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Determinants of Paddy Market Participation and Intensity in Iran: Evidence from a Generalized Two-Part Fractional Regression Model

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Abstract

Rice, as the second most important crop after wheat, plays a central role in sustaining rural livelihoods and generating income for farmers in Iran. Despite its importance, structural, institutional, and market-related constraints continue to limit effective commercialization among paddy producers. This study aimed to identify the determinants of both the participation decision and participation intensity in the paddy market of Golestan province. Data were collected during the 2023–2024 cropping season from 150 paddy farmers using a structured and validated questionnaire. The analysis employed a generalized two-part fractional regression model (GTP-FRM), which jointly estimates the binary participation decision and the value-based share of paddy marketed while accounting for the bounded nature of the dependent variable and potential interdependence between stages. The explanatory variables included human capital characteristics (education and household size), asset endowment (cultivated area and mechanization) and institutional and market access variables (milling services, storage facilities, market information, and marketing channels). The results show that 64% of farmers participate in the paddy market, and on average 49% of the gross value of production is sold. Education is negatively associated with paddy market participation, reflecting a strategic shift toward value addition, as more educated farmers tend to process paddy into rice rather than sell raw paddy. In contrast, larger farm size and greater surplus significantly increase participation probability and participation intensity. Institutional and market factors also play differentiated roles: access to market information enhances participation probability, while access to milling facilities encourages rice marketing instead of paddy sales. Overall, the findings suggest that commercialization in Golestan province is shaped not only by production capacity but also by value-addition strategies and transaction-cost considerations within existing policy and market structures. Policies aimed at improving rural processing infrastructure, strengthening market information systems, enhancing surplus generation, and reducing institutional barriers can more effectively support market-oriented behavior and sustainable commercialization among paddy producers in Golestan province.

Keywords: Fractional model, Institutional constraints, Market participation, Rice, Transaction costs

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Introduction

Rice, the second most strategic crop after wheat, plays a vital role in Iran's diet and rural economy (Rezaei *et al.*, 2022; Shafieyan & Fadaei, 2017). Given that per capita rice consumption in Iran is about 3.6 times higher than in EU countries, averaging 34.55 kg annually (FAO, 2024), a large share of agricultural activities is devoted to paddy cultivation (Mardani *et al.*, 2022). In Iran, in 2024, approximately 792,543 hectares were under paddy cultivation, producing about 3.4 million tons of paddy, equivalent to roughly 2.04 million tons of milled rice. In this context, Golestan Province stands out as one of the main paddy-producing regions, accounting for nearly 8% of national output (Jehad-Keshavarzi, 2024). Paddy farming has become the principal livelihood for smallholders in the province, ensuring both income generation and household food security (Kazemi & Samouei, 2024). According to the Ministry of Agriculture, around 20.3% of small rural farmers in Golestan cultivate paddy (Jehad-Keshavarzi, 2024). Consequently, improving market participation and access for these farmers is essential for enhancing income, reducing poverty, and promoting rural welfare (Abdullah *et al.*, 2019; Claude *et al.*, 2025; Lopera *et al.*, 2023).

Market participation reflects the extent of farmers' engagement in market activities as sellers (Abate *et al.*, 2022). For paddy producers, this can occur either through selling unprocessed paddy at the farm gate or marketing processed rice with higher value (Denis Ruhinduka *et al.*, 2020). In Iran, smallholder farmers mainly cultivate paddy for household consumption and sell only the surplus, while medium- and large-scale farmers operate more commercially and participate in both paddy and rice markets, where profit margins are greater (Mosavi & Alipour, 2019). Despite this potential, research indicates that paddy producers, particularly smallholders, face persistent challenges across production and marketing stages. These include limited access to inputs, inadequate market infrastructure, and high transaction costs, which together constrain the intensity of their market participation (Ataei *et al.*, 2021; Rezaei *et al.*, 2022). Such difficulties arise from the vulnerability of smallholder supply chains to sudden disruptions, reducing both production efficiency and market performance (Changalima & Ismail, 2022; Orr *et al.*, 2018).

Market participation reflects the extent to which farmers engage in market activities as sellers (Abate *et al.*, 2022). For paddy producers, commercialization may take the form of selling unprocessed paddy at the farm gate or marketing higher-value processed rice, depending on access to post-harvest services and marketing opportunities (Denis Ruhinduka *et al.*, 2020). In Iran, (Mosavi & Alipour, 2019) report that smallholders typically cultivate paddy primarily for household consumption and market only surplus, whereas medium- and large-scale farmers tend to operate more commercially and participate in both paddy and rice markets where margins are higher.

Despite this potential, empirical evidence suggests that paddy producers, particularly smallholders, face persistent constraints across both production and marketing stages, including limited access to inputs, inadequate infrastructure, and high transaction costs (Ataei *et al.*, 2021; Rezaei *et al.*, 2022). These constraints often persist because market services and institutional support are unevenly distributed across locations and farm categories, which amplifies disadvantages for smallholders who have weaker bargaining power and fewer options for value addition. Moreover, smallholder supply chains can be highly vulnerable to disruptions such as climatic shocks, input price fluctuations, and temporary marketing bottlenecks, which reduce production efficiency and weaken market performance (Changalima & Ismail, 2022; Orr *et al.*, 2018). These challenges underscore the need to identify the key determinants of both the decision to participate and participation intensity among paddy farmers in Iran, with particular attention to high-potential regions.

In addition, farmers often face limited access to information on prices, demand, and marketing methods, coupled with insufficient training in production and sales, which reflects weak institutional support and further raises transaction costs (John Kibara & Balázs Gyula, 2024; Zamanialaei *et al.*, 2022). Taken together, inadequate infrastructure, poor information flow, and rising transaction costs form critical barriers that limit farmers' access to value-added markets and constrain their effective market participation (Changalima & Ismail, 2022; John Kibara & Balázs Gyula, 2024; Mahuwi & Israel, 2023; Renkow *et al.*, 2004).

Rising transaction costs in input markets can limit farmers' access to essential materials such as fertilizers and micronutrients (Ataei *et al.*, 2021; Camara & Alhassane, 2017). (Ismail, 2022) and (Lopera *et al.*, 2023) show that restricted input access reduces yields and weakens farmers' ability to generate marketable surplus, thereby lowering market participation. These constraints are often compounded by gaps in market infrastructure. In many rural areas, limited access to milling facilities, storage infrastructure, and nearby sales centers reduces farmers' marketing options. As (Mosavi & Alipour, 2019) note, farmers may therefore sell unprocessed paddy at relatively low prices to brokers and wholesalers. This infrastructure gap contributes to inefficient marketing chains characterized by multiple intermediaries, higher transport and coordination costs, and limited price transparency, which restricts entry into higher-value rice markets and enables intermediaries to capture a substantial share of margins (Mahuwi & Israel, 2023).

In addition, weak institutional support is reflected in limited access to timely information on prices and demand conditions, as well as insufficient training in production and marketing practices, which further increases transaction costs (John Kibara & Balázs Gyula, 2024; Zamanialaei *et al.*, 2022). Taken together, infrastructure constraints, information gaps, and elevated transaction costs form key barriers that limit farmers' access to value-added markets and reduce effective market participation (Changalima & Ismail, 2022; Renkow *et al.*, 2004). These persistent constraints highlight the importance of analyzing the determinants of paddy market participation and participation intensity in Iran.

Recent studies show that supply chain conditions and related constraints can shape market participation intensity among smallholder farmers in developing countries (Asfaw *et al.*, 2022; Claude *et al.*, 2025; Dey & Singh, 2023; Lopera *et al.*, 2023; Mathenjwa *et al.*, 2025; Mdoda *et al.*, 2024; Morton & Martey, 2021; Ndlovu *et al.*, 2024; Tasila Konja & Mabe, 2023). This evidence indicates that participation decisions are influenced by institutional services, market infrastructure, farm assets, and demographic and human capital characteristics (Lopera *et al.*, 2023; Ndlovu *et al.*, 2024). The influence of these factors can differ across products and regions because transaction costs, market organization, price incentives, and access to processing and information systems are context-specific and vary with commodity characteristics and local institutional arrangements. Despite the critical role of paddy cultivation in supporting rural livelihoods in Iran, limited attention has been given to the constraints that restrict farmers' participation in paddy markets. In particular, evidence remains scarce for high-potential regions such as Golestan Province. To address this gap, the present study examines key determinants of both participation and participation intensity by considering market structure, institutional access, production inputs, and farmer characteristics related to assets and human capital. The findings are intended to inform policy and institutional measures that reduce transaction costs, strengthen market infrastructure and information systems, and support technology and input access to improve farmers' linkage to higher-value markets.

This study also addresses methodological challenges in modeling market participation as a two-stage decision process. Farmers first decide whether to participate in the paddy market, and conditional on participation, they determine the share of output marketed as paddy (Ellemare & Arrett, 2006; Holloway *et al*., 2001). Many empirical studies have analyzed these decisions using Tobit, Heckman two-step, or double-hurdle models (Abafita *et al*., 2016; Abu, 2015; Leta, 2018; Morton & Martey, 2021). However, the commercialization index, commonly defined as the ratio of sales to total production, is a fractional variable bounded between 0 and 1 (von Braun & Kennedy, 1994). Conventional linear specifications may generate predictions outside the feasible range, which can distort inference and marginal effect interpretation (Govereh *et al*., 1999; Yen, 2005).

To address these limitations, recent work has adopted fractional regression and related two-part approaches for bounded outcomes (Ndlovu *et al*., 2024; Tasila Konja & Mabe, 2023). Building on this literature, we employ the generalized two-part fractional regression model (GTP-FRM) developed by (Schwiebert & Wagner, 2015). The model consists of a first-stage participation equation and a second-stage fractional regression for participation intensity, and it allows for dependence between the unobserved determinants of the two stages. This feature is particularly relevant in the context of paddy farmers in Golestan Province, where participation and the share of output sold as raw paddy may be jointly influenced by unobserved constraints such as access to services, market connectivity, and post-harvest capacity. For robustness, we also compare the results with estimates from the Heckman two-step approach.

Conceptual Framework

The conceptual framework (Fig. 1) illustrates the variables hypothesized to influence both the decision to participate and the intensity of participation in the paddy market.

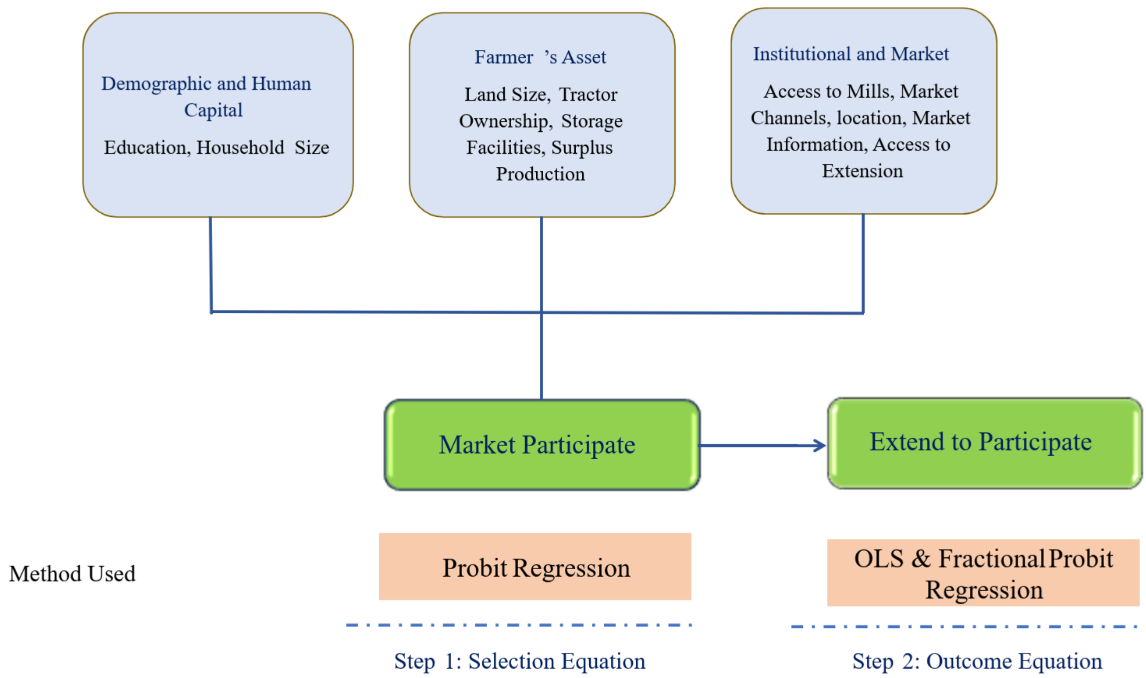

Figure 1- Conceptual framework, Source: Authors' construct

In this study, market participation is modeled as a two-stage process. The first stage, referred to as the decision to participate, captures whether a farmer sells raw paddy in the market (1 = participates, 0 = does not participate). The second stage measures participation intensity through the market participation index, defined as the share of the gross value of paddy production that is sold as unprocessed paddy. This index is a fractional variable bounded between 0 and 1, reflecting the proportion of output commercialized in raw form.

To avoid overfitting, mitigate multicollinearity, and identify the most relevant predictors, the LASSO (Least Absolute Shrinkage and Selection Operator) method was employed for variable selection (Ogundimu, 2022). The selected explanatory variables are grouped into three conceptual categories: demographic and human capital factors (e.g., education level and household size), farmer assets (e.g., cultivated area, storage facilities, Tractor Ownership) and institutional and market factors (e.g., access to milling services, market information, marketing channels, and location). Table A1 in the Appendix provides detailed definitions and measurement scales for all variables. For example, household size reflects the total number of household members.

To estimate the determinants of participation, a probit regression is applied in the first stage to model the binary decision to participate. In the second stage, different estimation strategies are employed depending on the modeling approach. Under the Heckman two-stage model, ordinary least squares (OLS) is used to estimate participation intensity conditional on participation. However, because the participation index is a bounded fractional outcome, OLS may generate predictions outside the feasible range and lead to biased marginal effects. To address this limitation, the generalized two-part fractional regression model (GTP-FRM) is employed. In this framework, the first stage models the participation decision, and the second stage applies a fractional probit specification to the bounded participation index. This approach ensures that predicted values lie within the unit interval and allows for dependence between the participation decision and participation intensity, thereby providing a more consistent and theoretically appropriate estimation strategy for fractional commercialization measures. For comparison and robustness, results from the Heckman model are also reported.

Theoretical Framework and Hypotheses

In deciding about market participation and the level of supply, paddy producers act as economic agents with bounded rationality who seek to maximize utility (Jijue *et al*., 2024). These decisions occur sequentially under the influence of several factors (Goetz, 1992; John Kibara & Balázs Gyula, 2024; Key *et al*., 2000). Farmers first decide whether to participate in the market and then determine the volume of sales. Identifying the determinants of these decisions can be understood through the lenses of transaction cost theory (Key *et al*., 2000; Omamo, 1998), market transition theory (Nee, 1989), and access theory (Ribot & Peluso, 2003). Within the transaction cost framework, which derives from the New Institutional Economics, farmers' market participation is associated with costs of exchange that depend on institutional efficiency (John Kibara & Balázs Gyula, 2024; Renkow *et al*., 2004). Lower transaction costs therefore increase the likelihood of market participation (Changalima & Ismail, 2022; John Kibara & Balázs Gyula, 2024).

According to market transition theory, economic reforms and improved infrastructure create new opportunities and incentives for farmers to engage in markets (Ismail, 2014; Nee, 1989). Similarly, access theory emphasizes that the ability to benefit from market opportunities depends on supply chain support systems, cost-efficiency, and the presence of enabling structures and processes (Ribot & Peluso, 2003). Elements such as transport infrastructure, distribution strategies, and product quality also affect these conditions and can enhance farmer participation (Mahuwi & Israel, 2023).

Overall, integrating these three theoretical frameworks provides a comprehensive analytical perspective, as no single approach can fully capture the complex interactions shaping farmers' participation decisions (Hagos *et al*., 2020; Hlatshwayo *et al*., 2021). In the specific context of Golestan province, where paddy production is characterized by smallholder dominance, spatial dispersion of farms, reliance on intermediary-based marketing channels, and uneven access to storage and processing facilities, these theoretical perspectives are particularly relevant for explaining both market entry decisions and participation intensity. Based on this integrated framework and the institutional and structural characteristics of Golestan province, the study develops a set of empirically testable hypotheses to examine the determinants of paddy market participation.

Consistent with the conceptual structure illustrated in Figure 1, the hypotheses are organized into three thematic groups reflecting the core dimensions of the analytical framework, namely farmer assets, institutional and market access factors, and demographic and human capital characteristics. This structured presentation maintains conceptual coherence while allowing each determinant to be tested separately. The complete set of operationalized and disaggregated hypotheses (H1a–H11b) is provided in Appendix A.

CH1: Farmers' Assets

Drawing on transaction cost theory, farmers' assets including land size, tractor ownership, storage facilities and surplus production influence production capacity, liquidity, and the ability to bear exchange costs in market transactions (Changalima & Ismail, 2022). In Golestan Province, where access to machinery and storage infrastructure varies considerably across farmers, differences in asset ownership are expected to shape both the probability and intensity of participation in the paddy market.

CH1: In Golestan Province, farmers' assets including land size, tractor ownership, storage facilities and surplus production are significantly associated with participation probability and participation intensity in the paddy market.

CH2: Institutional and Market Access Factors

Drawing on access theory, market transition theory, and transaction cost theory, farmers' participation decisions are shaped not only by their internal resource capacity but also by the institutional and market environment in which they operate (Renkow *et al*., 2004; Ribot & Peluso, 2003). Institutional mechanisms such as milling services, extension support, and access to market information influence farmers' ability to reduce transaction costs, interpret price signals, and coordinate with buyers (Kyaw *et al*., 2018; Morton & Martey, 2021; Ogbaro *et al*., 2022).

According to market access and transaction cost theories, geographic distance from markets and transportation costs are key constraints on farmers' direct market access (Mahuwi & Israel, 2023). In rural areas, limited processing facilities and weak transport infrastructure increase marketing costs and often compel farmers to sell through intermediaries (Andaregie *et al*., 2021; Changalima & Ismail, 2022). In Golestan Province, many paddy producers reside in rural villages located at considerable distances from urban markets and processing centers. Consequently, farm location, defined in this study as residence in rural versus more centrally connected areas, together with differences in marketing channels such as sales to consumers, millers, wholesalers, or brokers, may significantly influence both participation probability and participation intensity.

CH2: In Golestan Province, institutional and market factors, including access to mills, marketing channels, location, access to market information, and extension services, are significantly associated with participation probability and participation intensity in the paddy market.

CH3: Demographic and Human Capital Factors

Drawing on transaction cost theory and human capital theory, individual and household characteristics influence farmers' productivity, decision-making capacity, and engagement with markets (Baiyegunhi, 2024; Osmani & Hossain, 2015). Education may reduce transaction costs by improving farmers' ability to interpret market information, adopt improved technologies, and coordinate with buyers (John Kibara & Balázs Gyula, 2024;

Olwande & Mathenge, 2012). However, in contexts where processing facilities are available, more educated farmers may shift toward value addition through rice marketing rather than direct paddy sales (Denis Ruhinduka *et al.*, 2020).

Household size may also shape commercialization patterns. Larger households may increase labor availability and production capacity, yet their higher consumption needs may reduce marketable surplus (Changalima & Ismail, 2022; Khun & Lim, 2023; Mdoda *et al.*, 2024). In Golestan Province, where farm households vary considerably in demographic structure and human capital characteristics, these differences may influence both participation probability and participation intensity in the paddy market.

CH3: In Golestan Province, demographic and human capital factors, including education and household size, are significantly associated with participation probability and participation intensity in the paddy market.

Methodology

Study Area

The study was conducted in Golestan Province, in northern Iran (36°44′–38°05′ N, 53°53′–56°14′ E), covering an area of approximately 20,000 km². Influenced by the Alborz Mountains, the Caspian Sea, and the plains of Turkmenistan, the province enjoys a diverse climate favorable for agriculture. Golestan's economy relies heavily on crop production, with major crops including wheat, canola, rice, and soybeans (Motevali *et al.*, 2019). The province ranks as Iran's third-largest rice producer, cultivating about 64,000 hectares and yielding nearly 388,000 tons annually. Approximately 20.3% of the farmers grow paddy, with 126 mills processing it into rice.

Data Collection and Sample Size

This study employed a multi-stage cluster random sampling design to select paddy farmers in Golestan Province during the 2023–2024 cropping season. In the first stage, four counties (Azadshahr, Galikesh, Aliabad Katul, and Gorgan) were randomly selected from the 13 paddy-producing counties in the province (Fig. 2). In the subsequent stage, districts, sub-districts, and villages within each selected county were randomly chosen. Finally, paddy farmers within the selected villages were randomly selected and surveyed using structured questionnaires.

A preliminary survey was conducted in the four randomly selected counties, with 20 questionnaires collected from each county (80 observations in total). Based on operational considerations and proportional allocation across counties, the final sample size was set at 150 respondents. This sample size is consistent with similar empirical studies on smallholder market participation in developing countries, which commonly rely on samples ranging from approximately 140 to 180 observations (e.g.,(Hagos *et al.*, 2020; Tarekegn & Shitaye, 2022)).

Analytical Method

The market participation extent of paddy farmers was calculated using the market participation index (MPI) approach. The MPI approach, as proposed by (Govereh *et al.*, 1999) and (Strasberg *et al.*, 1999), is utilized in a modified form to determine an index quantifying the market participation intensity of paddy farmers. The paddy market participation index (*PMPI*) in eq (1). calculates the ratio of the gross value of paddy sales by i^{th} farmer in j^{th} year (j= 2023 farming season) to the gross value of all paddy produced by the same i^{th} farmer in that j^{th} year.

$$PMPI_{ij} = \frac{Gross\ value\ of\ paddy\ sale_{ij}}{Gross\ value\ of\ all\ paddy\ production_{ij}} \quad (1)$$

Figure 2- Geographical location of the study area (Golestan Province) in Iran

This measure complements the two-stage framework adopted in this study, in which the first stage models the probability of participation and the second stage evaluates the extent of participation (H1–H18). By providing a continuous indicator of commercialization intensity, the MPI enables a more detailed assessment of variation in market engagement among farmers. Research conducted by (Morton & Martey, 2021; Ndlovu *et al*., 2024; Tasila Konja & Mabe, 2023) employed this indicator to assess the extent of farmers' participation in markets.

The market participation index of paddy is calculated as the proportion of paddy sold relative to total paddy produced. Consequently, a fractional response variable arrives, providing the condition $0 \le PMPI_i \le 1$, where $PMPI_i = 0$ indicates that a paddy farmer does not engage in the market. Consequently, considering θ and a vector x comprising k covariates intended to explain the dependent variable, the emphasis is on estimating the mean response of *PMPI*, thereby estimating $E(PMPI \mid x)$. As the consequence, the linear specification $E(PMPI \mid x) = \theta$ becomes inconsistent, as it presumes a linear influence of explanatory variables on the predicted value of *PMPI*, potentially leading to predicted values outside of the limits [0, 1], and might produce nonsensical results, without valid interpretation, including that of the marginal effects (Faria *et al*., 2020).

Paddy market participation is viewed as a sequential decision-making process. In the first stage, farmers decide whether to supply paddy to the market, and in the second stage, those who participate determine the intensity of their participation. Estimating participation intensity using only market participants may lead to sample selection bias, since this group is not randomly drawn from the full farming population. If unobserved factors affect both the participation decision and sales intensity, results based only on participants cannot be generalized to all farmers. To address this issue, (Heckman, 1979) introduced the sample selection model, expressed as follows:

The model consists of two equations: a selection equation that models the participation decision, and an outcome equation that models participation intensity conditional on selection.

$$PMPI_i^* = x_i'\beta + u_i; \quad \text{Outcome equation (participation intensity)} \quad (2)$$

$$s_i = 1(w_i'\gamma + \varepsilon_i > 0); \quad \text{Selection equation (participation decision)} \quad (3)$$

$$PMPI_i = s_i PMPI_i^* \quad (4)$$

Where x_i' denotes the explanatory observed variables influencing the latent outcome $PMPI_i^*$ and defines the error term in the regression Eq. (2). s_i represents the selection equation, in this study, an observed binary variable showing a farmer's participation in the paddy market ($s_i = 1$) or non-participation ($s_i = 0$), with independent variables given by w_i', whereas ε_i is the error term of the selection Eq.(3). Both u_i and ε_i, which are assumed to follow a conditional bivariate normal distribution, capture the aggregated effects of the unobserved components in this model. They are expressed as follows:

$$\begin{pmatrix} u_i \\ \varepsilon_i \end{pmatrix} | x_i, w_i \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \rho \\ \rho & 1 \end{pmatrix}\right), \quad (5)$$

Where ρ is the correlation coefficient between u_i and ε_i. Thus, when $\rho \neq 0$, the estimation might suffer from sample selection bias. The Heckman selection model mitigates bias by calculating and including the inverse Mills' ratio (*IMR*) into the regression equation, hence facilitating unbiased outcomes (Faria et al., 2020).

Studies on the Heckman approach show that collinearity between the correction term and independent variables can substantially increase standard errors (Certo *et al.*, 2016; Clougherty *et al.*, 2016). *IMR* is statistically significant, this multicollinearity may distort coefficient estimates (Bushway *et al.*, 2007). This problem is exacerbated in the absence of exclusion restrictions, that is, variables that affect the selection equation but do not directly enter the outcome equation. Therefore, the Heckman model should include at least one variable in the first stage that is excluded from the second stage (Bushway *et al.*, 2007; Sartori, 2003). Including such restrictions reduces the correlation between the correction term and explanatory variables, improving model robustness. (Bushway *et al.*, 2007; Hoq *et al.*, 2021). Scholars agree that models with exclusion restrictions yield more reliable results, and the correlation between *w* and *IMR* can assess their strength (Bushway *et al.*, 2007; Certo *et al.*, 2016; Kennedy, 2008; Leung & Yu, 1996).

The main limitation of the Heckman sample selection model is that the regression equation (Eq. (2)) assumes a linear relationship between the regressors and the dependent variable, which may generate predicted values [0, 1] interval. Moreover, the model relies on the assumption of joint normality of the error terms in the selection and outcome equations and fails to capture unobserved individual-specific effects, which may lead to biased estimates and complicate interpretation (Faria *et al.*, 2020). Tobit models are sometimes used as an alternative; however, they are appropriate only when the dependent variable is censored at both lower and upper bounds, typically between 0 and 1. In most cases, boundary observations arise from selection mechanisms rather than true censoring. Furthermore, the Tobit specification also assumes normality and homoscedasticity of the dependent variable, which may not hold in practice (Faria *et al.*, 2020; Ramalho *et al.*, 2011).

To address these limitations, a fractional dependent variable (FDV) should be estimated using a different econometric method, providing that $E(PMPI\,|\,x)$ remains inside the valid interval [0,1], and that the estimation provides consistent and unbiased outcomes.

To address these issues, (Ramalho & da Silva, 2009) proposed the two-part fractional regression model (TP-FRM), which applies a binary specification to model the participation decision (whether to participate or not) and a fractional specification to model participation intensity, measured as the proportion of output sold. However, if the two decisions are interdependent, the model may suffer from selection bias, since unobserved factors influencing the participation decision may also affect the intensity decision, similar to the sample selection problem in the Heckman framework (Wulff, 2019). To overcome this limitation, (Schwiebert & Wagner, 2015) introduced the generalized two-part fractional regression model (GTP-FRM), which explicitly models the correlation between participation and intensity decisions. The GTP-FRM therefore generalizes the TP-FRM by allowing for dependence between the two stages, while the TP-FRM can be viewed as a restricted special case that assumes independence between them.

The estimation of the generalized two-step fractional regression model of (Schwiebert & Wagner, 2015) for the decision equation (s_i) is as follows.

$$s_i = 1(w_i'\gamma + \varepsilon_i > 0); \qquad (6)$$

Therefore, an observation (i) has a non-zero outcome if and only if $w_i'\gamma + \varepsilon_i > 0$. For simplicity, it is assumed that the error term u follows a standard normal distribution, indicating that

$$\Pr(s_i = 1 | w_i) = \Phi(w_i'\gamma) \qquad (7)$$

where $\Phi(.)$ denotes the standard normal cumulative distribution function. For the participation intensity equation in the paddy market, the conditional mean is determined as follows:

$$E(PMPI_i | x_i, w_i, s_i = 0) \qquad (8)$$

$$E(PMPI_i | x_i, w_i, s_i = 1) = \frac{\Phi_2(x'\beta, w'\gamma : \rho)}{\Phi(x'\beta)} = \frac{\Phi_2(\beta_0 + \beta_1 x_i, \gamma_1 w_{i1} + \gamma_2 w_{i2}; \rho)}{\Phi(\gamma_0 + \gamma_1 w_{i1} + \gamma_2 w_{i2})}$$

$\Phi_2(.)$ represents the bivariate standard normal distribution, with ρ denoting the correlation between participation and intensity decisions. Eq (8) is the fractional probit specification employed to simulate model nonzero values of *PMPI*.

If $\rho = 0$, the two processes in Eq (2) are independent, so the GTP-FRM simplifies to the TP-FRM, where $E(PMPI | x, w, s = 1) = \Phi(x'\beta)$. Nonetheless, if ρ > 0, the TP-FRM is specified incorrectly.

The GTP-FRM allows both x and w to influence the intensity decision. while x exerts a direct effect, w affects intensity indirectly through the participation equation (Schwiebert & Wagner, 2015). This additional complexity implies that the GTP-FRM requires an exclusion restriction for proper identification of the model. Specifically, at least one variable should affect the decision to participate in the paddy market without directly influencing the extent of participation. Such exclusion restrictions are necessary to ensure credible identification and to reduce potential collinearity between the correction term and the regressors in the second stage, which may otherwise inflate standard errors and bias the estimates(Bushway *et al*., 2007; Certo *et al*., 2016; Sartori, 2003; Wulff, 2019). In the absence of exclusion restrictions, the predicted correction component may be highly correlated with the explanatory variables in the outcome equation, weakening the robustness of the estimates (Hoq *et al*., 2021). Accordingly, in equation 7, $x_i = w_{i1}$ for all i= 1, 2, …, n. while w_{i2} is excluded from the second process and serves as the identifying restriction required for consistent estimation of the model (Schwiebert & Wagner, 2015).

The extended two-part model can be estimated using quasi maximum likelihood (QML). The log-likelihood function is expressed as:

$$\log L(\theta) = \sum_{i=1}^{n} l_i(\theta) \equiv \qquad (9)$$

$$\sum_{i=1}^{n} \{(1 - s_i)\log(1 - \Phi(w_i'\gamma)) + s_i \log\Phi(w_i'\gamma)$$

$$+ s_i \left[\begin{array}{l} (1 - PMPI_i)\log\left(1 - \dfrac{\Phi_2(x'\beta, w'\gamma : \rho)}{\Phi(x'\beta)}\right) \\ + PMPI_i \log\dfrac{\Phi_2(x'\beta, w'\gamma : \rho)}{\Phi(x'\beta)} \end{array} \right] \}$$

where $\theta = (\beta', \gamma', \rho)'$ denotes the parameter vector to be estimated. Also, the conditional mixed processes approach was used to estimate the generalized bipartite fraction model in Stata (Wulff, 2019).

In ordinary binary probit and fractional probit models, the estimated coefficients represent changes in the underlying latent index rather than direct changes in predicted probabilities. Because the relationship between the regressors and the probability is nonlinear, the coefficients cannot be interpreted directly in probability terms (Wulff, 2019). Therefore, marginal effects are computed to obtain meaningful interpretations in terms of changes in the probability of participation and the expected proportion of output sold. For the GTP-FRM model, the marginal effects of the variable x_k are calculated as follows:

$$E[PMPI_i | x_i, w_i] = \Pr(s_i = 0 | w_i)$$
$$E[PMPI_i | x_i, w_i, s_i = 0] + \Pr(s_i = 1 | w_i)$$
$$E[PMPI_i | x_i, w_i, s_i = 1] = 0 + \Phi_2(x_i'\beta, w_i'\gamma : \rho) \quad (10)$$

due to a small change in x_k. Consequently, the marginal effect is expressed as:

$$\frac{\partial E[PMPI_i | x_i, w_i]}{\partial x_k} = \frac{\partial \Phi_2(x_i'\beta, w_i'\gamma : \rho)}{\partial x_k} \quad (11)$$

For a specific individual *i*, where x_k may be present in both x and w. The average marginal effect is calculated as:

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial \Phi_2(x_i'\beta, w_i'\gamma : \rho)}{\partial x_k}, \quad (12)$$

which is simply the marginal effect averaged over all individuals (Schwiebert & Wagner, 2015; Wulff, 2019).

Therefore, the marginal effects of the explanatory variables are computed as follows: Equation (13) defines the marginal effects on the probability of participation in the paddy market, while Equation (14) specifies the marginal effects on the conditional mean of participation intensity. These expressions allow for an interpretable assessment of how changes in explanatory variables affect both stages of market participation (Diakité *et al.*, 2025; Schwiebert & Wagner, 2015; Wulff, 2019).

$$\frac{\partial \Pr(s_i = 1 | w_i)}{\partial w_k} \quad (13)$$

$$\frac{\partial E(PMPI_i | x, w, s = 1)}{\partial x_k} \quad (14)$$

Before starting the analysis, the assumption of collinearity and examination of the omitted variable and functional form were performed using the variance inflation factor (VIF) and Ramsey tests, respectively (Ramalho *et al.*, 2011; Wulff, 2019).

All estimations were performed using Stata 17. To further address the risk of overfitting and multicollinearity, and to systematically select the most relevant predictors for the participation decision, we employed the Least Absolute Shrinkage and Selection Operator (LASSO) prior to the main two-part model. Given the binary nature of the dependent variable in the selection equation, a probit LASSO was applied. The tuning parameter λ (lambda), which determines the strength of the penalty, was chosen by 10-fold cross-validation minimizing the cross-validated deviance. This procedure automatically shrinks the coefficients of irrelevant variables exactly to zero. At the optimal λ (0.018), 15 out of 21 candidate variables retained non-zero coefficients and were subsequently used as predictors in the estimation of both the two-stage Heckman model and the generalized two-part fractional regression. A detailed list of all candidate variables, their LASSO selection status, and standardized coefficients is provided in Table 1. This data-driven selection helps to preserve degrees of freedom and enhance statistical power in the subsequent non-linear multivariate analysis.

Empirical Results and Discussion

Descriptive Analysis

Table 2 provides a descriptive summary of the independent variables influencing farmers' participation in the paddy market, based on frequency distribution and chi-square analyses. Out of 150 respondents, 64% were active market participants.

Several binary factors, such as vehicle ownership, access to milling and storage facilities and extension contact, exhibited significant effects on market participation. Additionally, education level, cultivated land area, and market channel showed statistically significant differences at the 1% level. According to Table 3, the average market participation intensity among all farmers was 49%, while for active participants it reached 77%, suggesting that these farmers sold more than half of their total paddy production.

Table 1- Definition of variables and LASSO selection results

Variable name	Definition	LASSO coefficient (Standardized)
Dependent variable		
Market participation	Dummy: 1 if the farmers participate in the Paddy market, 0 otherwise	-
Paddy market participation index (PMPI)	Continuous: Gross value of paddy sold to gross value of all paddy production	-
Independent variable		
Land Ownership	1 If the farmer owns the land, 0 otherwise	-
Farm size		
Small scale	1= If the farm is less than three hectares	
Medium scale	2= If the farm is more than three and less than ten hectares	0.553
Large scale	3= If the farm is more than ten hectares.	
		0.075
tractor ownership	1 If the farmer owns the tractor, 0 otherwise	-0.015
non-farm income	1 If the farmer is engaged in a non-agricultural activity, 0 otherwise	-
Market surplus	The amount of surplus production (1000 tons)	0.931
Storage facilities	1 if the farmer has storage facilities, 0 otherwise	-0.136
Access to mill	1 if the farmer has access to a mill, 0 otherwise	-1.248
Market channels		
Consumer	1= Final consumer Buyer	
Miller	2= Mill Buyer	0.335
Wholesaler	3= Wholesale Buyer	0.163
Broker	4= Broker Buyer	0.921
Location	1 if the farmer lives in the village, 0 otherwise	0.322
Extension services	1 if the farmer has contacted the extension services, 0 otherwise	0.080
Market information	1 if farmer has access to market information, 0 otherwise	0.256
Access to fertilizer	1 if the farmer has access to fertilizer, 0 otherwise	-
Paddy variety	1 If the farmer grows a local variety of paddy, 0 otherwise	-
Age	Farmer age (year)	-
Education		
Below the diploma	1= Farmer with a degree below a diploma	
Diploma	2= Farmer with a diploma	-0.189
Bachelor or Above Bachelor	3= Farmer with a bachelor's or above a bachelor's degree	-0.138
Experience	Farming experience Number (year)	-
Household size	Household size of farmer	-0.171

Model Specification with Exclusion Restriction

This study employed the Heckman two-step model and the generalized two-part fractional regression to identify factors affecting farmers' participation decisions and the intensity of market involvement. Prior to estimation, appropriate exclusion restrictions for the outcome equation were identified following (Hoq *et al.*, 2021), taking into account multicollinearity diagnostics, correlations among explanatory variables, and the properties of the correction term. In the Heckman framework, a first-stage probit model was estimated to analyze the participation decision. The Inverse Mills Ratio (IMR) was then derived from the first-stage probit and included in the second-stage regression to correct for potential selection bias. Multicollinearity and correlations between the IMR and the explanatory variables were assessed using the Variance Inflation Factor (VIF) and pairwise correlation coefficients. In applied econometrics, a VIF below 5 and a correlation coefficient below 0.5 are commonly used benchmarks to indicate acceptable levels of multicollinearity (Hoq *et al.*, 2021; Kim, 2019). As reported in Table 4, the VIF for the IMR was 9.50, indicating potential multicollinearity concerns between the IMR and certain explanatory variables.

Table 2- Disaggregated descriptive statistics of market participation decision for classified variables

Variables	Category	Not Participated 54(36)	Participated 96 (64)	Total 150 (100)	Chi-square value
		Market participation decision			
Education	Below the diploma	25(46.3)	23(24)	48(32)	8.881**
	Diploma	11(20.3)	36(37.5)	47(31.3)	
	Bachelor or Above Bachelor	18(33.3)	37(38.5)	55(36.6)	
Farm size	Small scale	45(83.3)	41(42.7)	86(57.3)	23.445***
	Medium scale	6(11.1)	41(42.7)	47(31.3)	
	Large scale	3(5.6)	14(14.6)	17(11.4)	
Tractor ownership	No	28(51.9)	26(27)	54(36)	9.202***
	Yes	26(48.1)	70(73)	96(64)	
Storage facilities	No	12(22.2)	63(65.7)	75(50)	26.041***
	Yes	42(77.8)	33(34.3)	75(50)	
Access to mill	No	12(22.2)	71(74)	83(55.3)	37.427***
	Yes	42(77.8)	25(26)	67(44.7)	
Market channel	Consumer	23(42.6)	2(2)	25(16.7)	53.432***
	Miller	4(7.4)	16(16.7)	20(13.3)	
	Wholesaler	2(3.7)	28(29.2)	30(20)	
	Broker	16(29.6)	50(52.1)	66(44)	
Location	City	18(33.3)	34(35.4)	52(34.6)	0.066
	Village	36(66.6)	62(64.6)	98(65.4)	
Extension services	No	31(57.4)	35(36.5)	66(44)	6.155*
	Yes	23(42.6)	61(63.5)	84(56)	
Market information	No	8(14.8)	7(7.3)	15(10)	2.173
	Yes	46(85.2)	89(92.7)	135(90)	

Note: The value in parentheses is the percentage of frequency, (***, **, * indicates the 1%, 5% and 10% levels of significance)

Table 3- Market participation decision with continuous independent variables

Variables	Participated Mean	Participated Sta. Dev	Not Participated Mean	Not Participated Sta. Dev	t-value	Total Mean	Total Sta. Dev
	Market participated decision						
Market participation index	0.77	0.25	0	0	-21.85***	0.49	0.42
Household size	3.74	1.24	4.47	1.73	2.90***	4.01	1.48
Market surplus	29.52	30.92	6.98	14.03	5.06***	21.41	28.24

(***, **, * indicates the 1%, 5% and 10% levels of significance)

Fig. 3 shows that the variables related to storage facilities (0.625) and access to milling services (0.716) have the highest correlations with the IMR among all explanatory variables. As stated in Table 4, excluding these variables reduced the VIF from 9.50 to 2.48, confirming their strong correlation with other predictors and improving the model's specification.

Access to milling services influences the decision to participate in the market, as farmers with milling capacity usually sell their paddy in processed form (Rice) rather than as paddy (Denis Ruhinduka *et al.*, 2020; Nakazi & Sserunkuuma, 2013).

Table 4- Variance Inflation Matrix (VIF) of the independent variables used in probit model.

Variable name	VIF	
	Before of exclusion restriction	After of exclusion restriction
Diploma	1.81	1.77
Bachelor	2.14	2.08
Household size	1.18	1.17
Medium scale	1.94	1.67
Large scale	3.79	3.45
Tractor ownership	1.56	1.55
Market surplus	3.71	3.47
Storage facilities	2.75	-
Access to mill	8.23	-
Miller	4.48	2.47
Wholesaler	3.57	3.46
Broker	3.42	3.26
Location	1.36	1.23
Extension services	1.50	1.48
Market information	1.46	1.24
IMR	9.50	2.48
Mean VIF	3.27	2.20

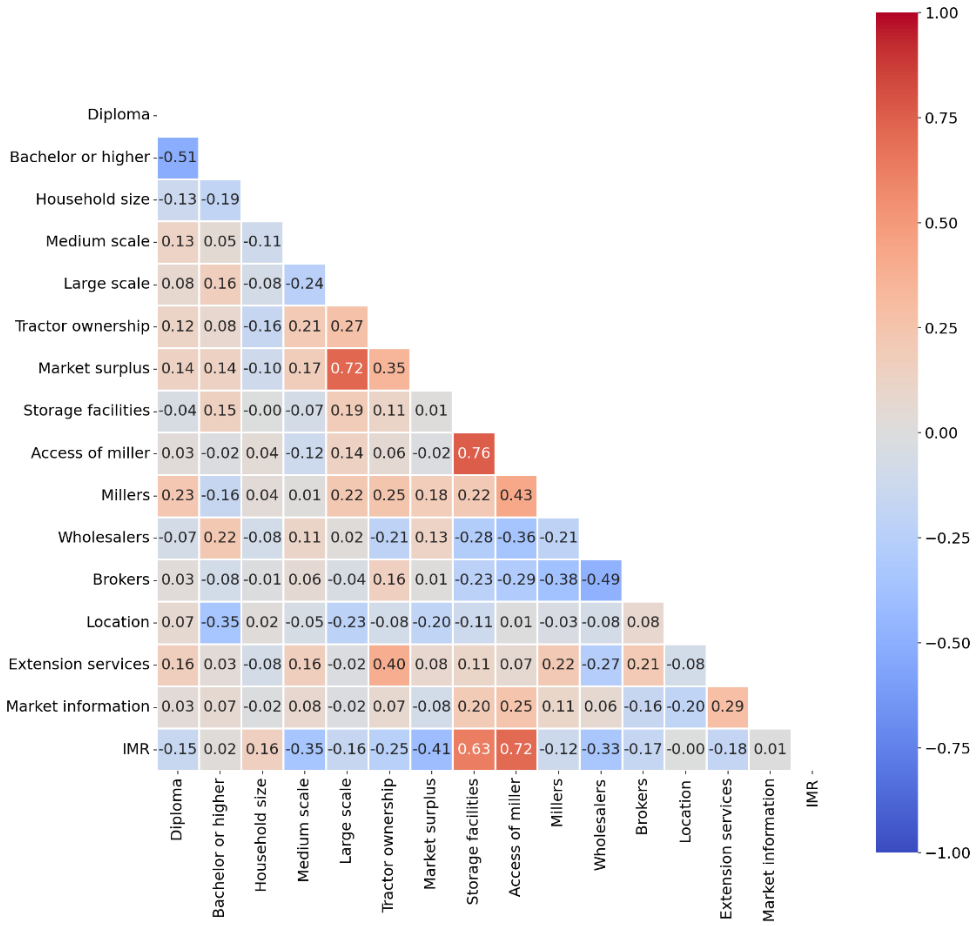

Figure 3- Heatmap of the correlation matrix of explanatory variables

Likewise, access to storage facilities primarily affects participation decisions by allowing farmers to store processed rice and sell it later during favorable market conditions (Dey & Singh, 2023). For these reasons, both variables were excluded from the second stage of estimation in both models.

Table 5 presents the estimation results of the Heckman two-step and GTP-FRM models. The Wald statistics for both models are statistically significant at the 1% level, indicating the joint significance of the explanatory variables and confirming that the models are properly specified.

Table 5- Estimation results of the two-stage Heckman model and generalized two- part fractional regression

Variable	Heckman's two-step selection model				GTP-FRM			
	Probit		OLS		Probit		Fractional	
	Coef	S. E	Coef	S. E	Coef	S. E	Coef	S. E
Storage facilities	0.155	0.901			0.156	0.579		
Access to mill	-4.419***	1.362			-4.382***	0.923		
Market surplus	0.034*	0.019	0.005***	0.001	0.032**	0.016	0.025***	0.007
Farm size	Small scale is a base category							
Medium scale	1.988**	0.872	-0.141***	0.056	2.029***	0.757	-0.590***	0.196
Large scale	0.663	1.214	-0.428***	0.121	0.685	1.104	-1.813***	0.438
Tractor ownership	-0.126	0.632	0.030*	0.063	-0.159	0.695	0.100**	0.234
Market information	2.561**	1.188	-0.232*	0.129	2.523***	0.953	-2.054***	0.431
Extension services	0.080	0.637	0.188**	0.054	0.122	0.547	0.505***	0.188
Market Channel	Consumer is a base category							
Miller	3.246**	1.392	0.156	0.169	3.257***	0.778	0.411	0.275
Wholesaler	2.847*	1.463	0.203	0.167	2.841***	1.007	0.583*	0.306
Broker	1.379	1.045	0.040	0.158	1.367***	0.518	0.144	0.235
Location	1.181*	0.713	-0.010	0.050	1.144***	0.577	0.010	0.189
Education	Below the diploma is a base category							
Diploma	-1.456	0.909	-0.034	0.061	-1.488**	0.725	-0.130	0.214
Bachelor or Above Bachelor	-1.017	0.897	0.015	0.068	-1.018	0.648	0.069	0.211
Household size	-0.249	0.216	-0.011	0.019	-0.249	0.160	-0.053	0.060
IMR			-0.751**	0.335				
Constant	-1.098	1.394	1.010***	0.269	-1.044**	0.943	2.188	0.361
rho					-0.477**	0.170		
Wald chi2	130.55***				146.54***			
RESET test					0.33		5.58*	

(***, **, * indicates the 1%, 5% and 10% levels of significance)

In the Heckman model, the coefficient of the Inverse Mills Ratio (IMR) is statistically significant at the 5% level, indicating that correcting for selection bias is necessary. In the GTP-FRM model, the estimated correlation coefficient ρ (−0.477) is statistically significant at the 1% level, reflecting dependence between the participation and intensity decisions. These results suggest that unobserved factors simultaneously influence both the decision to participate in the paddy market and the extent of participation, thereby confirming the presence of selection effects and interdependence between the two stages (Regasa Megerssa *et al.*, 2020; Schwiebert & Wagner, 2015).

Although the Heckman model corrects for selection bias, it assumes a linear relationship between the independent variables and the dependent variable in the outcome equation, making it inappropriate for modeling bounded fractional outcomes. As a result, 8 out of 150 predicted values for paddy market participation intensity fall outside the valid range of [0,1]. Predictions outside this admissible interval distort the calculation of average marginal effects, as they violate the bounded nature of the dependent variable and may bias the estimated effects (Faria *et al.*, 2020). In contrast, the GTP-FRM model, provides more stable and consistent estimates, with a larger number of statistically significant variables and stronger effects across both stages. Furthermore, the Ramsey RESET test was applied to assess functional form misspecification. The non-rejection of the null hypothesis for both components of the GTP-FRM at the 5% significance level indicates no evidence of functional form misspecification, thereby supporting the validity of the model specification. Accordingly, the discussion of average marginal effects in the following section focuses on the GTP-FRM results.

Determinants of Participation Decision and Intensity

The average marginal effects (AME) of explanatory variables on the probability and intensity of farmers' participation in the paddy market are presented in Table 6. Results related to farmers' assets indicate farm size positively affects the likelihood of participation. At the 1% significance level, the probability of participation among medium-scale farmers is 17.4% higher than small-scale farmers, supporting hypothesis H1a. However, the effect on participation intensity for medium-scale farmers is only 0.026 points on the fractional intensity scale (bounded between 0 and 1) and is statistically insignificant. Therefore, hypothesis H1b is rejected due to the absence of statistical significance, indicating that farm size does not have a meaningful effect on the share of the gross value of paddy production that is marketed. This suggests that although medium-scale farmers are more likely to enter the market, the value-based share of paddy sold does not differ significantly from that of small-scale farmers. These findings are consistent with previous studies on rice market participation (Lopera *et al*., 2023; Tesfahun *et al*., 2022).

For large-scale farmers, the probability of participation is slightly higher than small-scale farmers; however, their participation intensity is 0.273 points lower and statistically significant at the 1% level, confirming hypothesis H1b. This indicates that although large-scale farmers are more likely to participate, they allocate a smaller share of the gross value of their paddy production to paddy sales. Their lower participation intensity may reflect stronger financial capacity, better access to storage and milling facilities, and reduced transaction costs, which enable them to process paddy and market rice instead of selling paddy directly (Denis Ruhinduka *et al*., 2020).

Table 6- Average marginal effects for decision to participate and intensity of market participation

Variable	Decision to participate (1)		intensity of participation (2)	
	AME[a]	Std. E	CAME[b]	Std. E
Storage facilities	0.013	0.050	0.010	0.037
Access to mill	-0.377***	0.058	-0.280***	0.050
Market surplus	0.003**	0.001	0.006***	0.001
Farm size	Small scale is a base category			
Medium scale	0.174***	0.058	0.026	0.054
Large scale	0.058	0.093	-0.273***	0.093
Tractor ownership	-0.013	0.059	0.007	0.053
Extension	0.010	0.047	0.096**	0.040
Market information	0.217***	0.064	-0.198**	0.098
Market Channel	Consumer is a base category			
Miller	0.280***	0.069	0.280***	0.066
Wholesaler	0.244***	0.087	0.284***	0.080
Broker	0.117**	0.049	0.113**	0.054
Location	0.098**	0.042	0.075*	0.042
Education	Below the diploma is a base category			
Diploma	-0.128*	0.068	-0.118**	0.059
Bachelor or Above Bachelor	-0.087*	0.058	-0.053	0.054
Household size	-0.021	0.013	-0.025*	0.013

Note: [a] Reporting average marginal effects, [b] Reporting average marginal effects conditional, (***, **, * indicates the 1%, 5% and 10% levels of significance).

The volume of marketable surplus has a positive and statistically significant effect on the likelihood of participation in the paddy market at the 5% level, confirming hypothesis H3a. Specifically, a 1% increase in marketable surplus is associated with an increase in the probability of participation of approximately 0.3 percentage points. More importantly, the positive and statistically significant effect indicates that higher paddy productivity strengthens farmers' engagement in the market.

Similar evidence is reported by (Morton & Martey, 2021) for rice farmers. Among participants, the average marginal effects show that a 1 percent increase in surplus leads to a 0.6% rise in participation intensity, confirming hypothesis H3b at the 1% level. This result aligns with findings by (Kyaw *et al.*, 2018; Morton & Martey, 2021; Reyes *et al.*, 2012), who argue that higher rice output generates larger surpluses, encouraging stronger market participation.

According to Table 6, institutional and market variables such as access to mills, market channels, location, and market information significantly influence farmers' participation in the paddy market. Access to mills has a negative and statistically significant effect at the 1% level, confirming hypothesis H5a. Specifically, farmers with access to milling services are 37.7% less likely to sell paddy, as they prefer to process it into rice and sell it at a higher price. This finding is consistent with (Denis Ruhinduka *et al.*, 2020), who reported that distance to mills significantly affects farmers' decisions on whether to market their output as paddy or as rice.

Access to extension services shows no statistically significant effect on the probability of participation in the paddy market, leading to the rejection of H6a due to the absence of statistical significance in the participation decision equation. However, conditional on participation, access to extension services has a positive and statistically significant effect on participation intensity at the 5% level, with a coefficient of 0.096, thereby confirming H6b. This positive effect suggests that access to extension services improves production and market engagement by increasing awareness of input markets, modern practices, high-yielding varieties, and weather conditions. Similar findings were observed by (Abdullah *et al.*, 2019; Maesela *et al.*, 2023; Mathenjwa *et al.*, 2025), who also report that access to extension services improves production performance and consequently increases the intensity of market participation.

Access to market information has a positive and statistically significant effect on the probability of farmers participating in the paddy market at the 1% level, confirming hypothesis H7a. Improved access to information increases the likelihood of participation by 21.7%, as farmers use data on prices, buyers, and demand to reduce transaction costs and plan sales more effectively (Dlamini & Huang, 2019). However, access to market information has a significant negative effect on participation intensity at the 5% level, leading to the rejection of H7b. A one-unit increase in access reduces participation intensity by 0.19 points on the fractional intensity scale. This suggests that informed farmers, aware of price differences, are more likely to process and sell rice when milling facilities are available (Kyaw *et al.*, 2018; Tesfahun *et al.*, 2022). Overall, these findings are consistent with prior studies confirming that access to market information improves farmers' ability to engage strategically in agricultural markets (Claude *et al.*, 2025; Dey & Singh, 2023; Gebre & Deshmukh, 2024; Regasa Megerssa *et al.*, 2020).

Selling to wholesalers, mills, or brokers rather than directly to retailers or consumers significantly increases the probability of participating in the paddy market at the 1% level, confirming hypothesis H8a. Specifically, sales to millers, wholesalers, and brokers raise the likelihood of participation by 28%, 24.4%, and 11.7%, respectively. Among participating farmers, these channels also enhance the intensity of market participation by 28%, 28.4%, and 11.3%, respectively, confirming hypothesis H8b. These findings suggest that intermediaries such as wholesalers and brokers play a crucial role in facilitating market access, as they primarily purchase unprocessed paddy and possess stronger bargaining power and negotiation capacity. The predominance of paddy producers in rural areas, far from urban markets and processing centers, combined with high transaction costs, discourages direct sales to retailers and consumers. Similar conclusions are reported by (Changalima & Ismail, 2022; Mahuwi & Israel, 2023; Zhang *et al*., 2019), who emphasize that reliance on intermediaries reflects structural limitations and cost barriers within the marketing chain.

Location has a positive and statistically significant effect on the probability of farmers participating in the paddy market at the 5% level, confirming hypothesis H9a. The probability of participation for rural farmers is 0.098 higher than for urban farmers. Furthermore, location has a positive and statistically significant effect on the intensity of paddy market participation at the 10% significance level, with a coefficient of 0.075. Since the dependent variable in this model specifically captures participation in the paddy market, that is, the sale of raw paddy rather than processed rice, this result suggests that rural producers, who are typically located farther from modern processing facilities and face higher transaction costs, are more likely to sell their output as paddy at the farm gate to brokers and wholesalers. This finding aligns with previous studies showing that greater market distance reduces direct participation, as reported for rice by (Hoq *et al*., 2021) and for vegetables by (Gebre & Deshmukh, 2024). Similarly, (Mathenjwa *et al*., 2025) found that long travel distances discourage rural producers from accessing markets due to high transportation costs.

Among human capital factors, education level significantly influences the probability of participation in the paddy market. As shown in Table 6, higher education levels are associated with a decline in participation probability at the 10% level, confirming hypothesis H10a. Specifically, farmers with a high school diploma and a bachelor's degree are 12.8 and 8.7% less likely to participate compared with those having less than a diploma. Conditional marginal effects further indicate that, among participants, education negatively affects participation intensity, confirming hypothesis H10b. Farmers with a diploma exhibit 11.8 percentage points lower intensity, while those with a bachelor's degree also show reduced participation.

These results align with findings by (Musah, 2013) for maize and (Abdullah *et al*., 2019) for rice. Higher education improves farmers' knowledge and adoption of modern technologies (Asfaw *et al*., 2022; Regasa Megerssa *et al*., 2020), enhancing productivity and enabling more diversified marketing strategies. Educated farmers, aware of price differentials and market dynamics, often process and sell part of their produce as rice when milling facilities are available, thereby reducing their participation in the paddy market. A similar negative association between education and market participation was also reported by (Worku *et al*., 2021) with chickpea producers.

Household size shows no statistically significant effect on the probability of participation, leading to the rejection of H11a. Due to the absence of statistical significance in the participation decision equation. However, conditional on participation, household size has a negative and statistically significant effect on participation intensity at the 10% level, thereby confirming H11b. Specifically, each additional household member reduces participation intensity by approximately 2.5 ٪ points. Larger families tend to allocate a greater share of production to household consumption, which reduces the marketable surplus. Moreover, the availability of additional family labor provides labor capacity that facilitates rice processing and marketing, thereby reducing paddy sales and lowering participation intensity in the paddy market. Similar findings were observed by (Kyaw et al., 2018; Regasa Megerssa et al., 2020), who observed that higher household consumption lowers the volume of produce offered for sale.

Conclusion

This study contributes to the literature by applying the generalized two-part fractional regression model (GTP-FRM) to jointly examine both the participation decision and participation intensity among paddy farmers. By explicitly accounting for the bounded nature of the dependent variable and the interdependence between the two stages of market behavior, the model provides a more appropriate and robust framework for analyzing commercialization dynamics. The findings indicate that human capital, asset endowment, production capacity, and institutional factors jointly shape farmers' market outcomes. Education is negatively associated with paddy market participation; however, this does not imply withdrawal from markets. Rather, it reflects a strategic shift toward value addition, as more educated farmers tend to process paddy into rice to capture higher margins. Farm size exhibits heterogeneous effects: medium-scale farmers are more likely to participate, whereas large-scale farmers allocate a smaller share of the gross value of their paddy production to paddy sales.

Institutional and market factors display differentiated impacts. Access to market information increases the probability of participation but reduces participation intensity in paddy markets, suggesting that informed farmers strategically redirect output toward higher-value channels. Similarly, access to milling facilities encourages rice marketing rather than paddy sales, reinforcing the role of value addition in shaping market behavior.

Overall, the results reveal that participation intensity is driven not only by resource endowment but also by strategic marketing choices. From a policy perspective, reducing transaction costs while supporting value addition and productivity growth emerges as a central priority. Strengthening rural infrastructure, improving market information systems, expanding access to productivity-enhancing inputs, and facilitating financial and organizational support constitute four key policy pillars. These priorities are directly grounded in the empirical findings, particularly the heterogeneous effects of farm size, the dual impact of market information, and the role of surplus production in shaping participation intensity.

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Policy Recommendations

Increasing investment in rural infrastructure- The results highlight the importance of post-harvest infrastructure, particularly storage and milling services, in influencing marketing choices. Investment in rural storage facilities and modern milling infrastructure can reduce post-harvest losses and transaction costs while enabling value addition and improved market integration.

Strengthen market information systems- Access to market information was found to be positively associated with both participation probability and intensity. Enhancing real-time price dissemination and market transparency through digital platforms and extension networks can reduce information asymmetries and support more strategic marketing decisions among paddy producers.

Support formation and capacity-building of farmer groups- Given the significant role of marketing channels and location in shaping participation outcomes, strengthening farmer organizations can improve bargaining power, reduce intermediation costs, and facilitate access to more favorable market outlets. Cooperative structures may help farmers overcome spatial and transaction cost constraints identified in the analysis.

Expand access to agricultural credit and financial services- The empirical results indicate that factors such as surplus production and farm size are positively associated with both participation probability and participation intensity. Improving access to agricultural credit can enable smallholder farmers to invest in productivity-enhancing inputs and technologies, thereby increasing their marketable surplus and strengthening their engagement in the paddy market.

Tailor extension services to market orientation- Extension access was positively associated with participation outcomes. Expanding extension programs to include marketing literacy, value chain awareness, and price negotiation skills, alongside technical production advice, can further enhance farmers' commercialization capacity.

Future Research Directions

While this study provides valuable insights into the factors influencing market participation among paddy farmers in Golestan Province, several areas require further investigation. Comparative studies should be conducted in other paddy-producing provinces, such as Mazandaran and Gilan, to identify region-specific challenges and opportunities in the rice value chain. This will help develop a more comprehensive understanding of market participation dynamics across Iran.

The broader socio-economic impacts of market participation, including its effects on household welfare, food security, and rural development, remain underexplored. Future studies should assess these impacts to provide a comprehensive understanding of how market participation shapes farmers' livelihoods and contributes to sustainable agricultural development in Iran. In addition, subsequent research may explore potential interaction effects among structural, institutional, and production-related factors to examine whether certain determinants reinforce or moderate each other in shaping participation behavior. Expanding the analytical framework to incorporate financial intermediation, market risk, and organizational participation could further enrich the understanding of commercialization dynamics in the agricultural sector.

Methodological Improvements

The primary limitation of this study relates to the use of cross-sectional data, which constrains the ability to capture dynamic adjustments in farmers' market participation behavior and limits causal interpretation. Although the econometric framework corrects for observable heterogeneity and potential selection bias, unobserved time-varying factors cannot be fully addressed within a single-period dataset.

A second limitation concerns the identification strategy in the Heckman and GTP-FRM specifications. Access to mills and storage facilities has been used as exclusion restrictions. While these variables are theoretically justified and statistically valid within the model, alternative instruments could potentially strengthen identification robustness. In addition, certain environmental and infrastructural dimensions, such as climate variability, water availability, and transportation conditions, are not explicitly modeled, which may limit the comprehensiveness of the analysis.

A third methodological consideration relates to the sample size relative to the number of predictors. Although the LASSO procedure reduced the initial set of 21 candidate variables to 15 relevant predictors, the ratio of observations to estimated parameters in the two-part nonlinear framework remains modest. This may affect the precision of some estimates and the power of significance tests, especially for variables with small effect sizes. Nevertheless, the use of LASSO helped to preserve degrees of freedom and mitigate overfitting given the cross-sectional nature of the data.

Appendix

Appendix A: Disaggregated Hypotheses

H1: In Golestan Province, larger farm size is positively associated with the probability (H1a) and the extent (H1b) of participation in the paddy market.

H2: In Golestan Province, tractor ownership is positively associated with the probability (H2a) and the extent (H2b) of participation in the paddy market.

H3: In Golestan Province, greater paddy production surplus is positively associated with the probability (H3a) and the extent (H3b) of participation in the paddy market.

H4: In Golestan Province, access to storage facilities is negatively associated with the probability (H4a) and the extent (H4b) of participation in the paddy market.

H5: In Golestan Province, access to milling services is negatively associated with the probability (H5a) and the extent (H5b) of participation in the paddy market.

H6: In Golestan Province, access to extension services is positively associated with the probability (H6a) and the extent (H6b) of participation in the paddy market.

H7: In Golestan Province, access to market information is positively associated with the probability (H7a) and the extent (H7b) of participation in the paddy market.

H8: In Golestan Province, marketing channels are significantly associated with the probability (H8a) and the extent (H8b) of participation in the paddy market.

H9: In Golestan Province, farm location is significantly associated with the probability (H9a) and the extent (H9b) of participation in the paddy market.

H10: In Golestan Province, higher education level is negatively associated with the probability (H10a) and the extent (H10b) of participation in the paddy market.

H11: In Golestan Province, larger household size is negatively associated with the probability (H11a) and the extent (H11b) of participation in the paddy market.

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چکیده

برنج به‌عنوان دومین محصول راهبردی پس از گندم، نقشی محوری در پایداری معیشت روستاییان و تأمین درآمد کشاورزان ایران ایفا می‌کند. با وجود این جایگاه، موانع ساختاری، نهادی و مرتبط با بازار، همچنان تجاری‌سازی مؤثر را برای تولیدکنندگان شلتوک با محدودیت مواجه ساخته است. پژوهش حاضر با هدف شناسایی عوامل تعیین‌کننده تصمیم به مشارکت و شدت مشارکت در بازار شلتوک در استان گلستان انجام شد. داده‌ها در فصل زراعی ۱۴۰۳–۱۴۰۲ با استفاده از پرسشنامه‌ای ساختاریافته، از ۱۵۰ تولیدکننده شلتوک جمع‌آوری گردید. تحلیل داده‌ها با به کارگیری مدل رگرسیون کسری دو بخشی تعمیم یافته (GTP-FRM) صورت گرفت که به‌طور همزمان تصمیم دودویی مشارکت و سهم شلتوک عرضه شده به بازار را برآورد می‌کند و در عین حال ماهیت کران دار متغیر وابسته و وابستگی احتمالی بین مراحل مختلف مشارکت را نیز مدنظر قرار می‌دهد. متغیرهای توضیحی شامل ویژگی‌های سرمایه انسانی (تحصیلات و بعد خانوار)، دارایی‌های سرمایه‌ای (سطح زیر کشت و مکانیزاسیون) و متغیرهای نهادی و دسترسی به بازار (خدمات شالیکوبی، تأسیسات انبارداری، اطلاعات بازار و کانال‌های بازاریابی) بودند. یافته‌ها حاکی از آن است که ۶۴ ٪ از کشاورزان در بازار شلتوک مشارکت دارند و به‌طور میانگین ۴۹ ٪ از ارزش ناخالص تولید به فروش می‌رسد. تحصیلات رابطه منفی با مشارکت در بازار شلتوک دارد که بیانگر تغییر راهبردی به سوی ارزش افزایی است؛ به گونه‌ای که کشاورزان دارای سطح تحصیلات بالاتر، تمایل دارند محصول شلتوک خود را فرآوری و به‌صورت برنج به بازار عرضه نمایند. در مقابل، افزایش سطح زیر کشت و مازاد تولید، به‌طور معناداری احتمال مشارکت و شدت آن را افزایش می‌دهد. متغیرهای نهادی و بازار نیز نقش‌های متمایزی ایفا می‌کنند: دسترسی به اطلاعات بازار، احتمال مشارکت را افزایش می‌دهد، در حالی‌که دسترسی به تسهیلات شالیکوبی، احتمال مشارکت در بازار شلتوک را کاهش و می‌تواند باعث افزایش مشارکت در بازار برنج شود. به‌طور کلی، نتایج نشان می‌دهد که تجاری سازی در استان گلستان نه تنها تحت تأثیر ظرفیت تولید، بلکه تحت تأثیر راهبردهای ارزش افزایی و ملاحظات هزینه‌های مبادله در چارچوب سیاست‌ها و ساختارهای بازار موجود شکل می‌گیرد. از این رو، طراحی و اجرای سیاست‌هایی که بر بهبود زیرساختهای فرآوری روستایی، تقویت سامانه‌های اطلاعات بازار، افزایش مازاد تولید و کاهش موانع نهادی متمرکز باشند، می‌تواند به‌طور مؤثرتری از مشارکت و تجاری‌سازی پایدار در میان تولیدکنندگان شلتوک استان گلستان حمایت کند.

واژه‌های کلیدی: برنج، محدودیت‌های نهادی، مدل‌های کسری، مشارکت در بازار، هزینه‌های مبادله

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