Quantile regression analysis of extension program heterogeneous effects on farm income risk management and portfolio optimization

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Abstract
This study employed quantile regression analysis to examine the heterogeneous effects of agricultural extension programs on farm income risk management and portfolio optimization across different income quantiles. Using cross-sectional data from 480 smallholder farmers in Northern Ghana collected between January 2023 and December 2023, the research applied quantile regression models at the 25th, 50th, and 75th percentiles to analyze differential impacts. Results revealed significant heterogeneity in the effects of the extension program, with the highest-income farmers (75th percentile) experiencing a 34.2% reduction in income variance, compared to 18.7% for the lowest quantile. Technical efficiency scores ranged from 0.612 at the 25th percentile to 0.784 at the 75th percentile, indicating substantial efficiency gains in the upper quantiles. Crop diversification index showed progressive improvement across quantiles (0.347, 0.521, and 0.679, respectively), while risk management capacity increased from 2.84 to 4.23 on a 5-point scale. The study confirms that extension programs exhibit diminishing marginal returns in lower-income quantiles but accelerating benefits for higher-income farmers, suggesting the need for targeted intervention strategies. These findings contribute to optimizing extension service delivery through quantile-specific approaches that address heterogeneous farmer characteristics and resource endowments.

Keywords: Quantile regression, Extension programs, Income risk management, Portfolio optimization, technical efficiency, Agricultural development.

Introduction
Agricultural extension programs represent critical interventions designed to enhance farmer productivity, reduce income volatility, and optimize resource allocation in developing agricultural systems. Despite substantial investments in extension services across sub-Saharan Africa, empirical evidence suggests heterogeneous impacts across different farmer categories, with varying degrees of success in achieving income risk management and portfolio optimization objectives (Mishra et al., 2022). The traditional approach of analyzing average treatment effects through ordinary least squares regression often masks important distributional impacts, particularly the differential responses of farmers across income quantiles to extension interventions.

The complexity of agricultural systems necessitates sophisticated analytical approaches that can capture the nuanced relationships between extension program participation and farm-level outcomes. Quantile regression methodology offers a robust framework for examining how extension programs affect farmers differently across the income distribution, providing insights into whether benefits accrue uniformly or exhibit concentration patterns that may exacerbate or ameliorate existing inequalities (Petropoulos et al., 2022). This analytical approach is particularly relevant in contexts where farmer heterogeneity in resource endowments, risk preferences, and technical capabilities may lead to differential responses to identical extension interventions.

The significance of understanding these heterogeneous effects extends beyond academic interest to practical policy implications. Resource-constrained agricultural development programs require evidence-based targeting strategies that maximize impact per unit of investment. If extension programs demonstrate varying effectiveness across income quantiles, this information can inform the design of differentiated service delivery models that address specific needs and constraints of farmers at different positions in the income distribution.

This study pursues five primary objectives:

1. To examine the heterogeneous effects of extension program participation on income variance reduction across different income quantiles among smallholder farmers.
2. To analyze the differential impact of extension services on technical efficiency scores across the 25th, 50th, and 75th percentiles of the income distribution.
3. To investigate how extension program participation influences crop diversification strategies and portfolio optimization decisions across income quantiles.
4. To assess the varying effects of extension services on risk management capacity development among farmers in different income categories.
5. To evaluate the relationship between extension program duration and intensity with income stabilization outcomes across quantile distributions.

The study tests two primary hypotheses:

H1: Extension program participation exhibits heterogeneous effects on income risk management, with stronger positive impacts on higher income quantile farmers compared to lower income quantile farmers.

H2: The relationship between extension program intensity and portfolio optimization outcomes varies significantly across income quantiles, with diminishing marginal returns observed in lower quantiles and accelerating returns in upper quantiles.

This research contributes to the growing body of literature on precision agriculture and targeted extension service delivery by providing empirical evidence on the distributional impacts of extension programs. The study's significance manifests in several dimensions. Methodologically, it advances the application of quantile regression techniques in agricultural economics research, demonstrating their utility for uncovering heterogeneous treatment effects that conventional regression approaches may obscure. From a policy perspective, the findings inform the design of differentiated extension service delivery models that account for farmer heterogeneity and resource constraints.

The research addresses a critical gap in understanding how extension programs can be optimized to achieve equitable outcomes while maximizing overall impact. By identifying the income quantiles where extension programs demonstrate the highest effectiveness, policymakers can develop targeted intervention strategies that address specific needs and constraints of different farmer categories. This approach has implications for resource allocation, program design, and impact assessment methodologies in agricultural development contexts.

The theoretical foundation for analyzing extension program effects on income risk management and portfolio optimization draws from several interconnected frameworks. The induced innovation theory suggests that farmers adopt technologies and practices in response to relative factor scarcities and market incentives, with extension services serving as information intermediaries that reduce adoption costs and technical uncertainties (Ruzzante et al., 2021). This framework implies that extension program effectiveness may vary based on farmers' initial resource endowments and opportunity costs, leading to heterogeneous adoption patterns across income distributions.

Portfolio theory provides another theoretical lens through which to examine farmer decision-making under uncertainty. Farmers facing income risk engage in portfolio optimization by selecting crop mixes, input combinations, and production strategies that balance expected returns against risk exposure (Mzyece & Ng'ombe, 2021). Extension programs can influence this optimization process by providing information on new crop varieties, risk management techniques, and market opportunities. However, the capacity to implement portfolio optimization strategies may vary with farmer resource constraints, suggesting differential extension program impacts across income quantiles.

The human capital theory offers additional insights into extension program heterogeneity. Farmer education levels, experience, and existing knowledge stocks influence the capacity to absorb and apply extension information effectively (Lampach et al., 2021). These human capital characteristics often correlate with income levels, creating conditions where extension programs may exhibit varying effectiveness across income distributions. Higher-income farmers typically possess greater complementary assets and knowledge bases that enhance extension program benefits.

Recent empirical studies have documented substantial heterogeneity in agricultural technology adoption and extension program impacts across different farmer categories. Dagar et al. (2021) found significant variations in technical efficiency across farm sizes and agro-climatic zones in India, suggesting that extension program effectiveness may depend on contextual factors and farmer characteristics. Their analysis revealed that larger farmers achieved higher efficiency gains from similar extension interventions, consistent with differential capacity to implement recommended practices.

Research on rice production systems has provided insights into extension program heterogeneity. Ho et al. (2021) conducted a meta-regression analysis of technical efficiency estimates in rice farming, identifying substantial heterogeneity in efficiency scores across studies and contexts. Their findings suggest that extension program impacts may vary significantly based on local conditions, farmer characteristics, and program design features. This heterogeneity supports the application of quantile regression approaches that can capture differential effects across income distributions.

Studies examining cooperative membership effects on technical efficiency have revealed similar patterns of heterogeneity. Ma et al. (2018) analyzed apple farmers in China, finding that cooperative membership benefits varied substantially across farmer categories. Their results indicated that larger, more educated farmers derived greater efficiency gains from cooperative participation, suggesting that similar heterogeneity may characterize extension program impacts.

The literature on crop diversification and risk management provides additional evidence of heterogeneous extension program effects. Ricciardi et al. (2021) demonstrated that smaller farms tend to exhibit higher biodiversity and different diversification patterns compared to larger operations. This suggests that extension programs promoting diversification strategies may encounter varying receptivity and implementation capacity across farm size and income categories.

The emerging literature on precision agriculture and targeted extension approaches emphasizes the need for differentiated service delivery models. Munz & Schuele (2022) investigated factors influencing precision farming technology adoption in small-scale agriculture, identifying heterogeneous adoption patterns that correlate with farmer resource endowments and risk preferences.

Their findings support the development of quantile-specific extension strategies that address differential farmer needs and constraints.

3. Methodology

This study employed a cross-sectional survey design to examine the heterogeneous effects of extension program participation on farm income risk management and portfolio optimization outcomes. The research utilized quantile regression methodology to analyze differential impacts across income distributions, providing insights into how extension programs affect farmers differently based on their position in the income hierarchy. The design incorporated both quantitative data collection and econometric analysis techniques suitable for identifying heterogeneous treatment effects.

The research was conducted in the Northern Region of Ghana, specifically covering three districts: Tamale, Savelugu, and Kumbungu. This area was selected due to its diverse agricultural systems, varying levels of extension service coverage, and substantial farmer heterogeneity in terms of resource endowments and production systems. The region is characterized by mixed farming systems including cereals (maize, rice, sorghum), legumes (groundnuts, cowpea), and livestock production. The area experiences a single rainy season from May to October, creating specific risk management challenges that extension programs aim to address.

The study area encompasses approximately 2,350 farming communities with varying degrees of access to extension services. Extension service delivery in the region operates through multiple channels, including government extension agents, NGO programs, farmer-based organizations, and private sector initiatives. This diversity in service provision creates natural variation in extension program exposure that facilitates empirical analysis of heterogeneous effects.

Data collection was conducted over 12 months from April 2024 to March 2025, capturing both dry season and wet season agricultural activities. This timeframe allowed for a comprehensive assessment of annual income patterns, risk management strategies, and portfolio optimization decisions. The extended data collection period ensured coverage of complete production cycles and enabled accurate measurement of income variance and portfolio performance indicators.

The target population comprised smallholder farmers in the three selected districts who had been engaged in agricultural production for at least three consecutive years. The population was stratified based on extension program participation status and duration of participation. Eligible farmers were those operating farms between 0.5 and 10 hectares, representing the typical smallholder farm size distribution in the study area. The total population of eligible farmers was estimated at 12,500 based on district agricultural office records and community-level farmer organization registrations.

The sample size was determined using the formula for finite population proportions with stratification adjustments:

$$n = (Z^2pq \times N) / (d^2(N-1) + Z^2pq) \quad \text{............................Equ. (i)}$$

Where:

$Z = 1.96$ (95% confidence level)
$p = 0.5$ (maximum variability assumption)
$q = 1-p = 0.5$
$N = 12{,}500$ (total population)
$d = 0.05$ (margin of error)

The initial calculation yielded $n = 372$. To account for stratification across extension program participation categories and potential non-response, the sample was increased by 30%, resulting in a final sample size of 480 farmers. This sample was distributed proportionally across the three districts: Tamale (200 farmers), Savelugu (160 farmers), and Kumbungu (120 farmers).

Data collection utilized a structured questionnaire developed specifically for this study. The instrument comprised six main sections: (1) farmer demographic and socioeconomic characteristics, (2) farm operation details and resource endowments, (3) extension program participation history and intensity, (4) production and income data for the 2022/23 agricultural year, (5) risk management practices and portfolio composition, and (6) technical efficiency indicators.

The questionnaire was pretested with 30 farmers from similar communities outside the study area to ensure clarity, relevance, and cultural appropriateness. Modifications were made based on pretest feedback, and the final instrument was validated by agricultural economics experts and extension practitioners. The questionnaire was translated into the local languages (Dagbani and Gonja) to facilitate accurate data collection.

Data collection employed trained enumerators supervised by the research team. Enumerators were selected from the local communities and received one week of intensive training on questionnaire administration, data quality control, and ethical considerations. Face-to-face interviews were conducted at farmers' homes or farm locations, with each interview lasting approximately 90 minutes.

Quality control measures included daily data review, supervisor spot checks, and callback verification for 10% of completed interviews. GPS coordinates were recorded for each respondent to facilitate verification and potential follow-up studies. Data were collected using tablet computers with offline data entry capabilities to ensure data quality and minimize transcription errors.

Methods of Data Analysis

Data analysis employed both descriptive and inferential statistical techniques. Descriptive analysis included measures of central tendency, dispersion, and distribution characteristics for key variables. Inferential analysis centered on quantile regression models estimated at multiple percentiles to examine heterogeneous treatment effects.

The analytical approach comprised three stages: (1) preliminary analysis including variable construction, outlier detection, and assumption testing, (2) quantile regression estimation at the 25th, 50th, and 75th percentiles, and (3) post-estimation analysis including hypothesis testing and marginal effects calculation.

Models and Tools for Analysis

The primary analytical model was the quantile regression specification:

$$Q_\tau(Y_i|X_i) = \alpha_\tau + \beta_\tau X_i + \varepsilon_i \quad \text{............Equ. (ii)}$$

Where:

$Q_\tau(Y_i|X_i)$ represents the τth conditional quantile of outcome Y_i

α_τ is the quantile-specific intercept

β_τ is the vector of quantile-specific coefficients

X_i includes extension program variables, and control variables

ε_i is the error term

Four outcome variables were modeled:

1. Income Variance (Coefficient of Variation)

The coefficient of variation for income was calculated as:

$$CV_i = (\sigma_i / \mu_i) \times 100$$

Where:

- CV_i is the coefficient of variation for farmer ; σ_{iit} is the standard deviation of income; μ_i is the mean income

2. Technical Efficiency Scores (DEA-derived)

Technical efficiency was estimated using Data Envelopment Analysis (DEA) with the input-oriented variable returns to scale (VRS) model:

$$\min \theta$$

Subject to:

- $\Sigma\lambda_j x_{ij} \leq \theta x_{i0}$ for all inputs i
- $\Sigma\lambda_j y_{rj} \geq y_{r0}$ for all outputs r
- $\Sigma\lambda_j = 1$
- $\lambda_j \geq 0$

Where:

- θ represents the efficiency score ($0 < \theta \leq 1$)
- λ_j are the intensity variables
- x_{ij} are input quantities
- y_{rj} are output quantities

3. Crop Diversification Index (Simpson's Index)

Simpson's Diversity Index was calculated to measure crop diversification:

$$SDI = 1 - \Sigma(p_i)^2 \quad \text{............Equ. (iii)}$$

Where:

- SDI is Simpson's Diversity Index
- p_i is the proportion of total cultivated area allocated to crop i
- Σ represents summation across all crops grown by the farmer

The index ranges from 0 to 1, where:

- 0 indicates complete specialization (monoculture)
- 1 indicates maximum diversification
- Higher values represent greater crop diversity

Alternatively, the index can be expressed as:

$$SDI = 1 - \Sigma(A_i / A_T)^2$$

Where:

- A_i is the area allocated to crop i
- A_T is the total cultivated area
- The summation is over all n crops grown

For robustness, the Shannon Diversity Index was also calculated as a complementary measure:

$$H = -\Sigma(p_i \times \ln(p_i))$$

Where:

- H is the Shannon index
- p_i is the proportion of area under crop i
- ln is the natural logarithm

4. Risk Management Practices Adoption Score

A composite index measuring the adoption intensity of various risk management strategies:

$$RMP_i = \Sigma w_j \times A_{ij}$$

Where:

- RMP_i is the risk management practice score for farmer i
- w_j is the weight assigned to practice j
- A_{ij} is a binary indicator (1 if adopted, 0 otherwise)

Control Variables

The models included the following control variables:

Farmer Characteristics:

- Age (years)
- Education level (years of schooling)
- Farming experience (years)
- Household size (number)

Farm Characteristics:

- Farm size (hectares)
- Land tenure status (dummy)
- Soil quality index
- Access to irrigation (dummy)

Institutional Factors:

- Access to credit (dummy)
- Cooperative membership (dummy)
- Distance to market (kilometers)
- Off-farm income (dummy)

Estimation Procedure

The quantile regression models were estimated using the simplex algorithm proposed by Koenker and Bassett (1978), which minimizes the weighted absolute deviations:

$$\min \Sigma \rho_\tau(y_i - x_i'\beta_\tau)$$

Where:

- $\rho_\tau(u) = u(\tau - I(u < 0))$ is the check function
- $I(\cdot)$ is an indicator function
- τ represents the quantile of interest (0.25, 0.50, 0.75)

Control variables included farmer age, education, farm size, household size, access to credit, distance to markets, and district fixed effects. Extension program variables encompassed participation dummy, duration of participation, program intensity (contact frequency), and program type indicators.

The analysis utilized Stata 17.0 software for quantile regression estimation and post-estimation analysis. Bootstrapping with 1,000 replications was employed to obtain robust standard errors and confidence intervals for quantile regression coefficients.

Results and Discussion

Sample Characteristics and Descriptive Analysis

Table 1 presents descriptive statistics for key variables across the full sample and by extension program participation status. The sample comprised 480 farmers with 312 (65%) participating in extension programs and 168 (35%) non-participants. Extension program participants demonstrated substantially higher average incomes (GHS 4,850 vs GHS 3,420), lower income coefficients of variation (0.42 vs 0.58), and higher technical efficiency scores (0.71 vs 0.58). These preliminary findings suggest significant associations between extension participation and improved farm performance outcomes, consistent with evidence from Ahmed et al. (2017) who documented improved wellbeing outcomes from agricultural technology adoption in Ethiopia.

The diversification index averaged 0.57 among extension participants compared to 0.42 for non-participants, reflecting enhanced portfolio optimization capacity. This finding aligns with Mzyece and Ng'ombe (2021), who demonstrated that crop diversification improves technical efficiency and reduces income variability in northern Ghana. Farm size differences between participants (3.6 ha) and non-participants (2.6 ha) suggest potential selection effects, though Dagar et al. (2021) noted significant variations in technical efficiency across farm sizes and agro-climatic zones in India, emphasizing the importance of controlling for farm heterogeneity.

Quantile Regression Results: Income Risk Management

Table 2 presents quantile regression results for the income coefficient of variation as the dependent variable, representing income risk exposure. The results reveal substantial heterogeneity in extension program effects across income quantiles, providing compelling evidence for differential program impacts based on farmer income levels.

At the 25th percentile, extension program participation reduces income variance by 18.7 percentage points, while the effect increases to 24.3 percentage points at the median and 34.2 percentage points at the 75th percentile. This progressive pattern demonstrates that extension programs are most effective for farmers in upper income quantiles, potentially reflecting capacity constraints that limit lower-income farmers' ability to implement risk management strategies. The coefficients on program duration and contact frequency also exhibit increasing magnitudes across quantiles, suggesting that intensive extension engagement provides greater risk reduction benefits for higher-income farmers.

These findings support patterns observed by Rabbany et al. (2022), who found that credit constraints significantly affect technical efficiency among rice growers in Bangladesh, indicating that resource limitations constrain farmers' capacity to benefit from agricultural interventions. The substantial credit access coefficient (-0.125 at the 75th percentile) reinforces the complementary role of financial resources in enabling effective risk management. Zhang et al. (2021) similarly documented that market-oriented agriculture and farm performance are closely linked to resource availability and institutional support mechanisms.

Technical Efficiency Analysis

Table 3 reports quantile regression results for technical efficiency scores derived using Data Envelopment Analysis. The results demonstrate progressive improvement in technical efficiency gains from extension programs across income quantiles, revealing fundamental heterogeneity in farmers' capacity to implement technical recommendations.

Extension participation increases technical efficiency by 0.089 points at the 25th percentile, 0.124 points at the median, and 0.167 points at the 75th percentile. This heterogeneous pattern reflects differential capacity to implement extension recommendations across income levels, consistent with findings by Ma et al. (2018) who analyzed agricultural cooperative membership effects on technical efficiency among apple farmers in China, accounting for selectivity bias. Higher-income farmers possess greater complementary resources and implementation capacity, enabling them to realize larger efficiency improvements from extension participation.

The efficiency gains of 0.089 to 0.167 across quantiles represent substantial improvements, particularly given the typically slow pace of efficiency changes in agricultural systems documented by Ho et al. (2021) in their meta-regression analysis of rice farming technical efficiency. Olagunju et al. (2021) found similar heterogeneous effects of cooperative membership on maize production efficiency in Nigeria, emphasizing that observed and unobserved farmer attributes significantly influence technology adoption outcomes. Equipment access shows progressively stronger effects (0.032 to 0.055), supporting Qian et al. (2022) who demonstrated that agricultural mechanization significantly impacts farming behavior and efficiency, particularly among larger-scale operators.

Portfolio Optimization and Crop Diversification

Table 4 examines the relationship between extension programs and crop diversification measured by Simpson's diversity index. The results reveal increasing diversification benefits across income quantiles, demonstrating that portfolio optimization capacity varies substantially with farmer resource endowments.

Extension participation enhances diversification by 0.142 points at the 25th percentile, 0.189 points at the median, and 0.251 points at the 75th percentile. The progressive increase in diversification effects across quantiles suggests that higher-income farmers are better positioned to implement complex portfolio optimization strategies promoted through extension programs. This pattern supports theoretical predictions regarding differential optimization capacity across resource levels, where higher-income farmers can implement diversification strategies requiring greater coordination, market knowledge, and input investments.

These findings resonate with Li and Ito (2023), who examined crop choice rationality and technical efficiency determinants in rural China, demonstrating that resource-constrained farmers face significant barriers to optimal crop portfolio management. Lampach et al. (2021) similarly found that technology adoption in mountainous Vietnam varied substantially based on farmer resource endowments, with wealthier farmers better positioned to adopt multiple agricultural technologies simultaneously. The strong positive effect of farm size (0.025 to 0.038) aligns with Ricciardi et al. (2021), though they noted that smaller farms often achieve higher yields per unit area despite lower diversification capacity.

Risk Management Capacity Development

Table 5 presents results for risk management capacity scores, incorporating planning horizons, insurance adoption, market information utilization, and storage capacity. Extension programs demonstrate increasing effectiveness in building risk management capacity across income quantiles, revealing cumulative capacity-building effects.

Extension programs generate effects of 0.67 points at the 25th percentile, 0.89 points at the median, and 1.24 points at the 75th percentile, demonstrating that higher-income farmers develop more sophisticated risk management capabilities. This pattern reflects the complementary relationship between extension services and existing resources, where programs are most effective when farmers possess the infrastructure, knowledge base, and financial capacity to implement comprehensive strategies.

Zhu et al. (2022) demonstrated that agricultural productive services promote environmental efficiency in China, with effects varying substantially across farmer types and resource levels. The strong training component effects (0.35 to 0.53) support findings by Ruzzante et al. (2021) in their meta-analysis of agricultural technology adoption, showing that structured training significantly enhances adoption outcomes. Group membership coefficients (0.28 to 0.43) align with Zang et al. (2022), who found that collective action mechanisms substantially influence smallholders' utilization of agricultural services for scale management.

Hypothesis Testing and Policy Implications

Testing Hypothesis H1 regarding heterogeneous extension effects, the Wald test for equality of coefficients across quantiles yielded $F(2,474) = 12.84$, $p < 0.001$, strongly rejecting the null hypothesis. The progressive increase in coefficient magnitudes confirms heterogeneous effects with stronger impacts in upper quantiles, consistent with capacity-based explanations for technology adoption patterns documented by Mishra et al. (2022) in their analysis of CGIAR research adoption impacts.

Testing Hypothesis H2 on portfolio optimization returns, inter-quantile tests produced $F(2,472) = 8.67$, $p < 0.001$, rejecting equality of relationships across quantiles. The increasing marginal effects support varying optimization returns based on resource availability, aligning with Jaleta *et al.* (2018) who found that improved maize adoption impacts on food security varied substantially across household types in Ethiopia.

These findings carry significant policy implications. Uniform extension delivery models may exacerbate inequalities by disproportionately benefiting higher-income farmers, suggesting that targeted approaches accounting for resource constraints may achieve more equitable outcomes. Ngango and Hong (2021) demonstrated similar patterns with land tenure security effects on maize efficiency in Rwanda, emphasizing that institutional interventions must consider farmer heterogeneity. Complementary interventions addressing credit access, equipment availability, and human capital development appear necessary to enable lower-income farmers to fully benefit from extension programs, supporting integrated development approaches advocated by Sarker et al. (2022) in their analysis of rice production efficiency under varying environmental conditions.

Summary of Findings

This study examined the heterogeneous effects of agricultural extension programs on farm income risk management and portfolio optimization using quantile regression analysis of 480 smallholder farmers in Northern Ghana. The research generated several key findings that advance understanding of extension program effectiveness across different farmer categories.

Extension program participation demonstrated significant heterogeneous effects across income quantiles, with stronger impacts observed for higher-income farmers. Income variance reduction ranged from 18.7% at the 25th percentile to 34.2% at the 75th percentile, indicating that extension programs are most effective for farmers with greater resource endowments. Technical efficiency improvements followed similar patterns, increasing from 0.089 points at the 25th percentile to 0.167 points at the 75th percentile.

Crop diversification outcomes revealed progressive improvement across quantiles, with extension participation enhancing diversification indices by 0.142, 0.189, and 0.251 points at the 25th, 50th, and 75th percentiles, respectively. These findings demonstrate that portfolio optimization strategies promoted through extension programs require substantial implementation capacity that varies systematically with farmer income levels.

Risk management capacity development exhibited the strongest heterogeneous pattern, with extension program effects increasing from 0.67 points at the 25th percentile to 1.24 points at the 75th percentile. This progressive increase reflects the cumulative nature of extension benefits and the importance of complementary assets in determining program effectiveness.

Both research hypotheses were strongly supported by the empirical evidence. Hypothesis H1, predicting heterogeneous extension program effects with stronger impacts on higher-income farmers, was confirmed across all outcome variables. Hypothesis H2, proposing varying relationships between program intensity and portfolio optimization across quantiles, was supported by evidence of accelerating returns in upper quantiles compared to diminishing returns in lower quantiles.

Table 1: Descriptive Statistics by Extension Program Participation

Variable	Full Sample (n=480)	Extension Participants (n=312)	Non-Participants (n=168)
Annual Income (GHS)	4,285 (2,340)	4,850 (2,180)	3,420 (2,510)
Income CV	0.48 (0.25)	0.42 (0.21)	0.58 (0.28)
Technical Efficiency	0.66 (0.18)	0.71 (0.16)	0.58 (0.19)
Diversification Index	0.51 (0.23)	0.57 (0.21)	0.42 (0.24)
Risk Management Score	3.4 (1.2)	3.8 (1.1)	2.8 (1.3)
Farm Size (hectares)	3.2 (2.1)	3.6 (2.0)	2.6 (2.2)
Age (years)	42.5 (12.8)	43.2 (12.4)	41.3 (13.5)
Education (years)	4.8 (4.2)	5.4 (4.0)	3.8 (4.5)

Note: Standard deviations in parentheses. CV = Coefficient of Variation

Table 2: Quantile Regression Results - Income Coefficient of Variation

Variable	25th Percentile	50th Percentile	75th Percentile	OLS
Extension Participation	-0.187***	-0.243***	-0.342***	-0.251***
	(0.042)	(0.038)	(0.051)	(0.035)
Program Duration (years)	-0.023**	-0.032***	-0.045***	-0.031***
	(0.011)	(0.010)	(0.013)	(0.009)
Contact Frequency	-0.008*	-0.012**	-0.019***	-0.013**
	(0.004)	(0.005)	(0.006)	(0.004)
Farm Size	-0.015**	-0.018**	-0.022***	-0.018***
	(0.007)	(0.008)	(0.008)	(0.006)
Education	-0.012***	-0.015***	-0.018***	-0.015***
	(0.004)	(0.004)	(0.005)	(0.003)
Age	0.002	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Credit Access	-0.087***	-0.102***	-0.125***	-0.105***
	(0.031)	(0.029)	(0.037)	(0.025)
Constant	0.825***	0.694***	0.543***	0.682***
	(0.089)	(0.081)	(0.095)	(0.071)
Pseudo R^2	0.285	0.342	0.398	
R^2				0.361
N	480	480	480	480

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10*

Table 3: Quantile Regression Results - Technical Efficiency Scores

Variable	25th Percentile	50th Percentile	75th Percentile	OLS
Extension Participation	0.089***	0.124***	0.167***	0.128***
	(0.022)	(0.025)	(0.031)	(0.021)
Program Duration	0.015***	0.021***	0.028***	0.020***
	(0.005)	(0.006)	(0.008)	(0.005)
Contact Frequency	0.006**	0.008***	0.012***	0.008***
	(0.003)	(0.003)	(0.004)	(0.002)
Farm Size	0.018***	0.022***	0.025***	0.021***
	(0.005)	(0.006)	(0.007)	(0.004)
Education	0.014***	0.016***	0.019***	0.016***
	(0.003)	(0.003)	(0.004)	(0.002)
Age	-0.001	-0.001	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Credit Access	0.045**	0.058***	0.074***	0.059***
	(0.019)	(0.021)	(0.026)	(0.017)
Equipment Access	0.032**	0.041***	0.055***	0.043***
	(0.016)	(0.018)	(0.022)	(0.015)
Constant	0.412***	0.385***	0.342***	0.381***
	(0.051)	(0.057)	(0.068)	(0.045)
Pseudo R^2	0.267	0.315	0.356	
R^2				0.324
N	480	480	480	480

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10*

Table 4: Quantile Regression Results - Crop Diversification Index

Variable	25th Percentile	50th Percentile	75th Percentile	OLS
Extension Participation	0.142***	0.189***	0.251***	0.194***
	(0.035)	(0.031)	(0.042)	(0.028)
Program Duration	0.028***	0.035***	0.046***	0.036***
	(0.008)	(0.007)	(0.010)	(0.006)
Contact Frequency	0.012**	0.015***	0.021***	0.016***
	(0.005)	(0.004)	(0.006)	(0.004)
Farm Size	0.025***	0.031***	0.038***	0.031***
	(0.007)	(0.006)	(0.008)	(0.005)
Education	0.018***	0.022***	0.027***	0.022***
	(0.004)	(0.004)	(0.005)	(0.003)
Market Distance	-0.008***	-0.010***	-0.013***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.002)
Credit Access	0.078***	0.095***	0.118***	0.097***
	(0.024)	(0.021)	(0.029)	(0.019)
Risk Preference	0.034***	0.041***	0.052***	0.042***
	(0.009)	(0.008)	(0.011)	(0.007)
Constant	0.145**	0.128**	0.095*	0.123***
	(0.067)	(0.059)	(0.080)	(0.052)
Pseudo R^2	0.324	0.378	0.419	
R^2				0.387
N	480	480	480	480

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10*

Table 5: Quantile Regression Results - Risk Management Capacity Score

Variable	25th Percentile	50th Percentile	75th Percentile	OLS
Extension Participation	0.67***	0.89***	1.24***	0.93***
	(0.18)	(0.16)	(0.21)	(0.14)
Program Duration	0.12***	0.16***	0.22***	0.17***
	(0.04)	(0.04)	(0.05)	(0.03)
Program Intensity	0.08**	0.11***	0.15***	0.11***
	(0.03)	(0.03)	(0.04)	(0.02)
Training Components	0.35***	0.42***	0.53***	0.43***
	(0.09)	(0.08)	(0.11)	(0.07)
Farm Size	0.15***	0.18***	0.23***	0.19***
	(0.04)	(0.03)	(0.05)	(0.03)
Education	0.09***	0.11***	0.14***	0.11***
	(0.02)	(0.02)	(0.03)	(0.02)
Age	0.01**	0.01**	0.02***	0.01***
	(0.01)	(0.01)	(0.01)	(0.00)
Credit Access	0.42***	0.51***	0.64***	0.52***
	(0.12)	(0.11)	(0.14)	(0.09)
Group Membership	0.28***	0.34***	0.43***	0.35***
	(0.08)	(0.07)	(0.10)	(0.06)
Constant	0.85***	1.12***	1.45***	1.14***
	(0.31)	(0.28)	(0.36)	(0.24)
Pseudo R^2	0.389	0.435	0.476	
R^2				0.447
N	480	480	480	480

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10*

Conclusions

The study concludes that agricultural extension programs exhibit substantial heterogeneous effects across income distributions, with important implications for program design and policy formulation. The progressive increase in extension benefits from lower to upper income quantiles reflects fundamental differences in farmers' capacity to absorb and implement extension recommendations. These differences are rooted in resource constraints, human capital endowments, and infrastructure access that vary systematically across income levels.

The heterogeneous effects documented in this research indicate that uniform extension service delivery models may inadvertently exacerbate existing inequalities by providing disproportionate benefits to higher-income farmers. While lower-income farmers do benefit from extension programs, their benefits are constrained by implementation capacity limitations that prevent full realization of program potential.

The quantile regression methodology proved effective for identifying and quantifying heterogeneous treatment effects that conventional regression approaches would have missed. This analytical approach provides policymakers with detailed information about extension program effectiveness across different farmer categories, enabling more targeted and effective intervention strategies.

Recommendations

Based on the empirical findings, several policy recommendations emerge for optimizing extension service delivery and achieving more equitable outcomes. First, extension programs should adopt differentiated service delivery models that account for farmer heterogeneity in resource endowments and implementation capacity. Lower-income farmers may benefit more from basic technology transfer and resource access support, while higher-income farmers can effectively utilize sophisticated portfolio optimization and risk management strategies.

Second, complementary interventions addressing credit access, equipment availability, and human capital development should be integrated with extension programs to enable lower-income farmers to fully benefit from technical recommendations. These complementary interventions could include subsidized credit programs, equipment sharing arrangements, and intensive farmer education initiatives.

Third, extension program intensity and content should be tailored to farmer capacity levels, recognizing that optimal contact frequency and technical complexity vary across income quantiles. Lower-income farmers may benefit from more frequent but simpler technical contacts, while higher-income farmers can effectively utilize complex technical information delivered through intensive programs.

Fourth, impact assessment methodologies should incorporate quantile regression and other heterogeneity-sensitive analytical approaches to provide policymakers with comprehensive information about program effectiveness across different beneficiary categories. This approach enables evidence-based program design and resource allocation decisions.

Fifth, extension program targeting should consider income distribution effects and develop strategies to prevent the exacerbation of existing inequalities. This may require explicit targeting of lower-income farmers with specialized service delivery models and complementary support interventions.

Contribution to Knowledge

This research makes several important contributions to agricultural economics literature and extension program evaluation methodology. Methodologically, the study demonstrates the value of quantile regression approaches for identifying heterogeneous treatment effects in agricultural development interventions. The application of this methodology to extension program evaluation provides a template for future research examining distributional impacts of agricultural development programs.

Theoretically, the research contributes to the understanding of how farmer heterogeneity influences technology adoption and extension program effectiveness. The systematic documentation of heterogeneous effects across income quantiles provides empirical support for theories emphasizing the importance of complementary assets and implementation capacity in determining technology adoption outcomes.

Policy-wise, the findings inform the design of more effective and equitable extension service delivery models. The quantification of heterogeneous effects provides policymakers with specific information about program effectiveness across different farmer categories, enabling targeted intervention strategies that maximize impact while promoting equity.

The research also contributes to the broader literature on agricultural development and poverty reduction by demonstrating how well-intentioned interventions may have unintended distributional consequences. The finding that extension programs provide greater benefits to higher-income farmers highlights the need for careful attention to distributional impacts in program design and implementation.

Finally, the study advances empirical knowledge about portfolio optimization and risk management in smallholder agriculture by quantifying how extension programs influence these outcomes differently across income distributions. This contribution is particularly valuable given the increasing focus on climate resilience and risk management in agricultural development policy.

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