Farm to Non-Farm Transition and Diversification in Rwanda: A Path to Prosperity?

Abstract

This study investigates the drivers and impacts of transitions from farm to non-farm activities in Rwanda. Using nationally representative data from the Integrated Household Living Conditions Surveys (EICV), the Shapley Additive Explanation (SHAP) algorithm coupled with Random Forest was employed to identify key households and individual-level factors shaping livelihood choices. The Multinomial Endogenous Treatment Effects model was employed to examine the implications of the transition on household well-being, agricultural productivity, and rural economic diversification. The findings show that households specializing exclusively in non-farm activities experience modest reductions in poverty but without clear productivity gains, while those diversifying across farm and non-farm activities achieve substantial improvements in labor productivity but with limited poverty reduction effects. In terms of policy, these results imply that non-farm work alone is not a guaranteed pathway out of multidimensional poverty unless accompanied by improvements in job quality, stability, and earnings. By contrast, diversification offers resilience benefits that reduce vulnerability, though without significantly raising incomes per hour. These findings point to recommendations that Rwanda's rural development strategy should focus on (i) enhancing the quality and inclusiveness of non-farm employment, (ii) supporting multi-activity livelihood strategies through credit, infrastructure, and skills development, and (iii) promoting synergies between farm and non-farm sectors to ensure that productivity gains translate into broad-based poverty reduction.

Keywords: Non-farm transition; Rural livelihoods; Multidimensional Poverty; Land Scarcity; Rwanda

1. Introduction

Rural transformation is one of the structural economic changes recently experienced in developing countries. It is a manifestation of a progressive shift from traditional agricultural livelihoods to a more diversified portfolio of income-generating activities. In Sub-Saharan Africa (SSA), this transformation is occurring at an uneven pace due to national policies, demographic pressures, global economic shifts, and domestic institutional frameworks (Barrett et al., 2001; Haggblade et al., 2010). Unlike the experiences in East and Southeast Asia, where rural transformation was underpinned by sustained agricultural growth, agro-industrial linkages, and robust rural infrastructure, Africa's transition has occurred under conditions of economic dualism, land scarcity, and weak rural markets (Losch, Freguin-Gresh, and White, 2012).

Moreover, African rural economies are characterized by informality, limited employment elasticity in agriculture, and a growing youth population with aspirations that increasingly lie outside the farming sector (Fox and Pimhidzai, 2011). Consequently, many rural households diversify their livelihoods not only in pursuit of higher incomes but also as a strategy to manage risk, cope with shocks, and respond to constraints in the agriculture sector. In this regard, the emergence of a rural non-farm economy in SSA is not merely an outcome of surplus labor existing in agriculture, but also a reflection of structural challenges within the sector itself.

Rwanda presents a particularly dynamic case in this landscape. Following the devastating effects of the 1994 genocide against the Tutsi, Rwanda embarked on a recovery path characterized by strong government-led development planning through policy frameworks such as Vision 2050. Rwanda is one of the fastest-growing economies in Africa, with an average annual GDP growth exceeding 7% (World Bank, 2024). Despite these macro-level successes in Rwanda, poverty remains deeply entrenched in rural areas where agriculture continues to dominate (Kangondo *et al.,* 2023; NIRS, 2023).

Agriculture remains the backbone of Rwanda's rural economy, engaging over 70% of the population and contributing approximately 23.5% to national GDP (NISR, 2023). While this marks a decline of dependence on agriculture from over 40% in the 1990s, the sector remains crucial for Rwanda's food security and employment. According to Kangondo et al. (2024), low productivity, land fragmentation, climate vulnerability, and market inefficiencies have increasingly constrained the capacity of farming to deliver broad-based improvements in household welfare and wellbeing in Rwanda. As a result, many rural households are increasingly diversifying their income sources by engaging in non-farm economic activities, including petty trade, artisan work, transport services, construction, and wage employment in rural industries (NISR, 2023).

The household shift from farm to non-farm livelihoods is not unique to Rwanda. It echoes the patterns of structural transformation observed in many developing economies experiencing labor transition from low-productivity agriculture to informal non-farm sectors (Johnston & Mellor, 1961; Lewis, 1954). This structural shift is a typical feature of economies undergoing transformation, such as Rwanda. As productivity in agriculture stagnates and opportunities emerge in non-farm sectors, labor and capital gradually shift toward more remunerative and stable non-agricultural activities (Timmer, 2009).

Rwanda's farm to non-farm rural transition is catalyzed by a range of factors, including urbanization, demographic pressure on land and the government's Vision 2050 strategy, which emphasizes inclusive growth and economic modernization. With an average landholding size of less than 0.6 hectares and a youthful rapidly growing population, diversification beyond farming is increasingly seen as not merely beneficial but necessary for sustaining rural livelihoods and promoting economic resilience (Kangondo *et al.,* 2024). It reflects a broader pattern of rural economic diversification, wherein households seek to stabilize income, reduce vulnerability, and improve welfare by engaging in multiple sources of livelihood (Barrett et al., 2001; Matsuura-Kannari *et al.,* 2024).

While diversification is not a new strategy, its scale and significance in Rwanda have grown in recent years due to structural changes in the national economy and by constraints within the agricultural sector. However, the implications of this shift are not uniform. For some households, non-farm activities offer higher returns to labor and serve as a pathway out of poverty. For others, especially the poorest, engagement in non-farm work is a necessity born of agricultural distress, not opportunity (Reardon, 1997). The heterogeneity of outcomes necessitates a careful examination of the consequences of the transition from farm to non-farm activities on household well-being and agricultural performance. Moreover, the farm to non-farm transition in Rwanda is occurring in a context where land remains the most critical asset, and where off-farm labor supply can directly affect agricultural output. Against this backdrop, a key policy question arises: how can Rwanda harness the benefits of non-farm diversification without undermining the productivity of the agricultural sector?

This chapter, sheds light around the aforementioned question through lenses of patterns, drivers, and impacts of rural transition from farm to non-farm in Rwanda. In more specific terms, the chapter identifies the key socio-economic and spatial determinants that influence the likelihood of rural households engaging in non-farm economic activities and the impact of rural transition on multi-dimensional poverty and labour productivity.

While the existing literature has documented the rise of rural non-farm employment in Sub-Saharan Africa (Davis et al., 2017; IFAD, 2021), specific studies on farm and off-farm activities in Rwanda, such as Musafiri and Sjölander (2018); Hitayezu et al., (2014); and Schmidt et al., (2024) have only explored the productivity trade-offs between farm and non-farm labor. Given Rwanda's developmental trajectory and its emphasis on inclusive growth, understanding the dynamics of farm to non-farm transition through the combined lenses of patterns, drivers, and impact is critical for crafting targeted interventions that enhance rural livelihoods, promote resilience, and foster structural transformation.

The remainder of this chapter is organized as follows. The next section presents a comprehensive review of the theoretical and empirical literature on rural transition and diversification, followed by the conceptual framework and hypotheses. The methodology section outlines the data sources and analytical techniques. Subsequent sections present the findings, discuss the policy implications, and offer concluding reflections.

1. Literature Review, Conceptual Framework, and Hypotheses

2.1 Theoretical Underpinnings of the study

Focusing on rural economic transitions, this study is rooted in three prominent theories of structural transformation and labor mobility namely, the classical Lewis Dual Sector Model (Lewis, 1954); the Markov Transition Framework (Shorrocks, 1978) and Structural Transformation Theory (Timmer 2009). The Lewis Dual Model posits that economic development occurs when labor is gradually transferred from a subsistence agricultural sector with low productivity to a modern industrial sector with higher productivity and wages. This postulate is a vehicle to the understanding of patterns, drivers and impact of the transition from farm to non-farm sectors undertaken in this study. Although the Lewis Dual Sector Model focuses on urban-industrial transitions, it has been adapted to also explore intra-rural diversification, where labor shifts from agriculture to non-farm activities within rural areas (Fields, 2004).

The Markov Transition Framework partly underpinning the theoretical foundations of this paper models households' mobility across livelihood states over time. This stochastic model is valuable in explaining how households move in and out of farming or non-farm sectors, and the persistence of livelihood trajectories (Shorrocks, 1978). In the conceptualization of this paper, Markov's framework captures the role of shocks, policy changes, and social mobility in shaping household choices.

Another key theory in this chapter is the Structural Transformation Theory particularly articulated by Timmer (2009). This theory underscores the importance of sectoral shifts, technological progress, and urbanization in altering the rural economic landscape. Timmer emphasizes that successful transformation requires productivity growth in both agriculture and non-farm sectors, as well as institutional reforms that enable labor reallocation, capital mobility, and infrastructure development. In the context of Rwanda, structural transformation is being actively pursued through programs that promote industrialization, skills training, and rural entrepreneurship.

2.2. Conceptual Framework

The conceptual framework of this study is grounded in the dynamic process of rural transformation, where economic diversification emerges as both a response to and a driver of structural change. In Rwanda, this process unfolds against the backdrop of persistent rural poverty, high population density, limited land holdings, and an agriculture sector that, while still dominant, struggles with low productivity and structural constraints (McKay & Perge, 2011; MINAGRI, 2021). Within this setting, rural households increasingly engage in non-farm economic activities, a phenomenon rooted in classical and contemporary theories of structural transformation, notably the Lewis Dual Sector Model (Lewis, 1954), Timmer's transformation framework (2009), and the Markov Transition Model (Shorrocks, 1978).

At the heart of this framework lies the drivers of non-farm diversification. In rural Rwanda, engagement in non-farm work is not accidental; it is shaped by a household's endowments, geography, and institutional environment. Human capital including education, health, and vocational skills play a significant role by equipping individuals with the capabilities to access better-paying and more stable non-farm jobs (Barrett et al., 2001; Loison, 2015). Households with greater physical and financial assets such as land, access to credit, or remittance income possess the means to launch small enterprises or seek employment beyond subsistence farming.

Demographic variables also shape this transition. Younger, larger households, or those with high dependency ratios may feel greater pressure to supplement or replace farm income, especially as land becomes increasingly fragmented (NISR, 2023). Meanwhile, geographical factors such as proximity to roads, markets, and urban centers, as well as the agro-ecological zone, affect the availability and type of non-farm opportunities. Institutional factors such as cooperative membership, access to extension services, and targeted government programs (e.g., Vision 2050 strategy) can either facilitate or constrain the diversification process (Hitayezu et al., 2014; Schmidt et al., 2024).

Once households diversify into non-farm activities, the effects on household welfare become apparent, though not uniformly positive. For many, non-farm income provides a vital buffer against agricultural risks, enabling households to smooth consumption, stabilize income, and invest in health and education. It also opens up new investment pathways into agriculture itself such as acquiring improved inputs or irrigation technology creating potential synergy between the two sectors (Owusu et al., 2011; Ellis, 2000). However, not all non-farm work is created equal. The welfare gains are markedly higher in high-return, formal or skilled activities (e.g., salaried jobs, artisanal production) than in low-return informal engagements (e.g. hawking, daily wage labor), which often trap households in a cycle of precarious employment (Lanjouw & Lanjouw, 2001; Reardon, 1997).

These welfare outcomes, in turn, feedback into agricultural productivity, generating both opportunities and risks. On the one hand, additional income and exposure to innovation can enhance agricultural practices, allowing households to take calculated risks, purchase better inputs, or adopt improved farming techniques. Such complementary dynamics support the notion of a "virtuous cycle" where non-farm and farm sectors reinforce one another (Timmer, 2009).

Fundamentally, the conceptualization herein underscores the duality in outcomes: while the transition to non-farm livelihoods can offer pathways out of poverty and support resilience, it can also generate trade-offs, particularly when diversification is born of necessity rather than opportunity. In this chapter, we argue that diversification must be balanced to promote inclusive rural development.

2.3. Empirical Evidence and Hypotheses

There is consensus in the literature that non-farm income is shaping rural livelihood in Sub-Saharan Africa contributing between 30% and 50% of household income (Diao and McMillan, 2018). This is a reflection of a dynamic interplay between economic opportunity and agricultural constraints (Haggblade et al., 2010; Davis et al., 2017). It is driven not only by the pull of urbanization, infrastructure, and sectoral diversification, but also by the push of declining landholdings, climate shocks, and stagnating agricultural productivity. Drawing on multi-country evidence, Loison (2015), posits that such diversification is strongly correlated with increased resilience and asset accumulation particularly when supported by robust local institutions and market linkages.

In Rwanda, the empirical landscape reveals a similar evolution. Hitayezu et al. (2014) observe that non-farm engagement is often pursued as a risk management strategy, particularly among households facing the twin pressures of land scarcity and low farm returns. This observation, points to a significant equity concern. It alludes that better-off households (those with education, capital, or connections) tend to dominate high-return non-farm niches such as formal wage work or rural enterprise. In contrast, poorer households often remain confined to low-productivity informal jobs, with limited scope for income mobility. This socio-economic stratification is further elaborated by Schmidt et al. (2024), who highlight how Rwanda's rural opportunity structures remain unevenly distributed along class, gender, and geographic lines.

More recent analyses based on Rwanda's EICV5 (NISR, 2021) confirm both the growing participation in non-farm activities and the persistence of spatial disparities. Households in peri-urban areas or near secondary towns are significantly more likely to access formal or stable non-farm jobs, while remote or infrastructure-poor communities face more limited options. Schmidt *et al.* (2024) take this further, showing that households engaged in high-return non-farm activities often reinvest earnings back into agriculture, enabling input purchases, improved technologies, and enhanced farm productivity. However, this positive feedback loop is not guaranteed. When non-farm engagement is driven by agricultural failure or distress, it often leads to reduced labor inputs on the farm, declining yields, and erosion of agrarian capacity (Schmidt *et al.,* 2024).

The conceptual and empirical review of this study provides two critical lessons that justify the positioning of the present study. First, while the existing evidence acknowledges the importance of rural transition, previous research hardly traces the trade-offs and complementarities between farm and non-farm activities. This paper addresses this gap by evaluating the impact of transition on multi-dimensional poverty and labour productivity.

Second, the existing literature (Paternostro *et al.,* 2004; Hitayezu *et al.,* 2014; Musafiri and Sjölander, 2018; and Schmidt *et al.,* 2024) relies on conventional regression techniques that may not fully account for selection bias in household participation decisions. For instance, households choosing to engage in non-farm work may systematically differ from those who do not in unobservable ways. This study combines machine learning and econometric approaches to rigorously assess the causal effects of livelihood transitions. We first fit a Random Forest (Breiman, 2001) and explained the predictions with the SHAP values (Lundberg et al., 2017), to identify key individual-level drivers of movement from farm to non-farm activities. These drivers are then used as covariates in a Multinomial Endogenous Treatment Effects model, which accounts for selection bias and endogeneity across multiple transition states.

In line with the conceptual and theoretical framework, the following hypotheses guide the empirical investigation:

1. H_1: Households with higher levels of human capital (education, health), physical capital (land, credit), and favorable location (urban proximity, market access) are more likely to engage in non-farm economic activities.
2. H_2: Participation in non-farm activities leads to improved household welfare, measured through multi-dimensional poverty and labour productivity.

3. Methodology

3.1 Data Sources and Description

This study uses data from the Fifth Integrated Household Living Conditions Survey (EICV5), a nationally representative household survey conducted in Rwanda in 2016/2017. EICV5 is a multi-topic survey modeled on the World Bank's Living Standards Measurement Study (LSMS). Its primary objective is to monitor and evaluate progress in poverty reduction and welfare. Data collection took place over 12 months (October 2016 – October 2017) using Computer-Assisted Personal Interviewing (CAPI) for efficiency and data quality. The sample comprises 14,580 households (12,054 rural and 2,256 urban) across all 30 districts of Rwanda. A two-stage stratified sampling design was used to identify respondents: In the first stage, enumeration areas were selected with probability proportional to size; In the second stage, 12 households were randomly selected within each area. The survey distinguishes "urban" and "rural" based on NISR's official reclassification (NISR, 2018b).

At the household level, EICV5 collected information on all members aged 6 and above, covering demographics, agricultural and non-agricultural activities, migration, credit use, and employment. Additional modules captured housing conditions, consumption and expenditure, land ownership, income transfers, access to infrastructure, and assets. The employment section detailed each member's employment status, job search, occupation, nature of economic activity, and participation in unpaid work during the seven days prior to the interview. Community-level data (at the village or *umudugudu* level) documented local infrastructure availability and access.

3.1.1 Description of the Outcome Variables

The outcome variables conceptualized in this study are farm to non-farm transition and Multidimensional poverty. In terms of transition, we categorize each individual's primary economic activity in the past 12 months as *farm-only*, *non-farm-only*, or *diversified*. Individuals are classified as farm-only if they engaged exclusively in farming (cultivating their own farm or working as agricultural labor). Non-farm-only individuals worked only in non-agricultural wage employment or ran non-farm businesses. *Diversified* individuals combined farm and non-farm activities. As for the Multidimensional poverty, it is comprised of four equally weighted dimensions; Education, Health, Basic Services, and Living Standards; encompassing 13 indicators (e.g., school attendance, years of schooling, access to healthcare, health insurance coverage, electricity, clean water, sanitation, cooking fuel, housing materials, asset ownership, and engagement in subsistence agriculture). Each household is assessed against deprivation cutoffs for these indicators. A household is classified as *MPI-poor* if it is deprived in at least one-third (≥33.3%) of the weighted indicators; otherwise it is MPI-non-poor.

Labour productivity is defined as an individual's monthly labor income per unit of labor time. For individual i: $LPi = \frac{Yi}{Hi}$ where *LPi* denotes labor productivity of individual *i; Yi* is total labor income from all economic activities for i; and *Hi* is number of hours worked by *i* during the month.

3.2 Data Analysis

3.2.1 Multinomial Endogenous Treatment Effects (METE)

To rigorously assess both the determinants of transitioning out of farming and the consequences of such transitions, we use a Multinomial Endogenous Treatment Effects (METE) model. This econometric approach jointly estimates a selection equation (household's choice of livelihood strategy) and outcome equations (for poverty status and productivity), accounting for potential self-selection bias and endogeneity (Kim et al., 2019). In essence, households "select" into non-farm or diversified activities, and without correction, estimates could be biased if unobservable characteristics influence both the decision to transition and the outcomes. The METE model addresses this by incorporating latent factors that capture unobserved heterogeneity, thereby isolating true causal effects of the transition.

In the first Stage (selection equation) of the METE, we model the choice of economic activity using a multinomial logit with random latent effects to capture unobserved heterogeneity. Each household (or individual) chooses one strategy from three mutually exclusive alternatives: farm-only (baseline), non-farm-only or diversified.

Let EVij* denote the indirect utility that individual *i* obtains from choosing strategy j^{th} , j=0,1,2 . We specify this utility as a function of observable individual and household characteristics and an idiosyncratic error term, as well as latent factors capturing unobservable influences. In particular, this is specified as follow:

$$EV_{ij}^{*} = z_i'\alpha_j + \delta_j l_{ij} + \eta_{ij} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Where, Z_i is a vector of exogenous covariate including individual (i) characteristics, with associated parameters α_j and η_{ij} denoted as independently and identically distributed error terms. l_{ij} denotes unobservable characteristics to individual (i) choice of j^{th} alternative livelihood strategy and outcome variables such as household multidimensional poverty and labor productivity. Following Deb and Trivedi (2006a; 2006b), we assume that g has a mixed multinomial logit structure, defined as:

$$Pr(d_i|z_i, l_i) = \frac{exp\left(z_i'\alpha_j + \delta_i l_{ij} + \Pi\theta_{\mathrm{i}}\right)}{1 + \sum_{k=1}^{j} exp\left(z_i'\alpha_k + \delta_k l_{ik} + \Pi\theta_{\mathrm{i}}\right)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Where Z_i is a vector of exogenous covariate including individual's characteristics. The Π is a vector of the instrument; and θ_{i} is an instrumental variable denoting access to information on opportunities of livelihood through internet use. An important feature of our model is the inclusion of an instrumental variable θi, in the selection equation to aid identification. In the second stage, the model assesses the causal impact of the non-farm transition on two outcomes: (1) household multidimensional poverty status, and (2) labor productivity. We specify separate outcome equations for each of these, incorporating the selectivity correction term(s) derived from the first stage. For multidimensional poverty, which is a binary outcome (multi-dimensionally poor vs. non-poor), we use a binary logit model with endogenous treatment effects. The outcome equation for the household can be written as:

$$Pr(y_i = 1|d_i, z_i, l_i) = x_i'\beta + \sum_{j=1}^{J} (\gamma_j d_{ij}) + \sum_{j=1}^{J} (\lambda_j l_{ij}) \quad \text{......................................} (3)$$

$Pr(y_i = 0|d_i, z_i, l_i)$ Otherwise

Where, y_i represent outcome variables for household i, household multidimensional poverty. $Pr(y_i = 1|)$ is the probability of a household i, being multidimensionally poor ; x_i is a vector of exogenous covariates with associated parameters β, and γ_j (for j=1,2) denoting the treatment. The productivity outcome can be written as:

$$Yi = x_i'\beta + \sum_{j=1}^{J} (\gamma_j d_{ij}) + \sum_{j=1}^{J} (\lambda_j l_{ij}) + \varepsilon_i \quad \text{..} (4)$$

Where γ_i is now a continuous outcome (labor productivity); x_i are covariates (age, education, assets, etc.), d_{ij} are treatment dummies (transition categories, with one base outcome), l_{ij} are selection correction terms ; ε_i is the error term with usual assumptions.

3.2.2 SHAPLEY Additive explanations (SHAP)

Machine learning models are often “black boxes,” making it hard to see how predictors influence outcomes. To improve transparency, we use SHAP (SHapley Additive exPlanations; Lundberg et al., 2017), which applies cooperative game theory to attribute each feature its average contribution to predictions. SHAP quantifies both the importance and direction of each predictor’s effect on the probability of belonging to a given transition state. For a model prediction f(x), the SHAP value for a feature j is computed as the weighted average of its marginal contributions across all possible subsets of features S that exclude j:

$$\varphi_j = \sum_{S \subseteq F / \{j\}} \frac{|S|\,!(M-|S|-1)!}{|F|!} [\, f_{S\cup\{j\}}(x_{S\cup\{j\}} - f_S(x_S)] \quad \ldots\ldots(5)$$

Where, f_S denotes the model restricted to subset S, S⊆F\{j} is all possible feature subsets that exclude feature j, $\frac{|S|\,!(M-|S|-1)!}{|F|!}$ is factorial weights ensuring fairness, M: is total number of features, and $f_{S\cup\{j\}}(x_{S\cup\{j\}} - f_S(x_S)$ is the marginal contribution of feature j. The SHAP explains the model f(x) via the following relation:

$$f(x) = \varphi_0 + \sum_{j=1}^{M} \varphi_j \quad \ldots\ldots(6)$$

where $\varphi_0 = E[f(x)]$ is the expected model output and φ_j is the Shapley value for feature j. SHAP provides both a ranking of feature importance and the direction of influence on predicted transition probabilities. To compute these values, we applied a Random Forest together with TreeExplainer, an efficient SHAP algorithm that leverages the structure of decision trees to calculate exact feature contributions.

3.2.2.1 Identification of the Key Drivers of Farm to Non-farm Transition

To identify key drivers of the farm to non-farm transition, we employed a Random Forest (Breiman, 2001) and computed SHAP values (using TreeExplainer) for each feature and outcome class (Farm only, Non-farm only, Diversified). For each class, features were ranked by average absolute SHAP values, and the top *k* (here, *k*=12) were selected. The final set of drivers was the union of these class-specific subsets, capturing both class-specific and common predictors. Consider the set of transition state E_T :$\{Farm, Nonfarm, Diversification\}$, the average SHAP score for feature j ∈ $F = \{1,2,\cdots,p\}$ at each transition state (class) $c \in E_T$, defined as follows.

$$I_j^{(c)} = \frac{1}{n} \sum_{i=1}^{n} |SHAP_{i,j}^{(c)}|\}, \ \forall c \in E_T \ldots\ldots (7)$$

where $SHAP_{i,j}{}^{(c)}$ denotes the SHAP value of feature j for observation i with respect to class c.

For each class c and feature set F, the top k features are defined as

$$T^{(c)} = TopK_c(\{I_j{}^{(c)}: j \in F\}, k)\,, \qquad (8)$$

where $$TopK_c = arg \max_{S \subseteq F, |S|=k} \sum_{j \in S} I_j(c). \qquad (9)$$

(Eq.9) means for a class **c,** we rank all features by their importance and keep the top k. The final set of key drivers is given by the union (U_k) defined as follows:

$$U_k = \cup_{c \in C} \quad T^{(c)}.. \qquad (10)$$

4. Results and Discussion

4.1 Characteristics of respondents and their economic activities

Descriptive statistics presented in Table 1 show that the mean age of farm-only individuals is 41 years compared to 30 years in non-farm households. The farm group is female-dominated with only 30 % males. In contrast, non-farm households are younger and overwhelmingly male, consistent with national trends that find women much more likely to work in agriculture and men in paid non-farm jobs.

Educational attainment further highlights the divide; while 12 % and 1 % of farm workers have secondary and university education respectively, with an average of about 4.7 years of schooling, about 43 % and 16 % of non-farm households have primary and secondary education qualifications, respectively. This gap reflects a rural–urban poverty divide, where poorer rural households such as those engaged solely in farming have far lower literacy and education levels. National statistics show 80 % literacy in the poorest quintile versus 94 % in the richest (NISR, 2025a). Higher education is well known to raise non-farm employment prospects.

In terms of geography and infrastructure, the data indicate that the majority of the households engaged in farming (farm-only households) live outside urban centers, whereas 62 % of non-farm individuals live in urban areas. This pattern mirrors labor statistics showing that 62 % of rural workers are independent farmers compared with 16 % in urban areas (NISR, 2018a). About 55 % of the urban labor force is in waged non-farm jobs, while only 13 % is in rural farm jobs (NISR, 2018a). Farm households also report much longer travel times and distances to markets and services, averaging 41 minutes and 3.7 km than non-farm households, which average 22 minutes and 1.9 km, underscoring limited access to roads and services in farming areas. In contrast, non-farm households enjoy urban advantages such as proximity to markets, infrastructure, and networks that facilitate off-farm work.

Assets and livelihood capital reveal equally stark contrasts. The mean household asset values in the data are roughly an order of magnitude higher in the non-farm group than in the farm group, reflecting much higher incomes. Similarly, mobile and computer ownership are far more common in non-farm households, with 81 % owning a phone and 36 % owning a computer, compared to only 28 % and 3 % among farm-only households. These differences point to an ICT gap in which non-farm households are far more connected than farming households.

Apparently, farm households are resource-poor, holding an average of 0.6 ha of land and low asset values. According to Schmidt et al. (2024), the smallest agricultural households often rely on wage labor to survive, and households with minimal land tend to sell labor rather than hire others.

Table 1: Descriptive results of the Study

Employment type	Farm Only		Non-farm Only		Diversifying		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
MPI	0.44	0.13	0.20	0.13	0.3355	0.1386	0.3228	0.1437
MPI-Poor	0.38	0.49	0.09	0.30	0.34	0.47	0.32	0.47
Labour Productivity	8700	6491	26133	73376	15342	23344	17573	48791
Age (Years)	41.23	19.07	29.81	10.49	34.83	13.24	37.25	16.77
Hh_Head	0.44	0.50	0.56	0.50	0.62	0.49	0.51	0.50
Primary_school	0.53	0.50	0.69	0.46	0.53	0.50	0.56	0.50
Sec_school	0.12	0.33	0.43	0.50	0.17	0.37	0.20	0.40
University	0.01	0.08	0.16	0.36	0.03	0.16	0.04	0.21
Schooling_Years	4.68	2.77	8.04	4.51	5.33	3.23	5.59	3.59
Computer use	0.03	0.17	0.36	0.48	0.09	0.29	0.12	0.32
Male_Respondent	0.31	0.46	0.70	0.46	0.62	0.48	0.47	0.50
Urban resident	0.06	0.23	0.62	0.48	0.11	0.31	0.17	0.38
Male_HHead	0.50	0.50	0.83	0.38	0.82	0.38	0.68	0.47
Mobile-phone ownership	0.28	0.45	0.81	0.39	0.54	0.50	0.45	0.50
Own computer	2.00	0.05	1.91	0.28	1.99	0.11	1.98	0.14
Migrated	0.64	0.48	0.27	0.45	0.57	0.50	0.55	0.50
Loan_Amount (“000”RWF)	102.70	142.92	148.79	755.11	132.10	105.10	328.66	324.87
Land_Size(ha)	0.58	2.44	0.78	3.50	0.59	3.63	0.60	2.97
Land_Value (“000”RWF)	125.23	244.96	225.74	968.05	112.40	291.39	128.80	370.66
Asset_value (“000”RWF)	40.60	833.42	600.12	293.78	74.63	669.16	151.70	144.77
Inherited land	0.43	0.49	0.32	0.47	0.38	0.49	0.40	0.49
Purchased land	0.23	0.42	0.30	0.46	0.22	0.41	0.23	0.42
Gift_Land	0.07	0.25	0.07	0.26	0.06	0.23	0.06	0.25
Irrigation use	0.05	0.22	0.07	0.25	0.06	0.24	0.05	0.23
Erosion control	0.67	0.47	0.62	0.49	0.67	0.47	0.67	0.47
Land_Consolidat.	0.14	0.35	0.14	0.35	0.14	0.35	0.14	0.35
Land_title	0.66	0.47	0.69	0.46	0.59	0.49	0.64	0.48
Land_Ownership	0.72	0.45	0.69	0.46	0.66	0.47	0.70	0.46
HHead_age	53.23	17.23	33.59	10.34	38.58	13.23	44.09	16.89
Avg_time(min)	41.08	16.48	22.62	14.10	37.13	16.18	36.57	17.36
Average distance(km)	3.72	1.94	1.88	1.44	3.36	1.87	3.28	1.96

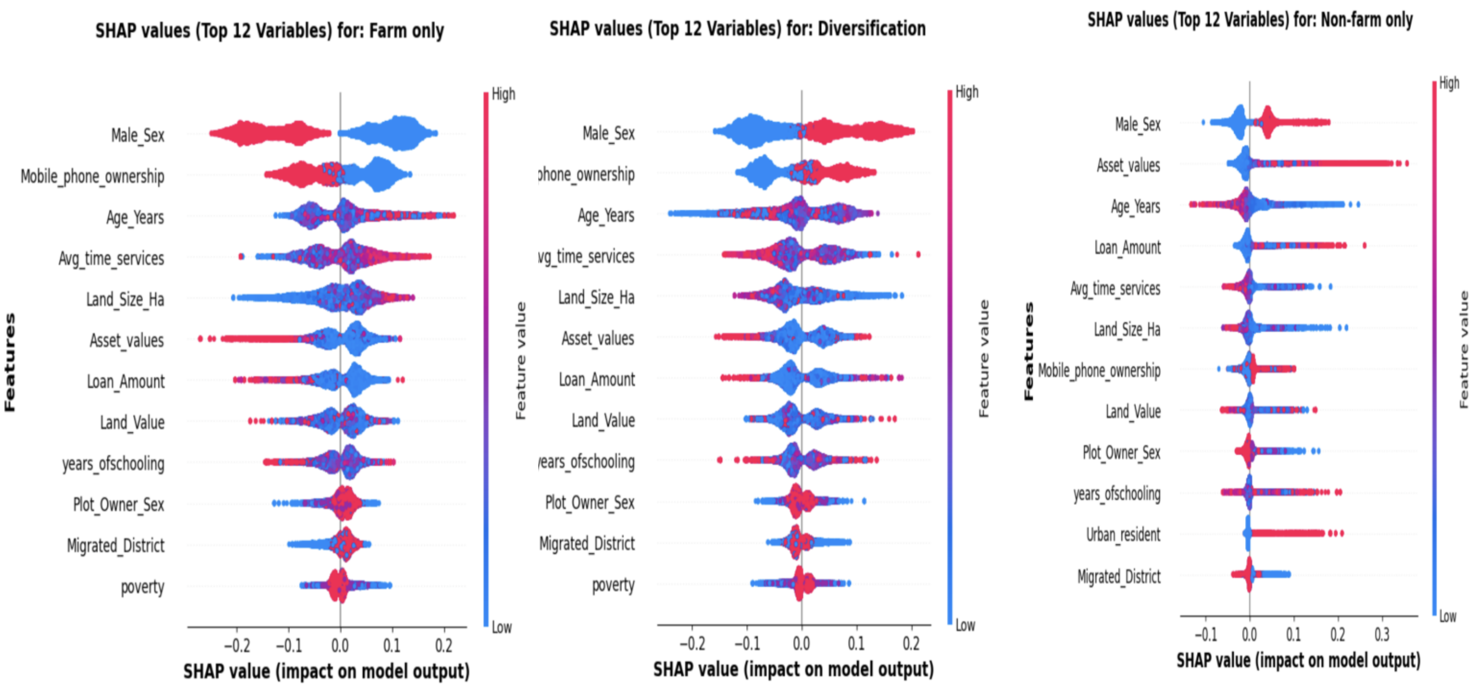
Turning to the main outcome indicators, Table 1 shows that Multidimensional Poverty Index scores are highest among farm-only households (mean = 0.44) compared with 0.34 for diversified and just 0.20 for non-farm households, suggesting deeper multidimensional deprivation in farming communities. The share of households classified as MPI-poor mirrors this pattern with 38 % of farm-only households MPI-poor compared to 34 % of diversified and only 9 % of non-farm households.

Labour productivity also varies sharply, averaging roughly 8,700 RWF per worker in farm-only households, 15,342 RWF in diversified households, and a striking 26,133 RWF in non-farm households. These results underscore that non-farm participation is likely to be strongly associated with lower multidimensional poverty and substantially higher labour productivity, while purely farm-based livelihoods remain both more poverty-prone and less productive. To further interrogate our descriptive results, the econometric results are presented in the next sections.

4.2 Drivers of farm to non-farm transition

The top 12 features for the three transition states (Farm only, Non-farm only, and Diversified) are presented in Fig. 1 (Beeswarm plot). The color indicates the raw feature value (red = higher, blue = lower), while the x-axis position shows whether that value increases (right) or decreases (left) the likelihood of belonging to a given transition class. The SHAP analysis highlights that livelihood transitions in Rwanda are driven by a set of interrelated structural, economic, and demographic factors, with distinct pathways for farm persistence, non-farm specialization, and diversification.

Figure1: SHAP Value Per Transition States



Demographic factors emerge as an important driver of livelihood transitions. Men are less likely to remain in farming and more likely to engage in non-farm or diversified activities, while women face greater barriers to transition, reflecting persistent gender gaps in access to assets, credit, and mobility. On the other end, male plot ownership aligns more with farming and diversification while reducing the likelihood of purely non-farm engagement. Urban residents are substantially more likely to specialize in non-farm activities, which is consistent with the concentration of opportunities outside agriculture (Nilsson, 2016; Losch et al., 2012). Migration across districts raises the likelihood of remaining in farm-only or diversified strategies but lowers the chance of being non-farm only. This could reflect the nature of migration in Rwanda, which might be land-seeking (moving to farm in less crowded areas) or distress-driven migration where people still rely on agriculture.

Poverty and vulnerability constrain transitions. Individuals in poor households are more likely to remain in farming and less likely to diversify, a pattern that is consistent with structural poverty traps documented in Africa (Barrett et al., 2001). This underscores the structural barriers faced by poor individuals. Human capital exerts a consistent and positive influence. More years of schooling significantly raise the probability of participating in non-farm or diversified activities, while individuals with low education levels remain concentrated in farming. This confirms findings from Rwanda that education raises the probability of wage and self-employment outside agriculture (Dabalen et al., 2004; Hitayezu et al., 2014).

Access to information and services is a central driver of livelihood transitions. Households with mobile phones and closer proximity to markets or essential services are more likely to engage in non-farm or diversified activities, while poor connectivity and long travel times reinforce reliance on farming. This aligns with evidence that better access and connectivity lower search costs and expands opportunities (Caldarola et al., 2022; Rajkhowa & Qaim, 2022; Hitayezu et al., 2014).

Credit access also matters: limited loans keep individuals in farming, whereas larger loans support non-farm entry. However, the effect on diversification is mixed, as outcomes depend on how loans are used, reflecting conditional pathways shaped by local contexts.

Asset ownership strongly shapes livelihood choices. Individuals with higher asset values are more likely to specialize in non-farm activities, while poorer individuals face entry barriers that keep them excluded from non-farm participation (Dabalen et al., 2004; Woldenhanna & Oskam, 2001). However, evidence from eight sub-Saharan African countries shows that targeted financial inclusion can help broaden access to diversification (Musumba et al., 2022). Land presents a more complex picture: Larger land holdings tend to anchor individuals in farming, while discouraging non-farm and diversification participation, suggesting that higher land productivity reduces time allocated to non-farm activities (Hitayezu et al., 2014). Smaller holdings, by contrast, can have divergent effects: in rural areas, limited plots often constrain diversification due to subsistence needs and resource scarcity, while in peri-urban settings, they may open opportunities for real estate activities such as plot sales or rental ventures.

The analysis shows that transitions from farm to non-farm livelihoods in Rwanda are shaped by access to education, finance, services, and information, while poverty, remoteness from markets and essential services, limited credit, and land constraints keep many households tied to farming. Gender and spatial inequalities further restrict women and rural households from benefiting equally from non-farm opportunities. This underscores that successful structural transformation in Rwanda requires deliberate and inclusive policy action informed by the key factors shaping livelihood transitions. Accordingly, expanding education and vocational training, improving infrastructure and access to services, strengthening financial inclusion, and actively reducing gender and spatial inequalities are essential measures. Only through such comprehensive measures can the transition from farm to non-farm activities become a broad-based pathway to prosperity rather than one reserved for the better-off.

4.3 The Impact of farm to non-farm transition on Multidimensional Poverty and Labor Productivity

4.4.1 Impact on MPI

The results in Table 2 show that transitioning away from a purely farming livelihood is strongly associated with lower household multidimensional poverty. Relative to farm-only households, those relying solely on non-farm activities have an Average Treatment Effect (ATE) of 0.0903 on the MPI score ($p < 0.001$), while households that diversify into both farm and non-farm work have an ATE of 0.0697 ($p < 0.001$). These reductions are substantial when viewed against Rwanda's national MPI, which averages about 0.25 (National Institute of Statistics of Rwanda (NISR, 2023). They indicate that engaging in non-farm employment, whether partially or fully, significantly reduces deprivations across education, health, and living-standard dimensions. Similar evidence across sub-Saharan Africa confirms that non-farm earnings lower multidimensional poverty by providing liquidity for better housing, nutrition, and schooling (Danso-Abbeam et al., 2020; Amare & Jensen, 2018). The findings support the broader view that rural households benefit from a diverse portfolio of activities that smooth income and finance basic services (Barrett, Reardon, & Webb, 2001).

Important covariates of the MPI outcome reinforce known poverty determinants. Urban residence lowers MPI by about 0.047 points ($p < 0.001$), reflecting better access to services and jobs in towns and cities (World Bank, 2023). Land assets are equally critical: each additional hectare reduces MPI by roughly 0.0023 ($p < 0.001$), purchasing land lowers it by about 0.009 ($p < 0.001$), and holding a formal land title decreases it by 0.0197 ($p < 0.001$). These results echo findings from Rwanda's land tenure regularization program, which improved investment incentives and household welfare (Ali, Deininger, & Goldstein, 2014). Education has mixed effects. Completing primary school reduces MPI by around 0.0092 ($p < 0.001$), consistent with abundant evidence that education protects against poverty (UNDP, 2022). Yet years of schooling show a positive coefficient, possibly reflecting younger, better-educated household heads who are still in early asset-accumulation stages or collinearity with other education indicators.

In terms of digital access, owning a mobile phone lowers MPI by about 0.078 ($p < 0.001$), supporting research that mobile connectivity improves welfare through financial inclusion and market access (Aker & Mbiti, 2010). Older household heads experience slightly lower MPI (–0.0011 per year, $p < 0.001$), consistent with life-cycle accumulation of assets. Insurance ownership, conversely, is positively associated with MPI (1.43, $p < 0.001$), likely reflecting Rwanda's community-based health insurance that targets poor households (Binagwaho et al., 2014).

4.4.2 Impact on Labor Productivity

Findings in Table 2 show that livelihood transitions also raise household labour productivity, measured as the log of net value of output (income) per man-day. Diversified households exhibit the largest gain. An ATE of +0.6095 log-points ($p < 0.001$), equivalent to roughly 61 percent higher productivity than farm-only households. Non-farm-only households also experience a significant increase of +0.1237 log-points ($p = 0.001$), or about 12 percent. That diversification yields a greater boost than complete exit from farming suggests strong complementarities: non-farm income can finance on-farm investments such as improved inputs or small-scale mechanization, while continued farming supplies raw materials and a food security buffer. This aligns with structural transformation theory (Lewis, 1954) and empirical work showing that mixed livelihoods raise productivity in rural Africa (Barrett et al., 2001; Davis et al., 2017). At the macro level, Rwanda's rapid reallocation of labour from agriculture to more productive non-farm sectors have been a key driver of growth and poverty reduction (World Bank, 2021).

Several covariates significantly influence labour productivity. Urban residence is associated with a +0.233 log-point increase ($p < 0.001$), reflecting agglomeration benefits and access to markets and infrastructure. Migration to another district raises productivity by about 0.067 log-points ($p < 0.001$), indicating that geographic mobility allows workers to access higher-return opportunities, a pattern emphasized in studies of rural structural change (Christiaensen, De Weerdt, & Todo, 2013). Digital connectivity again plays a role: owning a mobile phone increases productivity by about 0.079 log-points ($p < 0.001$), consistent with evidence that mobile technology improves farm profits and business coordination (Aker & Mbiti, 2010). Household wealth, captured by total income and asset values, is also positively associated with productivity, highlighting how capital enables investment in inputs and technology. The age of the household head shows a small but significant positive effect (0.005 log-points per year, $p < 0.001$), consistent with experience accumulation. Two results merit special comment. First, male-headed households have lower productivity (–0.169, $p < 0.001$), supporting research that, when women have equal access to resources, gender productivity gaps disappear or reverse (Kilic et al., 2015). Second, insurance ownership is negatively related to productivity (–0.79, $p = 0.005$), probably because poorer households are more likely to hold subsidized insurance, mirroring the MPI finding and indicating selection rather than a causal effect. Overall, the results from Table 2 paint a coherent picture about farm-to-non-farm transition. Apparently, diversification simultaneously reduces multidimensional poverty and increases labour productivity. Households that diversify appear to capture the advantages of both sectors: stable food production and the higher wages or profits available in non-farm activities. These micro-level findings complement macro evidence that labour reallocation toward non-farm sectors has powered Rwanda's structural transformation and poverty reduction (World Bank, 2021). They suggest that policy should not force a binary choice between agriculture and non-farm work. Instead, strategies that facilitate diversification such as rural enterprise promotion, vocational training, microfinance, and investment in secondary towns can generate substantial welfare and productivity gains. Strengthening land tenure, expanding digital infrastructure, and supporting women's equal access to assets will further amplify these benefits.

Table 2: The Effect of Farm-Non-Farm Transition on Poverty and Labor Productivity

Variables	Outcome 1 (MPI)			Outcome 2 (Ln_Labour_Productivity)		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Male_head_houshold	-0.0010	0.0024	0.6670	-0.1685	0.0228	0.0000
total_monthly_income	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Land_Size_Ha	-0.0023	0.0005	0.0000	-0.0061	0.0051	0.2330
Purchased_Land	-0.0089	0.0019	0.0000	0.0194	0.0182	0.2860
completed_primschool	-0.0092	0.0019	0.0000	0.0042	0.0188	0.8220
Years_Schooling	1.0535	0.0231	0.0000	0.0462	0.2282	0.8400
Urban_resident	-0.0472	0.0041	0.0000	0.2334	0.0321	0.0000
Migrated_District	0.0032	0.0017	0.0690	0.0674	0.0172	0.0000
Mobile_phone_ownership	-0.0782	0.0019	0.0000	0.0792	0.0194	0.0000
Land_Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.4340
Asset_values	0.0000	0.0000	0.8430	0.0000	0.0000	0.0000
Irrigated_land	-0.0065	0.0044	0.1360	0.0527	0.0437	0.2270
Land_title	-0.0197	0.0018	0.0000	0.0105	0.0174	0.5450
HHead_Age	-0.0011	0.0001	0.0000	0.0051	0.0008	0.0000
insurance	1.4277	0.0284	0.0000	-0.7928	0.2799	0.0050
_cons	0.4695	0.0052	0.0000	8.3684	0.0439	0.0000
_TNon_Farm_Only (ATE)	**-0.0903**	**0.0065**	**0.0000**	**0.1237**	**0.0369**	**0.0010**
_TDiversifying (ATE)	**-0.0697**	**0.0042**	**0.0000**	**0.6095**	**0.0218**	**0.0000**
/lnsigma	-2.7506	0.0454	0.0000	-0.9862	0.0453	0.0000
/lambda_Non_Farm_Only	0.0396	0.0068	0.0000	-0.1005	0.0291	0.0010
/lambda_Diversifying	0.0637	0.0051	0.0000	-0.5967	0.0160	0.0000
sigma	0.0639	0.0029	-	0.3730	0.0169	-

Number of observations: 42,258; Farm only is the control group; 100 Halton sequence-based quasi random draws per observation

5. Conclusion and Recommendations

This study examined the pathways through which rural households in Rwanda move from farm-based livelihoods into non-farm or diversified strategies, and what such transitions mean for poverty and labour productivity. We used machine learning with SHAP applied to Random Forest predictions to identify key drivers, and the Multinomial Endogenous Treatment Effects (METE) model for causal estimation.

The machine learning analysis highlighted that transitions are strongly conditioned by individual access to information and services, education, finance, and assets, as well as demographic and spatial characteristics. Individuals with mobile phones, shorter travel times to markets, and higher levels of schooling are consistently more likely to move into non-farm or diversified activities, while poverty, limited credit access, and landholding patterns keep many tied to farming. Gender and settlement differences further reinforce these patterns: men and urban residents are better positioned to transition, while women and rural dwellers face higher barriers. These findings confirm that livelihood transitions are not random but emerge from a complex interplay of resources, opportunities, and constraints at individual level, and they highlight the deep inequalities between those able to access non-farm opportunities and those left behind.

The METE analysis then revealed what such transitions mean for household outcomes. Rwandan households specializing exclusively in non-farm activities achieve significant gains in labor productivity and experience notable reductions in multidimensional poverty, although the quality of many non-farm jobs may limit the depth of poverty escape. In contrast, households that diversify across farm and non-farm activities record substantial reductions in poverty while also raising productivity. The complementarity of mixed strategies, where non-farm earnings support farm investments and farming ensures food security, proves especially powerful in the Rwandan context. Taken together, the evidence suggests that the road to inclusive rural prosperity cannot be a binary choice between farming and non-farm work. Rwanda's development strategy must instead nurture balanced, multi-activity livelihoods while upgrading the quality of rural non-farm employment.

This implies three interlinked directions. First, enhancing non-farm job quality is crucial. The productivity and poverty benefits shown in the METE model are real, but without higher wages, stability, and formalization, they may not translate into lasting welfare gains. Skills training, SME support, and agro-processing industries can create a more robust and rewarding non-farm sector.

Second, supporting multi-activity strategies is equally important. The evidence from diversification points to resilience: households that combine farming with non-farm work smooth their income, reduce poverty risk, and create synergies between the two sectors. Credit, infrastructure, and social safety nets can empower households to pursue this balancing act effectively.

Third, the drivers uncovered by machine learning, education, digital access, migration, and gender dynamics point to levers for more inclusive transformation. Investments in rural schools, vocational training, mobile and internet infrastructure, and gender-responsive programs will determine who can access non-farm opportunities. Without these, transitions will remain uneven and exclusionary.

Rwanda's rural transformation is not simply about moving labor out of farming. It is about enabling households to maintain a productive agricultural base while accessing dignified and stable non-farm opportunities. The combination of SHAP and METE findings reinforces that policies must work on both fronts: expand the doorways into non-farm sectors while ensuring those pathways lift people out of poverty. Only then can the farm-to-non-farm transition become a genuine path to broad-based prosperity.

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