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Tea marketing channels in developing countries: does informal marketing impact household income resilience in Kenya?

RESEARCH ARTICLE

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Abstract

The liberalization of Kenya's tea sector has created a more market-oriented supply chain but also encouraged the growth of informal market actors. However, the factors driving farmers' participation in informal tea markets and their effects on household income remain underexplored. Using cross-sectional data from smallholder tea farmers, this study applies an endogenous switching regression (ESR) model to examine these relationships. The results show that farming experience, access to extension services, and education significantly influence participation in informal market. Notably, farmers who sell through informal channels earn about 3% higher household income, mainly due to reduced regulatory costs and prompt payments. Despite this benefit, informal marketing poses risks to tea quality control, as plucking standards of "two leaves and a bud" are often compromised. This leads to price instability and poses challenges for maintaining consistent tea quality standards. The study recommends policy interventions to promote sustainable marketing systems by improving access to credit, ensuring timely payments, and strengthening extension services to share market information and uphold quality standards.

Keywords: endogenous switching regression (ESR), informal tea marketin, Kenya, smallholder tea farmers
JEL codes: M31, O13, Q13

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1. Introduction

The tea sector in developing countries, particularly in Sub-Saharan Africa, operates within a competitive marketing environment dominated by private multinationals and intermediaries (Chauvin *et al*., 2017). These dynamics have disrupted traditional marketing systems, driving many smallholder farmers towards informal markets (Bello-Bravo *et al*., 2022). Characterized by a lack of transparency and weak institutional regulation, these informal markets expose farmers to exploitation and economic vulnerability, thereby undermining progress toward Sustainable Development Goals (SDGs) 1 and 2 on poverty and hunger reduction (Bassaganya-Riera *et al*., 2021; Mondal and Palit, 2020). Despite contributing over 60% of global tea output, smallholders in developing countries remain among the most economically vulnerable, facing persistent food insecurity and unstable livelihoods (Giller, 2020). These vulnerabilities have been further exacerbated by increasing climatic variability, rising input costs, weak institutional regulation, and persistent market power asymmetries within tea value chains (WTO, 2022).

Historically, Kenya's tea industry was centrally managed under the Tea Board of Kenya (TBK), established to regulate exports and maintain quality standards (Kenya Tea Board 2022a,b). The sector's dual structure, comprising smallholders and large estates, spurred the creation of institutional actors such as the Kenya Tea Growers Association (KTGA). Subsequent reforms, including the establishment of the Kenya Tea Development Authority (KTDA) in 2000, aimed to enhance marketing efficiency and coordination. Nevertheless, persistent constraints such as limited access to finance, climate-related risks, and governance inefficiencies have eroded smallholders' confidence in formal markets, pushing many toward informal intermediaries (Kenya Tea Board, 2022). Consequently, tea marketing in Kenya now operates through dual channels: a formal system coordinated by the KTDA and informal networks driven by middlemen. The formal market ensures quality control, standardized pricing, and access to export platforms but is often hampered by bureaucratic inefficiencies and delayed payments. These shortcomings incentivize farmers to engage in informal channels, which are characterized by minimal documentation, price volatility, and weak regulatory oversight, ultimately hindering access to credit and stable income(Jayaram and Varma, 2020; Were, 2016). A recent Tea Board of Kenya report highlights the scale of this issue, estimating that smallholders lose nearly 50 billion Kenyan shillings annually to "tea hawking" (Kenya Tea Board, 2023).

Existing literature underscores that participation in formal markets improve smallholders' income and market stability (Barrett *et al*., 2012; Kalejaiye *et al*., 2021), while engagement in informal channels often diminishes returns and excludes farmers from value-added opportunities (Ranasinghe, 2020). However, prior empirical studies in developing countries have primarily focused on the determinants of marketing channels, tea performance, sustainable supply chain methods, and organic tea adoption (Ghosh *et al*., 2023; Hilal and Mubarak, 2016; Munishi *et al*., 2017; Prodhan *et al*., 2023). Consequently, limited empirical attention has been devoted to the transaction costs, institutional asymmetries, and behavioral drivers underlying smallholders' engagement in informal tea markets. Furthermore, the economic implications of informality within Kenya's tea sector remain underexplored, as most existing studies have concentrated on production efficiency (Kanyua *et al*., 2015), planetary tea supply chain sustainability (Mwangi *et al*., 2022), and institutional innovation (Mose *et al*., 2016), with little attention given to exploring the informal market's role in value chains and quality outcomes (Mohan, 2016). By integrating these gaps, our study advances the understanding of how informal participation shapes household income and resilience in Kenya's tea value chain. Against this backdrop, this study seeks to address two interrelated research questions: (i)What socio-economic and institutional factors influence smallholder farmers' participation in informal tea marketing channels? (ii)How does participation in informal markets affect household income and financial stability among smallholder tea farmers in Kenya? To answer these questions, the study utilizes cross-sectional data and applies an Endogenous Switching Regression (ESR) model, which effectively accounts for selection bias and unobserved heterogeneity in farmers' marketing decisions(Abdulai and Huffman, 2014; Tesfay, 2020). Robustness is further ensured through propensity score matching and sensitivity analyses.

This study makes two key contributions. First, it expands the analytical understanding of smallholder tea farmers' engagement with informal markets by integrating transaction cost theory and institutional perspectives to explain marketing participation behavior and household income outcomes. Second, it advances methodological rigor beyond previous studies that relied on Heckman selection and ordinary least squares (OLS) models, which inadequately address endogeneity in marketing choice (Harrizon *et al*., 2016; Kanyua *et al*., 2015). These studies have demonstrated that, in the context of tea markets, smallholder tea farmers' preferences for more profitable outlets and stable buyer relationships significantly influence their choice of marketing channels. However, they often rely on counterfactual income assumptions for non-participants in formal markets, such as those supplying the Kenya Tea Development Agency (KTDA), thereby limiting the accuracy of their estimates. This study addresses this limitation by employing an Endogenous Switching Regression (ESR) model, which more robustly accounts for selection bias in the decision to participate in informal versus formal markets. The ESR model also accounts for correlation between the error terms in the selection and outcome equations through a shared random effect (Abdul-Rahaman *et al*., 2021; Tufa *et al*., 2019). This methodological approach enhances the reliability of the findings and provides a more nuanced understanding of how informal market participation influences smallholder household income and financial stability.

The remainder of this paper is structured as follows: Section 2 outlines the methodology, Section 3 presents the results, and Section 4 discusses their implications. Section 5 concludes with policy recommendations.

2. Materials and methods

2.1 Description of the study site

This study was conducted in the Nandi Hills constituency, a highland region located in the Rift Valley of southwestern Kenya. The site was purposively selected due to its status as the country's third-largest tea-producing hub, providing a critical context for examining market dynamics within a smallholder-dominated agricultural system. Geostrategically, the region borders Uganda to the west and Tanzania to the south, a position with implications for cross-border trade and potential market leakages (Figure 1). The map provides a spatial overview of the study domain, delineating administrative boundaries and tea-growing zones that guided the stratified sampling procedure. The agroecological conditions of Nandi Hills are characterized by a humid subtropical highland climate, with moderate annual temperatures (averaging 16–22°C) and bimodal rainfall ranging between 1200 and 2000 mm per annum (Kenya Tea Board, 2022a). These conditions, combined with deep, well-drained Nitisols (red volcanic soils), create an environment highly conducive to the cultivation of *Camellia sinensis*. As of 2022, approximately 9050 hectares of land were under tea cultivation, yielding an annual production of 36 980.6 metric tons of fresh green leaf (Kanya Tea Board, 2022a). Tea cultivation is the primary socioeconomic activity, with over 70% of the local agrarian population engaged in its production, forming the backbone of the rural economy.

While a formal, centralized marketing system exists, a significant trend has emerged: smallholder farmers diverting their produce to informal intermediaries, attracted by immediate liquidity and dissatisfaction with the payment cycles and deductions inherent in the formal system. However, proliferation of informal marketing channels has introduced profound economic inefficiencies and value chain distortions, which can be conceptualized through two primary mechanisms: it disrupts economies of scale at formal processing factories, raising per-unit production costs, and it leads to quality degradation of the tea, which erodes auction prices. Consequently, these distortions undermine the sector's overall profitability and financial stability, as corroborated by local SACCO and KTDA recent reports. The resulting income volatility and reduced earnings directly amplify socio-economic vulnerabilities among smallholder farmers, thereby challenging the attainment of Sustainable Development Goals related to poverty and hunger alleviation in the region.

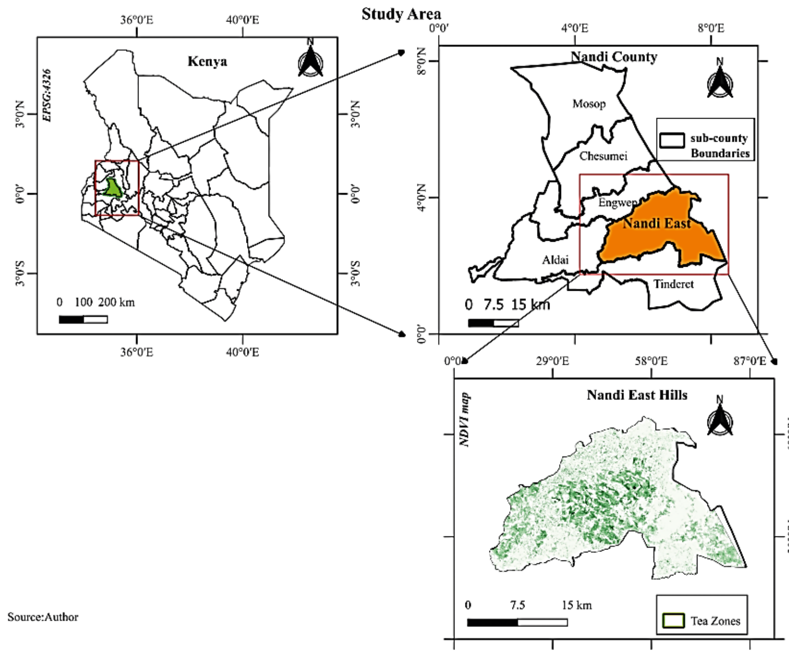

Figure 1. Map of the study domain.

2.2 Sampling method and data collection

The study employed a stratified three-stage sampling procedure to ensure a representative sample of tea farmers across the selected regions. First, research authorization was obtained from Nanjing Agricultural University. Second, villages were selected using data from the 2019 Kenya Population and Housing Census, focusing on areas with a long history of green tea cultivation and established marketing centers. Six regions were purposively identified, each comprising several villages, as detailed in the Appendix (Table A1). In the final stage, 19 farmers per village were randomly selected from household lists to ensure balanced representation across all regions.

Face-to-face interviews were conducted using a smartphone-based questionnaire to collect comprehensive farm-level and socioeconomic data. The sample size was determined using Yamane's (1967) formula, which estimates an appropriate sample when the population size is known and a desired precision level is specified. Following Israel (1992), the formula is expressed as:

$$n = \frac{N}{1 + N(e^2)} \tag{1}$$

The survey instrument comprised 30 structured questions covering tea production practices, farm characteristics, marketing channels, and household income. After excluding 79 incomplete or inconsistent responses, a total of 512 valid observations were retained for statistical analysis.

2.3 Analytical techniques

Three experienced researchers performed data coding and entry with a guide from an extension officer from the Ministry of Agriculture. Responses were recorded directly into tablets using the Kobo Toolbox and Google Forms software, which minimized transcription errors and ensured real-time data capture. Additionally, Data were collected through a structured household survey administered to smallholder tea farmers using trained enumerators. Prior to the main survey, the questionnaire was pre-tested to ensure clarity and relevance. During data collection, senior supervisors conducted on-site monitoring, including spot checks and daily review of completed questionnaires to ensure consistency and completeness. As part of the quality control (QC) process, selected responses particularly those related to production practices and marketing arrangements were cross-verified with local agricultural extension officers to validate their plausibility and accuracy. Following data entry, additional consistency and range checks were performed to identify and correct errors. To handle missing observations, listwise deletion was applied so that only complete cases were included in the final analysis. All econometric analyses were conducted using STATA 17, employing an Endogenous Switching Regression (ESR) model to address potential self-selection bias and endogeneity in marketing channel choice.

2.4 Theoretical framework

Tea farmers' decisions on marketing channels for their tea can be based on two primary theoretical models:

Random utility model (RUM)

Tea farmers' decisions on marketing channels for their tea can be based on the RUM following previous works (Duong *et al*., 2023; Frick *et al*., 2019). According to this model, a risk-neutral, utility-maximizing tea farmer will select the marketing channel that provides the highest utility. The decision rule for a risk-neutral is given by $U_{t,A}$, > $U_{t,n}$, where the farmer prefers the marketing channel A such as non-informal or informal) if its utility exceeds that of the alternative N. Let S_t latent variable that denotes the difference between benefits from adopting a specific marketing channel (e.g., non-informal or informal). S* can be expressed as a function of observable variables, and therefore be simplified in Eq as follows:

$$S_t = X_{t,A,\mathrm{Ch}} - Z_{t,N,\mathrm{Ch}} > \begin{cases} 1 \text{ if } S_t > 0 \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

Where $X_{t,A,\mathrm{Ch}}$ represents observable variables specific to the tea marketing channel (like transaction costs, market prices, and accessibility). $X_{t,N,\mathrm{Ch}}$ represent random variables capturing uncertainties or unobservable factors influencing the decision-making process for that particular marketing channel. On participation, we used the Probit model to illustrate the choice resulting probability of household participation in tea marketing; we assigned 1 and 0 to represent the choice of smallholder farmers in participation of informal (1) and non-informal tea marketing (0) by following Gelata *et al*. (2024) and Tarekegn *et al*. (2017).

Transaction cost theory

In addition to the RUM, this study draws on Transaction cost theory to elucidate the dynamics of marketing channel choice. The theory emphasizes the costs associated with market transactions, which influence farmers' decisions regarding where and how to sell their produce. In the context of tea marketing, smallholder tea farmers choose marketing channels that minimize overall transaction costs. These costs include search and information costs, reflecting the time and resources spent identifying buyers and obtaining market information; bargaining and decision-making costs associated with negotiating prices and contractual terms with buyers, intermediaries, or tea factories; transportation costs related to moving fresh green leaf from farms to buying centers or factories, which depend on distance, road conditions, and mode of transport; and monitoring and enforcement costs arising from ensuring compliance with agreed terms, such as quality standards, accurate weighing, and timely payment. When transaction costs particularly transportation, bargaining, and enforcement costs are high in formal markets due to distance, delayed payments, or weak enforcement mechanisms, farmers may opt for informal marketing channels despite the associated risks. The transaction cost framework is expressed as follows:

$$\mathrm{TC} = C_s + C_\mathrm{b} + C_\mathrm{t} + C_\mathrm{e} + C_\mathrm{m} \tag{3}$$

where TC is total transaction cost, C_s search and information costs, C_b bargaining and decision-making costs, C_t transport costs, C_e enforcement costs and C_m monitoring costs.

According to this theory, transaction costs, particularly transportation, bargaining, and enforcement costs are high in formal markets due to distance, delayed payments, or weak enforcement mechanisms, farmers may opt for informal marketing channels despite the associated risks.

2.5 Econometric model estimation

The study employed an endogenous switching regression (ESR) model to estimate the impact of informal tea marketing on key binary outcomes. This approach corrects for selection bias arising from both observed and unobserved heterogeneity. Unlike conventional methods such as Instrumental Variables (IV) or Two-Stage Least Squares (2SLS), the ESR framework estimates separate outcome equations for participants and non-participants, capturing regime-specific effects where market participation is self-selected rather than random (Kehinde and Ogundeji, 2022).

Using this econometric, the model quantifies the effects of informal tea marketing while controlling for endogeneity, which is crucial for obtaining unbiased and consistent estimates of treatment effects. From the first stage I of this model, a probit selection model is estimated to determine participation in informal tea marketing, represented by a latent variable C_i^*, which takes the value of 1 if the farmer participates and 0 otherwise, as expressed in Eq 4 below.

$$C_i^* = X_{ij}\phi_1 + Z_{it}\phi_2 + \varepsilon_{it} \text{ with } C_i = \begin{cases} 1 \text{ if } C_i^* > 0 \\ 0 \text{ if } C_i^* \le 0 \end{cases}, \tag{4}$$

Where C_i^* is an unobserved latent variable of informal participation recipients, X_{ij} represents vector control variables for households I residing in t, Z_{it} represents vector instruments and ε_{ik} is a standard distribution error term with zero means and variance σ_ε^2 In the second stage, the effects of informal tea marketing on the outcome of interest Y_{it} estimated for two regimes (informal marketing (R1) and non-informal marketing (R2)):

$$\mathrm{R1}: Y_{it}^1 = X_{ij}^1\gamma^1 + \mu_{it}^1 \text{ if } C_i = 1 \tag{5}$$

$$\mathrm{R2}: Y_{it}^2 = X_{ij}^2\gamma^2 + \mu_{it}^2 \text{ if } C_i = 0 \tag{6}$$

The error terms $\varepsilon_{ijt}, \mu_{it}^1$, and μ_{it}^2 follow a trivariate normal distribution with zero mean, and their variance-covariance structure includes $\sigma_\varepsilon^2\sigma_1^2$ and σ_2^2, representing variances in the selection equation and outcome equations, respectively. Additionally, $\sigma_{2\varepsilon}$ signifies the covariance between εijt and μ^{2}it, and $\sigma_{1\varepsilon}$ denotes the covariance that indicates selection bias, tested by rejecting the null hypothesis of no selection bias if significant.

$$cov(\varepsilon_{i1}, \varepsilon_{i2}, \sigma_{2\mu} \left\{ \begin{pmatrix} \sigma_\varepsilon^2 \ \sigma_{2\varepsilon} \ \sigma_{1\varepsilon} \\ \sigma_{1\varepsilon} \ \sigma_2^2 \ \sigma_{I\varepsilon} \\ \sigma_{1\varepsilon} \ \sigma_{i2} \ \sigma_1^2 \end{pmatrix} \right. \tag{7}$$

An ERS regression model's primary benefit is its ability to calculate the variable's effect on treatments and counterfactuals. Following Maddala (1986), this simultaneous switch leads to the ESR model, which has been effectively examined by use of total maximum likelihood estimation in Stata 18 as shown in Equation.

$$E(Y_{it}^{1} \mid C_1 = 1) = E(v_{1F} \mid \varepsilon_i > -Z_{it}) = \sigma_{1\varepsilon}\left[\frac{\phi\left(\frac{Z_{it}}{\sigma}\right)}{\Phi\left(\frac{Z_i\beta}{\sigma}\right)}\right] \equiv \sigma_{1\varepsilon}\lambda_1 \tag{8}$$

$$E(Y_{it}^{2} \mid C_1 = 0) = E(v_{1I} \mid \varepsilon_i, \leq -Z_{it}) = \sigma_{2\varepsilon}\left[\frac{\phi\left(\frac{Z_{it}}{\sigma}\right)}{\Phi\left(\frac{Z_{it}}{\sigma}\right)}\right] \equiv \sigma_{2\varepsilon}\lambda_2 \tag{9}$$

Where ϕ represents the standard normal probability density function, Φ represents the standard normal cumulative density function and Z_{it} is used for instruments that are included in equations (8) and (9) (Duncan and Leigh, 1985). Conditional expectations, outcomes, and counterfactuals can be computed and expressed following (Heckman and Li, 2004) as shown below:

$$E(Y_{it}^{1} \mid C = 1) = X_{ij}^{1}\gamma^{1} + \sigma_{1r}\lambda^{1} \tag{10}$$

$$E(Y_{it}^{2} \mid C = 1) = X_{ij}^{1}\gamma^{2} + \sigma_{2\varepsilon}\lambda^{1} \tag{11}$$

$$E(Y_{it}^{1} \mid C = 0) = X_{ij}^{2}\gamma^{1} + \sigma_{1\varepsilon}\lambda^{2} \tag{12}$$

$$E(Y_{it}^{2} \mid C = 0) = X_{ij}^{2}\gamma^{2} + \sigma_{2\varepsilon}\lambda^{2} \tag{13}$$

Where λ^1 and λ^2 represent the inverse mills ratio that results from the selection equation for informal marketing participants users and non-informal, respectively. Equations (10) and (13) show observable expected outcomes, Equation (11) represents counterfactual expected outcomes for non-informal users, and Equation (13) shows counterfactual expectations if non-informal users would have participated in informal marketing. Finally, we estimated the Average treatment effect on treated (ATT), from differences from equations (10) and (12), as it provides the change in average outcome from treated households (informal marketing users), unlike treatment effects on untreated (ATU) which can be estimated from the difference in Equation (12) and (13) as it's not considered due to tendency of giving unreliable policy implications. We therefore computed ATT as expressed in Equation (14):

$$\text{ATT} = E(Y_{it}^{1} \mid C = 1) = X_{ij}^{1}\gamma^{1} + \sigma_{1r}\lambda^{1} \_ E(Y_{it}^{2} \mid C = 1) = X_{ij}^{1}\gamma^{2} + \sigma_{2\varepsilon}\lambda^{1} \tag{14}$$

Propensity score matching (PSM)

As an initial robustness check, this study employs Propensity score matching (PSM) to estimate the impact of informal tea marketing on household income under the assumption of selection on observables as shown in equations (15) and (16). PSM reduces selection bias by matching households participating in informal markets with comparable households participating in formal markets based on observable characteristics (Rosenbaum and Rubin, 1983). Let D_i denote a binary treatment indicator equal to 1 if household iii participates in informal tea marketing and 0 otherwise. The propensity score is defined as the conditional probability of participation given a vector of observed covariates (X_i) includes household demographic characteristics, farm attribute, and institutional factors that jointly influence marketing choice and income outcomes.

$$P(X_i) = \Pr(D_i = 1 \mid X_i) \tag{15}$$

Conditional on the propensity score, outcomes are assumed to be independent of treatment assignment (the conditional independence assumption). The average treatment effect on the treated (ATT) is then estimated as:

$$\mathrm{ATT}_{\mathrm{PSM}} = E[Y_i(1) - Y_i(0) \mid D_i = 1] \tag{16}$$

where and $Y_i(1)$) and $Y_i(0)$) denote potential household income outcomes with and without participation in informal markets, respectively. Matching was implemented using nearest-neighbor and kernel-based algorithms to ensure robustness of the estimated treatment effects.

3. Results

The analysis consists of four sections: comparing informal and non-informal marketing, examining determinants of informal tea participation, analyzing impacts of informal tea business, and confirming findings through quality matching and sensitivity analysis.

3.1 Dependent variable

The dependent variable in this study is informal marketing participation, which refers to a farmer's involvement in informal tea markets. These markets are characterized by direct transactions between producers and buyers, bypassing formal regulatory frameworks. Informal marketing participation is influenced by socio-economic factors such as access to credit, immediate cash needs, and transaction costs.

3.2 Outcome variable: household income

The outcome variable in this study is household income, reflecting the financial earnings from tea farming. Income is measured from informal and formal markets, focusing on how participation in informal tea marketing affects household income. The income data were collected in Kenyan Shillings (Ksh)**,** with an exchange rate of 1 USD=123 Ksh during the survey period.

3.3 Descriptive statistics

Table 1 summarizes the socioeconomic and market characteristics of formal and informal tea marketers in the study area. The results indicate that informal sellers tend to be younger, predominantly male, and receive faster payments than their formal counterparts. This finding aligns with recent evidence by (Kidane *et al.*, 2022; Vercillo, 2020) which suggests that younger and male farmers often prefer informal markets to secure quick cash flow and flexible transactions.

On average, both groups possess similar land sizes and educational levels, implying that smallholder farmers, regardless of marketing channel, operate under comparable socioeconomic conditions. However, formal market participants travel longer distances to deliver tea and experience delayed payments, reflecting more complex logistics and limited accessibility. Conversely, informal sellers benefit from shorter market distances (0.16 km vs. 0.91 km), as middlemen or private firms often collect tea directly from farmers' homes, thereby reducing transport costs.

Formal marketing channels are more closely associated with cooperative membership and adherence to ISO plucking standards, which enhances tea quality, traceability, and access to premium markets. In contrast, informal participants report greater access to agricultural extension services, potentially improving production practices and short-term income outcomes. Payment duration emerges as a critical differentiator: informal sellers are paid immediately or within days, while formal systems involve longer processing periods. This

Table 1. Descriptive mean characteristics between households involved in informal tea marketing and nonparticipants using χ^2.

Variable	Description	Informal participants		Non-informal participants		Difference
		Mean	SD	Mean	SD	
Age	Age of household head in (years)	49.56	11.70	50.82	11.22	−1.26
Gender	Sex of the household head (1=male, 0=female)	0.65	0.48	0.60	0.49	0.05
Occupation	Household's head occupation (1=farming, 0=otherwise)	0.59	0.04	0.65	0.03	−0.03
Household size	Number of family members (persons)	6.00	1.36	5.48	1.65	0.52***
Farm size	Farm size of the household in acres	0.72	0.79	0.78	1.15	−0.06
Education level	Education level of household head in years	2.24	0.81	2.09	1.89	0.15
Price of Tea	Price difference per kilogram in Ksh	0.18	0.32	0.22	0.30	−0.04***
Farmers group	Household head group membership (1=member, 0=otherwise)	0.12	0.32	0.65	0.48	−0.53***
Tea Income	Income from the sale of tea in the survey year (2022) in Ksh	11 838.19	11581.68	15234.15	25626.80	−3395.96**
Access to extension service	Household head access to extension (yes=1,0 otherwise)	0.98	0.15	0.52	0.51	0.46*
Plucking standards	Adherence to the plucking tea standards (1=adhere, 0=none)	0.16	0.37	0.87	0.33	−0.71***
Duration of payment	Duration for the household to receive payment in months	0.27	0.48	0.41	0.49	−0.14***
Market distance	Distance to nearest sales market in km	0.16	0.37	0.91	0.29	−0.75***

***p<0.01, **p<0.05, *p<0.1. Ksh, Kenya Shillings. 1 USD=123 Ksh in Survey (2022). Source: Authors' computation based on survey data (2022).

feature attracts resource-constrained farmers who require quick liquidity, thereby reinforcing informal market participation.

Overall, these descriptive results highlight distinct demographic and institutional patterns between market groups. Because non-informal and informal sellers differ in both observable and unobservable characteristics, the mean income differences in Table 1 cannot be interpreted causally. Hence, econometric modeling such as the Endogenous Switching Regression (ESR) applied in subsequent sections is necessary to control for self-selection bias and accurately estimate the income effects of informal market participation. Finally, diagnostic checks for multicollinearity (Table A2 in the Appendix) shows a Variance Inflation Factor (VIF) of 1.12, well below the acceptable threshold (VIF < 10), confirming that the explanatory variables do not exhibit multicollinearity (Gujarati, 2014).

3.4 Determinants of informal market participation and household income

The results presented in Table 2 are derived from estimating an endogenous switching regression model using full information maximum likelihood (FIML). Regime 1 corresponds to households participating in formal tea markets, while Regime 2 represents those engaged in informal markets. Column (1) reports the determinants of market participation, and Columns (3) and (5) present the income equations for formal and informal participants, respectively.

Model diagnostics confirm the appropriateness of the ESR specification. The likelihood ratio (LR) test rejects the null hypothesis of independence between the selection and outcome equations, implying that unobservable factors simultaneously influence market choice and household income. This validates the use of the ESR framework over a simple treatment effect model(Addai *et al*., 2023). The observed differences in coefficient estimates between regimes particularly in education and access to extension further underscore the model's robustness. Following the methodological approach of Lokshin and Sajaia (2004), the model included all key covariates and was properly identified using an instrumental variable. Distance to the nearest market was selected for this role, as it is posited to influence market participation decisions without directly affecting household income. Diagnostic tests (Tables A3–A4 in the Appendix) confirmed the instrument's validity and strength, indicating no presence of weak instrument or endogeneity bias, corroborating evidence from Aggarwal *et al*. (2024), Gáfaro and Pellegrina (2022) and Yu *et al*. (2021).

Table 2. Estimation of the endogenous switching regression model using FIML.

Explanatory variable	**Selection equation**		**Regime 1**		**Regime 2**	
	(1) Coeff	**(2) SE**	**(3) Coeff**	**(4) SE**	**(5)**	**(6)**
Age	0.013	0.070	0.071	0.056	0.025	0.053
Gender	0.127	0.141	−0.093	0.108	0.123	0.107
Occupation	−0.070	0.133	0.191*	0.104	−0.281***	0.101
Farm size	−0.014	0.068	0.236***	0.047	−0.032	0.062
Educational level	0.047*	0.026	−0.004	0.022	0.007	0.047
Farm experience	0.365***	0.066	−0.135**	0.063	0.074	0.061
Access to credit	−0.079	0.150	0.038	0.115	−0.238**	0.112
Farmers group	−0.146	0.168	0.107	0.113	0.049	0.162
Plucking standards	−0.341***	0.064	−0.197	0.156	−0.050	0.059
Duration of payments	−0.334**	0.141	0.089	0.111	−0.122	0.110
Availability of extension	1.240***	0.161	−0.139	0.163	0.543**	0.236
Distance to Market (IV)	−0.263***	0.079				
Constant	−2.640***	0.483	8.891***	0.378	7.256***	0.634
Model diagnostics						
N	512					
Log-likelihood	818.0635					
Wald χ^2	18.86*					
sigma_1			−0.316***	0.089		
sigma_2					−0.037	0.064
rho_1			0.766**	0.303		
rho_2					−0.748**	0.296
LR test of index equations	4.70**					

****p*<0.01, ***p*<0.05, **p*<0.1. In Regime 1 and Regime 2, the dependent variable is income for farmers participating in formal and informal markets, respectively. Source: Authors' computation based on survey data (2022).

Regarding determinants of informal market participation, the results indicate that education level, farming experience, and access to extension services are significant positive predictors. Although this finding may appear counterintuitive, it reflects the strategic behavior of more informed and experienced smallholder tea farmers. Beyond liquidity considerations and immediate cash payments particularly when formal market payments are delayed, educated and experienced farmers are better positioned to assess price differentials, negotiate favorable terms, and exploit short-term arbitrage opportunities across marketing channels. Their accumulated market knowledge, stronger social networks, and greater confidence in informal transactions reduce perceived risks associated with informal trade. Moreover, such farmers may deliberately diversify marketing outlets to manage income risk, smooth cash flow, and reduce dependence on monopsonistic formal buyers. This behavior aligns with free marketing principles and evidence that better-informed farmers selectively engage in informal markets when institutional rigidities, delayed payments, or unfavorable pricing prevail in formal channels (Graham, 2019; Liu *et al*., 2021) .In contrast, compliance with plucking standards and longer payment durations negatively influence informal participation, both significant at the 1% and 5% levels, respectively. Farmers adhering to strict plucking standards are more integrated into formal value chains that emphasize quality and traceability, discouraging informal participation (Munasinghe *et al*., 2017). Similarly, long payment durations deter liquidity-constrained farmers, who instead favor informal channels with faster payments(Begho and Ambali, 2021).

For household income outcomes, Regime 1 (formal) and Regime 2 (informal) equations reveal distinct drivers. In the informal regime, access to credit and off-farm occupation are negatively associated with income, suggesting that farmers with alternative income sources or credit access are less dependent on informal marketing (Asante-Addo *et al*., 2017; Nazir *et al*., 2018; Ogundeji *et al*., 2018; Richards, 2020). On the other hand, extension access shows a positive effect on income, emphasizing its role in improving farmers' knowledge, market information, and resilience against market fluctuations (McKague, 2012; Tibasiima *et al*., 2022).Overall, these findings demonstrate that while informal markets offer short-term liquidity advantages, they are associated with lower income potential and weaker compliance with quality standards. The results highlight the dual challenge facing Kenya's tea sector: balancing immediate income needs of smallholders with the long-term economic sustainability of the value chain. The findings align with the research conducted by Ankrah Twumasi *et al*. (2022) and Chaiya *et al*. (2023). The evidence underscores the importance of designing inclusive market interventions such as affordable credit and adaptive payment systems to reduce smallholders' dependence on informal outlets without compromising livelihood security.

4. Discussion

4.1 Impact of informal marketing participation on household income

Table 3 presents the estimated income effects of informal tea marketing using both PSM and ESR to correct for observable and unobservable selection bias. The ESR model provides the most robust estimate, showing that participation in informal tea markets increases household income by approximately 3.3%, confirming a statistically significant and positive welfare effect.

Table 3. Impacts of informal tea participation on household income from ESR and PSM.

Treatment effect	Income from informal market participation	Income from non-informal market participation	ATT	SE	% change
ESR	8.569	8.298	0.271***	0.042	3.3
PSM–NNM	8.569	8.493	0.075	0.339	0.88
PSM–Kernel	8.569	8.563	0.005	0.297	0.06

*** Significance at the 1% probability level. Source: Own computation based on a survey (2022).

Compared to ESR, the PSM estimates derived from nearest-neighbor, kernel, radius, and weighted matching yield smaller, statistically weaker effects, reflecting their limitation in accounting for unobserved heterogeneity. Covariate balancing diagnostics (Figure 2) confirm that the matching procedure effectively minimized observable bias, supporting the reliability of the ATT estimates (Caliendo and Kopeinig, 2008); Rosenbaum and Rubin (1983).

The positive income effect reflects the economic advantages of informality: reduced transaction costs, tax avoidance, and flexible payment systems that improve liquidity and cash flow, consistent with neo-liberal market theory (Alter Chen, 2005; Mhella, 2025). Moreover, they serve as a buffer during market disruptions such as quality downgrades or delayed payments in formal chains enhancing short-term resilience. The findings corroborate with those of Ashraf *et al*. (2009), Barrett *et al*. (2001) and Bellemare (2012) that informal marketing, while outside formal regulation, can provide efficiency gains and income stability for liquidity-constrained smallholders. The results reveal a fundamental trade-off between short-term income resilience and the preservation of long-term market integrity in Kenya's liberalized tea economy. Addressing this misalignment of economic incentives necessitates a coherent policy mix focused on three priorities: (i) shortening payment intervals within formal marketing systems to mitigate liquidity constraints; (ii) expanding access to affordable credit to enhance financial stability; and (iii) reinforcing extension services to ensure adherence to quality standards. Collectively, these interventions would realign private actor behavior with the collective goal of a sustainable and high-value tea sector, thereby safeguarding the industry's long-term export value.

4.2 Policy implications

Beyond the income benefits of non-informal markets presented in Table 4, the policy implications of farmer engagement in informal markets require a broader analysis. To this end, we used ESR to estimate ATT for compliance with plucking standards. The analysis shows that compliant farmers achieve an approximate 6% income increase, while non-compliant farmers see a 2% increase.

These income effects, however, are driven by multiple factors. Compliant farmers would gain greater financial benefits in non-informal markets, yet they often choose informal ones, primarily motivated by immediate payment. Non-compliant farmers are also drawn to informal markets due to the absence of stringent regulations, which facilitates the sale of substandard tea leaves. This contrasts with non-informal markets, which enforce the international "two leaves and a bud" standard. Consequently, the prevalence of informal markets adversely affects the quality of tea for export. To enhance quality and increase farmer income, we recommend that tea boards and research institutions encourage participation in non-informal markets. Key interventions include (i)reducing payment durations, (ii)ensuring fair prices, and (iii) raising awareness of sustainable quality standards. This would secure a supply of high-quality tea while entitling farmers to more stable financial rewards, such as monthly payments and annual bonuses.

4.3 Quality of matching

Table 5 illustrates the quality matching process across three methods: PSM-NNM, Kernel, and Radius. Before matching, the model had a modest explanatory power with a pseudo-R^2 of 0.03, significant differences in covariates (p<0.001), and a high standardized bias of 8.9%. After matching was performed, the Pseudo-R^2 dropped to 0.01 across all methods, indicating an improved balance between the groups. Additionally, the likelihood-ratio tests ($p>\chi^2$) became statistically insignificant (ranging from 0.40 to 0.45), revealing no significant differences in covariates after matching. Furthermore, the mean bias, defined as the standardized mean difference, decreased to values between 4.4 and 5.1%, falling below the 5% threshold for acceptability balance (Ricome *et al*., 2024). These results reveal that the matching process effectively minimized selection bias, enhancing the impact estimates' reliability.

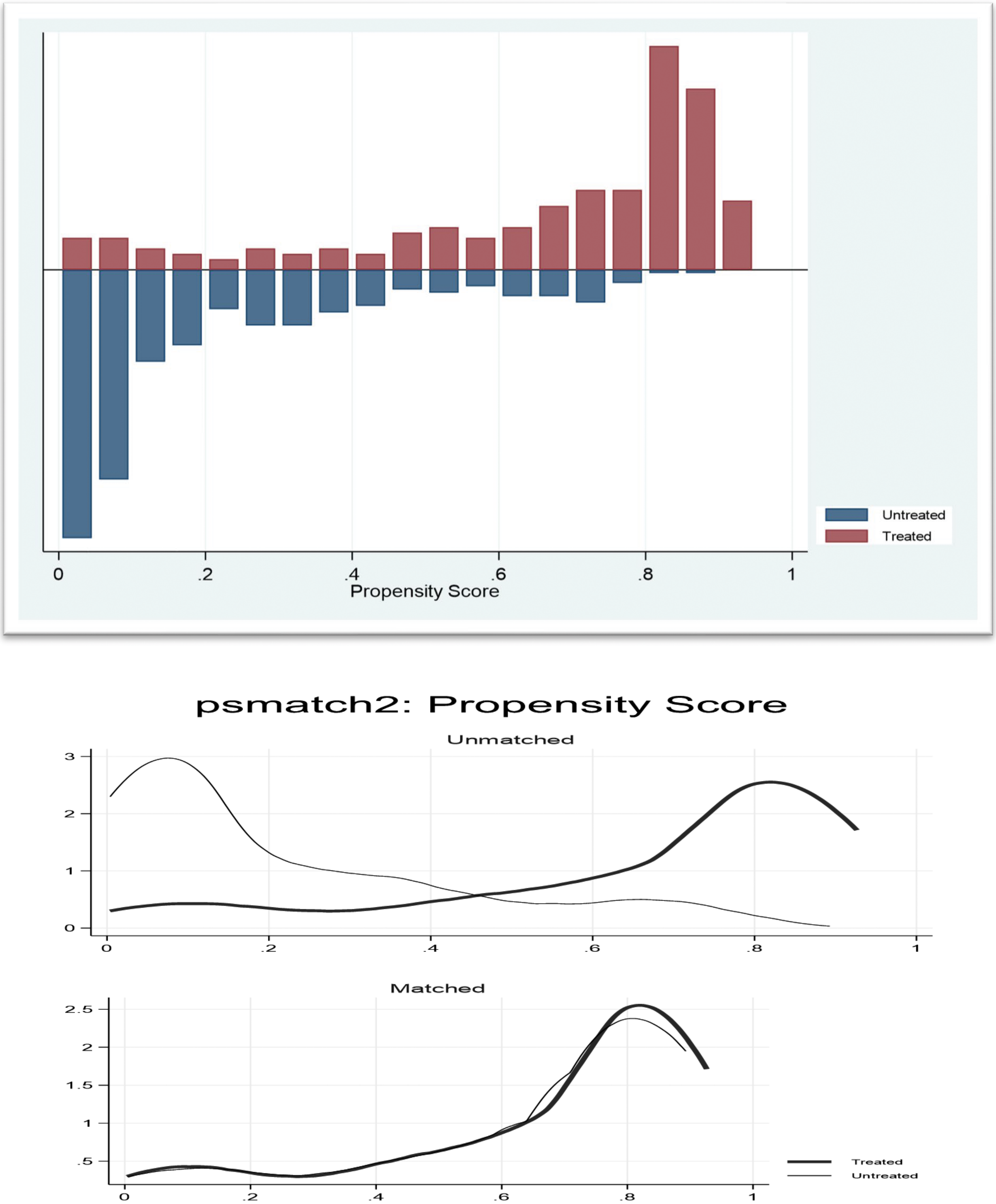

Figure 2. (Top) Distribution of estimated propensity scores across informal and non-informal treatments. (Bottom) Kernel density plots of propensity scores. The figure shows that the matching quality ensures balanced covariates and reduced bias, leading to comparable group characteristics between treatments and control groups. The *y*-axis represents the density of the scores.

Table 4. Showing benefits for non–compliance with tea plucking standards.

Group	Income from informal market participation	Income from non-informal market participation	ATT	SE	% change
Adhere to tea–plucking standards	8.574	8.042	0.532***	0.042	6.60
Do not adhere to plucking standards	8.560	8.412	0.147***	0.027	1.74

*** Significance at the 1% probability level. Source: Own computation based on a survey (2022).

Table 5. Quality of the matching.

	PSM–NNM kernel radius								
	Pseudo R^2	$p>\chi^2$	Mean bias	Pseudo R^2	$p>\chi^2$	Mean bias	Pseudo R^2	$p>\chi^2$	Mean bias
Unmatched	0.03	0.00	8.9	0.03	0.00	8.9	0.03	0.00	8.9
Matched	0.01	0.40	5.1	0.01	0.45	4.4	0.01	0.45	4.6

4.4 Sensitivity analysis

Sensitivity analysis is performed in the final stage of non-randomized experiments, as it evaluates the robustness of inferences against potential unobserved factors (Rosenbaum, 2002). It is crucial for solving optimization problems. Table 6 presents the Rosenbaum bounds sensitivity analysis results, demonstrating that the propensity score findings remain valid, even when considering potential hidden bias. As the Gamma (Γ) value increases, it assesses the extent to which the ATT estimates maintain significance if unobserved factors affect treatment assignment. According to our study estimates, the ATT remained statistically significant across various matching algorithms up to a Γ threshold of 1.5. The results remain robust at this point, with a *p*-value of 0.0419, suggesting that the findings are not sensitive to substantial unobserved confounders (DiPrete and Gangl, 2004). This threshold corroborates with those of previous studies, Caliendo and Tübbicke (2020) Caliendo and Tübbicke (2020) and Stuart (2010)Stuart (2010) similarly found Γ thresholds of 1.5 to be acceptable for the robustness of treatment effects in observational studies.

5. Conclusions

Tea market liberalization, despite creating a market-oriented platform, has exacerbated price volatility in rural areas and introduced uncertainty into the sale of green tea leaves due to heightened competition. Using data from Kenya, we examined the causal impact of informal tea market participation on household income through a cross-sectional comparative analysis. Employing, propensity score matching (PSM), and endogenous switching regression (ESR), our analysis indicates that involvement in informal tea markets raises household income by approximately 3% on average. This positive effect stems primarily from short-term. Obtained through reduced regulatory compliance, lower transaction costs, and immediate payment systems. However, these private benefits generate significant negative externalities at the systemic level. Informal participation fosters adverse selection, incentivizing producers with lower-quality or non-compliant tea leaves to exit the formal system. This erodes quality control, compromising critical factory-level processing stages specifically the cutting, tearing, curling (CTC), and fermentation phases which directly constrains the production of premium-grade made tea, undermining Kenya's competitive edge in international auctions. Furthermore, supply chain fragmentation increases traceability costs, inflates certification expenses, and exacerbates price volatility, creating a collective action problem that jeopardizes the sector's long-term competitiveness.

Table 6. Rosenbaum bounding sensitivity analysis results.

Gamma*	sig+	sig–	*t*-hat+	*t*-hat–	CI+	CI–
1	5.10E–07	5.10E–07	10.58	10.57	10.49	10.65
1.1	1.80E–05	7.70E–09	10.54	10.62	10.45	10.68
1.2	0.00	9.60E–11	10.5	10.65	10.42	10.71
1.3	0.00	1.00E–12	10.46	10.67	10.39	10.73
1.4	0.011	9.30E–15	10.43	10.70	10.36	10.75
1.5	0.042	1.10E–16	10.41	10.72	10.34	10.78
1.6	0.11	0	10.39	10.73	10.32	10.81
1.7	0.30	0	10.37	10.75	10.30	10.84
1.8	0.37	0	10.35	10.77	10.28	10.87
1.9	0.53	0	10.33	10.79	10.26	10.91
2	0.68	0	10.32	10.81	10.24	10.93

Source: Authors' computation based on survey data (2022).

Therefore, the core policy challenge is to realign private incentives with the public goods of quality and stability. Policy interventions should focus on the non-informal sector's attractiveness gap through strategic reforms. These should focus on: (i) rationalizing the cost structure by reviewing burdensome taxes and non-profit certification schemes, which farmers often perceive as delivering no substantial gain since they depress net pay once labor costs are deducted; (ii) enhancing credit access to alleviate the liquidity constraints that make immediate cash from informal buyers appealing; and (iii) strengthening extension services to demonstrate the long-term economic benefits of loyalty to certified buyers, increased bonus. Such a coordinated approach is essential to internalize the negative externalities of informal trade, stabilize the supply chain, and secure Kenya's position in the global tea market.

6. Limitations

Despite robustness checks and the valuable insights provided, this study is constrained by its reliance on cross-sectional data, which limits causal inference and restricts understanding of the temporal dynamics of informal tea marketing. Consequently, observed relationships should be interpreted as associations rather than definitive causal effects. Future research employing panel data with fixed-effect or difference-in-differences estimators could capture longitudinal effects and strengthen causal identification. Additionally, examining gender-specific participation and outcomes would provide a more nuanced understanding of equity and inclusiveness, enhancing the policy relevance of future findings.

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Conflicts of interest

The authors declare that they have no conflict of interest.

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Appendix A

A1. Sampling size approach

The study targeted out–growers and smallholder tea farmers as the core population, comprising 4012 farmers across the selected villages. Following Yamane (1967), the appropriate sample size for a known population was determined using the formula.

$$n = \frac{N}{1 + N(\mathrm{e}^2)}$$

where n is the required sample size, N is the population size, and e represents the level of precision. Applying a 7% precision level yielded an initial sample of 603 farmers. Considering logistical and cost constraints, the final survey targeted 591 farmers, proportionally distributed across sublocations using proportional stratified sampling to ensure representativeness. Data collection involved structured, face–to–face interviews using a smartphone-based questionnaire. After rigorous data screening, 79 observations were excluded due to incomplete responses, inconsistencies, or extreme outliers. The final valid sample comprised 512 farm households, representing 86.6% of the initially targeted sample, and was used for the empirical analysis. This sample size is statistically robust and adequately reflects the population distribution of tea farmers in the study area.

Table A1. Sample distribution statistics from each tea collection center.

Cluster	Number of farmers in tea out growers in tea shades	Stratified sampling ($n_i = (N_i * S)/N$)	Sample size
Kepchomo	384	(384*602)/4012	48
Barasendu	105	(105*602)/4012	15
Kibwari	212	(212*602)/4012	31
Siret	483	(484*602)/4012	73
Savani	512	(512*602)/4012	77
Chemomi	584	(584*602)/4012	88
Kipkoimet	335	(335*602)/4012	50
Kapsumbeiwa	242	(242*602)/4012	36
Musombor	143	(143*602)/4012	21
Cheptabch	188	(188*602)/4012	28
Kamarich	182	(182*602)/4012	28
Chebarus	241	(241*602)/4012	36
Chematich	401	(401*602)/4012	60

Source: Authors' computations.

Table A2. Multicollinearity test.

Variable	VIF	1/VIF
Availability of extension	1.44	
Farmers group	1.29	0.78
Plucking standards	1.23	0.81
Distance to market	1.23	0.81
Duration of payments	1.04	0.96
Farm size	1.04	0.96
Age	1.03	0.97
Education level	1.03	0.97
Price difference	1.02	0.97
Gender	1.01	0.98
Access to credit	1.03	0.98
Occupation	1.01	0.99
Mean	1.12	

Table A3. Instrumental variable validation and F-statistic test.

Variable	R^2	Adjusted R^2	Partial R^2	F (1,499)	Prob>F
Informal marketing~S	0.4389	0.4254	0.0451	23.5834	0.0000

F-statistic > 10 indicates a strong instrument (valid for 2SLS); F–statistic < 10 suggests a weak instrument (a poor instrument for addressing endogeneity).

Table A4. 2SLS Relative Bias.

2SLS relative bias	5%	10%	20%	30%
2SLS size of nominal 5% Wald test	16.38	8.96	6.66	5.53
LIML size of nominal 5% Wald test	16.38	8.96	6.66	5.53