Impacts of Railway Development Induced Land Displacement on Households' Livelihoods in South Wello Zone of Amhara Region, Ethiopia

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Abstract:

This study analyzed the impacts of land displacement due to railway development on households' livelihoods in the South Wello Zone of the Amhara Region, Ethiopia. Using both primary and secondary data, the research relied on the responses of 213 randomly selected households. It utilized ordered logistic regression analysis and propensity score matching. The findings demonstrated that advancing from elementary to tertiary education increases the likelihood of developing human capital in terms of skills and education by 3.80 ($p < 0.001$). Similarly, progressing from elementary to certificate training raises this likelihood by 1.90 ($p < 0.001$). Employment status also plays a pivotal role, with own-farm employment showing higher livelihood sustainability compared to other types of employment such as private business or organizational work. The findings emphasized the critical roles of education, employment opportunities, and resource accessibility in post-displacement livelihood recovery. The study calls for strategic interventions to address the challenges of land displacement and promote sustainable livelihoods throughout development intervention.

Keywords: *Land displacement, Railway development, Sustainability, Human capital, Education*

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1. Introduction

The development of transportation infrastructure, particularly railways, connects remote regions, stimulates trade, and fosters local economic development (Rodrigue 2024; Ranjan 2020). Ethiopia, recognizing the importance of transportation, has embarked on an ambitious plan to construct a 5,000-kilometer standard gauge railway network connecting 49 towns (Chen 2021; ERC 2016). However, these advancements often impose significant costs on communities residing along the project paths (Chen 2021; Gnade, Blaauw, and Greyling 2016). One of the most pressing challenges is land displacement, which disrupts livelihoods and social cohesion, especially in developing regions where land-based activities are vital for subsistence and survival (Nisa and Khalid 2024; Vanclay 2017).

Ethiopia's dual challenge lies in balancing rapid infrastructure development with the well-being of its agrarian population. While railway projects like the Addis Ababa-Djibouti Railway represent national efforts to enhance connectivity and economic growth (Chen 2021; ERC 2016), they also displace communities, causing socio-economic and cultural disruptions (Egze, Zeleke, and Seyoum 2023).

In administrative zones such as the South Wello Zone of the Amhara Region, the challenges associated with land displacement underscore the profound significance of land resources. Land is an essential element for many households, and it is far more than an economic asset; it serves as a cornerstone of identity, culture, and survival. Farming, the primary livelihood in these areas, is deeply intertwined with social and cultural traditions, reflecting the essential role of land in maintaining community cohesion and heritage (Shrestha et al. 2022; Sapkota 2021). Displacement undermines these foundations, threatening household incomes, food security, and community cohesion (Egze, Zeleke and Seyoum, 2023; Kapur 2019).

The challenges extend beyond land loss. Displacement often forces families into precarious circumstances, leaving them vulnerable to poverty and social exclusion (Makacha, Mgale, and Kinyashi 2022; Gnade, Blaauw and Greyling 2016). Moreover, restricted access to natural resources and economic prospects exacerbates these hardships (Ben and Agnes 2023; Kapur 2019). Although compensation and resettlement programs aim to mitigate these impacts, inadequate implementation frequently leaves displaced households struggling to rebuild their livelihoods (Zoomers and Otsuki 2017; Vanclay 2017). Additionally, Ethiopia's complex land tenure system, which provides most rural households with usufruct rights rather than full ownership, restricts their ability to secure adequate compensation or alternative livelihoods (Nisa and Khalid 2024; Adamie 2021).

The South Wello Zone railway projects disrupted agricultural productions, thus limiting local employment opportunities, exacerbating economic inequality, and altering social dynamics. While promising regional economic growth, the displaced communities demand inclusive strategies and careful planning to ensure equitable and sustainable outcomes (Belda et al. 2024; Ben and Agnes 2023).

This study analysed the socio-economic impacts of railway development-induced land displacement on households in the South Wello Zone, focusing on coping strategies and policy implications. By analyzing the experiences of land displaced communities, this study intended to provide actionable insights for policymakers and planners to balance economic growth with social equity.

1.1. Sustainable Livelihoods Framework: A Comprehensive Perspective

The concept of Sustainable Livelihoods (SL) has emerged as a response to debates surrounding development theories, providing a more balanced and comprehensive view of livelihoods. It goes beyond mere income generation to encompass capabilities, assets, and viable opportunities, thus recognizing the diverse nature of livelihoods and emphasizing human agency within the context of power dynamics and resource distribution (Natarajan et al. 2022; Turner 2017).

At its core, the sustainable livelihood framework offers a holistic understanding of livelihoods by considering various dimensions, constraints, and opportunities (Makacha, Mgale, and Kinyashi 2022). By incorporating the experiences of individuals, households, networks, and communities, it presents an alternative perspective to traditional income-based approaches. This approach focuses on the interplay of different forms of capital-human, social, natural, physical, and financial-identifying key factors that impact rural survival (Turner 2017; Makacha, Mgale, and Kinyashi 2022; Ben and Agnes 2023). Central to this approach is the recognition of how capital assets and institutions interact to shape livelihood strategies, with institutions, policies, and governance structures playing a crucial role in determining outcomes for rural households (Robert and Gordon 2014).

Emphasizing sustainability as a core principle, the Sustainable Livelihoods Approach (SLA) transforms it into a comprehensive framework that integrates economic, social, and environmental dimensions. The SLA aims at poverty reduction, opportunity creation, and sustainable practices to enhance rural livelihoods and build resilience emphasizing the significance of traditional practices in rural livelihoods and addressing the complex social, political, and economic relationships within communities (Natarajan et al., 2022; Kapur, 2019; Turner 2017).

Capital assets, encompassing human, social, natural, physical, and financial capital, are fundamental to individual well-being and the sustainability of livelihoods. Effective distribution and management of these assets, considering structural and relational factors that influence access, are crucial. Social relations shape vulnerabilities and opportunities within communities, while policies and institutional frameworks determine resource availability (Natarajan et al. 2022; Makacha, Mgale, and Kinyashi 2022). Sustainable livelihoods strive to balance resource use and adaptation without depleting critical assets (Sapkota 2021).

Infrastructure improvements are essential to support sustainable livelihood development (Kapur 2019), as disruptions such as displacement can impact overall well-being by hindering access to assets (Egze, Zeleke, and Seyoum 2023). Beyond income generation, a comprehensive understanding of livelihoods involves education, community support, and environmental sustainability. Therefore, policies play a significant role in promoting economic well-being and guiding interventions to enhance livelihood outcomes while mitigating vulnerabilities (Kapur, 2019; Turner, 2017).

Natural resources and ecosystem services are integral to rural livelihoods, yet their value is often underestimated, resulting in underinvestment and mismanagement (Ben and Agnes 2023; Mutandwa, Grala, and Petrolia 2019; Turner 2017). Land ownership influences diversification opportunities (Habib, Ariyawardana, and Aziz 2023), while the depletion of natural capital poses risks to vulnerable populations (Ben and Agnes 2023). Innovative approaches are required to regenerate and sustain ecosystem services, essential for livelihoods. Physical assets like infrastructure and equipment also contribute to sustainable development by facilitating market access and services (Ben and Agnes 2023; Calow 2017; Grebner et al. 2017).

Financial assets are crucial for risk management and livelihood stabilization, but limited access to capital and economic opportunities restrict participation in rural economies. Strengthening social assets, such as networks, community support, and local institutions, enhances resilience, enabling communities to respond effectively to challenges and adapt to changing conditions (Ben and Agnes 2023; Kapur 2019).

The interaction among the five capital assets shapes livelihood strategies and determines the sustainability of rural communities. By addressing resource distribution, strengthening community networks, and promoting ecosystem conservation, the Sustainable Livelihoods Approach offers a holistic strategy to enhance livelihoods, reduce poverty, and foster long-term development in vulnerable regions (Ben and Agnes 2023; Kapur 2019; Turner 2017).

2. Materials and Methods

2.1. Study Area

The survey was conducted in South Wello, a Zone in Amhara Region, sharing borders with Oromia, Afar, Tigray, Benishangul Gumuz states, and Sudan. The study has focused on the Kemissie to Hayk railway line through Kombolcha, encompassing four Woredas, a vital link with port terminals in the rail network (Ranjan 2020; ERC 2016). The area ranges from 1500 to 1840 meters above sea level, receiving 725 to 1613 mm of rain annually, with temperatures averaging 14.8 to 20.9°C. Its topography includes 14% high altitude-Dega, 34% mid-highland-Weina Dega, 52% low altitude-kola, featuring mountains, hills, plateaus, rivers, and streams essential for water supply and power generation (Addis et al. 2019; Abegaz 2020).

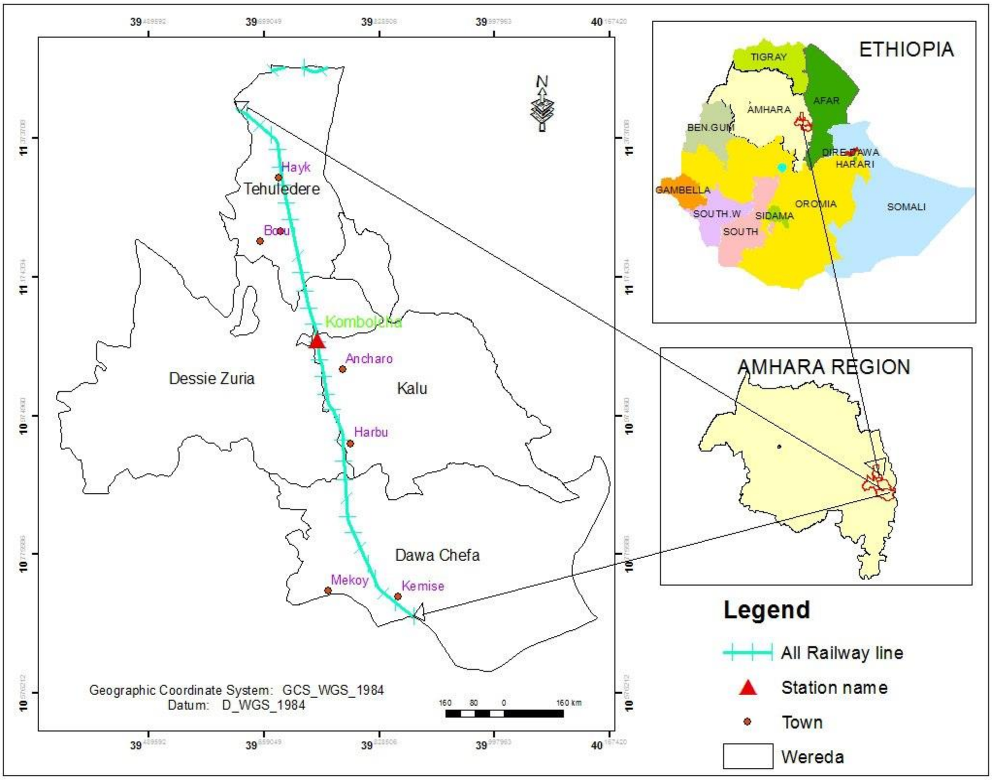


Figure 1: Map of the Study Area

2.2. Research Approach and Design

Using a quantitative research approach, the study analyzed the impact of railway projects on households' livelihoods, providing insights into the impact of rail way development induced land displacement on livelihood outcomes (comprising of five capital assets: Natural, Financial, Physical, Social, and Human capitals). The cross-sectional research design was structured and administered to apply an ordered logistic regression (Barros and Hirakata 2003), and propensity score matching method was also used. By adopting these types of quantitative research methods, the study was able to provide a thorough and objective analysis of the impacts of land displacement on household livelihoods. The analytical approach enabled the authors to analyze the impacts of railway development on different livelihood assets, ensuring a comprehensive understanding of this complex relationship (Islam and Filho 2023; Siltan 2019).

2.3. Sources of Data

The study employed both primary and secondary data sources. Primary data were collected through a household survey and key informant interviews. The household survey utilized structured and semi-structured questionnaires to obtain households' perceptions on how the railway project impacted their livelihoods across natural, financial, physical, social, and human capital dimensions. Key informant interviews were also conducted to gather information from experts on the impacts of land displacement on households' livelihoods.

In addition to primary data, the study incorporated secondary data sources, such as household documents from the Ethiopia Railway Corporation and relevant data from the respective regional administration office. Furthermore, other pertinent documents, including research works on the area, were collected to complement the primary data. The inclusion of secondary data sources enabled the researchers to obtain supplementary information and perspectives regarding the impacts of displacement on affected households, thereby enhancing the robustness of the findings. The integration of both primary and secondary data sources facilitated a more comprehensive understanding of the impacts of railway development from the affected households' perspectives.

2.4. Population and Sample size

Based on the Ethiopian Railway Corporation's report in 2019 and data verified from the woreda administration, 1,261 households were identified as the population affected by the project along the railway project in the study area. This number includes both households that were displaced with replacement land and those that were not displaced but economically affected. In order to determine the sample size, the study employed Yamane's formula, stated as follows: $n = N / (1 + Ne^2)$

Where; n represents the desired sample size, N represents the population size (1261), e represents the level of precision/sampling error, assuming the population's characteristics are relatively consistent (set at 6%).

Using this formula, the sample size was calculated as follows:

$n = 1261 / (1 + 1261 * 0.06^2) = 228$

Consequently, the study was conducted with a sample size of 228. This sample included both the treatment group of 160 households displaced with replacement land and 68 control groups unaffected by the railway project (neither displaced nor had a compensation claim). In addition to the project-affected households, approximately 40 administrative staff members from different levels (including Municipality, Woreda, Zone, and Region) were also considered valuable sources of information for the study.

2.5. Sample Design and Technique

The study employed a random sampling method to select participants from the local community in the South Wello zone of the Amhara region, specifically from the Kemissie to Hayk railway section. Using stratified sampling selection methods, both the control and treatment groups were assigned. By utilizing a random sample selection technique, the study ensured that the selected participants represented the diverse characteristics of the displaced people for control and treatment groups.

2.6. Research Variables

Table 1: Description of the Variables

Types of Variables	Variable	Description
Dependent Variables	human	Members of the household have an advantage in education and skill trainings after the resettlement (1=strongly disagree, 2=disagree, 4=agree, 5=strongly agree)
	physical	The current resettlement area is not different from the previous one in terms of access to basic services (1=strongly disagree, 2= disagree, 4 =agree,5=strongly agree)
	fiancial	Household income has substantially increased after displacement (1=strongly disagree, 2= disagree, 4 =agree,5=strongly agree)
	natural	The current resettlement area is not different from the previous one in terms of natural resource access (land, water, forest and natural amenities) (1=strongly disagree, 2= disagree, 4 =agree,5=strongly agree)
	social	Given resettlement due to the railway project, the social networks among the community are not disintegrated (1=strongly disagree, 2= disagree, 4 =agree,5=strongly agree)
	overall_sust	Overall sustainability of household livelihoods in the railway project-affected area
Independent Variables	sex	Sex of the household head/ respondent (1 = male or 0 = female)
	age	Age of the household head/respondent (categorized into 6 groups)

edu	Schooling status of the household head education (categorized as 1=Elementary School; 2=Secondary School; 3=Certificate; 4=Tertiary Education)
empt	After eviction the households employment status (categorized as 1=Own-farm; 2= Own Business; 3=Private Organization; 4=Government; 5= No Job)
gotrepl	Household land displaced and got replaced land (categorized as 1 = Yes and 0 =No)
sati2com	Household satisfied with the given amount of compensation (categorized as 1 =Yes and 0 =No)
miswater	Due to displacement, the household lacked access to water resources (categorized as 1 =Yes and 0 =No)
misforest	Due to displacement the household missed forest resource (categorized as 1 =Yes and 0 =No)

2.7. Model Specification

Ordered Logit Model

The study utilized ordered logistic regression as the analytical method to explore the effects of different factors on capital assets. This method demonstrates the ordered nature of the categories among dependent variables. The formulation of the ordered logit model for analyzing relationships between a set of independent variables and an ordinal dependent variables-natural, financial, physical, social, and human capital-were derived from the survey responses of the participants. These outcome variables are ordered from 'strongly disagree' to 'strongly agree' with assigned values from 1 to 5.

For each dependent variable Y, representing levels of agreement from 'strongly disagree' to 'strongly agree' (denoted as y = 1, 2, 3, 4, 5, respectively), the study collected cross-sectional data at a specific time to measure how household livelihoods across the five capital assets fell into the specified categories. This analysis aimed to analyse the impacts of railway development on the livelihoods of households in the study area.

The model is formulated as follows:
For a single latent variable Y*,

$$Y_i^* = X'_i\,\beta + \varepsilon_i \quad \text{……………………..……………………} \ (1)$$

$$Y_i = j \ \ if \ a_{j-1} < Y_i^* < a_j \quad \text{……………………..…………} \ (2)$$

Where Y_i* represents unobservable variable for the households' livelihoods captured under the five capital assets, and X'_irepresents the vectors of independent variables. β denotes the vectors of coefficients for each respective independent variable, α_j represents the cut of four points (intercepts) between the two thresholds among the five categories (if α_1 is set to zero, and the remaining thresholds (α_2, α_3, α_4, α_5) are estimated), and $\mathcal{E}_i$ represents the error terms of the unexplained part of the dependent variable.

The probability that observation i is selected alternative j, P_{ij} is:

$$p_{ij} = p(Y_i = j) = p(a_{j-1} < Y_i^* < a_j) = F\left(a_j - X'_i\beta\right) - F\left(a_{j-1} - X'_i\beta\right) \quad \text{………} \ (3)$$

For ordered logit, F is the logistic CDF could be explained as:

$$F(z) = {e^z}/{(1+e^z)} \quad \text{……………………..……………………} \ (4)$$

The ordered logit model with j alternatives has one less set of coefficients with (j-1) intercepts. In this case, there are four intercepts, which demonstrates an ordered logit model. This model, therefore, has five alternatives with four sets of influence for each respective independent variable.

Thus, the influence of each variable on the various alternatives sums up to zero, where a one-unit increase in an independent variable either raises or lowers the log of odds of being in a higher or lower category level compared to a reference group. This approach facilitates the analysis of potential relationships between household livelihood capital assets and various independent variables, explaining how land displacement is influenced in the context of railway development initiatives.

Propensity Score Matching (PSM)

The railway project intervention requires assessments to determine whether it has had a positive or negative impact on households' livelihoods. Similarly, human capital was chosen to affirm the findings of the Ologit model and enhance the understanding of its interconnectedness with the benefits for households in education and skill training following successful resettlement with land displacement, particularly in contrast to those of who are not displaced.

To measure such an intervention, the following equation can be developed:

$$P(x) = P(D=1|x) = E(D|x)$$

D is a binary variable indicating whether an observation has experienced land displacement as the treatment group (D=1 for households with displaced land) or without displacement as the control group (D=0 for households not displaced), with human capital being considered as an outcome variable directly linked to education and skill training. The variable x represents the independent variables that influence the probability of being assigned to the railway project-affected groups. By applying a kernel matching method, we can match observations between households with land displacement and households without displacement based on their propensity scores (Kane et al. 2020).

This comparison can be expressed as: $y=\begin{cases} y1 \text{ if } D = 1 \\ y2 \text{ if } D = 0 \end{cases}$

The kernel matching method is distinguished by its flexibility, balance, efficiency, robustness, local adaptation, and ability to provide valid inference, making it a valuable tool for matching observational data in various research contexts (Miao, Farahat, and Kamel 2015). Thus, kernel matching involves matching each affected observation (i) with multiple control observations (j). The weights used in this matching process are inversely proportional to the distance between the propensity scores of households with land displacement (Pi) and households without displacement (Pj). The matching is based on the propensity scores, and the weight applied to each control observation j is determined as:

$$w(i,j) = \frac{K\left(\frac{Pj-Pi}{h}\right)}{\sum_{j=1}^{n_o} K\left(\frac{Pj-Pi}{h}\right)}$$

In the propensity score weighting method, K refers to the kernel matching function used to determine the weights for the control group (households without land displacement). The propensity score Pj represents the likelihood of a household being in the control group, while Pi represents the propensity score for each affected household with displaced land in the project area. The bandwidth parameter h determines the degree of weighting between the affected observations i and the control observations j.

The Treatment-Effects estimation then involves weighting the households with land displacement and the households without displacement observations before computing the average treatment effect (ATE). The ATE indicates the difference in outcomes between these two groups, providing insight into the impact of the land displacement on the affected households' human capital: $\Delta = y_1 - y_0$

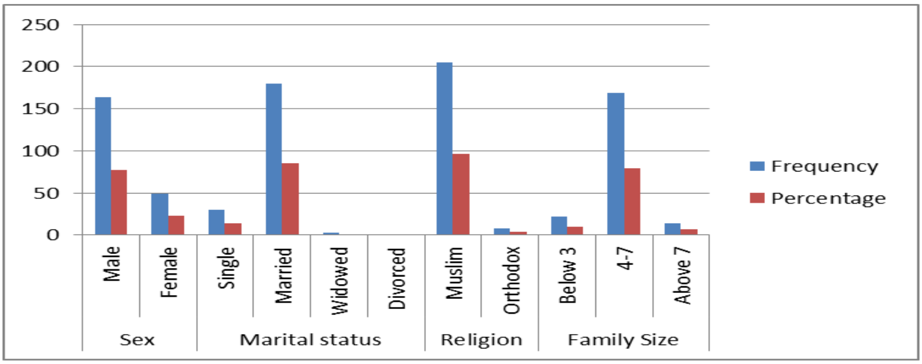
$$ATE = E(\Delta) = E(y_1|x, D=1) - E(y_0|x, D = o)$$

3. Data Presentation and Findings

Data Presentation

In the study, a total of 228 survey questionnaires were distributed and collected, with notable return of 213 surveys, leading to a commendable response rate of 93%. These results not only highlight the effectiveness of the survey distribution and collection process, but also signify the success of engaging participants in the study.

Figure 2: Demographic Information (Head of the Household)



Source: Sample Survey, 2023

Figure 2 presents the demographic characteristics that the male respondents accounted for 77%, while the remaining 23% were female. Respondents identifying as Muslim were 96%, with 3.8% as Orthodox. Those married, single or divorced were 84.5%, 14% and 1.4%, respectively. The analysis of family size that reveals 79.4% having a family size ranging from 4 to 7 members, 10% having family members with less than 3, and the remaining 6.5% having more than 7 family members.

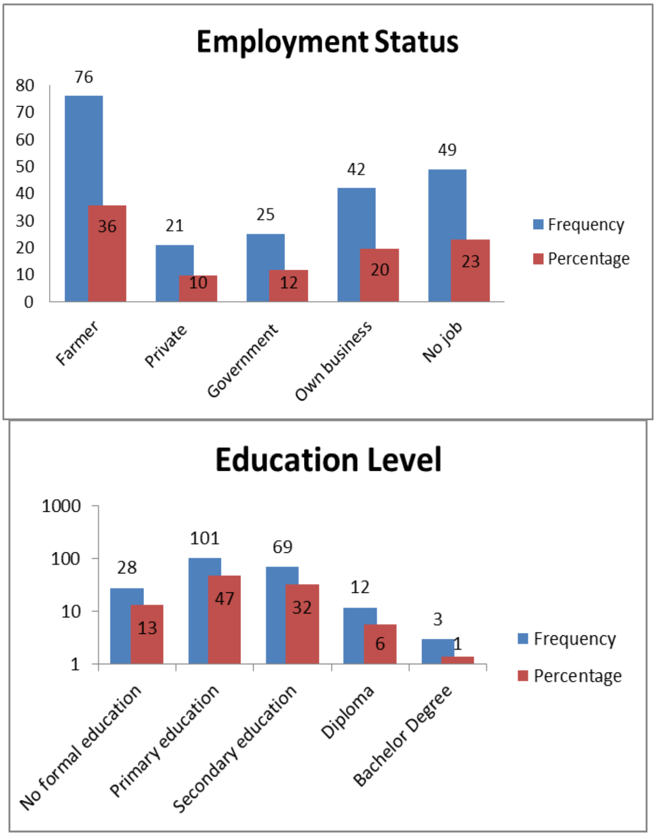


Figure 3: Head of the households' Employment and Education
Source: Sample Survey, 2023

The survey provided insights into the respondents' employment status and education. While the railway line crosses rural Woredas and Kebeles, the study area of the railway is in close proximity to towns and cities such as Kombolcha, where residents are involved in both agriculture-based and non-agriculture-based economies. Consequently, a significant proportion of respondents (36%) relied on farming for their livelihoods, while 20% owned businesses, showcasing entrepreneurial activities. Additionally, 23% were unemployed, and 12% were civil servants. In terms of education, 47% had completed primary education, and 32% had finished secondary education. A smaller percentage held a diploma (6%) or a bachelor's degree (1%), while 13% had no formal education. These findings highlighted occupational diversity, with a substantial number engaged in farming, and varied educational backgrounds among the respondents. Any actions taken to impact land size, such as development projects like railway infrastructure, necessitate long-term programs to train and support individuals with lower educational backgrounds in adapting to the resulting changes.

In terms of the age distribution among respondents, 31% fell within the range of 25-35 years, 23% between 35-45 years, 20% between 45-55 years, 13% between 55-65 years, 8% above 65 years, and the remaining 5% between 20-25 age range. The project-affected community's shows predominantly working-age demographics that necessitates job opportunities, with targeted training holding promise for fostering positive outcomes for individuals and the broader community.

Analysis and Discussions

Utilizing Ordered Logistic Regression and Propensity Score Matching (PSM), the study examined the impact of the railway development project on diverse capital assets. This reveals the intricate interplay among human, natural, social, physical, and financial capitals within the sustainable livelihood framework (Makacha, Mgale, & Kinyashi, 2022). Thus, these assets play a pivotal role in influencing individuals' capacity to build and maintain their livelihoods (Dehghani Pour et al., 2018). Consequently, the research studied a scale of household livelihood elements, encompassing natural resources like water and forests, infrastructure, social networks, human capital emphasizing skills and education, and financial resources like savings.

Ordered Logistic Analysis

Socioeconomic status significantly predicts quality of life, with individuals of higher socioeconomic status implying a better quality of life (Nutakor et al. 2023). To dissect the intricate interplay among factors impacting capital assets-spanning natural, financial, physical, social, and human capital-ordered logistic analysis was utilized to illuminate the dynamics of household livelihood, particularly within the context of railway development. Consequently, the results of the ordered logit analysis conducted in Stata are shown in Table 2, revealing a robust alignment of the model with the data concerning the pivotal variable of human capital. Noteworthy is the Chi-square value of 71.86, with a p-value below 0.001. Likewise, robust fits were evident across different capital assets such as: physical capital (Chi-square = 124.1, $p < 0.001$), natural capital (Chi-square = 68.22, $p < 0.001$), financial capital (Chi-square = 114.33, $p < 0.001$), and social capital (Chi-square = 107.04, $p < 0.001$), validating the null hypothesis. The statistical analysis indicates significant revelations concerning the sustainability of owning capital assets post-land displacement, as highlighted by a chi-square value of 87.468 and a p-value below 0.001.

Table 2: Ordered Logistic Regression for Sustainable Livelihood Elements

Independent Variables		Outcome Variables (Capital Assets)					
		Human Coef (SE)	Physical Coef (SE)	Natural Coef (SE)	Financial Coef (SE)	Social Coef (SE)	overall_sust Coef (SE)
Sex		0.30 (047)	0.65(0.37)*	0.50(0.38)	0.65(0.60)	0.80(0.47)*	0.73(0.32)**
Age		0.04(0.01)**	0.01 (0.01)	0.05(0.04)***	0.17(0.03) ***	-0.03(0.02)*	0.05(0.01)***
Edu	Elementary	0	0	0	0	0	-
	Secondary	0.02(0.54)	0.45(0.53)	1.65(0.55)***	22.72(1409.99)	-1.72(0.64)***	0.95(0.47)**
	Certificate	1.90(0.66)***	1.18(0.63)**	2.24(0.66)***	21.331(1409.99)	-1.29(0.80)	2.27(0.56)***
	Tertiary	3.80(0.89)***	-1.51(1.04)	1.21(0.80)	20.34(1409.99)	-1.34(1.35)	1.50(0.71)**
Empt	On-farm	0	0	0	0	0	-
	Own-business	-1.87(0.68)***	-3.04(0.81)***	0.53(0.56)	5.32(1.31) ***	-2.82(1.15)**	-1.07(0.55)*
	Private-organization	-1.88(0.65)***	-0.65(0.57)	0.81(0.53)	5.54(1.30)***	-1.23(0.80)	-0.62(0.47)
	Government	-0.63(0.49)	-1.73(0.47)***	-0.02(0.43)	2.13(0.92) **	-0.37(0.64)	-0.70(0.43)
	Unemployed	-1.86(0.56)***	-0.71(0.46)	-0.67(0.49)	1.35(0.98)	-0.26(0.60)**	-1.27(0.41)***
Gotrepl		0.43(0.39)	0.53(0.40)	0.86(0.37)**	-0.28(0.73)	1.28(0.51) **	0.93(0.37) **
Sati2com		-0.66(0.45)	2.44(0.53)***	-1.52(0.43)***	-1.99(0.64) ***	3.33(1.22) ***	-0.29(0.37)
Miswater		0.72(0.41)*	1.34(0.39)***	0.74(0.36)**	0.04(0.74)	3.26(0.51) ***	1.99(0.35)***
Misforest		0.56(0.63)	2.06(0.80)***	-1.40(0.53)***	-21.27(1598.60)	-1.76(0.66) ***	-1.59(0.54)***
Constant		3.13(1.42)	9.12(1.66)	1.58(1.33)	7.53(2131.56)	9.82(2.74)	2.13(1.17)
Pseudo r-squared		0.179	0.272	0.152	0.523	0.318	0.1029
Chi-square		71.86	124.10	68.22	114.33	107.04	87.47
Prob > chi2		0.000	0.000	0.000	0.000	0.000	0.000
log likelihood		-165.26	-165.95	-190.29	-52.19	-114.65	-381.27

Note:P-values are denoted by *** for 1%, ** for 5% and * for 10%;Coef & SE represents for Coefficient & Standard Error respectively

Human Capital

Recognizing the predictive impact of determinants such as sex, education, age of the household head, employment status, water and forest resources, as well as land displacement on the community's livelihood dynamics, a thorough investigation was conducted using the rigorous method of ordered logistic analysis. Female-headed households, particularly those with dependent children and no partner, faced distinct challenges compared to male-headed households (Boudet et al., 2018), prompting women to strive for a transformation in gender dynamics within the community's livelihood framework (De Haan, 2012). Household characteristics, as emphasized by Liu et al. (2022), can serve as indicators of an individual's work capabilities, skill gaps, and limited employment prospects, shedding light on the potential hardships individuals encounter during development-induced land displacement. Education levels and other independent variables were found to be interconnected with various facets of livelihoods, encompassing human, physical, natural, financial, and social capital, which collectively influence household sustainability, suggesting that individuals with differing educational backgrounds and other factors may be affected in distinct ways when these elements are considered.

The research revealed that variables like employment status, education level, and age demonstrated statistical significance concerning various capital assets. Interestingly, factors such as gender and access to forest resources did not exhibit significant correlations with the development of human capital assets.

An advancement in education from elementary to tertiary level was associated with a 3.80 increase in the likelihood of possessing enhanced skills, exposures, and training that enrich human capital, all while maintaining other factors constant. Similarly, progressing from elementary to certificate-training education was linked to a 1.90 increase in the probability of acquiring improved skills and networks that contribute to human capital, with all other variables remaining steady.

Moreover, factors like owning a business, working in the private sector, and experiencing unemployment were identified as statistically significant influencers on human capital development, unlike a civil servant status. Furthermore, an increased number of businesses owned, compared to owning a farm, resulted in a 1.87 decrease in the likelihood of developing strong skills and networks within human capital, with all other variables in the model held constant. Consequently, farm-based employment is perceived to provide better opportunities for investing in education or other dimensions of human capital.

Similarly, an extended period of unemployment, compared to farm ownership, led to a 1.86 decrease in the likelihood of achieving a higher level of human capital, with all other variables held constant. Notably, this decrease rose to 1.88 for individuals in the private-organization category compared to owning a farm. Thus, farm ownership appears to foster greater human capital development compared to private-sector jobs, which may lack supportive benefits. (Please refer to Annex A for the Stata output.)

Physical and Natural Capital Assets of Displaced Households

As highlighted by Choi (2015), residents' physical capital suffered a decline in livelihood impacts due to displacement, primarily stemming from land clearance. The intervention's development further disrupted household and individual interactions, exacerbating these challenges. Concerning education, only the certificate level displays weak statistical significance compared to elementary school, while other education levels do not exhibit a significant relationship with households' physical capital in livelihoods. This suggests a limited and uneven impact of education levels on enhancing physical capital.

Regarding job opportunities, both owning a business and being a civil servant emerged as strong influencing factors compared to farm ownership. However, unemployment and private sector jobs do not show a significant influence on physical capital. In specific context, an upgraded business, as opposed to owning a farm, signifies a 3.04 reduction in the likelihood of reaching a higher level of physical capital, with all other variables remaining constant. Likewise, there is a 1.73 decrease in the likelihood of achieving a higher level with a rise in civil servant status compared to owning a farm. This indicates that owning businesses and government positions have a more pronounced impact on the physical aspects of households' capital assets.

Conversely, the presence of water enhances the likelihood of attaining a higher level of physical capital by 1.34 for each advance in water supply. Similarly, satisfaction with compensation yields a significant boost of 2.44 in the same direction. Additionally, access to forests exerts a notable impact, resulting in a 2.06 increase in the probability of achieving a superior level of physical capital with each progression. Hence, the availability of water, accessibility of forests, and contentment with compensation all play essential roles in enriching the physical capital within household livelihoods.

As noted by Aboda et al. (2019), the loss of natural resources often leads to a loss of income and livelihoods. Household characteristics reflect an individual’s work abilities, skill deficits, and limited job opportunities, highlighting how development interventions and reliance on natural resources can negatively affect individuals (Liu et al., 2022). Additionally, the depletion of natural capital further exacerbates these challenges (Ben & Agnes, 2023).

Liu et al. (2022) emphasizes that household characteristics act as indicators of an individual’s work abilities, skill deficits, and limited job opportunities. This underscores the potential negative impacts of development interventions, particularly for those heavily dependent on natural resources. Furthermore, the depletion of natural capital intensifies these difficulties (Ben & Agnes, 2023).

Although employment status may not exhibit a significant influence, the level of education, particularly at the secondary and certificate levels, demonstrates strong effects compared to elementary education concerning natural capital. This implies that education plays a crucial role in mitigating the impact of development interventions on the natural capital assets of livelihoods. Secondary education shows a notable increase of 1.65 in the probability of reaching a higher level for each grade increase, while the certificate level displays a substantial difference of 2.24 in the same direction compared to elementary education. Additionally, age and satisfaction with compensation carry significant implications. Age indicates an increase in the likelihood of being at a higher level of natural capital for each year increase, whereas compensation satisfaction reveals a notable decrease of 1.52 in the opposite direction. Furthermore, displaced land and water availability show meaningful associations. Households with displaced land experience a significant increase of 0.86 in the likelihood of their living status for each incremental change, while water availability demonstrates a rise of 0.74 in the same direction. Therefore, secondary education, certificates, age, displaced land, and water availability positively influence attaining a higher level of natural capital. (Please refer to Annex B & C for the Stata outputs.)

Financial and Social Capital Assets of Displaced Households

As noted by Choi (2015), the impact of displacement extended beyond the customer base, disrupting the broader livelihood network that supported local businesses. Socioeconomic status is a key predictor of quality of life, with higher status leading to better outcomes, suggesting that social capital may play a mediating role in these dynamics (Nutakor et al., 2023).

From the employment status perspective, age, and compensation satisfaction, statistically significant relationships are observed, while sex, education, water and forest resources, do not show meaningful thought regards to households' financial capital during land displacement. More specifically, when it comes to the influences of financial capital, one year increase in the household head's age results in a 0.17 increase, while compensation satisfaction shows a 1.99

decrease in the likelihood of being in higher groups of financial capital. In contrast, an enhanced investment in one's own business and advancement in private sector employment correspond to increases of 5.32 and 5.54, respectively, in the probability of being in higher financial capital groups. This suggests that the age of the household head has a modest positive effect, compensation satisfaction has a negative impact, and owning a business or working in a private organization significantly boosts the chances of being in higher financial capital groups, unlike sex, and education.

Education and employment categories, with the exceptions of secondary education and the own-business category, do not demonstrate statistical significance. On the other hand, some studies support the idea that access to economic resources, which contributes to social development, is influenced by various factors (Niaz 2022). Among these factors, sex, age, compensation satisfaction, water resources, forest resources, and displaced lands show statistical significance, although the impact of sex and age is relatively weaker compared to the others.

The research findings suggest that being identified as a business owner is linked to a decreased likelihood of being in higher social groups. In this context, an improved status in own-business employment corresponds to a decrease of 2.82 in this likelihood. Furthermore, the variables of compensation satisfaction and water resources demonstrate significant impacts. A one-level increase in compensation satisfaction and water resources is associated with increases of 3.33 and 3.26, respectively, in the likelihood of being in higher social element groups. However, the forest resource variable shows a decrease of 1.76 in the probability of being in higher groups. Therefore, the research indicates that own-business ownership; compensation satisfaction, water and forest resources significantly influence social development. (Please refer to Annex D & E for the Stata outputs.)

Sustainability

As noted by Aboda et al. (2019), development projects have been observed to induce vulnerability if sustainability is not adequately maintained afterward. Particularly, variables such as sex, age, education, employment (compared to the base category), and access to displaced land and water resources exhibit a significant association concerning the overall sustainability of owning capital assets post-land displacement. Compensation satisfaction, however, does not show a significant relationship with overall sustainability, setting it apart from these influential factors. (See Annex F for the Stata output.)

The meticulous analysis conducted using ordered logistic regression in Table 2 clearly demonstrates the significant impact of several key factors on the community's livelihood elements. These factors include education level, employment status, age of the household head, access to water and forest resources, as well as the displacement of plots of land. Each of these factors plays a pivotal role in shaping the various dimensions of households' livelihoods.

Education level emerges as a significant determinant, exhibiting strong associations with livelihood strategies across capital assets. Higher educational attainment consistently correlates with an increased likelihood of belonging to higher groups concerning these livelihood elements. This underscores the critical role of educational achievements in influencing the diverse dimensions of livelihoods, particularly in scenarios involving displacement due to development projects.

Moreover, employment status emerges as a pivotal factor, with own-business ownership, employment in the private sector, and unemployment showcasing significant relationships. The age of the household head and satisfaction levels with compensation notably influence the capital assets of households' livelihoods. Furthermore, access to water and forest resources, along with the displacement of land, exerts a detrimental impact on the physical and natural capital of households.

The study underscores the intricate interplay of socioeconomic, demographic, and environmental factors in molding the livelihood strategies of land-displaced households, especially within the framework of development projects.

Propensity Score Matching Analysis

The research utilized propensity score matching and non-parametric tests, such as the Wilcoxon rank-sum test, to explore the relationship between human capital and the advantages for households in education and skill training after land displacement. In this particular investigation, households experiencing land displacement were directly compared with those without displacement. Non-parametric tests, being less influenced by outliers and not requiring a normal data distribution, were deemed appropriate for studies with limited sample sizes while attaining a comparable statistical accuracy to parametric tests. The selection of non-parametric tests aligned with the research objective, which aimed to pinpoint notable distinctions between the two groups under examination, namely the treated and controlled groups (Mann and Whitney, 1947).

To estimate the propensity score and account for any potential treatment effects, the observations were matched based on their propensity scores within each group (Austin 2011). A probit regression model was then used to compare the households that experienced land displacement due to the railway project, while controlling for other factors that may affect these outcomes.

Hypothesis Test

The study employed the Two-sample Wilcoxon rank-sum (Mann-Whitney) test and found a p-value of 0.007 (Table 3), and consequently, this finding offers compelling evidence to reject the null hypothesis, which assumes no difference in the median human capital elements between households with land displacement and those without. Hence, it can be inferred that there exists a substantial contrast in the human capital medians between the two groups.

Table 3: Two-sample Wilcoxon rank-sum (Mann-Whitney) test

Displaced land	Observation	Rank sum	Expected
0	78	9366	8346
1	135	13425	14445
Combined	213	22791	22791
Unadjusted variance	187785.00		
Adjustment for ties	-41417.04		
Adjusted variance	146367.96		
Ho: human(gotrepl==0) = human(gotrepl ==1)			
z = 2.666			
Prob >	z	=	0.0077

Source: Sample survey, 2023; (Please refer to Annex H for the Stata output.

Estimating Treatment Effect

As noted by Austin (2011), the statistical analysis of Treatment-effect Estimation aims to establish the causal impact of involuntary displacement on the human capital of affected households using Propensity Score Matching (PSM). Assessing the impacts on households affected by land displacement for railway projects is an important aspect to consider, given that land serves as a significant livelihood asset for the majority of rural communities, as highlighted by Aboda et al. (2019). Kernel density on annexed number G proves that the data is distributed normally.

Table 4: Treatment-effects Estimation with and without Replaced Land

human	Coef.	SE	t-value	p-value	[95% Conf	Interval]	Sig
r1vs0	-.52	.142	-3.65	0	-.799	-.241	***
Mean dependent var		1.690	SD dependent var			0.873	

**** p<.01, ** p<.05, * p<.1, '1' represents land displacement, and '0' without land displacement*

Within Table 4, the statistical outcomes are delineated to assess treatment effects, encompassing scenarios both with and without land displacement. The coefficient assigned to the 'human' variable stands at -0.52 (P-value < 0.001), suggesting an adverse association between human capital and the dependent variable in instances of land displacement, attributed to the railway development mandating households to give up their land.

This discovery implies that the occurrence of land displacement correlates with an average reduction of 0.52 in human capital. Various factors likely contribute to this 0.52 downturn in human capital across the two groups, including the absence of educational infrastructure in the new location after land displacement, the loss of assets from the original area, and challenges in accessing social networks and support systems due to the relocation. The impact of the development project adversely affects households' access to education, leading to a decline in their human capital. Consequently, the study's results reveal a significant negative impact on human capital resulting from land displacement. These outcomes underscore one of the detrimental effects of the development project on human capital in the project regions, specifically attributable to the presence of displacement.

As a result of employing both ordered logistic regression and propensity score matching (PSM), the study examined the complex interplay influencing the capital assets and livelihood strategies of land-displaced households due to railway projects. Ordered logistic regression reveals the significant impact of education level, employment status, age, and resource access on capital assets, underscoring the crucial role of education in shaping households' livelihood outcomes. Furthermore, PSM highlights the detrimental effects of land displacement, with human capital assets demonstrating a negative association, resulting in a 0.52 decrease, influenced by factors such as the lack of educational infrastructure and asset loss.

These results show the many difficulties that affected households face and emphasize how important economic and environmental factors are in shaping their ability to bounce back after being forced from their lands. This means it is really important to carefully study and think through any development plans that might change how households make a living, to avoid causing them harm.

4. Conclusion

Research findings demonstrated that the critical importance of education, employment, and resource access in shaping land-displacement livelihoods, indicating the necessity for careful interventions to ensure long-term sustainability. Education emerges as a key factor influencing the capital assets of livelihoods, with higher education levels aligning with improved livelihood outcomes. This underscores the essential role of education in crafting livelihood strategies, particularly in scenarios of development-induced displacement. Therefore, policy interventions should prioritize educational opportunities to enhance overall livelihood prospects within development projects.

Furthermore, employment status significantly impacts livelihood groupings, with own-farm roles displaying stronger associations with higher livelihood tiers. Understanding these employment dynamics is crucial for targeted interventions aimed at elevating livelihood standards. Similarly, the age of the household head and satisfaction levels with compensation play significant roles in determining physical, natural, and financial capital within livelihoods. Addressing compensation issues and considering demographic characteristics are vital for promoting sustainable livelihood development post-displacement.

Moreover, access to water, forest resources, and adequate land plots profoundly influence the physical and natural capital of households. Interventions must prioritize sustained access to essential resources while mitigating the adverse effects of land displacement to support livelihood resilience. The study also points to a notable decline in human capital following land displacement, attributed to challenges like inadequate educational infrastructure, asset loss, and disrupted social networks. Targeted support mechanisms are essential to prevent human capital loss upon land displacement, necessitating a detailed examination of the long-term impacts of railway development on socioeconomic factors, accounting for temporal variations for a comprehensive analysis.

Funding Information

This research received no external funding.

Acknowledgments

The authors wish to convey their genuine appreciation to all the individuals who took part in this investigation for their valuable time and cooperation. Furthermore, we would like to extend our profound gratitude to the personnel in the area of study for granting us the privilege to conduct interviews, and to the community members residing in the study areas for their warm reception and collaborative efforts.

Conflict of Interest

The authors declare no conflict of interest.

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ANNEXES

A. Ologit for outcome variable Human

```
. ologit human sex age i. edu i. empt gotrepl sati2com miswater misforest

Iteration 0:   log likelihood =  -201.1922
Iteration 1:   log likelihood = -166.11714
Iteration 2:   log likelihood = -165.26688
Iteration 3:   log likelihood = -165.26276
Iteration 4:   log likelihood = -165.26276

Ordered logistic regression                     Number of obs     =        211
                                                LR chi2(13)       =      71.86
                                                Prob > chi2       =     0.0000
Log likelihood = -165.26276                     Pseudo R2         =     0.1786
```

human	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.3038963	.4201735	0.72	0.470	-.5196286	1.127421
age	.036347	.014449	2.52	0.012	.0080274	.0646666
edu						
2	.0182716	.5428938	0.03	0.973	-1.045781	1.082324
3	1.90342	.6583693	2.89	0.004	.6130396	3.1938
4	3.804471	.8912528	4.27	0.000	2.057648	5.551295
empt						
2	-1.865961	.6807582	-2.74	0.006	-3.200223	-.5316992
3	-1.882971	.625532	-3.01	0.003	-3.108992	-.6569511
4	-.6286676	.4868036	-1.29	0.197	-1.582785	.3254499
5	-1.863999	.5595198	-3.33	0.001	-2.960638	-.7673607
gotrepl	.4340426	.3995403	1.09	0.277	-.3490419	1.217127
sati2com	-.6643502	.4479307	-1.48	0.138	-1.542278	.2135778
miswater	.7223414	.4094813	1.76	0.078	-.0802271	1.52491
misforest	.5595436	.6285846	0.89	0.373	-.6724595	1.791547
/cut1	3.130938	1.41549			.3566289	5.905247
/cut2	4.033614	1.429462			1.23192	6.835308

B. Ologit for outcome variable physical

```
. ologit physical sex age i. edu i. empt gotrepl sati2com miswater misforest

Iteration 0:   log likelihood = -228.00372
Iteration 1:   log likelihood = -167.59727
Iteration 2:   log likelihood = -165.96083
Iteration 3:   log likelihood = -165.95443
Iteration 4:   log likelihood = -165.95443

Ordered logistic regression                     Number of obs     =        211
                                                LR chi2(13)       =     124.10
                                                Prob > chi2       =     0.0000
Log likelihood = -165.95443                     Pseudo R2         =     0.2721
```

physical	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.6487473	.3700517	1.75	0.080	-.0765408	1.374035
age	.0107696	.0138793	0.78	0.438	-.0164333	.0379725
edu						
2	.4469495	.5337522	0.84	0.402	-.5991856	1.493085
3	1.17809	.6347388	1.86	0.063	-.0659756	2.422155
4	-1.513533	1.039503	-1.46	0.145	-3.550922	.5238558
empt						
2	-3.036342	.8081534	-3.76	0.000	-4.620293	-1.45239
3	-.651953	.570646	-1.14	0.253	-1.770399	.4664927
4	-1.726002	.467812	-3.69	0.000	-2.642896	-.8091073
5	-.7078731	.4604759	-1.54	0.124	-1.610389	.1946431
gotrepl	.5264654	.3950019	1.33	0.183	-.2477241	1.300655
sati2com	2.440155	.5323604	4.58	0.000	1.396748	3.483562
miswater	1.339805	.3905689	3.43	0.001	.5743037	2.105306
misforest	2.056416	.7995297	2.57	0.010	.4893663	3.623465
/cut1	9.10836	1.655558			5.863525	12.35319
/cut2	11.65666	1.738482			8.249295	15.06402

C. Ologit for outcome variable Natural

```
. ologit natural sex age i. edu i. empt gotrepl sati2com miswater misforest

Iteration 0:   log likelihood = -224.40266
Iteration 1:   log likelihood = -191.39382
Iteration 2:   log likelihood = -190.29847
Iteration 3:   log likelihood = -190.29277
Iteration 4:   log likelihood = -190.29277

Ordered logistic regression                      Number of obs     =        211
                                                 LR chi2(13)       =      68.22
                                                 Prob > chi2       =     0.0000
Log likelihood = -190.29277                      Pseudo R2         =     0.1520
```

natural	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.5027915	.3809435	1.32	0.187	-.2438439	1.249427
age	.0563885	.0138288	4.08	0.000	.0292845	.0834924
edu						
2	1.646632	.5511598	2.99	0.003	.566379	2.726886
3	2.237083	.6561797	3.41	0.001	.9509949	3.523172
4	1.206875	.8024112	1.50	0.133	-.3658216	2.779572
empt						
2	.5326924	.5610527	0.95	0.342	-.5669508	1.632336
3	.8053038	.5251472	1.53	0.125	-.2239657	1.834573
4	-.0243955	.4339082	-0.06	0.955	-.8748399	.8260489
5	-.6731517	.4867863	-1.38	0.167	-1.627235	.2809321
gotrepl	.8637342	.3652931	2.36	0.018	.1477728	1.579696
sati2com	-1.523198	.4349073	-3.50	0.000	-2.3756	-.6707952
miswater	.738433	.3632846	2.03	0.042	.0264083	1.450458
misforest	-1.404184	.5280356	-2.66	0.008	-2.439114	-.3692528
/cut1	1.579019	1.33345			-1.034494	4.192533
/cut2	3.882843	1.365228			1.207045	6.55864

D. Ologit for outcome variable Financial

```
. ologit financial sex age i. edu i. empt gotrepl sati2com miswater misforest

Iteration 0:   log likelihood = -109.35228
Iteration 1:   log likelihood = -71.503033
Iteration 2:   log likelihood = -56.347508
Iteration 3:   log likelihood = -52.823048
Iteration 4:   log likelihood = -52.311974
Iteration 5:   log likelihood = -52.215492
Iteration 6:   log likelihood = -52.193079
Iteration 7:   log likelihood = -52.188022
Iteration 8:   log likelihood = -52.186934
Iteration 9:   log likelihood = -52.186747
Iteration 10:  log likelihood = -52.186727
Iteration 11:  log likelihood = -52.186723

Ordered logistic regression                     Number of obs     =        211
                                                LR chi2(13)       =     114.33
                                                Prob > chi2       =     0.0000
Log likelihood = -52.186723                     Pseudo R2         =     0.5228
```

financial	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.6534979	.6034695	1.08	0.279	-.5292806	1.836276
age	.1658135	.0341398	4.86	0.000	.0989007	.2327262
edu						
2	22.72438	1409.987	0.02	0.987	-2740.799	2786.247
3	21.33187	1409.986	0.02	0.988	-2742.191	2784.854
4	20.33849	1409.986	0.01	0.988	-2743.184	2783.861
empt						
2	5.32499	1.30937	4.07	0.000	2.758671	7.891309
3	5.537241	1.297988	4.27	0.000	2.993232	8.081251
4	2.12647	.9165336	2.32	0.020	.330097	3.922843
5	1.349703	.9781782	1.38	0.168	-.5674907	3.266897
gotrepl	-.2828192	.7323079	-0.39	0.699	-1.718116	1.152478
sati2com	-1.995232	.6371106	-3.13	0.002	-3.243946	-.7465185
miswater	.0439269	.7353633	0.06	0.952	-1.397359	1.485213
misforest	-21.27204	1598.594	-0.01	0.989	-3154.458	3111.914
/cut1	7.530394	2131.564			-4170.259	4185.319

E. Ologit for outcome variable Social

```
. ologit social sex age i. edu i. empt gotrepl sati2com miswater misforest

Iteration 0:   log likelihood = -168.16819
Iteration 1:   log likelihood = -123.41448
Iteration 2:   log likelihood = -115.17861
Iteration 3:   log likelihood = -114.65407
Iteration 4:   log likelihood = -114.64724
Iteration 5:   log likelihood = -114.64723

Ordered logistic regression                     Number of obs     =        211
                                                LR chi2(13)       =     107.04
                                                Prob > chi2       =     0.0000
Log likelihood = -114.64723                     Pseudo R2         =     0.3183
```

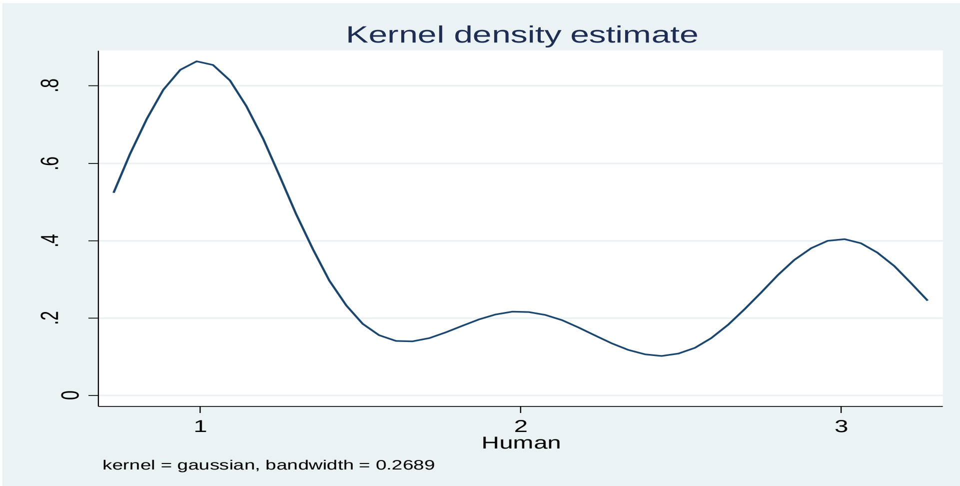
social	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.8012115	.4671164	1.72	0.086	-.1143198	1.716743
age	-.0294567	.0168487	-1.75	0.080	-.0624796	.0035663
edu						
2	-1.718438	.6432708	-2.67	0.008	-2.979225	-.45765
3	-1.293994	.7979034	-1.62	0.105	-2.857856	.2698678
4	-1.339943	1.350138	-0.99	0.321	-3.986165	1.306279
empt						
2	-2.826915	1.154709	-2.45	0.014	-5.090104	-.5637267
3	-1.229411	.7975712	-1.54	0.123	-2.792621	.3338002
4	-.3735311	.6456549	-0.58	0.563	-1.638991	.8919291
5	-.2607727	.5972346	-0.44	0.662	-1.431331	.9097855
gotrepl	1.275402	.5075878	2.51	0.012	.2805481	2.270256
sati2com	3.335253	1.215826	2.74	0.006	.9522769	5.718228
miswater	3.264779	.5072904	6.44	0.000	2.270508	4.25905
misforest	-1.76211	.6621314	-2.66	0.008	-3.059864	-.4643565
/cut1	9.823961	2.735975			4.461549	15.18637
/cut2	11.60929	2.775459			6.169491	17.04909

F. Ologit for outcome variable Overall Sustainability

```
. gen overall_sust = ( human+ physical+ natural+ financial+ social)/5

. ologit overall_sust sex age i. edu i. empt gotrepl sati2com miswater misforest

Iteration 0:   log likelihood = -425.00572
Iteration 1:   log likelihood = -383.13871
Iteration 2:   log likelihood = -381.28259
Iteration 3:   log likelihood = -381.27178
Iteration 4:   log likelihood = -381.27178

Ordered logistic regression                     Number of obs     =        211
                                                LR chi2(13)       =      87.47
                                                Prob > chi2       =     0.0000
Log likelihood = -381.27178                     Pseudo R2         =     0.1029
```

overall_sust	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
sex	.7261388	.3195547	2.27	0.023	.0998231	1.352455
age	.0474172	.0120821	3.92	0.000	.0237368	.0710976
edu						
2	.949521	.474434	2.00	0.045	.0196474	1.879395
3	2.269885	.5633639	4.03	0.000	1.165712	3.374058
4	1.500571	.7069951	2.12	0.034	.1148866	2.886256
empt						
2	-1.067988	.5512939	-1.94	0.053	-2.148504	.0125286
3	-.617679	.474931	-1.30	0.193	-1.548527	.3131687
4	-.6982124	.4260921	-1.64	0.101	-1.533338	.1369128
5	-1.265332	.409009	-3.09	0.002	-2.066975	-.4636896
gotrepl	.9282186	.3667267	2.53	0.011	.2094474	1.64699
sati2com	-.293485	.3730486	-0.79	0.431	-1.024647	.4376769
miswater	1.990214	.3513236	5.66	0.000	1.301632	2.678796
misforest	-1.589488	.5447219	-2.92	0.004	-2.657123	-.5218525
/cut1	2.129467	1.178488			-.1803272	4.439261
/cut2	3.873121	1.173856			1.572405	6.173836
/cut3	4.983398	1.194403			2.642411	7.324386
/cut4	5.461747	1.20432			3.101323	7.822171
/cut5	5.982278	1.217285			3.596444	8.368113
/cut6	6.60039	1.232174			4.185373	9.015407
/cut7	8.022512	1.26687			5.539491	10.50553

G. Kernel density



H. Two-sample Wilcoxon rank-sum (Mann-Whitney) test

```
. ranksum human , by ( gotrepl )

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

     gotrepl |      obs    rank sum    expected
-------------+---------------------------------
           0 |       78        9366        8346
           1 |      135       13425       14445
-------------+---------------------------------
    combined |      213       22791       22791

unadjusted variance    187785.00
adjustment for ties    -41417.04
                       ----------
adjusted variance      146367.96

Ho: human(gotrepl==0) = human(gotrepl==1)
             z =   2.666
    Prob > |z| =   0.0077
```