihoods of farmers who adopt agricultural diversification to mitigate the effects and associated risks of climate change can be ensured by being supported by the government in the selection and production of crop combinations compatible with climate change [39,40].

6. Conclusions and Implications

The relationship between the adoption of agricultural diversification to mitigate the impact of climate change and its effects on the farmers' income was investigated. This study uses plot-level cross-sectional datasets to estimate the adoption of the impact of agricultural diversification on households' farm income in the Punjab province, Pakistan. We applied the Maximum Likelihood GTE model to estimate the agricultural diversification determinants and their conditional and unconditional impact on the farmers' income. The Maximum Likelihood GTE model accounts for the endogenous treatment effects framework to control the endogeneity problem arising from both observed and unobserved heterogeneity and to correct selection bias issues.

Results of the model show that the farmers who adopted agricultural diversification to cope with environmental variability were less benefited as compared to their untreated peers, while untreated farmers would, on average, experience a significant loss of income if they had chosen agricultural diversification. Even if it is low, the average positive earnings of those who adopt diversification and the significant loss of farm income if they had preferred to diversify should be included in the state's agricultural policy agenda, and solutions that will minimize the income gap between the two groups should be developed. As it is known, adopting new product diversification, and ensuring resource efficiency in this product or product types are both time-consuming and require great effort and cost. While product diversification that is compatible with the environment and more resistant to changing climatic conditions requires combating all kinds of plant pests, productivity can only be achieved by using human and production resources more efficiently. In addition to providing technical and economic support to farmers who want to combat climate change in growing new products, these farmer groups should be constantly informed by agricultural extension organizations so that the search for production efficiency can be improved. Perhaps these farmers offer the opposite group an advantage in crop diversification due to the loss of productivity of their production resources. Thus, the findings of the study suggested the need for establishing specific policies such as giving subsidies and providing training to the farmers for the adoption of new technology, to provide the knowledge, and awareness regarding agricultural diversification adaptation measures for mitigating the impact of climate change. This study suggests the important policy implications for promoting the adoption of agricultural diversification to generate tangible benefits for the farmers to raise the farm income, and for sustainable agricultural livelihood.

This study has focused on the cross-sectional dataset. Therefore, our results may not fully capture the dynamics presented in the adoption of agricultural diversification over time. Hence, future research should focus on the dynamics of agricultural diversification and investigate the long-run effects of this adaptation on farm income, poverty, and households' welfare.

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