

Heterogeneous impact of crop diversification on farm net returns and risk exposure: Empirical evidence from Ghana

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Abstract

Increasing frequency of extreme weather events threatens the livelihoods of low-income farm households due to the heavy dependence on rain-fed agriculture coupled with the under-developed formal markets for risk management products. Thus, crop diversification is one of the widely used *ex ante* adaptation strategies to hedge against weather risk exposure. In this study, we use survey data from the northern Savanna zone of Ghana merged with historical weather data to shed light on the heterogeneous impact of crop diversification on farm net returns and risk exposure. We employ the dose response function and instrumental variable techniques to address potential endogeneity concerns. Overall, our findings show that crop diversification is a welfare-enhancing strategy that significantly increases farm net returns, lowers the probability of crop failure, and thus decreases downside risk exposure. Notably, our dose-response function analysis demonstrates that the positive benefits of crop diversification are particularly pronounced at lower intensities, reaching an optimal threshold. Beyond this point, the incremental advantages tend to diminish, suggesting the importance of carefully considering the optimal level of diversification for maximum benefits. The results further underscore the significant impact of both access to agricultural extension services and fertilizer usage on the adoption of crop diversification.

KEYWORDS

climate risk management, crop diversification, dose response function

JEL CLASSIFICATION

D81, Q12, Q54, C31

Résumé

La fréquence croissante des événements météorologiques extrêmes menace les moyens de subsistance des ménages agricoles à faible revenu en raison de leur

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forte dépendance à l'égard de l'agriculture pluviale et du sous-développement des marchés formels pour les produits de gestion des risques. Ainsi, la diversification des cultures est l'une des stratégies d'adaptation *ex ante* largement utilisées pour se prémunir contre l'exposition aux risques climatiques. Dans cette étude, nous utilisons des données d'enquête de la zone de savane du nord du Ghana fusionnées avec des données météorologiques historiques pour mettre en lumière l'impact hétérogène de la diversification des cultures sur les rendements nets des exploitations agricoles et l'exposition aux risques. Nous utilisons la fonction dose-réponse et les techniques de variables instrumentales pour répondre aux problèmes potentiels d'endogénéité. Dans l'ensemble, nos résultats montrent que la diversification des cultures est une stratégie d'amélioration du bien-être qui augmente considérablement les rendements nets des exploitations agricoles, réduit la probabilité de mauvaises récoltes et diminue ainsi l'exposition au risque de baisse. Notamment, notre analyse de la fonction dose-réponse démontre que les avantages positifs de la diversification des cultures sont particulièrement prononcés à des intensités plus faibles, atteignant un seuil optimal. Au-delà de ce point, les avantages supplémentaires ont tendance à diminuer, ce qui suggère l'importance d'examiner attentivement le niveau optimal de diversification pour obtenir un maximum d'avantages. Les résultats soulignent en outre l'impact significatif de l'accès aux services de vulgarisation agricole et de l'utilisation d'engrais sur l'adoption de la diversification des cultures.

1 | INTRODUCTION

Production and income risks represent significant challenges in sub-Saharan Africa (SSA), primarily stemming from weather-induced factors such as prolonged dry spells, floods, and infestations of crop pests and diseases, coupled with market risks like fluctuating crop prices (Adhikari et al., 2015; Kray et al., 2018). Climate variability and extreme weather events adversely impact both the quantity and quality of crop production, escalating the volatility of farm income. Consequently, these factors contribute to heightened food and nutrition insecurity, particularly among marginalized households lacking sufficient assets to cushion against such risks (Kray et al., 2018; Issahaku & Abdulai, 2020a). According to the Food and Agriculture Organization (FAO), global average crop yields are projected to decrease by 1.1% by 2050 due to climate change, with sub-Saharan Africa expected to experience the most significant decline (FAO, 2018).

Farm households' decisions to diversify or specialize crop production affect their resilience, and hence their capacity to cope with these risks. Therefore, understanding the implications of these cropping decisions and the efficacy of risk management strategies is crucial in responding to weather-related shocks (Issahaku & Abdulai, 2020b). The literature highlights a plethora of both *ex-ante* and *ex-post* risk management instruments, encompassing credit, insurance, and the adoption of drought-tolerant varieties, all of which contribute to enhancing the resilience of vulnerable farm households. However, the prevailing imperfect conditions in credit and insurance markets, coupled with information asymmetry, high transaction costs, and governance challenges inherent in rural economies, especially in sub-Saharan Africa, serve as compelling reasons for the adoption of crop diversification as a vital risk-hedging alternative (Jensen & Barrett, 2017; Arslan et al., 2018).

There is renewed interest by development organizations and governments in promoting crop diversification as an effective strategy to minimize the risk of crop failure and to mitigate income risks for marginal and low-income farm households. For example, the FAO's 2021 State of Food and Agriculture (SoFA) report underscores the imperative of strengthening the resilience of agricultural households through crop diversification. This approach aims to establish diverse pathways for absorbing shocks linked to climate variability and market volatility (FAO, 2021). Moreover, in Ghana,

the governments' flagship program on Planting for Food and Jobs (PFJ)¹, which is aimed at boosting agricultural production among smallholder farm households, encourages the intensification and diversification of farm enterprises for job creation and sustainable agri-food systems (Pauw, 2021).

Crop diversification in our context refers to the practice of shifting from monoculture to cultivating additional crops through, e.g., multiple cropping or intercropping within the same farming season (Chemura et al., 2020). Economic theories that study agent's behavior under uncertainty, such as the Portfolio Theory by Markowitz (2010, 1952) are useful for explaining farm households' response mechanisms to shocks. The theory assumes that if the cultivation of two crops is not perfectly correlated with each other, combining them in a portfolio under a diversified system contributes to a reduction of the risk associated with crop production (Paut et al., 2019). Specifically, more diverse cropping systems increase the resilience of agro-ecosystems to climate-related stressors and shocks by providing different levels of susceptibility and traits such as drought tolerance, and by providing key ecosystem services such as fixation of atmospheric nitrogen, soil carbon sequestration, or disease and pest control (Altieri et al., 2015).

Thus, crop diversification tends to reduce income variability and downside risk exposure for risk-averse and low-income farm households operating under marginal farmlands and rain-fed agriculture (Bozzola & Smale, 2020). Although crop diversification may improve the adaptive capacity of farm households to weather-related and market shocks, heterogeneity in socio-economic drivers and the level of diversification decisions may shape the distribution and the extent of the welfare gains among farmers (Makate et al., 2022). Therefore, unpacking possible heterogeneous effects of crop diversification across different intensities rather than a mean causal effect is an important first step in developing effective policies and programs for household risk management in sub-Saharan Africa. To this end, we employed a recent survey data of farm households from the northern Savanna zone of Ghana merged with geo-referenced historical weather data (rainfall and temperature) to examine the heterogenous impact of crop diversification on farm performance and risk exposure.

The study contributes to the literature on crop diversification and risk exposure as follows: First, despite the extensive application of variance in measuring risk exposure, there are concerns in the literature about its limitation in distinguishing between "downside risk" and "upside risk" (Chavas & Shi, 2015). As a result, we use in addition to variance, the skewness of the farm net returns distribution in our risk analysis. The focus on skewness in measuring risk is consistent with the maximization of expected utility and gives a clearer picture of downside risks. In other words, this approach helps determine if crop diversification is beneficial for farm households that are most vulnerable to climatic shocks (Antle, 2010; Bozzola & Smale, 2020).

Second, recent studies in Ghana (Bellon et al., 2020; Dagunga et al., 2020), Uganda (Asfaw et al., 2018; Tesfaye & Tirivayi, 2020), and Namibia (Mulwa & Visser, 2020) have shown positive impacts of crop diversity on poverty reduction, dietary diversity and household income. Other studies in Ethiopia (Di Falco & Chavas, 2009; Michler & Josephson, 2017), Bangladesh (Moniruzzaman, 2019), and Kenya (Bozzola & Smale, 2020) also found that crop diversification tends to decrease the variance and downside risk of crop yields and farm revenues. Notwithstanding, the contribution of the above-mentioned studies in understanding its impact on household welfare and risk exposure, they fail to disaggregate the effect of diversification with respect to the level of intensity. This limitation is non-trivial because crop diversification intensity varies and provides different levels of responses to farm net returns and risk exposure. We assume that farmers are risk-averse and choose the level of intensity to maximize their expected utility. Thus, increasing climatic risks lead farm households to increase their intensity of diversification, as it may provide them with greater natural insurance (Baumgärtner & Quaas, 2010). Furthermore, and more importantly, the impact of diversification may, however, flatten or diminish once a certain threshold is reached, particularly due to competition for the same nutrients and water, thus lowering crop productivity (Pellegrini & Tasciotti, 2014; Kray et al., 2018).

Therefore, the present study fills the knowledge gaps by employing the dose response function (DRF) approach to evaluate the heterogeneity in the impact of crop diversification on farm net returns and risk exposure (i.e., variance and skewness) across different intensities. Our estimation approach incorporates a zero-treatment probability mass, addresses the potential endogeneity of crop diversification in farm net returns, and thus restores the consistency of the estimates using instrumental variable (IV) estimation (Cerulli, 2015; Esposti, 2017). To the best of our knowledge, the use of dose response approach for the analysis of crop diversification is a novelty as it disaggregates the causal effect of different diversification intensities rather than a single average causal effect.

¹ The Planting for Food and Jobs (PFJ) initiative, which began in 2017, provides seed and fertilizer subsidy and of boosting smallholder agricultural production and creating jobs along agricultural value chains through other complementary interventions. In addition, it provides services to smallholder farmers, such as extension advice and marketing support (MoFA, 2017).

The remainder of the paper is organized as follows: The next section describes the impact pathways of crop diversification. The survey data is described in Section 3. The conceptual framework is outlined in Section 4. Section 5 presents the empirical strategy of the study. The empirical results and discussions are presented in Section 6, while the final section concludes the study.

2 | PATHWAY OF CROP DIVERSIFICATION

The literature conceptualizes crop diversification in terms of “push” and “pull” factors that are influenced by socio-economic and institutional factors, as well as biophysical conditions. In the absence of perfect agricultural insurance and credit markets (Jensen & Barrett, 2017), farm households faced with uncertainties of crop production are pushed to cultivate a portfolio of crops instead of specializing (Tesfaye & Tirivayi, 2020). As weather-related risks increase, crop diversification reduces the variance of production and farm incomes, and limits exposure to downside risk because of its natural insurance function (Baumgärtner & Quaas, 2010). This can be explained by the “sampling effect” hypothesis which asserts that greater diversity enables greater productivity and increases the goodness of fit between species traits and environmental conditions. Therefore, different crops occupy multitude of niches, facilitate ecosystem functioning and tend to reduce the variance of outcomes, hence, buffer against crop failure (Tilman et al., 2005). Furthermore, under a diverse cropping system, unsystematic risks, that is, those risks that do not have the same effect on crops, such as risk of crop-specific pests and diseases can potentially be reduced.

Conversely, in contexts shaped by market orientation, ample resources, and higher education levels, farm households with enhanced market access tend to gravitate toward crop diversification. This strategic choice serves the dual purpose of income stabilization and risk mitigation, especially in the face of market uncertainties such as fluctuations in produce prices (Kray et al., 2018). Within the framework of an unpredictable market environment characterized by imperfect output markets, the adoption of diversified production systems is perceived as a mechanism through which farm households can proactively diminish their vulnerability to price volatility.

Moreover, crop diversification fosters synergies and complementarities among various enterprises. Through practices like intercropping, where certain crops are grown together (e.g., with legumes), there are mutual benefits such as enhanced soil health, improved pest management, and efficient nutrient cycling (Adam & Abdulai, 2022). These positive interactions within diversified enterprises contribute to heightened productivity and increased profitability.

3 | DATA AND DESCRIPTIVE STATISTICS

3.1 | Data sources

The data used in the analysis come from 487 farm households in the northern savanna zone of Ghana: A survey was conducted for the 2018/2019 cropping season in 15 communities across six districts and three regions under the Sustainable Land and Water Management Project intervention areas. We purposively selected six districts from the three regions based on the operational areas of the project. Further, we randomly selected three to six communities from each district. Finally, 487 farm households were randomly sampled in proportion to the farmer population in the community. The survey data were collected using a structured questionnaire by trained and qualified researchers and enumerators with good working knowledge of the farming systems in the study areas. The survey also collected household data on crop production, household demographic characteristics, access to market information, and extension contacts.

Based on a review of the literature on crop diversification, (e.g., Di Falco & Chavas, 2009; Tesfaye & Tirivayi, 2020; Bozola & Smale, 2020), we present in Table 1 a detailed description of the control variables used in our empirical analysis. We include household-level information and demographic characteristics. The risk management decisions of farm households depend on factors such as age, gender, education of household head, household size, and asset ownership (e.g., farm size, livestock ownership). Other factors include access to extension service, membership of Farmer Based Organizations (FBO), and access to credit. We define credit-constrained farmers following the approach of Abdulai and Huffman (2014), as those who received credit but expressed a desire to borrow more at the existing interest rate, or those whose credit request was denied, although they needed credit for farming activities. We also include location-fixed effects, to account for the different agro-climatic zones.

TABLE 1 Variable descriptions and descriptive statistics.

| Variable | Description | Mean | Std. Dev |
|------------------------------------|---|---------|----------|
| Outcome variables | | | |
| Farm net returns | Value of crop production less variable costs (GHS) per acre | 1662.31 | 1755.48 |
| Variance | Second central moment of farm net returns distribution | 0.73 | 0.92 |
| Skewness | Third central moment of farm net returns distribution | −0.27 | 2.04 |
| Treatment variables | | | |
| Diversification index ^a | Margalef index of diversification | 20.41 | 16.10 |
| Number of crops | Number of crops cultivated by households | 3.45 | 1.70 |
| Explanatory variables | | | |
| Age | Age of household head in years | 42.50 | 12.62 |
| Male headed | Male = 1, Female = 0 | 0.65 | 0.48 |
| Household size | Size of Household | 6.00 | 2.96 |
| Education | Years of schooling of household head | 3.80 | 4.80 |
| FBO | 1 if a member of Farmer Based Organization (FBO), 0 otherwise | 0.32 | 0.46 |
| Farm size | Total farm size of HH in acres | 5.45 | 4.30 |
| Extension | Number of extension contacts per annum | 10.61 | 7.02 |
| Credit constraint | 1 if HH is credit constrained, 0 otherwise | 0.35 | 0.48 |
| Livestock | Number of Livestock in Tropical Livestock (TLU) Units | 1.91 | 4.16 |
| Market distance | Distance to the nearest market (km) | 8.50 | 4.64 |
| Asset | Value of HH durable assets ('000 GHS) | 2.70 | 2.46 |
| Negative rainfall shock | 1 if the metrics indicate a level of rainfall with a standard deviation below the long-term mean, 0 otherwise | 0.46 | 0.50 |
| Mean temperature | Mean temperature in °C (1981–2002) | 27.34 | 0.47 |
| Improved seeds | 1 if farmer used improved seed varieties, 0 otherwise | 0.92 | 0.27 |
| Fertilizer use | Quantity of fertilizer use per acre (kg) | 95.75 | 70.99 |
| Fertility | 1 if the soil is considered moderately to fertile, 0 otherwise | 0.89 | 0.31 |
| Distance input dealer | Distance from homestead to the nearest input dealer (km) | 2.47 | 1.61 |
| Sudan | Sudan savanna zone = 1, 0 otherwise | 0.49 | 0.50 |
| Guinea | Guinea savanna zone = 1, 0 otherwise | 0.51 | 0.50 |
| Number of observations | | 487 | |

^aWe transform the diversification index to take values in the [0, 100] range, where 0 is the treatment level of the untreated units, with 100 being the maximum dose.

To control for the impact of rainfall shocks and increased temperatures, we draw on rainfall and temperature data (from the Prediction of Worldwide Energy Resources data archive)² that provides global data at high-resolution (0.5 × 0.5 degree) to generate a gridded rainfall and temperature time series. Using the farm household geographical coordinates, we generate negative rainfall shock³ and mean temperature, using long-term mean rainfall and temperature data from 1981 to 2002 for the months within the cropping seasons.

3.2 | Cropping systems

Cropping systems in the study area encompass major crops such as maize, rice, groundnut, soybean, sorghum, millet, and yam (Boansi et al., 2021). Although maize stands out as the predominant crop cultivated by all households in our sample, its susceptibility to weather-related shocks poses challenges to farm livelihoods (FAO, 2018; Kray et al., 2018; Boansi et al.,

² <https://power.larc.nasa.gov/data-access-viewer/>

³ Following Michler et al. (2018), the rainfall shock is computed as follows: $RS_{kt} = \left| \frac{R_{kt} - \bar{R}_k}{\sigma_{R_k}} \right|$ if $R_{kt} < \bar{R}_k$, 0 otherwise, where R_{kt} is the observed rainfall for the previous year season, \bar{R}_k is the mean historical rainfall, and σ_{R_k} depict the standard deviation of rainfall for the same period

TABLE 2 Comparison of mean differences in characteristics across cropping patterns

| Variables | Maize monocropping | | Maize-legume | | Maize-staple | | Maize-legume-staple | |
|-------------------------|--------------------|-----------|--------------|-----------|--------------|-----------|---------------------|-----------|
| | 1 | | 2 | | 3 | | 4 | |
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Farm net returns | 565.56 | 1036.43 | 2202.62*** | 1865.23 | 1246.78*** | 1228.70 | 2016.15*** | 1944.78 |
| Skewness | −2.67 | 3.55 | 0.51*** | 0.99 | −0.16*** | 0.93 | 0.20*** | 0.74 |
| Variance | 1.63 | 1.56 | 0.58*** | 0.61 | 0.52*** | 0.55 | 0.51*** | 0.47 |
| Age | 41.82 | 13.71 | 41.67 | 12.07 | 43.64 | 12.71 | 43.19 | 12.55 |
| Male headed | 0.37 | 0.49 | 0.68*** | 0.47 | 0.67*** | 47 | 0.77*** | 0.42 |
| Household size | 6.05 | 6.04 | 5.99 | 2.78 | 5.80 | 2.70 | 6.19 | 2.99 |
| Education | 3.10 | 3.95 | 4.39** | 5.11 | 3.72 | 4.84 | 3.50 | 4.81 |
| FBO | 0.15 | .36 | 0.40*** | 0.49 | 0.35*** | 0.48 | 0.31*** | 0.46 |
| Farm size | 6.23 | 5.68 | 5.46 | 4.14 | 5.46 | 3.83 | 4.87** | 3.70 |
| Extension | 7.10 | 4.86 | 13.18*** | 8.16 | 10.44*** | 6.47 | 9.56*** | 5.58 |
| Credit constraint | 0.44 | 0.55 | 0.27*** | 0.44 | 0.43 | 0.50 | 0.34 | 0.47 |
| Livestock | 1.09 | 2.20 | 2.10* | 5.03 | 2.40** | 5.15 | 1.83** | 2.56 |
| Market distance | 11.61 | 3.94 | 7.55*** | 4.40 | 8.44*** | 4.50 | 7.74*** | 4.65 |
| Asset | 1180.07 | 1091.29 | 3481.95*** | 2875.93 | 2765.21*** | 2275.37 | 2633.82*** | 2152.42 |
| Negative rainfall shock | 0.15 | 0.36 | 0.30*** | 0.46 | 0.35*** | 0.48 | 0.36*** | 0.48 |
| Mean temperature | 27.12 | 0.32 | 27.42*** | 0.49 | 27.35*** | 0.48 | 27.37*** | 0.485 |
| Improved seeds | 0.77 | 0.42 | 0.97*** | 0.17 | 0.92*** | 0.27 | 0.95*** | 0.21 |
| Fertilizer use | 121.02 | 63.93 | 88.86*** | 59.85 | 96.17** | 87.41 | 87.47*** | 71.52 |
| Fertility | 0.85 | 0.36 | 0.91 | 0.29 | 0.88 | 0.32 | 0.90 | 0.30 |
| Distance input dealer | 2.35 | 1.26 | 1.86*** | 1.24 | 2.14 | 1.59 | 2.01 | 1.51 |
| observations | 86 | | 174 | | 104 | | 123 | |

Note: The base-category is maize monocropping. Exchange rate at the time of survey: 1 USD = 5.14 Ghana Cedis (GHS).

Significance level at * $p < .1$, ** $p < .05$, *** $p < .01$.

2021). Diversified farm households, recognizing these challenges, engage in cultivating various combinations of crops, either of the same kind or through intercropping different species on the same piece of land or separate plots.

For analytical consistency, we focus on major crops, including cereals, legumes, and root and tubers, as identified under the Planting for Food and Jobs program in the study area (see Figure A1) (Pauw, 2021). This study categorizes these crops into three groups: (1) maize-monocropping; (2) legumes (groundnut, cowpea, soybean); and (3) alternative staples (millet, sorghum, rice, yam). As outlined in Table 2, these crop categories manifest in different combinations (e.g., Maize-legume, Maize-staple, Maize-legume-staple), offering diverse degrees of commercialization, agronomic benefits, and climate resilience.

3.3 | Measurement of crop diversification

We define diversified farm households to include those who cultivated more than one of the above-mentioned crops. This study employs the Margalef index of richness (number of species or varieties) to measure crop diversification as follows:

$$d = \frac{S - 1}{\ln(A)},$$

where A is the total area planted for the portfolio of crops and S is the total number of crops planted.

Several studies have used different indices such as Simpson diversification index (e.g., Bellon et al., 2020), Herfindahl index of diversity (e.g., Mulwa & Visser, 2020), Shannon-diversity index (e.g., Tesfaye & Tirivayi, 2020) to compute crop

diversification among farm households. Nevertheless, Margalef provides better goodness of fit compared to the other indices and can capture the richness of crop species. More importantly, the above-mentioned indices such as the Simpson diversification index require the computation of the area share occupied by the various crops planted by households. In our setting, farmers commonly intercrop different crops on the same piece of land, posing challenges for measuring the actual area allocated to each crop. Therefore, utilizing the Margalef index provides a more practical and consistent approach to computing crop diversification. This index ranges from zero to one, where a larger index indicates greater diversity within the cropping system.

3.4 | Summary statistics

In this section, we briefly present the descriptive statistics on the different cropping patterns and levels of diversification among farm households. With respect to the cropping systems, the results of the *t*-test statistics in Table 2 show that maize mono-cropping is dominated by farm households with lowest average farm net returns (565.56 GHS/acre), negative skewness (−2.67) and a higher variance (1.63). This indicates that maize mono-cropping households are basically pulled into this cropping system in an attempt to meet their food consumption needs given that maize is the most widely consumed and cultivated staple crop *albeit* with limited appeal as commercial crop (Gage et al., 2012; GSS, 2018).

Moreover, the relatively higher fertilizer usage (121.02 kg/acre) is probably due to depleted soil nutrients due to the continuous practice of monocropping, hence increased application of inorganic fertilizer to improve soil fertility and support plant growth. Compared to maize-staple system, the net farm returns of legume-based systems are higher, either in combination with maize (2202.62 GHS/acre) or in a maize-legume-staple system (2016.15 GHS/acre). This heterogeneity in benefits can be explained by economic and agronomic reasons affecting these crops and their respective combinations. The commercialization potential of legumes such as groundnut and soybean may pull households to incorporate them into maize-based cropping systems (Maggio et al., 2018).

Table 3 further compares the differences in mean between “non-diversified,” “somewhat diversified” (i.e., diversification index less than 50%) and “very diversified” (i.e., diversification index greater than 50%) households. In particular, the net farm returns are higher among “somewhat diversified” (1318.43 GHS/acre) and “very diversified” (2587.37 GHS/acre) households compared to non-diversified households (565.56 GHS/acre). The results also show that the average farm size is larger among “somewhat diversified” (6.8 acres) compared to “very diversified” (3.47 acres) and non-diversified households (6.23) households. Also, the amount of inorganic fertilizer use is lower among “somewhat diversified” (85.21/acre) compared to “very diversified” (96.43/acre) and non-diversified (121.2/acre) households.

The results in Table 3 imply that crop diversification in agricultural activities can be a viable strategy for enhancing farm profitability. However, the specific optimal diversification approach and benefit may vary depending on factors such as local market dynamics, resource availability, and individual plot and farmer characteristics. It is important for farmers to carefully assess their own contexts and consider the potential benefits and challenges associated with diversification in order to make informed decisions and reap the needed benefits.

It is worth noting that, the significant differences in the outcome variables and the household characteristics may not indicate impact of diversification, as this comparison do not account for selection bias arising from observed and unobserved factors.

4 | CONCEPTUAL FRAMEWORK

We assume that farm households are risk-averse and maximize their expected utility of farm net returns π , through optimal utilization of a vector of inputs X_n to produce N multiple outputs $y_n = (y_1, y_2, \dots, y_N)$. The output prices are denoted as $P_n = (P_1, P_2, \dots, P_N)$ while C_n is the corresponding vector of input prices for inputs X_n . We assume that the input and output prices are non-random, since smallholder farmers are mostly price-takers with respect to both input and output markets. Therefore, we represent φ as the vector of random variables that captures observed factors that are beyond the control of farmers (e.g., rainfall shocks, temperature variation, seasonal dry spells). The corresponding production technology can be represented by a stochastic production function $y = f(X, \varphi)$. Under risk aversion, farm households' expected utility maximization problem can be expressed as follows:

$$\text{Max } E [U(\pi)] = \text{Max } E \left\{ U \left[\left(\sum_{n=1}^N P_n y_n(X_n, \varphi) \right) - C_n X_n \right] \right\} \quad (1)$$

TABLE 3 Comparison of mean differences in characteristics across levels of crop diversification

| Variables | Non-diversified | | Diff. (t-stat.) (2–1) | Somewhat diversified | | Diff. (t-stat.) (3–2) | Very diversified | |
|-------------------------|-----------------|-----------|-----------------------------|----------------------|-----------|-----------------------------|------------------|-----------|
| | 1 Mean | Std. Dev. | | 2 Mean | Std. Dev. | | 3 Mean | Std. Dev. |
| Farm net returns | 565.56 | 1036.43 | 752.87*** | 1318.43 | 1324.63 | 1268.94*** | 2587.37 | 2016.17 |
| Skewness | −2.67 | 3.55 | 2.96*** | 0.29 | 1.07 | −0.11 | 0.18 | 0.77 |
| Variance | 1.63 | 1.56 | −1.03*** | 0.60 | 0.60 | 0.12** | 0.48 | 0.49 |
| Age | 41.82 | 13.71 | 0.82 | 42.65 | 12.38 | 0.00 | 42.65 | 12.43 |
| Male headed | 0.37 | 0.49 | 0.37*** | 0.74 | 0.44 | −0.07 | 0.67 | 0.47 |
| Household size | 6.05 | 6.04 | 0.256 | 6.30 | 2.96 | −0.66** | 5.64 | 2.62 |
| Education | 3.10 | 3.95 | 0.285 | 3.389 | 4.59 | 1.22** | 4.61 | 5.29 |
| FBO | 0.15 | 0.36 | 0.28*** | 0.43 | 0.50 | −0.16*** | 0.27 | 0.45 |
| Farm size | 6.23 | 5.68 | 0.57 | 6.80 | 4.07 | −3.33*** | 3.47 | 2.85 |
| Extension | 7.10 | 4.86 | 6.15*** | 13.26 | 7.929 | −4.15*** | 9.10 | 5.41 |
| Credit constraint | 0.44 | 0.55 | −0.14** | 0.30 | 0.46 | −0.08* | 0.38 | 0.48 |
| Livestock | 1.09 | 2.20 | 1.40** | 2.48 | 5.64 | 0.85** | 1.63 | 2.28 |
| Market distance | 11.61 | 3.94 | −2.95*** | 8.65 | 4.43 | −1.79*** | 6.86 | 4.41 |
| Asset | 1180.07 | 1091.29 | 2284.17*** | 3464.24 | 2744.65 | −938.57*** | 2525.67 | 2185.32 |
| Negative rainfall shock | 0.15 | 0.36 | 0.22*** | 0.37 | 0.48 | −0.08* | 0.29 | 0.45 |
| Mean temperature | 27.12 | 0.32 | 0.22*** | 27.34 | 0.47 | 0.11** | 27.45 | 0.50 |
| Improved seeds | 0.77 | 0.42 | 0.18*** | 0.94 | 0.23 | 0.02 | 0.96 | 0.19 |
| Fertilizer use | 121.02 | 63.93 | −35.81*** | 85.21 | 69.36 | 11.22 | 96.43 | 73.34 |
| Fertility | 0.85 | 0.36 | 0.04 | 0.88 | 0.32 | 0.04 | 0.92 | 0.27 |
| Distance input dealer | 2.35 | 1.26 | −0.21 | 2.14 | 1.342 | −0.18 | 1.96 | 1.49 |
| Observation | 86 | | | 218 | | | 183 | |

Note: “Nondiversified” (i.e., maize monocropping), “somewhat diversified” (i.e., diversification index less than 50%), and “very diversified” (i.e., diversification index greater than 50%). Exchange rate at the time of survey: 1 USD = 5.14 Ghana Cedis (GHS).

Significance level at * $p < .1$, ** $p < .05$, *** $p < .01$.

where $U(\cdot)$ is the von Neumann–Morgenstern utility function, E denotes the expectation operator, and π is the farm net returns. Risk-averse farmers will thus diversify their crop production systems if the expected utility (i.e., farm net returns) to be derived $E[U(\pi^d)]$ is greater than not diversifying $E[U(\pi^m)]$, that is, $E[U(\pi^d)] - E[U(\pi^m)] > 0$

Assuming a strictly interior solution, the first-order conditions from Equation (1) for crop diversification can be specified as:

$$C_n^d = E[\partial U(\pi^d) / \partial \pi^d | C_n] = E\left[\left(\partial U(\pi^d) / \partial \pi^d\right) \cdot \frac{P(\partial y_n^d(\cdot) / \partial X_n^d)}{\partial X_n^d}\right] \quad (2)$$

Equation (2) can be reformulated to obtain the following specification:

$$\frac{C_n^d}{P} = E\left[\frac{(\partial y_n^d(X_n, \emptyset))}{\partial X_n^d}\right] + \frac{\text{cov}[\partial y_n^d(\cdot) / \partial X_n^d; \partial U(\pi^d) / \partial \pi^d]}{E[\partial U(\cdot) / \partial \pi^d]} \quad (3)$$

The term with the covariance in Equation (3), which is associated with production uncertainty, is the risk premium associated with the farmer's decision problem. For a risk-neutral farmer, $\text{cov}[\partial y_n^d(\cdot) / \partial X_n^d; \partial U(\pi^d) / \partial \pi^d] = 0$, and the ratio $\frac{C_n^d}{P}$ would be equal to the expected marginal product of the inputs (i.e., different crop seeds) used for diversification.

However, in the case of a risk-averse farmer, this term is different from zero. Risk preferences generally influence farmers' behavior and welfare, and risk-averse decision-makers are motivated to reduce their risk exposure (Di Falco & Chavas, 2009). As showed by Pratt (1964), risk-aversion can be examined using the Arrow–Pratt risk-aversion coefficient, $R^d = -(\frac{\partial^2 U(\pi^d)/\partial \pi^{2d}}{\partial U(\pi^d)/\partial \pi^d})$. When $(\partial U(\pi^d)/\partial \pi^d) > 0$ risk aversion corresponds to $\frac{\partial^2 U(\pi^d)}{\partial \pi^{2d}} > 0$, and $R^d > 0$. In line with previous studies, we use variance and skewness to capture farmers' exposure to risks (Antle, 2010; Chavas & Shi, 2015; Issahaku & Abdulai, 2020b). In a typical agrarian setting, smallholder farmers are mostly concerned about the exposure to downside risk or unfavorable risky occurrences located in the lower part of the income distribution. Exposure to downside risk often creates liquidity challenges that impact negatively on household welfare (Bozzola & Smale, 2020). Thus, we incorporate aversion to downside risk by considering this term, $\frac{\partial R^d}{\partial \pi^d} = -(\frac{\partial^3 U(\pi^d)/\partial \pi^{3d}}{\partial U(\pi^d)/\partial \pi^d}) + (R^d)^2$, where R^d represents Arrow–Pratt measure of absolute risk aversion, and decreasing absolute risk aversion means $\frac{\partial^3 U(\pi^d)}{\partial \pi^{3d}} > 0$, implying aversion to unfavorable downside risk. Smallholder farmers experiencing downside risk aversion consider management strategies such as crop diversification to reduce variability and downside risk exposure.

5 | ECONOMETRIC FRAMEWORK AND EMPIRICAL APPROACH

To proceed with the estimation process, we rely on the moment-based approach of the stochastic production function (Antle, 1983) to test how different intensities of crop diversification affect farm net returns and its higher moments. Specifically, we account for the extent of risk exposure by approximating the variance and skewness of farm net returns to examine the effect of crop diversification on volatility and downside risk. Thus, we regress farm net returns on production inputs and other farm-level variables from which the residuals are generated to compute the different moments (i.e., variance and skewness) in Equations (4)–(6).

$$E \left[f(X_n, \varphi) - q_1(X_n, \varphi)^k \right] = q_1(X_n, \varphi, \beta_k) \forall k \geq 2 \quad (4)$$

where $q_1(\cdot) = E(f(X_n, \varphi))$ denotes the mean of the production function. Given Equation (4), we express the variance, which reflects the second moment of the farm net returns distribution as:

$$E \left[(f(X_n, \varphi) - E(f(X_n, \varphi)))^2 \right] = \mu_2 \quad (5)$$

Similarly, the skewness (reflecting the third moment of farm net returns distribution) is given as:

$$E \left[(f(X_n, \varphi) - E(f(X_n, \varphi)))^3 \right] = \mu_3 \quad (6)$$

The skewness approximates downside risks. In other words, positive skewness means a decrease in downside risk exposure and for that matter a decrease in the probability of crop failure. Thus, smallholder farmers maximize their expected utility with an increase in farm net returns, a lower variance, and a positive skewness. We focus on farm net returns because it considers the fluctuations in the quantity and quality of production, as the quality is indirectly considered in the output prices. Therefore, variability in farm net returns provides the opportunity to effectively assess the risks farmers encounter in their production activities (Bozzola & Smale, 2020).

5.1 | Econometric framework

Given that farm households differ in the intensity of adoption and choose the level of crop diversification to maximize the expected utility, as argued in the conceptual framework, we examine the heterogeneous impact of crop diversification intensity using the dose response function (DRF) (Cerulli, 2015). The econometric puzzle in identifying and consistently estimating the dose response function and the average treatment effect (ATE) is the potential endogeneity of the crop diversification, as diversification decisions are not random. In other words, farm households' diversification decisions may be influenced by latent traits (e.g., motivation, entrepreneur skills) that could also influence the output variable and hence may lead to inconsistent estimates of the parameters.

To tackle this potential source of endogeneity, our estimation approach proposed by Cerulli (2015) accounts for the potential threat of treatment endogeneity through an instrumental variable (IV) estimation procedure. The approach further takes advantage of the continuous treatment (i.e., diversification intensity) and does not require the full normality assumption, and considers both treated (i.e., diversified) and non-treated (i.e., non-diversified) units to identify the dose response functions and the average treatment effects, thus making use of the complete information in the dataset. Furthermore, it estimates other causal parameters of interest such as average treatment effect (ATE), average treatment effect on the treated (ATET), and average treatment effect on the untreated (ATENT).

Given that our sample contains a sizeable number of non-diversified (untreated) farmers, crop diversification intensity can be modeled by employing the type-1 Tobit model or Heckman two-step procedure (i.e., type-2 Tobit model). However, a limitation of the type-1 Tobit model is that it assumes that one set of variables and coefficients accounts for the two different behaviors in question: that is, the adoption of crop diversification and the intensity of diversification. Hence, following Cerulli (2015), we employ Heckman's two-step procedure (or type-2 Tobit model) to model crop diversification decisions. We also use a two-stage least squares (2SLS) model to estimate the outcome equations using the predicted values computed from the type-2 Tobit model as instruments that provide consistent estimation of the model coefficients (Wooldridge, 2010; Chatzimichael et al., 2022).

5.2 | Empirical strategy

We represent adoption as binary treatment indicator denoted by (d_i), with y_{i1} and y_{i0} denoting potential outcomes (i.e., farm net returns) for a diversified farmer ($d_i = 1$) and a non-diversified ($d_i = 0$), and x_i the vector of farm and household characteristics (see Table 1) for farmer $i = 1, \dots, N$; where N is the total number of observations (including diversified and non-diversified). Let $g_1(x)$ and $g_0(x)$ represent two functions as farmers' responses to x when diversified and non-diversified units, respectively: with α_1 and α_0 as constants, and ε_1 and ε_0 as the error terms with zero mean and a constant variance.

$$\begin{cases} d_i = 1 : y_{i1} = \alpha_{i1} + g_{i1}(x) + h(t_i) + \varepsilon_{i1} \\ d_i = 0 : y_{i0} = \alpha_{i0} + g_{i0}(x) + \varepsilon_{i0} \end{cases} \quad (7)$$

where t represents the intensity of diversification, which is continuous and takes on values in the range $[0, 100]$, and $h(t)$ is a function different from zero and is a response of a given intensity or t . Given the above notations, we express the two potential outcomes as follows:

Given Equation (7), we express the treatment effect (TE) as $TE = (y_1 - y_0)$ and the causal parameters of interests as the population ATEs conditional on x and t as follows:

$$\begin{aligned} ATE(x, t) &= E(y_1 - y_0 | x, t) \\ ATET(x, t > 0) &= E(y_1 - y_0 | x, t > 0) \\ ATENT(x, t = 0) &= E(y_1 - y_0 | x, t = 0) \end{aligned} \quad (8)$$

Assuming a linear parametric form for $g_1(x_i) = x\delta_1$ and $g_0(x_i) = x\delta_0$, the ATE conditional on x and t can be expressed as follows:

$$ATE(x, t, d) = d * [\alpha + x\delta_1 + h(t)] + (1 - d) * [\alpha + x\delta_0] \quad (9)$$

where $\alpha = (\alpha_1 - \alpha_0)$

5.3 | Estimation procedure

The baseline regression for estimating the parameters of interest ($\alpha_1, \alpha_0, \delta_1, \delta_0, ATE$) and other treatment effect parameters (i.e., ATET, ATENT) is given as:

$$y_i = \alpha_0 + d_i * ATE + x_i\delta_0 + d_i\delta * (x_i - \bar{x}) + d_i * \{h(t_i) - \bar{h}\} + \eta_i \quad (10)$$

where $\eta_i = \varepsilon_{0i} + d_i * (\varepsilon_{1i} - \varepsilon_{0i})$ and represents the error term; \bar{h} is the sample mean of $h(t_i)$; and \bar{x} is the vector of averages of the observed covariates of farmer i .

To obtain consistent estimates of Equation (10), we may assume unconfoundedness in Equation (11), which indicates that both d and t are exogenous, given the observable variables in x .

$$E(y_{ji}|d_i, t_i, x_i) = E(y_{ji}|x_i) \text{ with } j = \{0, 1\} \quad (11)$$

Thus, by invoking this assumption, the ordinary least square (OLS) estimation of Equation (10) could generate consistent and unbiased estimates of the basic coefficients of the model. However, in our context, this assumption might not hold because of the non-randomness of crop diversification decisions. Consequently, d and t are potentially endogenous and might produce biased estimates. Thus, we further express Equation (10) as follows (i.e., Equations 12.1–12.3) consisting of outcome equation, the crop diversification equation, and the level of intensity equation:

$$y_i = \alpha_0 + x_i\delta_0 + d_iATE + d_i\delta * (x_i - \bar{x}) + ad_iK_{1i} + bd_iK_{2i} + cd_iK_{3i} + \eta_i \quad (12.1)$$

$$d_i^* = x_{id}\beta_d + z_{id}\omega_d + \varepsilon_{id}, \quad d_i = 1, \text{ if } d_i^* > 0 \quad (12.2)$$

$$t'_i = x_{it}\beta_t + z_{it}\omega_t + \varepsilon_{it} \quad (12.3)$$

where d_i^* is a latent variable, which is the difference between expected utility of farm net returns from crop diversification $E[U(\pi^d)]$ and without $E[U(\pi^m)]$. Farm household i will choose to diversify if $d_i^* > 0$; t_i is observed only when $d_i = 1$; $K_{1i} = t_i - E(t_i)$, $K_{2i} = t_i^2 - E(t_i^2)$, and $K_{3i} = t_i^3 - E(t_i^3)$, where these terms are the polynomial functions of the level of intensity and are different from zero when the treatment is positive. The terms x_{id} and x_{it} are two sets of observed covariates; $z_{it}\omega_t$ and $z_{id}\omega_d$ are the vectors of the instrumental variables for the crop diversification decision and level of intensity equations, respectively; and ε_{id} and ε_{it} are error terms with zero unconditional means. Equation (12.2) is the selection model with a vector of household and farm characteristics x_{id} , while Equation (12.3) is the level of intensity equation.

The endogenous terms include d_i , K_{1i} , K_{2i} , K_{3i} , with the latter three being functions of the endogenous variable t . Thus, z_{id} and z_{it} are the vectors of instrumental variables used to explain treatment selection (d_i^*) and treatment levels (t'_i), respectively. We assume that these identifying instruments are directly correlated with d_i^* and t'_i , but uncorrelated with the error term of the equations estimating the impact of crop diversification on farm net returns and risk exposure, y_i (referred to as exclusive restriction).

We employ the walking distance from agro-input sellers, following the approach of Di Falco and Chavas (2009), as our instrument. Our rationale is that the decision of smallholder farm households to mitigate risks by diversifying crops can be influenced by enhanced access to agricultural inputs (such as various crop seeds and fertilizers). Importantly, this instrument is not correlated with the outcome variables of interest, establishing its validity in the econometric estimation.

It is crucial to note that a potential concern with this identification strategy could arise if firms strategically choose to locate near the best farmers, rendering the distance to input sellers endogenous. Fortunately, this is not applicable in our context. The study area, being predominantly rural, sees the majority of input sellers typically locating near other shops or retailers, not farmers (Asante et al., 2021). This context differs from urban farming areas where input sellers might strategically position themselves closer to the best farmers. Additionally, the government's Planting for Food and Jobs program has collaborated with private agricultural input providers to enhance supply at the community and district level (MoFA, 2017). We test the relevance of the instrument⁴ employing an F -test of the joint significance of the excluded instrument, the results of which are shown in the bottom of Table 4.

⁴ We examine the validity of the instrument for the crop diversification decision d_i^* , following the approach of Di Falco et al. (2011) we run separately a probit model of the selection equation and OLS regression for the outcome equations of the untreated. The results show that the instrument negatively and significantly affect crop diversification decisions (see the down part of Table 4) but did not show any statistically significant impact on the outcome variable among the untreated farm households (see first column of Table A1).

TABLE 4 Drivers of crop diversification: First stage regression.

| Variables | Marginal effects 1 | Standard error | Diversification level 2 | Standard error |
|-------------------------------|-----------------------|----------------|----------------------------|----------------|
| Age | 0.001 | 0.001 | 0.056 | 0.062 |
| Male headed | 0.040* | 0.022 | −2.113 | 1.710 |
| Household size | −0.001 | 0.002 | −0.268 | 0.287 |
| Education | 0.001 | 0.001 | 0.021 | 0.144 |
| FBO | 0.047*** | 0.015 | −1.531 | 1.616 |
| Farm size | 0.033** | 0.014 | −1.070*** | 0.201 |
| Extension | 0.007*** | 0.002 | −0.115 | 0.142 |
| Credit constraints | 0.022 | 0.013 | 0.914 | 1.608 |
| Market distance | −0.013*** | 0.003 | −0.182 | 0.345 |
| Livestock | 0.002 | 0.003 | −0.88 | 0.159 |
| Asset (log) | 0.022** | 0.007 | 0.423 | 0.729 |
| Negative rainfall shock | 0.087*** | 0.023 | 1.620 | 3.244 |
| Mean temperature | 0.059** | 0.024 | −0.999 | 2.292 |
| Improved seeds | 0.215*** | 0.076 | 1.401 | 3.548 |
| Fertilizer use (log) | −0.001*** | 0.002 | 0.403* | 0.402 |
| Fertility | −0.010 | 0.014 | 1.353 | 2.265 |
| Distance input dealer | −1.600*** | 0.510 | | |
| Sudan | 0.017 | 0.017 | 0.524 | 1.594 |
| Constant | | | 56.446 | 65.703 |
| χ^2 test of instrument | 36.71 | | | |
| <i>p</i> -value of instrument | .0000 | | | |
| Number of observations | | 487 | | |

Note: Table 4 reports the marginal effects estimates of the crop diversification decision from the probit selection model in column 1. In column 2, we report the estimates on the drivers of the level of crop diversification using the Margalef index of diversification. The *p*-value for the excluded instrument (Distance to input dealer) is reported.

Significance level at **p* < .1, ***p* < .05, ****p* < .01.

We then proceed to jointly estimate the crop diversification decision (12.2) and the level of intensity (12.3) using the Heckman two-step procedure (or type- 2 Tobit model), assuming that the errors are jointly normally distributed. We further estimate Equation (12.1) employing a two-stage least squares (2SLS) approach using the predicted values of d_i and t_i computed from the previous Tobit estimation as instruments to obtain consistent and unbiased estimates of the basic parameters ($\alpha_0, \delta, \delta_0, a, b, c, ATE$) in Equation 12.1. Based on the above estimates, we estimate the dose response function as:

$$\hat{ATE}(t_i) = d_i (\hat{ATE}T + \hat{a}(t_i - \bar{t}) + \hat{b}(t_i^2 - \bar{t}^2) + \hat{c}(t_i^3 - \bar{t}^3)) + (1 - d_i) \hat{ATE}NT \quad (13)$$

where $\hat{a}, \hat{b}, \hat{c}$ are coefficients of the estimated polynomials; \bar{t}, \bar{t}^2 , and \bar{t}^3 are the sample means for polynomial functions of the levels of intensity. The standard errors and confidence intervals for ATET and ATENT are correctly estimated via bootstrapping.

6 | EMPIRICAL RESULTS AND DISCUSSION

6.1 | Drivers of crop diversification

We first report the results of the crop diversification decision from Equation (12.2). To ease interpretation, we report the marginal effects computed after estimation of the probit model in Table 4. To establish a causal link on the impact of crop diversification on farm net returns and its higher moments, we check the relevance and validity of the instrument by

reporting test diagnostics of a generalized method of moments (IV-GMM) estimations of the effect of crop diversification on farm net returns in Table A1. The diagnostics test statistics reported at the in the second column of the Table indicate that the instrument is relevant, and as such good predictor of crop diversification decisions. In particular, the Cragg–Donald F-statistic of 202.30, the Kleibergen–Paap rk Wald F-statistic of 136.46 and the associated Angrist and Pischke (2009) p -value ($p = .000$) all reject the null hypothesis that the instrument is weak.

The marginal effects results show that the variable representing negative rainfall shock is a positive and statistically significant driver of crop diversification, suggesting that past rainfall shocks act as a push factor for a diversified crop production system. As discussed earlier, our study area is dominated by maize farming, which is sensitive to weather shocks. Therefore, as rainfall shocks and temperature increases, farmers move away from maize monocropping to a more diversified cropping system. This finding is consistent with recent empirical studies (e.g., Tesfaye & Tirivayi, 2020; Bozzola & Smale, 2020) that show a positive association between crop diversification and climate-related shocks. Also, increase in mean temperatures significantly increases the probability of crop diversification by 0.065.

The estimates also show that a unit increase in household assets (i.e., proxy of household wealth) increases the probability of crop diversification by 0.022. If farm households have more assets, they can either convert these to cash or use them as collateral to secure credit for the procurement of inputs such as improved seeds, fertilizers, and other inputs to enhance their diversified crop production systems. We also find that increase in distance to the main market decreases the probability of diversifying crop production systems by 0.013. As discussed in section 2, farm households within shorter distances to main markets are more likely to be pulled into cultivating portfolio of crops to smooth their incomes. Furthermore, the variable representing extension contacts is positively associated with crop diversification, suggesting that farm households that obtain information on adaptive strategies through agricultural extension services tend to diversify more. The coefficient of the variable representing farm size is positive and statistically significant, suggesting that increase in farm size increases the probability of diversifying crop production by 0.033, a finding consistent with the results reported by Asfaw et al. (2018).

We then focus on the results from the level of intensity Equation (12.3) presented in column 2 of Table 4. Starting with the instrumental variable of the model, the results show that walking distance to input dealer is an important driver that explains farm household's decisions on the level of crop diversification. Shorter distances to input dealers increase the level of diversified crop production systems. Also, the coefficient associated with fertilizer use is positive and statistically significant, implying that a unit increase in the use of inorganic fertilizer increases the level of diversification.

6.2 | Determinants of farm net returns, variance, and skewness: Second-stage estimation results

In this section, we present the estimation parameters of the outcome Equations (12.1) in Table 5. Focusing first on the farm net returns equation (reported in column 1, Table 5), the coefficient of the variable representing extension is positive and statistically significant, indicating the positive effect of increased extension contacts on increasing farm net returns. The importance of agriculture extension as a mechanism for knowledge transfer has become necessary due to increasing demands by smallholder farmers to adapt their production activities to changing climatic conditions, to manage soil degradation, and above all to increase farm net returns.

The regression results for the variance and the skewness equations are shown in columns 2 and 3 of Table 5, respectively. The coefficient of the variable representing improved seeds is negative and statistically significant in the case of variance and positive in the case of skewness, indicating that the cultivating with improved seeds contributes to decreasing the volatility of farm net returns, as well as decreasing downside risk exposure.

6.3 | Impact of crop diversification

An important motivation of this study is to ascertain whether farm households benefit from diversified crop production systems and how this effect varies with respect to the crop diversification decision and the level of intensity. In doing so, we present the estimation results of the key treatment effect parameters in columns 1, 2, and 3 of Table 6 for farm net returns, variance, and skewness, respectively, as well as illustrate the distribution of the treatment effects conditional on the covariates in Figure 1. We further illustrate the estimated dose response functions in Figure 2.

TABLE 5 Second stage estimates of determinants.

| Variables | Farm net returns (log) | | Variance | | Skewness | |
|-------------------------|------------------------|-------|-------------|--------|-------------|--------|
| | 1 | | 2 | | 3 | |
| | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E. |
| Age | −0.010** | 0.005 | 0.007 | 0.005 | −0.010 | 0.012 |
| Male headed | 0.069 | 0.109 | −0.062 | 0.121 | 0.223 | 0.275 |
| HH size | 0.018 | 0.018 | −0.029 | 0.0212 | 0.004 | 0.047 |
| Education | −0.002 | 0.011 | 0.013 | 0.012 | −0.044 | 0.027 |
| FBO | 0.273 | 0.455 | −0.274 | 0.521 | 0.701 | 1.144 |
| Farm size | −0.066** | 0.028 | 0.013 | 0.033 | −0.097 | 0.072 |
| Extension | 0.042*** | 0.009 | 0.001 | 0.011 | 0.077*** | 0.024 |
| Credit constraints | 0.228* | 0.127 | −0.152 | 0.145 | 0.751** | 0.319 |
| Market distance | −0.009 | 0.039 | 0.016 | 0.044 | −0.044 | 0.097 |
| Livestock | −0.067 | 0.083 | 0.052 | 0.095 | −0.094 | 0.209 |
| Asset (log) | −0.340* | 0.197 | 0.082 | 0.226 | −0.406 | 0.497 |
| Negative rainfall shock | 0.048 | 0.156 | 0.149 | 0.178 | −0.127 | 0.392 |
| Mean temperature | −0.124 | 0.172 | 0.280 | 0.197 | −0.904** | 0.433 |
| Improved seeds | 0.376** | 0.175 | −0.070* | 0.201 | 0.506 | 0.441 |
| Fertilizer use (log) | −0.017 | 0.028 | −0.026 | 0.032 | 0.095 | 0.071 |
| Fertility | 0.153 | 0.138 | −0.037 | 0.159 | −0.547* | 0.349 |
| Sudan | −0.045 | 0.108 | 0.091 | 0.123 | −0.264 | 0.271 |
| Constant | 12.792** | 4.951 | −6.555 | 5.676 | 24.915** | 12.460 |
| R-squared | 0.456 | | 0.423 | | 0.386 | |
| Number of observations | | | 487 | | | |

Note: The Table shows the estimates of the outcome Equation (9) for farm net returns, variance and skewness. S.E reports the bootstrapped standard errors. Significance level at * $p < .1$, ** $p < .05$, *** $p < .01$.

TABLE 6 Estimates of treatment effects parameters.

| Parameter | Farm net returns (log) | | Variance | | Skewness | |
|------------------------------|------------------------|--|----------|--|----------|--|
| | (1) | | (2) | | (3) | |
| ATE | 1.699** | | −1.401** | | 3.059** | |
| | (0.849) | | (0.847) | | (1.648) | |
| ATET | 1.563** | | −1.383** | | 2.962* | |
| | (0.838) | | (0.559) | | (2.004) | |
| ATENT | 2.335 | | −1.487 | | 3.511 | |
| | (3.015) | | (2.510) | | (5.003) | |
| Number of observations = 487 | | | | | | |

Note: This Table presents the estimates of different treatment effects parameters; ATE (average treatment effect), ATET (effect of treatment on the treated), ATENT (effect of treatment on the untreated). ATET and ATENT standard errors in parenthesis are obtained by 200 bootstrap simulations. Significance level at * $p < .1$, ** $p < .05$, *** $p < .01$.

In particular, the coefficients of the binary treatment variable show a positive average treatment effect (ATE) of 169.9 and 305.9 percentage points for farm net returns and skewness, respectively, implying that for a farmer picked at random from the population of farmers, adopting crop diversification increases farm net returns by 169.9 percentage points, and contributes to a decline in downside risk exposure and crop failure by 305.9 percentage points. On the other hand, the ATE of the variance of farm net returns is negative and statistically significant, suggesting a reduction in the volatility of farm net returns by 140.1 percentage points. Furthermore, the estimated treatment effect on the treated (ATET), whose standard errors are computed by running 200 bootstraps, are positive for farm net returns (1.563) and skewness (2.962), and negative (−1.383) in the case of variance. The estimated treatment effects on the untreated (ATENTs) have the expected coefficients in all cases but are not statistically significant.

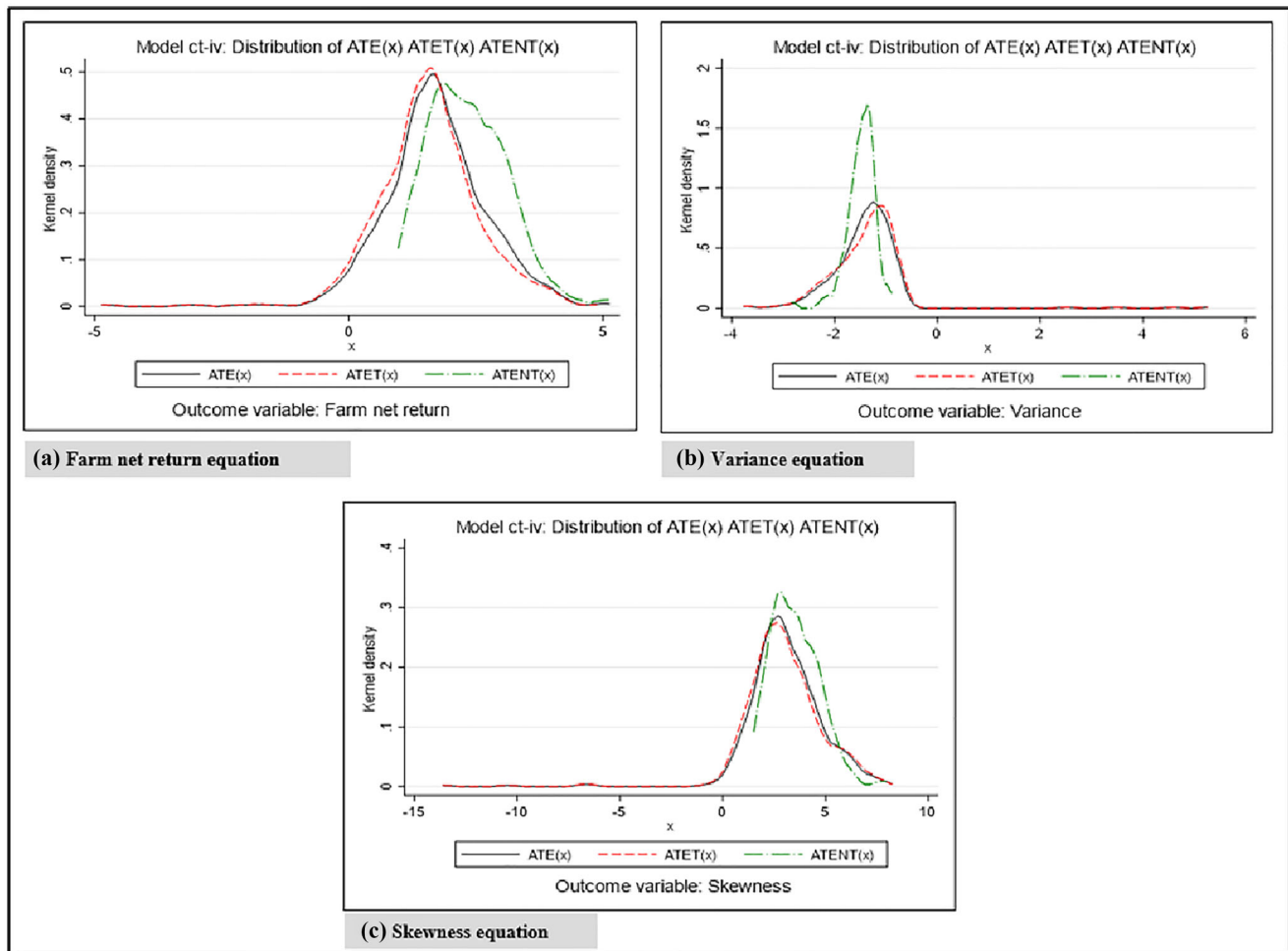


FIGURE 1 Distribution of treatment effects conditional on the covariates.

Based on the above results, we further illustrate the distribution of the causal effects given the covariates for the diversified, non-diversified, and the whole sample in Figure 1. Consistent with the results in Table 6, the distributions (see Figure 1) depict a larger probability mass of positive values for farm net returns (see Figure 1a) and skewness (see Figure 1c), and negative values for variance (see Figure 1b). Furthermore, and in the case of farm net returns and skewness the peak of ATENT appears to be shifted to the right side of both ATE and ATET, suggesting that non-diversified farm households would have obtained higher farm net returns if they diversified, *albeit* only statistically significant (at 10%) in the case of farm net returns. This finding shows evidence of reverse selection on gains ($ATENT > ATE > ATET$), suggesting that farm households who are less likely to diversify their crop production system tend to benefit more if they diversify.

The above results show evidence of heterogeneous responses to crop diversification. In order to provide more information on this phenomenon, we illustrate in Figure 2 the estimated dose response functions (i.e., farm net returns, variance, and skewness) at each level of crop diversification, together with 95% confidence interval bounds. The results show average effect of crop diversification with respect to its intensities. In particular, an inverted U-shaped pattern is observed in Figure 2a and c, with a region of positive and significant effect up to the dose of about 85% (i.e., ATE of 1.747) and about 80% (i.e., ATE of 4.043) in the case of farm net returns and skewness, respectively.

The trend shows a maximum and significant effect of diversification around the dose of about 65% (i.e., ATE of 4.255) for farm net returns and about 60% (i.e., ATE of 8.193) for skewness. After these thresholds, a further increase in the intensity of crop diversification results in a decline in farm net returns and skewness, suggesting diminishing returns in the benefits from crop diversification.

Regarding the variance (see Figure 2b), we observe a region of negative effects up to the dose of about 84% (i.e., ATE of -0.216), and statistically significant up to 72% (i.e., ATE of -2.246), after which we observe increase in volatility (i.e.,

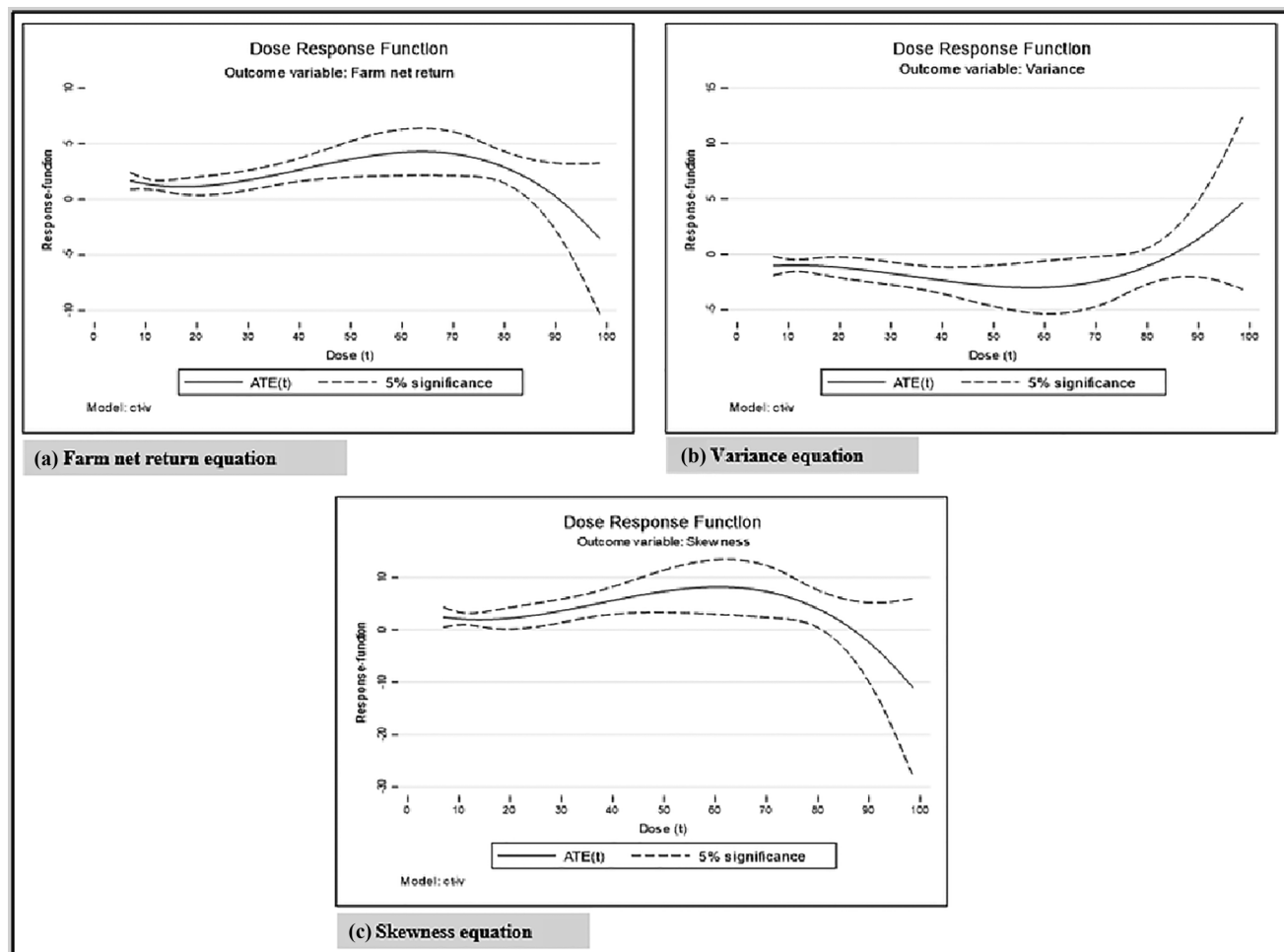


FIGURE 2 The figure shows the estimated dose-response functions (i.e., farm net returns, variance, and skewness) at each level of crop diversification together with 95% confidence interval bounds. NB: Crop diversification intensity in these figures are scaled over [0, 100] interval.

positive values). This implies that diversification reduces the variability of farm net returns up to a threshold and starts to increase as intensity increases.

Overall, the findings highlight heterogeneous responses between crop diversification, farm performance, and risk exposure. In particular, we find that crop diversification increases farm household utility with respect to farm net returns, lowers variance (i.e., reduces farm net returns variability), and increases the skewness of farm net returns (i.e., decreases the risk of crop failure). However, far from being constant and homogeneous, our results indicate that crop diversification benefits in terms of increased farm net returns start to diminish after a certain threshold. The same pattern is also observed with respect to skewness, where crop diversification lowers the probability of crop failure and therefore decreases the exposure to downside risk exposure up to a threshold, beyond which the effect decreases with each additional level of diversification. Similarly, the results show a non-linear relationship between crop diversification and variance, where a relatively lower diversified crop production system stabilizes farm net returns, while increased levels tend to increase the volatility of farm net returns.

A plausible explanation for these findings is the trade-off towards the allocation of resources as diversified crop production systems increase. In other words, as diversification increases and more crops are grown, limited resources, such as land, capital, and labor, may be spread thinly and could affect the efficient allocation of resources, thereby impacting their ability to achieve optimal yields and profitability (FAO, 2021). Moreover, highly diversified crop systems may lead to some crops being cultivated at a smaller scale, potentially under-utilizing their comparative advantage. It is essential to note that the heterogeneity in the benefits of cropping systems is largely linked to the agronomic significance and economic attributes of the crops within the diversified system. For instance, certain alternative crops (e.g., millet, sorghum), while

TABLE 7 Estimates of treatment effects parameters.

| | ATE | ATET | ATENT |
|----------------------|---------------------|---------------------|-------------------|
| Semi-variance | −1.666** (0.710) | −1.581** (0.813) | −2.060 (3.339) |

Note: This Table presents the estimates of different treatment effects parameters; ATE (average treatment effect), ATET (effect of treatment on the treated), ATENT (effect of treatment on the untreated) for the semi-variance equation. ATET and ATENT standard errors are obtained by 200 bootstrap simulations. Significance level at * $p < .1$, ** $p < .05$, *** $p < .01$.

less susceptible to weather fluctuations, may have limited commercial viability, primarily serving household consumption. Consequently, they might not contribute significantly to enhancing overall farm income (Maggio et al., 2018).

6.4 | Robustness check

To test the robustness of our estimation results, we employ the semi-variance approach⁵ to approximate downside risk exposure. This approach captures losses that are below a certain threshold. The semi-variance and the variance differ when the farm net returns distribution is skewed. Further, the negative semi-variance is larger than the variance if the farm net returns distribution is negatively skewed (i.e., downside risk) (Bozzola & Smale, 2020). The resulting estimates of the dose response function (see Figure A2) show a U-shaped pattern, suggesting that as crop diversification increases, the downside risks significantly decrease up to a threshold (i.e., dose of about 65) and begins to increase upward. In comparison with the variance, the negative semi-variance can differentiate between upside and downside risks. Intuitively, these findings are of a similar pattern and corroborate the results of the skewness equation (which also approximates downside risks). Furthermore, the estimated treatment effect parameters in Table 7 have the expected signs and magnitude and thus affirm the robustness of our estimation results.

7 | CONCLUSION AND POLICY IMPLICATION

This study contributes to the growing empirical literature and policy discourse by examining the heterogeneous impact of crop diversification on farm performance and risk exposure, using survey data merged with historical weather data from the northern Savanna regions of Ghana. We employed the dose response function (DRF) and instrumental variable techniques to address potential endogeneity concerns and to estimate the distribution of the impact of crop diversification across different intensities (dose). The study explored how crop diversification as a risk management mechanism could boost farm net returns and minimize risks emanating from climate-related shocks, particularly when risk-buffering instruments such as crop insurance, agricultural credit, and irrigation systems are virtually non-existent.

The empirical results revealed that past climatic shocks (i.e., rainfall shocks, mean temperature) and household-farm level characteristics such as farm size, agricultural extension, and climate information strongly affect crop diversification decisions. In addition, access to input, in particular fertilizer usage, also significantly influence the intensity of crop diversification. Our findings further showed that, in general, crop diversification is beneficial to farm households. The gains, however, are not the same as the returns are heterogeneous across households. In particular, the results uncovered a non-linear relationship between crop diversification intensity and farm net returns as well as risk exposure. In other words, at relatively lower levels of crop diversification, farm net returns and skewness appeared to have a positive and significant effect up to a threshold (i.e., 75% and 70% levels for farm net returns and skewness, respectively), beyond which further diversification resulted in a decline in farm net returns and increased downside risk exposure. Similarly, the impact of diversification on volatility of farm net returns is positive (i.e., lower volatility), particularly at lower levels of crop diversification, and slightly negative (i.e., higher volatility) as the intensity of diversification increased.

Our findings carry several policy implications. Firstly, emphasizing access to climate-related information is crucial, fostering awareness that enables farm households to anticipate and adapt to weather-related hazards. Secondly, a well-designed extension communication strategy, particularly focusing on crop diversification, is essential. This communication should be customized for the diverse landscape of farmers, recognizing that different categories of farmers may find varying levels of crop diversification suitable (Kray et al., 2018).

⁵ We express the semi-variance, which focuses on farm net return realization below the expected value as follows: $E(f(X, d, \mu) - E(f(X, d, \mu)))^2 \forall f(X, d, \mu) < E(f(X, d, \mu)) = \mu_2^-$ (13)

Thirdly, the study aligns with the ongoing policy emphasis on diversified crop production systems under the Planting for Food and Jobs program. This initiative seeks to promote diversified cropping systems to generate employment and enhance farmer livelihoods. However, the non-linear impact of crop diversification on farm net returns and risk exposure underscores the importance of considering factors such as farm size, crop types, and market access in the promotion of diversified crop production systems, given their significant influence on diversification decisions and associated benefits.

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CONFLICT OF INTEREST STATEMENT

Author confirms that there are no conflicts of interest to disclose for any of the authors associated with this work.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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