# Determinants of Young People not in Employment, Education and Training (NEET) in Rural Ethiopia

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## Abstract

This study examines the determinants of NEET (Not in Education, Employment, or Training) status among rural Ethiopian youth using panel data from the Ethiopian Socioeconomic Survey (ESS) for 2019 and 2022. The analysis utilizes samples of 3,503 and 3,538 individuals aged 15–29 from the respective survey rounds. The prevalence of NEET status among Ethiopian youth represents a significant socio-economic challenge. Given that youth constitute most of the population, their exclusion from educational and labour markets not only diminishes individual well-being but also jeopardizes the country's long-term development and its potential to realize a demographic dividend. Descriptive statistics show that the rural NEET rate rose from 25.2% in 2019 to 30.8% in 2022, with inactivity accounting for 73% of the cases. Regional disparities are evident, with Dire Dawa recording the highest rate (36.9%) and Benishangul-Gumuz the lowest (19.23%) in 2019. To account for unobserved heterogeneity, conditional fixed-effects logit models were estimated for total, inactive, and unemployed NEET categories, with robustness confirmed through conditional random effect, pooled logit and OLS checks. Results highlight poor health, marital disruption, and gender as major risk factors, while father's employment and parental literacy reduce NEET odds. Age effects are strongest for the 25–29 cohort, and tertiary education shows a dual effect reducing unemployed NEET but increasing inactivity suggesting skills mismatches. These findings underscore the multifaceted drivers of NEET status and point to policy priorities: strengthening household employment, expanding health services, promoting gender-sensitive programs, improving school-to-work transitions, and aligning higher education with labour market needs.

**Keywords:** NEET, rural youth, employment, education and training, unemployed and inactive

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## 1. Introduction

Rural youth represent a heterogeneous population that confronts the combined challenges of age-specific vulnerabilities and underdevelopment. In Africa, rural youth face significant barriers, including scarce job opportunities, suboptimal educational quality, and insufficient access to skills development training (FAO, 2017). Their participation in the labour market is often constrained by limited access to critical resources such as skills, innovation, finance, and land (Kubik, 2022). Moreover, a notable disparity exists between rural and urban youth, with the former having restricted access to learning opportunities and training facilities (Morsy et al., 2019; Yeboah and Justin, 2021). This is often exacerbated by inadequate educational infrastructure in rural regions, such as a lack of schools, training centres, and libraries, compounded by poor road and transportation systems that impede physical access (ILO, 2014). These limitations on socioeconomic opportunities have profound consequences, perpetuating cycles of poverty and underemployment, leading to social exclusion, and negatively impacting the overall well-being of rural youth (FAO, 2017).

Ethiopia's labour market is fundamentally shaped by its economic structure, in which agriculture accounts for approximately 34% of GDP and employs about 65% of the workforce (CSA, 2021a; Gebissa, 2021). Despite strong average annual economic growth over the past two decades, driven primarily by public investments in infrastructure that have expanded services and improved living standards (World Bank, 2024), the agricultural sector remains a key area of concern (Gebissa, 2021). It is characterized by its largely informal nature, low productivity, and limited opportunities for economic advancement.

While urban areas have seen growth in the services and manufacturing sectors, spurred by economic reforms and urbanization (Wieser & Wondimagegn, 2021), this has not been sufficient to absorb the country's rapidly growing workforce. With around two million new job seekers entering the market each year, Ethiopia faces a significant challenge in creating enough employment opportunities to meet this demand, a situation further complicated by the need to transition workers from subsistence farming to more productive sectors (Getahun & Fetene, 2020).

Ethiopia's education system, structured around primary, secondary, and tertiary levels, has seen significant expansion over the past two decades. Primary education (grades 1-8) is free and mandatory, and a focus on universal access has successfully laid a foundation for future development, with the Net Enrolment Ratio (NER) reaching 83.3% (MoE, 2023). This progress, however, highlights a major bottleneck at the secondary level (grades 9-12), where the NER lags significantly at 32.9%. To address skills gaps, the government has invested heavily in Technical and Vocational Education and Training (TVET), with 1,613 institutions training nearly 400,000 individuals by 2021 (AUDA-NEPAD, 2022). Higher education has also seen remarkable growth, with undergraduate participation jumping from 0.7% in 1996 to 12% in 2019 (MoE, 1997, 2020).

However, these national averages mask a profound rural-urban divide. Rural youth, who constitute 73.62% of the country's youth population, face a compounding set of barriers (ESS, 2021). Despite infrastructure improvements, they have limited access to quality education, with rural schools often underfunded, understaffed, and distant, leading to late enrolment or dropouts due to poverty (Nega, 2012; Kamanga, 2020). This educational disadvantage, combined with land scarcity and a lack of rural job opportunities, results in widespread unemployment and underemployment, compelling many to migrate to urban centres in search of work (CSA, 2021a).

These educational challenges are driven by both supply-side factors, like inadequate resources and a lack of trained teachers, and demand-side factors, including poverty, cultural barriers and early marriage. As Le Mat (2020) indicates, capacity gaps and a lack of practical skills among trainers further limit the quality of vocational education, hindering the ability of these institutions to equip youth for employment.

The combined impact of these systemic constraints has contributed to a significant rise in young people categorized as NEET (Not in Employment, Education, or Training). According to the ILO (2023), the share of youth aged 15-29 in this status in rural Ethiopia surged from 8.2% in 2013 to 18% in 2021. This trend traps millions of young people outside the labour market, unable to gain experience or skills, and perpetuates an intergenerational cycle of poverty (Rahman, 2006).

In response, the government has implemented a series of policies, including the National Youth Policy (2004), the TVET strategy (2008), and the Rural Job Opportunity Creation Strategy (2019). However, a critical flaw identified by the ILO (2023) is that these initiatives focus broadly on employment and lack any explicit strategies for the unique needs of NEET youth, particularly those in rural areas who face the most significant barriers to education and social support.

Empirical studies confirm that being NEET has severe consequences for individuals and societies, including lower well-being, social exclusion, and hindered economic growth (Rahmani & Groot, 2023). These impacts have established NEET youth as a key focus of social policies globally. This international attention is formalized within the 2030 Agenda for Sustainable Development, specifically under SDG 8, which aims to promote inclusive economic growth and decent work for all. Target 8.6 explicitly calls for a significant reduction in the proportion of NEET youth, urging states to look beyond simple unemployment and address all young people disconnected from employment and educational systems (UN, 2015; Abbott & Teti, 2017). Consequently, policymakers and researchers increasingly prioritize the NEET rate over traditional unemployment metrics, as it provides a more comprehensive and accurate measure of youth vulnerability and inactivity (Crismaru et al., 2017).

A review of previous empirical studies on the determinants of NEET youth reveals significant methodological gaps (e.g., Erdogan et al., 2017; Alfieri et al., 2015; Anggraini et al., 2020; Abayasekara and Gunasekara, 2019). Most research relies on cross-sectional data, limiting the ability to capture dynamic changes in NEET status over time, a weakness that longitudinal research could address. Furthermore, existing studies often treat NEETs as a single homogenous group, failing to differentiate between unemployed and inactive sub-groups, which is crucial for targeted policy recommendations. These evidence gaps are particularly acute in the context of Ethiopia, where research on the drivers and consequences of being NEET remains sparse. Despite having one of the highest NEET rates in the region (Perry et al., 2022), this lack of nuanced data forces policymakers to rely on traditional labour market metrics that are ill-suited to address the unique challenges faced by NEET youth.

This study aims to bridge these knowledge gaps by utilizing a panel dataset from two survey rounds conducted in rural Ethiopia in 2019 and 2022. The primary objective is to identify the determinants of a young person's likelihood of becoming NEET. Specifically, the research analyses individual, family, and community-level characteristics associated with NEET status and explores its dynamics over time. The paper is structured as follows: Section 2 reviews the relevant literature, Section 3 outlines the methodology, Section 4 presents and discusses the results, and Section 5 concludes with key insights and policy recommendations including highlighting limitations and the need for future research.

## 2. Literature Review

This study defines youth as individuals aged 15-29, aligning with Ethiopia's National Youth Policy (2004) and the International Labour Organization's (ILO, 2013) framework. This definition varies globally, with the UN using 15-24 and the African Union 15-35, reflecting diverse cultural and institutional factors. The concept of NEET originated in the United Kingdom in the late 1980s to identify young people (typically aged 16-18) who were disengaged from both the economy and the education system (Mascherin, 2018). The term has since gained global prominence as a key indicator of youth vulnerability and has been adopted in numerous countries, including Japan, China, and across Europe (Eurofound, 2012; Abayasekara and Gunasekara, 2019).

Youth transitions into education, employment, or inactivity can be understood through several economic and social theories. Human capital theory conceptualizes education as an investment decision, where households weigh expected returns against the opportunity cost of youth labor (Becker, 1964). Under budget or credit constraints, enrolment decisions are shaped by resource availability, explaining why wealth and parental education emerge as strong predictors of NEET status. Social reproduction theory emphasizes the intergenerational transmission of cultural capital, showing how parental literacy and education influence youth aspirations and opportunities (Bourdieu, 1977). Intra-household bargaining models highlight that youth choices are embedded within family decision-making structures, where parental employment and household resource allocation affect whether young people continue schooling or enter the labor market (Manser & Brown, 1980; McElroy & Horney, 1981). Finally, the capability approach underscores how health, literacy, and agency expand or constrain young people's ability to participate productively (Sen, 1999). These theoretical perspectives provide a conceptual foundation for the empirical analysis, guiding the selection of explanatory variables such as education, gender, household background, health, and wealth.

The concept of NEET gained prominence because traditional labour market indicators, like unemployment rates, do not accurately reflect the complex challenges young people face. As Erdogan et al. (2017) highlight, a simple employed/unemployed dichotomy is insufficient. It fails to account for the large number of youths in low-paying or informal jobs, a particularly significant issue in countries like Ethiopia where such employment is widespread (OECD and ILO, 2014).

In response to these limitations, the NEET framework was adopted to provide a more holistic view. It draws attention to a wider range of vulnerabilities, including not only unemployment but also early school leaving and labour market discouragement (Elder, 2015; Mascherini, 2018). This has led to a crucial policy shift, with an increasing focus on the NEET rate as a primary indicator of youth disengagement (O'Higgins et al., 2023). This broader perspective fosters a more systemic approach to understanding the causes of youth inactivity and developing more effective, targeted interventions.

Studies have shown that young people who are NEET are a diverse group with varied experiences, characteristics, and needs (Eurofound, 2012, 2016; Abayasekara and Gunasekara, 2019; Fabrizi and Rocca, 2024). This population can be broadly divided into two main subgroups: the unemployed, who are actively seeking work, and the inactive. The reasons for inactivity are numerous and can include discouragement, family responsibilities, illness or disability, or a voluntary decision based on self-fulfilment (Eurofound, 2012, 2016; ETF, 2015; Abayasekara and Gunasekara, 2019).

The status of being NEET among youth is determined by a confluence of micro- and macro-level factors, from individual educational attainment and family background to broader labor market policies and economic conditions (Caroleo et al., 2020). Seminal studies underscore that personal characteristic related to education, family, and health are particularly strong predictors of NEET risk (Bynner and Parsons, 2002 and Robson, 2008). Consequently, identifying these micro-level drivers is a critical prerequisite for designing effective interventions aimed at fostering youth engagement in education and employment and preventing their societal disconnection (Rahmani & Groot, 2023).

Previous empirical studies have examined the determinants of youth who are NEET.[4] In Turkey, Erdogan et al. (2017) analysed nationally representative survey data from 1,804 young people and found that several factors reduced the likelihood of being NEET. These included being male aged 18-19, having a secondary-level education, belonging to a household with average or above-average economic standing, and having parents with higher education levels.

In Italy, Alfieri et al. (2015) surveyed 9,087 young adults and similarly found that higher parental education decreased the chances of being NEET. Their study also identified a gender-specific factor: parental intrusiveness, defined as overly controlling behaviour, predominantly increased the likelihood of young women being NEET. A separate Italian study by Quintano et al. (2018), using Labour Force Survey data from 12,774 individuals between 2005 and 2015, confirmed that both personal and parental education were significant protective factors. However, this research also found that the probability of being NEET increases with age and, for women, is significantly higher when living with a partner.

In an insightful analysis, Abayasekara and Gunasekara (2019) examined NEET status among young people in Sri Lanka using data from the 2016 Labour Force Survey. The study employed a binary logit model to compare the NEET and non-NEET populations, and a

[4] See Erdogan *et al.,* 2017; Alfieri *et al.,* 2015; Anggraini *et al.,* 2020; Abayasekara and Gunasekara*.,* 2019.

multinomial logit model to investigate distinct subgroups within the NEET category. Their findings revealed several key risk factors associated with NEET status, including being female, belonging to an ethnic or religious minority, being in the 20–24 age bracket, having either very low or high levels of education, lacking English proficiency, and coming from a low-income household. Furthermore, the study highlighted that being female, married, having children under five, and belonging to ethnic and religious minority groups significantly increased the likelihood of falling into specific NEET categories, such as family caring.

A similar study in Bangladesh by Uddin and Nabila (2015) used data from the 2013 Labour Force Survey to analyse a sample of 30,090 respondents aged 15–24. Applying Logit and Probit models, their research also identified several key determinants of NEET status. On an individual level, factors such as age, disability, and educational attainment (both low and high) were associated with an increased likelihood of being NEET. Conversely, certain family and social aspects were found to be protective factors; these included higher education of the household head, greater family assets (proxied by land holdings), and urban residency, all of which reduced the probability of a young person being NEET.

In a separate study in Indonesia, Anggraini et al. (2020) analyzed panel data from the 2017 and 2018 National Labor Force Surveys. Using a logistic regression model on a sample of over 3,600 respondents, they found that young people in rural areas face a higher likelihood of being NEET. Notably, the study also revealed that individuals with higher levels of education were more vulnerable to NEET status, a finding that contrasts with research from other regions.

In Turkey, a study by Susanli (2016) analysed data from the Household Labor Force Surveys (2004–2013) to explore the factors influencing NEET status. The research used Probit regression to identify determinants and a Markov Chain Model to analyse transitions between education, employment, unemployment, and inactivity. The analysis highlighted that gender and educational attainment were significant factors, and that having more employed household members reduced the likelihood of a young person being NEET. Furthermore, the transition analysis revealed that the state of inactivity was highly persistent, even though it declined over the period studied.

A more recent study in Ethiopia by Perry et al. (2022) examined the determinants of NEET youth using data from the 2019 Ethiopian Socioeconomic Survey (6894 households) focusing on young individuals aged 15–24. The multivariate logistic regression showed that married women were more likely to be NEET than unmarried women, whereas higher educational attainment reduced this probability. The effect of urban residency varied significantly by age: for those aged 15-19, it decreased the likelihood of being NEET, but for those aged 20-24, it increased it. Finally, the study found that engagement in family agriculture for personal use also increased a young person's likelihood of being in NEET status.

The findings from the reviewed empirical studies exhibit notable inconsistencies. For instance, regarding educational attainment, the evidence is contradictory. While some studies conclude that higher education reduces the likelihood of being NEET (Erdogan et al., 2017; Perry et al., 2022), others report a more complex relationship. Research by Uddin and Nabila (2015), Abayasekara and Gunasekara (2019), and Anggraini et al. (2020) found that individuals at both the lowest and highest ends of the educational spectrum are more vulnerable to NEET status. In contrast to these varied findings, parental education emerges as a consistently significant protective factor across studies by Alfieri et al. (2015), Uddin and Nabila (2015), and Erdogan et al. (2017), which all concur that it reduces the probability of youth being NEET.

Most research treats NEET youth as a single, homogenous group, overlooking crucial distinctions between subgroups like the unemployed (actively seeking work) and the inactive (not seeking work). Understanding the unique challenges of these subgroups is vital for effective policymaking, yet studies that provide such nuanced analysis remain scarce.

# 3. Materials and Methods
## 3.2 Data and variables
### 3.2.1 Data for the study

This study utilizes data from the fourth (2018/19) and fifth (2021/22) rounds of the Ethiopian Socioeconomic Panel Survey (ESPS), hereafter referred to as the 2019 and 2022 waves. The ESPS is a long-term panel data project conducted by the Ethiopian Statistical Services (ESS) in partnership with the World Bank's Living Standards Measurement Study (LSMS-ISA). Designed to be representative at national, regional, rural, and urban levels, the survey collects comprehensive, multi-topic data on subjects including demographics, education, health, labour, wealth, and agriculture. The resulting datasets are publicly accessible through the World Bank's microdata library. For the purposes of this analysis, we restrict our focus to the rural subsample, enabling us to specifically examine the determinants of NEET status among rural youth.

The ESPS employed a two-stage stratified sampling approach. In the first stage, rural Enumeration Areas (EAs) were randomly selected from the 2018 Agricultural Sample Survey, resulting in data from 297 EAs in 2019 and 223 in 2022. In the second stage, a systematic random sample of 10 agricultural and 2 non-agricultural households was drawn from each selected EA. These survey rounds covered all regional states of the country, except for Tigray in the 2022 wave.[5]

The initial 2019 survey included 297 rural enumeration areas (EAs) and 3,239 rural sample households; a subsequent survey in 2022 revisited 223 of these EAs and 2,325 households. The analytical sample consisted of 3,503 youths aged 15–29 in 2019, compared to 3,538 youths in 2022. Despite a slight imbalance in the dataset between the two waves, the number of youths included in the analysis remained relatively stable.

[5] Tigray was excluded from the 2022 survey wave due to the conflict in Northern Ethiopia at that time, which made data collection infeasible and unsafe.

Community-level surveys were administered to gather data on aggregate socioeconomic indicators within the enumeration areas where sample households were situated. Both the household and community-level surveys were conducted concurrently, from June to August in 2019 and from April to June in 2022.

To ensure the external validity of our findings, we employed sampling weights derived from the survey data. This approach adjusts the sample respondents to be representative of the national youth population, accounting for potential imbalances in the sampling process. Consequently, this allows for more robust insights and evidence-based policy recommendations (Johnson, 2008; Boto, 2023).

### 3.2.2 Study Variables

Informed by the literature reviewed in section 2, this study incorporates several variables to analyse the determinants of youth NEET status. We defined the primary dependent variable as a dichotomous indicator of whether a young person is NEET (coded 1) or not (coded 0), where NEET refers to individuals not in employment, education, or training. To capture heterogeneity, we distinguished between unemployed-NEETs (not working but actively seeking employment or attempting to start a business in the past four weeks) and inactive-NEETs (not working and not engaged in job search or business start-up activities). These classifications were based on responses to the ESPS labour and time use survey question: "During the last four weeks, did the individual do anything to find a paid job or start a business for pay/profit?" Individuals enrolled in education or training were excluded from all NEET categories.

Explanatory variables were selected based on economic theory and a review of prior empirical literature (e.g., Erdogan et al., 2017; Alfieri et al., 2015; Abayasekara and Gunasekara, 2019; Heckert et al., 2021; Uddin and Nabila, 2015), contingent on their availability in the dataset. The independent variables used to predict NEET status are broadly categorized as individual, household, and community/regional factors.

At the individual level, this study incorporates a youth's gender, age, marital status, health, and educational attainment. Recognizing that the probability of being NEET is also influenced by parental and household characteristics (Heckert et al., 2021; Alfieri et al., 2015), our analysis includes the literacy status of the youth's father and mother and the father's employment status. Furthermore, to examine the influence of economic standing, the household's asset position was included. We constructed wealth quartiles using an asset index, which was generated via Principal Component Analysis (PCA) to weight various durable assets owned by the household (Filmer and Pritchett, 2001). The results of the PCA are available in Appendix Table 5.

Community-level infrastructural variables were also incorporated into the analysis. These include the presence of weekly markets, business enterprises/cooperatives, and access to microfinance services within the community. Such factors are hypothesized to generate employment opportunities for young people, thereby decreasing their likelihood of becoming NEET (Crismaru et al., 2017).

Table 1. Definition of variables used in the model

| Variables | Type of data | Category |
|---|---|---|
| **Dependent variables** | | |
| Status of youth | Dummy | 1= NEET, 0=Otherwise |
| Status of unemployed youth | Dummy | 1=unemployed NEET, 0=otherwise |
| Status of inactive youth | Dummy | 1=inactive NEET, 0=Otherwise |
| **Independent Variables** | | |
| **Individual characteristics** | | |
| Gender | Dummy | 1= Male, 0=female |
| Age cohorts | | |
| Age 15-19 | Dummy | 1=youth belong to 15-19 age group, 0=otherwise |
| Age 20-24 | Dummy | 1=youth belong to 20-24 age group, 0=otherwise |
| Age 25-29 | Dummy | 1=youth belong to 25-29 age group, 0=otherwise |
| Marital Status | | |

| | | |
|---|---|---|
| Never married | Dummy | 1=youth is never married, 0=otherwise |
| Married | Dummy | 1=youth is married, 0=otherwise |
| Divorced | Dummy | 1=youth is divorced/separated, 0=otherwise |
| Educational attainment | | |
| Primary | Dummy | 1=if youth are grade 1-8, 0=otherwise |
| Secondary | Dummy | 1= if youth are grade 9-12, 0=otherwise |
| Tertiary | Dummy | 1= if youth are grade 12 and above, 0=otherwise |
| Health status | Dummy | 1= has sickness, 0= otherwise |
| **Household characteristics** | | |
| Literacy level of father | | |
| Literate | Dummy | 1= if father is literate either in formal or informal education, 0= otherwise |
| Illiterate | Dummy | 1=if father has either in education formal or informal 0=otherwise |
| Literacy level of mother | | |
| Literate | Dummy | 1= if mother is literate in formal or informal education, 0= otherwise |
| Illiterate | Dummy | 1=if father has either in education formal or informal 0=otherwise |
| Employment status of father | Dummy | 1=employed father, 0=otherwise |
| Wealth index (in quartile) | | |
| First quartile | Dummy | 1= if the youth is in first quartile,0= Otherwise |

| | | |
|---|---|---|
| Second quartile | Dummy | 1= if the youth is in second quartile,0= Otherwise |
| Third quartile | Dummy | 1= if the youth is in third quartile,0= Otherwise |
| Fourth quartile | Dummy | 1= if the youth is in fourth quartile,0= Otherwise |
| Community characteristics | | |
| Access to weekly market | Dummy | 1=if weekly market is available in the EA 0= otherwise |
| Access to business opportunity | Dummy | 1=if there is microenterprise/cooperative in the community 0= otherwise |
| Access to microfinance | Dummy | 1= if there a micro finance institution in the community, 0= otherwise |

Sources: Based on Theoretical and Empirical review Determinants of NEET

### 3.2 Estimation strategy

The household survey data were analysed using Stata 17, employing both descriptive and econometric estimation techniques. The longitudinal nature of the survey generated a panel dataset, which tracks individuals over multiple time points (Baltagi, 2005; Hsiao, 2014). According to Hsiao (2003), panel data offers several advantages, including the ability to control for unobserved heterogeneity, increase the efficiency of estimators, and analyse dynamic change.

In this study, we acknowledge that unobservable characteristics of young people—such as individual motivation, social networks, and family dynamics—may be correlated with the observable variables, potentially biasing the estimated effects on NEET status. To address the impact of this unobserved heterogeneity, Fixed-Effects (conditional logit) and Random-Effects models are commonly employed (Williams, 2018). While the choice between these models often involves the Hausman test, the Akaike Information Criterion (AIC) is particularly effective for comparing logit models (Greene, 2012). Therefore, AIC was utilized in our analysis to select the most appropriate model specification.

### 3.2.1 Econometric Estimation Models

Given that the dependent variable is a binary indicator of a youth's NEET status, binary choice models like probit and logit are commonly used to estimate the influencing factors. While the choice between these two models is often a matter of convention, as they yield similar results (Greene, 2002), their interpretation differs. A logit model estimates changes in the log-odds of an outcome, whereas a probit model relates to changes in a z-score of the outcome. In practice, logistic regression is frequently preferred for its mathematical simplicity and more straightforward coefficient interpretation (Mustafa, 2023). Accordingly, we selected a binary logit panel data model for our analysis. To assess potential multicollinearity among the explanatory variables, we computed Variance Inflation Factors (VIFs)[6]

### 3.2.2 Conditional Logit/Fixed Effect Logit versus Radom Effect Logit Models

Since this study utilizes panel data, we can employ models that account for unobserved heterogeneity, such as fixed-effects and random-effects models. As our dependent variable is a binary indicator of NEET status, the Fixed-Effects (Conditional) Logit and Random-Effects Logit models are the appropriate specifications, offering advantages over a standard binary logit model.

A key challenge with fixed-effects estimation in short panels is the incidental parameter problem, where a large number of individual-specific effects can lead to biased coefficients. The Conditional Logit model is specifically designed to overcome this issue in binary choice contexts by effectively removing the fixed effects from the estimation (Wooldridge, 2002; Greene, 2012). Both the fixed-effects and random-effects models address unobserved heterogeneity, but they differ in

[6] Variance Inflation Factors (VIFs) were computed to assess multicollinearity. While education level dummies showed higher VIFs due to their categorical nature, the mean VIF was 3.33, well below the conventional threshold of 10, indicating that multicollinearity is not a serious concern.” (see the results of VIF in Appendix Table 6).

their underlying assumptions and how they handle variability between individuals.

#### 3.2.2.1 The Conditional Logit

Following Cameron and Trivedi (2005) and Wooldridge (2010), the conditional probability for individual i with T observations, given the sufficient statistic $\sum_t y_{it}$=c is;

$$P(y_{i1},\ldots,y_{iT}|s_i, x_{i1}, \ldots x_{iT}, \beta)=\frac{\prod_{i=1}^{T}\exp(y_{it}\,x'_{it}+\beta)}{\sum_{d\in\beta_c}\prod_{i=1}^{T}\exp(d_t\,x'_{it}\,\beta)} \quad (1)$$

Where:

- $y_{i1}$: Binary dependent variable (e.g., NEET status: 1 = NEET, 0 = not NEET).
- $x'_{it}$ : Time-varying covariates for individual i at time t.
- $\beta$: Coefficient vector to be estimated.
- $\beta_c$: The set of all sequences of binary outcomes for T periods such that $\sum_t y_{it} = c$

The conditional likelihood is

$$L_c(\beta) = \prod_{i=1}^{N} P(y_{i1},\ldots,y_{iT}|s_i, x_{i1}, \ldots x_{iT}, \beta)$$

and the log-likelihood is maximized to obtain estimates of β (2)

Estimation of coefficients of the predictors through the Maximum

Likelihood Estimator:

$$\ln L_c(\beta)= L_c(\beta) = \prod_{i=1}^{N} P(y_{i1},\ldots,y_{iT}|s_i, x_{i1}, \ldots x_{iT_i}, \beta) \quad (3)$$

#### 3.2.2.2 Conditional Random Effect Logit Model

The conditional random-effects logit model (Greene, 2012; Wooldridge, 2010) assumes individual-specific effects αi follow a random distribution, typically Gaussian, and are uncorrelated with the covariates. The likelihood for individual i is**.**

$$P(y_i|x_i,\beta,\sigma_\alpha^2)=\int \prod_{i=1}^{T_i} \frac{\exp(y_{it}\,(x'_{it}\beta+\alpha_i)}{1+\exp(y_i\,(x'_{it}\beta+\alpha_i)} f(\alpha_i)d\alpha_i \qquad (4)$$

Where:

$\alpha_i \sim N[0, \sigma_\alpha^2]$.: Random effect following a normal distribution

$f(\alpha_i)$: Probability density function of $\alpha_i$

The likelihood for all individuals is

$$L(\beta,\sigma_\alpha^2) = \prod_{i=1}^{N} \int \prod_{i=1}^{T_i} \frac{\exp(y_{it}\,(x'_{it}\beta+\alpha_i)}{1+\exp(x'_{it}\beta+\alpha_i)} f(\alpha_i)d\alpha_i \qquad (5)$$

# 4. Results and Discussion

## 4.1 Descriptive characteristics of NEET youth

### 4.1.1 Individual and household level characteristics

According to the descriptive statistics, an average of 28% of rural youth in the sample were categorized as NEET between 2019 and 2022 (Table 2). A disaggregation of this figure shows that 21% of youth were inactive NEETs, while 8% were unemployed NEETs. This indicates that inactivity is the predominant status, accounting for over 73% of the NEET population.

Furthermore, the descriptive statistics reveal a notable increase in the overall NEET rate, which rose from 25% in 2019 to 31% in 2022. This trend was primarily driven by an increase in the proportion of inactive NEET youth, which grew from 18% to 23%. The percentage of unemployed NEET youth also increased, albeit more modestly, from 7% to 8% during the same period.

The descriptive results reveal important shifts in the characteristics of NEET youth between 2019 and 2022. By gender, male NEET prevalence rose markedly from 18.6% in 2019 to 27.4% in 2022, while female NEET rates remained consistently high at around 38%. This suggests that the pandemic period disproportionately affected young men’s employment opportunities, narrowing the gender gap but through worsening male outcomes rather than improvements for women.

Table 2. NEET Status of young people in 2019 and 2022

| Youth Status | 2019 | | | 2022 | | | Average | | |
|---|---|---|---|---|---|---|---|---|---|
| | N | Mean (%) | Std | N | Mean (%) | Std | N | Mean (%) | Std |
| Total NEET | 3503 | 25.18 | 43.4 | 3538 | 30.78 | 46.16 | 7041 | 27.99 | 44.9 |
| Inactive NEET | 3285 | 18.23 | 38.6 | 3264 | 2.70 | 41.89 | 6549 | 20.46 | 40.34 |
| Unemployed NEET | 2860 | 7.31 | 26.8 | 2729 | 8.08 | 27.84 | 5589 | 7.53 | 27.6 |

Source: computed from ESPS

Age cohort analysis shows that older youth (25–29 years) became increasingly vulnerable, with NEET prevalence rising from 33.1% in 2019 to 39.2% in 2022. Younger cohorts (15–19 years) also experienced increases, though less pronounced. These results align with life-course perspectives, indicating stalled transitions into stable employment and adulthood among older youth.

Educational attainment patterns highlight that schooling no longer guarantees protection against NEET status. Primary-educated youth saw NEET prevalence rise from 22.2% to 31.1%, while tertiary-educated youth increased from 25.3% to 28.1%. This supports human capital theory's emphasis on returns to schooling but also points to structural constraints in the labour market, where even higher education does not secure employment.

Marital status further differentiates NEET risks. Married youth had higher NEET prevalence in both rounds, rising from 33% to nearly 39%, while never-married youth also saw increases. This reflects intra-household bargaining dynamics, where family responsibilities and resource constraints may limit youth participation in education or employment.

Health status emerged as a critical factor. Sick youth had NEET prevalence of 26% in 2019, which nearly doubled to 49% in 2022. This finding underscores the capability approach, showing how health constraints severely limit productive participation.

Parental background remained influential. Youth with illiterate fathers had NEET rates of 27% in 2019, rising to 33% in 2022, while those with illiterate mothers increased from 26% to 32%. Similarly, youth with unemployed fathers faced extremely high NEET prevalence (81% in 2019 and 69% in 2022). These results are consistent with social reproduction theory, highlighting intergenerational disadvantage and the importance of household employment in shaping youth outcomes.

Finally, wealth status strongly differentiated NEET risks. Youth in the poorest quartile saw NEET prevalence rise from 25% to 31%, while those in higher quartiles also experienced increases, though less pronounced. This reflects budget constraint models, where limited household resources reduce the ability to invest in education and support youth transitions in the labour market (Rahmani, Groot, & Rahmani, 2024).

Table 3. Mean percentage of individual and household level characteristics of the NEET groups

| | 2019 | | | | | | | | | 2022 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | NEET | | | Unemployed NEET | | | Inactive NEET | | | NEET | | | Unemployed NEET | | | Inactive NEET | | |
| Variables | N | Mean (%) | Std. | N | Mean (%) | Std. | N | Mean (%) | Std. | N | Mean (%) | Std. | N | Mean (%) | Std. | N | Mean (%) | St |
| **Gender** | | | | | | | | | | | | | | | | | | |
| Male, | 2337 | 18.57 | 38.90 | 2001 | 4.806 | 21.38 | 2234 | 15.09 | 35.80 | 2452 | 27.41 | 44.61 | 1917 | 6.16 | 24.04 | 2300 | 20.96 | 40 |
| Female | 1166 | 38.42 | 48.66 | 860 | 13.26 | 33.93 | 1036 | 24.52 | 43.04 | 1085 | 38.43 | 48.67 | 811 | 12.82 | 33.46 | 951 | 26.50 | .44 |
| **Age cohort** | | | | | | | | | | | | | | | | | | |
| 15-19 | 1587 | 17.71 | 38.18 | 1360 | 3.90 | 19.36 | 1534 | 14.34 | 35.06 | 1548 | 26.36 | 44.07 | 1226 | 6.77 | 2513 | 1454 | 20.01 | 25 |
| 20-24 | 941 | 29.54 | 45.65 | 740 | 8.64 | 28.13 | 869 | 21.28 | 40.96 | 1059 | 29.84 | 45.78 | 817 | 73.4 | 2610 | 979 | 22.37 | 26 |
| 25-25 | 975 | 33.13 | 47.09 | 761 | 12.22 | 32.77 | 867 | 21.45 | 41.07 | 931 | 39.21 | 48.85 | 685 | 11.53 | 31.97 | 818 | 27.38 | 31 |
| **Education level** | | | | | | | | | | | | | | | | | | |
| Unenrolled | 34 | 32.35 | 47.49 | 27 | 11.11 | 32.02 | 30 | 16.67 | 3790 | 27 | 44.44 | 50.64 | 18 | 11.11 | 32.34 | 24 | 37.50 | 49 |
| Primary | 1096 | 22.17 | 41.56 | 907 | 5.95 | 23.68 | 1038 | 16.57 | 37.20 | 1108 | 31.05 | 46.29 | 851 | 7.87 | 26.95 | 1026 | 23.49 | 42 |
| Secondary | 367 | 31.34 | 46.44 | 288 | 9.72 | 29.68 | 335 | 21.79 | 41.34 | 409 | 30.56 | 46.12 | 318 | 9.43 | 29.28 | 373 | 20.38 | 40 |
| Tertiary | 494 | 25.30 | 4352 | 406 | 6.65 | 24.95 | 463 | 17.71 | 38,22 | 545 | 28.07 | 44.98 | 425 | 7.76 | 26.79 | 504 | 20.04 | 40 |
| **Marital status** | | | | | | | | | | | | | | | | | | |
| Never married | 1841 | 17.65 | 38.14 | 1593 | 4.96 | 21.72 | 1761 | 13.97 | 34.68 | 1888 | 26.96 | 44.39 | 1493 | 6.70 | 25.00 | 1768 | 20.53 | 40 |
| Married | 1145 | 33.01 | 47.05 | 883 | 10.99 | 31,29 | 1029 | 21.19 | 40.88 | 739 | 39.38 | 48.89 | 550 | 12.55 | 33.15 | 642 | 27.26 | 44 |
| Divorced/Separated/widowed | 95 | 37.89 | 48.79 | 71 | 12.68 | 3351 | 84. | 25.00 | 43.56 | 73 | 42.47 | 497.7 | 49 | 10.20 | 33.15 | 65 | 33.85 | 47 |
| **Health status** | | | | | | | | | | | | | | | | | | |
| Sick | 2769 | 26.25 | 44.00 | 2231 | 7.35 | 26.10 | 2586 | 19.14 | 39.35 | 160 | 48.75 | 50.14 | 114 | 18.42 | 38.94 | 128 | 31.25 | 46 |
| Non-sick | 174 | 53.45 | 50.02 | 110 | 21.82 | 41.49 | 146 | 42.45 | 49.60 | 2754 | 27.56 | 44.69 | 2192 | 7.20 | 25.87 | 2548 | 19.62 | 39 |
| **Education father** | | | | | | | | | | | | | | | | | | |
| Literate | 948 | 16.46 | 44.59 | 828 | 4.23 | 20.13 | 909 | 1221 | 32.76 | 1101 | 26.70 | 44.26 | 878 | 6.38 | 24.45 | 1030 | 19.61 | 39 |
| Illiterate | 2123 | 27.37 | 37.10 | 1709 | 8.72 | 28.22 | 1956 | 19.12 | 39.34 | 1592 | 33.35 | 47.16 | 1210 | 9.59 | 29.45 | 1441 | 24.71. | 43 |
| **Education Mother** | | | | | | | | | | | | | | | | | | |
| Literate | 456 | 14.47 | 43.68 | 407 | 3.43 | 18.25 | 441 | 10.65 | 30.89 | 453 | 26.05 | 43.94 | 364 | 6.59 | 24.85 | 422 | 18.25 | 38 |
| Illiterate | 2614 | 25.66 | 35.22 | 2129 | 7.98 | 2711 | 2423 | 18.08 | 38.49 | 2240 | 315.6 | 46.49 | 1724 | 8.58 | 280.2 | 2049 | 23.47 | 42 |
| **Employment status of father** | | | | | | | | | | | | | | | | | | |
| Employed | 3034 | 23.20 | 42.22 | 2514 | 6.88 | 25.35 | 2845 | 16.52 | 37.14 | 2583 | 28.69 | 45.24 | 2041 | 7.69 | 26.65 | 2381 | 20.83 | 40 |
| Unemployed | 43 | 81.39 | 39.37 | 28 | 42.86 | 50.40 | 25 | 64.00 | 49.00 | 133 | 69.17 | 46.35 | 66 | 24.24 | 43.18 | 111 | 59.46 | 49.3 |
| **Wealth index quartile** | | | | | | | | | | | | | | | | | | |
| 1st quartile | 1436 | 25.28 | 43.48 | 1181 | 8.30 | 27.60 | 1332 | 17.57 | 38.07 | 1461 | 30.80 | 46.18 | 1121 | 8.39 | 27.73 | 1343 | 23.75 | 42 |
| 2nd quartile | 364 | 24.73 | 43.20 | 292 | 5.14 | 22.11 | 345 | 19.71 | 39.84 | 356 | 27.53 | 44.73 | 282 | 6.38 | 24.49 | 332 | 18.37 | 38 |
| 3rd quartile | 842 | 25.89 | 43.83 | 680 | 7.50 | 26.36 | 787 | 18.93 | 39.20 | 898 | 31.18 | 46.35 | 699 | 8.44 | 27.82 | 816 | 21.45 | 41 |
| 4th quartile | 861 | 24.51 | 43.04 | 708 | 6.50 | 24.67 | 806 | 17.37 | 37.91 | 822 | 31.75 | 46.58 | 626 | 8.15 | 27.38 | 760 | 23.55 | 42 |

Source: Author's calculation

### 4.1.2 Regional Distribution of Young People in NEET Status

The regional distribution of NEET youth shows both spatial disparities and notable changes between 2019 and 2022. Nationally, the NEET mean rose from 25.18% in 2019 to 30.78% in 2022, a 5.6 percentage-point increase, but this overall trend conceals significant regional variation. Oromia and Harar recorded the sharpest increases, each rising by about 10%, while Somali, Gambella, and Amhara also experienced substantial growth of between 6% and 9%. These results suggest that both large agrarian regions and peripheral areas faced heightened vulnerabilities, likely reflecting limited labor absorption and structural constraints in rural and semi-urban economies. Benishangul-Gumuz and SNNPR showed more moderate increases, indicating some resilience, while Dire Dawa was the only region to record a decline, with NEET prevalence falling from 36.9% in 2019 to 28.7% in 2022. This decline may point to relatively stronger recovery in urban labour markets or better integration of youth into informal employment compared to other regions.

Overall, the regional analysis underscores the heterogeneity of NEET risks across Ethiopia, highlighting that youth disengagement is shaped not only by individual and household characteristics but also by spatial and structural factors. The sharp increases in Oromia, Harar, Somali, and Gambella emphasize the need for region-specific interventions, while the decline in Dire Dawa illustrates that urban centres may offer pathways for recovery that could inform broader policy responses.

Table 4. Regional Distribution of youth NEET rate in Rural Ethiopia

| Region | 2019 | | 2022 | | Percentage changes |
|---|---|---|---|---|---|
| | N | Mean | N | Mean | |
| Afar | 135 | 31.69 | 62 | 32.63 | 0.94 |
| Amhara | 147 | 23.94 | 171 | 30.11 | 6.17 |
| Oromia | 138 | 22.70 | 189 | 32.70 | 10.00 |
| Somali | 96 | 22.64 | 188 | 31.18 | 8.54 |
| B/Gumz | 45 | 19.23 | 37 | 26.43 | 7.20 |
| SNNPR | 145 | 26.03 | 200 | 28.13 | 2.10 |
| Gambella | 60 | 22.64 | 103 | 31.31 | 8.67 |
| Harar | 54 | 26.09 | 89 | 36.33 | 10.24 |
| Dire Dawa | 62 | 36.90 | 50 | 28.74 | -8.16 |
| Total | 882 | 25.18 | 1,089 | 30.78 | 5.60 |

Sources: Authors computation

### 4.1.3 Transition probabilities of NEET youth

This study also identified the dynamics of movement and stability between non-NEET and NEET statuses, as presented in the transition matrix in Table 5. The results show considerable flux. Of the individuals who were not NEET at the start of the period, 70.1%

remained non-NEET, while 29.9% transitioned into a NEET status. For those who began in a NEET status, there was a high rate of exit: 72.8% transitioned out to become non-NEET, while 27.2% remained NEET in 2022.

A disaggregation of the NEET category reveals different levels of persistence: unemployed NEET status was highly temporary. The vast majority (96.3%) of unemployed NEET youth exited this category, with only 3.7% remaining. In the same fashion, inactive NEET status demonstrated greater stability. Although 77.6% of inactive NEET youth transitioned to a non-NEET status, 22.4% remained inactive.

These findings suggest that while the NEET status is often transient, persistence is significantly higher for inactive youth compared to unemployed youth.

Table 5. Transition probabilities of NEET youth

| NEET | NEET | | | | Unemployed NEET | | | | Inactive NEET | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | | 1 | | 0 | | 1 | | 0 | | 1 | |
| | N | Mean (%) | N | Mean (%) | N | Mean (%) | N | Mean (%) | N | Mean (%) | N | Mea |
| 0 | 251 | 70.08 | 108 | 29.92 | 261 | 91.26 | 25 | 8.74 | 263 | 77.58 | 76 | 22.4 |
| 1 | 115 | 72.78 | 43 | 27.22 | 26 | 96.30 | 1 | 3.70 | 76 | 79.17 | 20 | 20.8 |
| **Total** | **368** | **70.91** | **151** | **29.09** | **287** | **91.05** | **26** | **3.70** | **339** | **77.70** | **96** | **22.3** |

Sources: Authors competition

An analysis of transitions between states reveals a balanced flow of individuals. Over the study period, 608 young people entered NEET status, and an equal number exited (Appendix Table 1). Disaggregating this flow, the number of entrants and exiters for the unemployed NEET category (32 and 29, respectively) and the inactive NEET category (91 and 89, respectively) were also closely matched. Most individuals in the sample remained in their initial 2019 status through 2022 (Appendix Table 1).

Furthermore, a gender analysis of these transitions highlights distinct patterns (Table 6). Males were significantly overrepresented among those moving between statuses, constituting 61.8% (797 individuals) of individuals entering (for female this is 38.2% - 493 individuals) NEET and 61.9% (793 individuals) of those exiting it (for female this is 38.1% - 489 individuals). In contrast, females were overrepresented among the persistently NEET population, accounting for 71.6% of the individuals who remained NEET in both survey years.

**Table. 6. NEET Transitions Dynamics by Gender**

| NEET category | Entered | | Exited | | No change | |
|---|---|---|---|---|---|---|
| | No. | Percentage | No. | Percentage | No. | Percentage |
| Male | 797 | 61.8% | 793 | 61.9% | 1,269 | 28.4% |
| Female | 493 | 38.2% | 489 | 38.1% | 3,200 | 71.6% |
| Total | 1,290 | 100.0% | 1,282 | 100.0% | 4,469 | 100.0% |

Sources: Author's calculation

### 4.2 Regression Models Results

#### 4.2.1 Conditional and Random Effect Logit Models

Table 7 presents the estimation results for the probability of falling into the overall NEET, unemployed NEET, and inactive NEET categories. Following Greene (2012), the Akaike Information Criterion (AIC) was employed to compare the relative fit of a binary conditional logit model and a random-effects logit model. Across all three categories, the conditional specification consistently yielded lower AIC values, confirming its superiority in terms of model fit. For this reason, the conditional fixed-effects logit is adopted as the preferred model for interpretation, while the random-effects results are reported for completeness. Results of the Stata analysis are presented in Appendix Table 2-4.

The conditional fixed-effects logit results highlight several important determinants of NEET status. Age cohort effects are evident: compared to the youngest group (15–19 years), youth aged 25–29 face significantly higher odds of being NEET, about 37% greater (OR=1.367, $p<1\%$). This supports previous research suggesting that older youth are particularly vulnerable during the school-to-work transition due to structural barriers (Erdogan et al., 2017; Quintano et al., 2018). Poor health is another strong predictor, with sickness more than doubling the odds of NEET (OR=2.418, $p<0.1\%$), consistent with Robertson (2018), who identifies health as a critical driver of disengagement.

Education plays a complex role. While tertiary education reduces the odds of unemployed NEET by more than half (OR=0.390, p<5%), it is also associated with higher risk of inactivity (OR=0.697, p<1%). This counter-intuitive finding contrasts with human capital theory, which suggests education should reduce NEET risk (Uddin and Nabila, 2015; Erdogan et al., 2017). It points instead to a potential skills mismatch, where the education system does not adequately prepare graduates for the labor market.

At the individual level, marital disruption (divorce/ separation/ widowhood) significantly increases the likelihood of being NEET (OR=2.086, p<0.1%), while literacy is a powerful protective factor across categories. Mother's literacy reduces the odds of inactivity by about 30% (OR=0.697, p<1%) and total NEET by 21% (OR=0.789, p<5%), while father's literacy lowers the odds of unemployed NEET by one-third (OR=0.683, p<5%). These findings underscore the importance of foundational skills for accessing employment (Perry et al., 2022).

Parental background is also highly influential. Father's employment status emerges as a decisive factor, reducing the odds of NEET by nearly 90% (OR=0.121, p<1%), unemployed NEET by 80% (OR=0.197, p<1%), and inactive NEET by 86% (OR=0.144, p<1%). This aligns with Susanli (2016), who demonstrated that parental employment contributes to reducing NEET risk among youth, likely through financial stability and role modelling.

Results of other contextual variables such as wealth index, access to markets, business opportunities, microfinance services, and year dummies were also analyzed. The wealth index shows mixed effects: youth in the 2nd quantile face lower odds of NEET (OR=0.737, p<10%), while those in the 3rd and 4th quantiles do not differ significantly from the poorest group. For unemployed NEET, the 2nd quantile is again protective (OR=0.468, p<10%), whereas higher quantiles remain insignificant. Access to markets, business opportunities, and microfinance services did not exhibit significant effects across categories, suggesting limited direct influence on NEET outcomes. By contrast, year dummies reveal a temporal increase in NEET risk, with odds ratios of 1.186 (p<10%) for total NEET and 1.373

(p<10%) for unemployed NEET, indicating that vulnerability has risen over time, likely reflecting the combined impact of the COVID-19 pandemic and conflict-related disruptions.

Finally, time-invariant variables such as gender cannot be estimated in the conditional fixed-effects logit model. To address this limitation, the conditional random-effects logit results are reported for completeness. These results show that males are significantly less likely to be NEET compared to females, with odds ratios of 0.437 (p<0.1%), 0.355 (p<0.1%), and 0.536 (p<0.1%) for total NEET, unemployed NEET, and inactive NEET respectively. This consistent pattern highlights gender as a key determinant of NEET status, even though it cannot be captured within the fixed-effects specification.

Table 7. Estimation results of conditional (fixed-effects) and random effect logit models

| Variables (Odds ratio) | Conditional Fixed Effect | | | Conditional Random Effect | | |
|---|---|---|---|---|---|---|
| | Total NEET | Unemployed | inactive | Total NEET | Unemployed | inacti |
| Gender (Female[a]) | 1.000 | 1.000 | 1.000 | 0.437*** | 0.355*** | 0.536* |
| Male | (.) | (.) | (.) | (0.04) | (0.13) | (0.06) |
| Age Cohort (15-19[a]) | 1.193 | 0.922 | 1.407** | 0.123* | 1.232 | 1.325* |
| 20-24 | (0.15) | (0.22) | (0.19) | (0.46) | (0.40) | (0.18) |
| 25-29 | 1.367** | 1.104 | 1.392** | 1.343** | 1.707 | 1.239 |
| | (0.19) | (0.28) | (0.23) | (0.18) | (0.064) | (0.19) |
| Education (unenrolled[a]) | 0.588 | 0.538 | 0672 | 0.598 | 0.325 | 0.732 |
| Primary | (0.21) | (0.31) | (0.28) | (021) | (0.30) | (0.30) |
| Secondary | 0.718 | 0.617 | 0.811 | 0.762 | 0.508 | 0.874 |
| Tertiary | (0.26) | (0.36) | (0.34) | (0.27) | (0.46) | (0.37) |
| | 0.460** | 0.390 | 0.572 | 0.497** | 0.266 | 0.617 |
| | (0.16) | (0.23) | (0.24) | (0.18) | (0.25) | (0.26) |
| Marital Status (never married[a]) | 1.059 | 0.947 | 1.012 | 1.099 | 1.384 | 0.991 |
| Married | (0.15) | (0.24) | (0.16) | (0.16) | (0.45) | (0.14) |
| Divorced/separated/widowed | 2.086*** | 1638 | 1.810** | 2.083*** | 2.297 | 1.724* |
| | (0.50) | (0.74) | (0.49) | (0.50) | (1.58) | (0.46) |
| Health Status (non-sick[a]) | 2.418*** | 2.348*** | 1.932*** | 2.137*** | 4.049*** | 1.762* |
| Sick | (0.44) | (0.67) | (0.40) | (0.38) | (2.15) | (0.36) |
| Employment status (Unemployedf[a]) | 0.121*** | 0.197*** | 0.144*** | 0.155*** | 0.130*** | 0.163* |
| Employedf | (0.03) | (0.08) | (0.04) | (0.04) | (0.10) | (0.04) |
| Education of father (Illiterat[c]) | 0.915 | 0.683* | 0.912 | 0.867 | 0.548* | 0.881 |
| Literate | (0.10) | (0.14) | (0.11) | (0.90) | (0.17) | (0.10) |
| Education of mother (Illiterat[c]) | 0.789* | 0.816 | 0.697** | 0.810 | 0.895 | 0691* |
| Literate | (0.11) | (0.22) | (0.12) | (0.11) | (0.33) | (0.12) |
| Wealth Index quantiles (1st | 0.737* | 0.468* | 0.868 | 0.75 | 0.312* | 0.897 |
| quartile[a]) | (0.12) | (0.17) | (0.16) | (0.12) | (0.18) | (0.16) |
| 2nd quantile | 1.503 | 1.155 | 1.055 | 1.030 | 1.190 | 1.041 |
| 3rd quartile | (0.12) | (0.23) | (0.14) | (0.12) | (0.35) | (0.14) |
| 4th quartile | 0.941 | 0782 | 1.014 | 0.949 | 0.733 | 1.061 |
| | (0.11) | (0.17) | (0.14) | (0.11) | (0.24) | (0.14) |
| Access market (Noa) | 0.921 | 0977 | 0.955 | 0.916 | 0.987 | 0.986 |
| Yes | (0.09) | (0.17) | (0.11) | (0.08) | (0.24) | (0.10) |
| Access business opp(No[a]) | 1.183 | 1.541 | 0992 | 1.173 | 1.804 | 0986 |
| Yes | (0.19) | (0.40) | (0.18) | (0.18) | (0.73) | (0.18) |
| Access to MFI services (No[a]) | 1.091 | 1.404 | 1.249 | 1.079 | 1.460 | 1.243 |
| Yes | (0.15) | (0.33) | (0.19) | (0.14) | (0.52) | (0.18) |
| Year | 1.186* | 1.373* | 1.012 | 1.133 | 1.260 | 1.052 |
| | (0.11) | (0.24) | (0.11) | (0.10) | (0.32) | (0.11) |
| N | 2,765 | 2,197 | 2,565 | 2,765 | 2,221 | 2,565 |
| AIC | 2917.319 | 1059.034 | 2340.952 | 3012.032 | 1127.939 | 2417.3 |
| LR chi2(18), Conditional FE) | 166.14 | 57.98 | 101.38 | - | - | - |
| Wald chi2(19) Conditional RE | - | - | - | 212.86 | 16.00 | 125.8 |

Statistics in parentheses are t-value *** p<.01, ** p<.05, * p<.1 [a]base category

Sources: ESS 2019 and 2022.

### 4.2.2. Robustness Tests of the Models

To assess the structural validity of our regression models, we performed a robustness check, a practice highlighted as essential by White and Xun (2010). This involved comparing our primary Conditional Logit model (Model 1) with alternative estimation methods: a pooled logit (Model 2) and a pooled OLS model (Model 3), with results presented in Table 8. As noted by Neumayer and Plümper (2017), the consistency of core regression coefficients across different specifications indicates that the findings are robust and not artifacts of a specific modelling choice.

Robustness checks across conditional logit, pooled logit, and pooled OLS specifications confirm that several core predictors of NEET status remain consistently significant. Father's employment status and health shocks emerge as the most stable determinants, with strong and statistically significant effects across all three models and NEET categories. Tertiary education also shows a robust negative association with NEET outcomes, indicating that higher educational attainment reduces the likelihood of both unemployment and inactivity, although the strength of significance varies slightly by subgroup. Similarly, the age cohort of 24–25 years consistently exhibits elevated NEET risk across specifications, reinforcing the vulnerability of this transition age group. These findings demonstrate that the main results are not sensitive to model choice and underscore the reliability of the identified key predictors (Table 8).

## 5. Conclusion and Recommendation

### 5.1. Conclusion

The purpose of this study was to identify the determinants of NEET status among rural Ethiopian youth, a critical issue given the rising vulnerability of young people in contexts of limited opportunities. Using data from the Ethiopian Socioeconomic Panel Survey (ESPS) for 2019 and 2022, and applying conditional fixed-effects logit models complemented by conditional random effect logit, pooled logit and OLS specifications, we accounted for unobserved heterogeneity and ensured robustness of the results.

Based on descriptive and econometric analyses, this study finds that the average NEET rate among rural youth in Ethiopia was 28%, rising from 25% in 2019 to nearly 31% in 2022. This upward trend, evident across all NEET categories, reflects the combined effects of the COVID-19 pandemic and persistent structural barriers to education and employment. Regional disparities are notable, with Dire Dawa recording the highest NEET rate and Benishangul-Gumz the lowest, underscoring the influence of local economic structures.

Table 8. Model Comparison of the conditional logit Models

| | Total NEET | | | Unemployed NEET | | | Inactive NEET | | |
|---|---|---|---|---|---|---|---|---|---|
| Variables | Model1 C-logit | Model2 (Pooled Logit) | Model3 (Pooled OLS) | Model1 C-logit | Model2 (Pooled Logit) | Model3 (Pooled OLS) | Model1 C-logit | Model2 (Pooled Logit) | Model3 (Poole OLS) |
| Gen (female) | | | | | | | | | |
| **Male** | 1.000 | -0.825*** | -0.162*** | 1.000 | -0.702*** | -0.051*** | 1.000 | -0.624*** | -0.099*** |
| | (.) | (0.10) | (0.02) | (.) | (0.18 | (0.01) | (.) | (0.11) | (0.02) |
| Age cohort (15-19) | | | | | | | | | |
| 20-24 | 0.176 | 0.204* | 0.034 | -0.081 | 0.157 | 0.008 | 0.341** | 0.281** | 0.040** |
| | (0.12) | (0.12) | (0.02) | (0.23) | (023) | (0.01) | (0.14) | (0.13) | (0.02) |
| 24-25 | 0.312** | 0.295** | 0.054** | 0.099 | 0.354 | 0.024 | 0.330** | 0.214 | 0.030 |
| | (0.14) | (013) | (0.02) | (0.27) | (0.24) | (0.02) | (0.16) | (0.15) | (0.02) |
| **Education level (unenrolled)** | | | | | | | | | |
| **Primary** | -0.531 | -0.514 | -0.102 | -0.620 | -0.800 | -0.062 | -0.397 | -0.312 | -0.050 |
| | (0.35) | (0.35) | (0.07) | (0.57) | (0.57) | (0.05) | (0.45) | (0.41) | (0.07) |
| Secondary | 0.332 | -0.722 | -0.056 | -0.483 | -0.494 | -0.040 | -0.209 | -0.135 | -0.022 |
| | (0.36) | (0.35) | (0.07) | (0.58) | (0.58) | (0.05) | (0.42) | (0.42) | (0.07) |
| **Tertiary** | -0.776** | -0.698** | -0.135** | -0.941 | -0.924 | -0.070 | -0.599 | -0.483 | -0.075 |
| | (0.34) | (0.35) | (0.07) | (0.58) | (0.58) | (0.05) | (0.42) | (0.42) | (0.07) |
| Marital status (never married) | | | | | | | | | |
| Married | 0.057 | 0.094 | 0.018 | -0.055 | 0.246 | 0.020 | 0.012 | -0.009 | -0.0004 |
| | (0.14) | (0.12) | (0.02) | (0.25) | (0.22) | (0.02) | (0.16) | (0.14) | (0.02) |
| Divorced/separate widow | 0.735*** | 0.732*** | 0.150*** | 0.494 | 0.612 | 0.043 | 0.593** | 0.544** | 0.096** |
| | (0.24) | (0.24) | (0.05) | (0.45) | (0.44) | (0.03) | (0.27) | (0.27) | (0.05) |
| Health | | | | | | | | | |
| Sickness | 0.883*** | 0.757*** | 0.154*** | 0.853** | 0.901*** | 0.092*** | 0.658*** | 0.567*** | 0.098*** |
| | (0.18) | (0.18) | (0.35) | (0.28) | (0.27) | (0.03) | (0.21) | (0.21) | (0.03) |
| Employment farther (unemployed) | | | | | | | | | |
| mployed | -2.109*** | -1.859*** | -0.408*** | -1.624*** | -1.386*** | -0.175*** | -1.940*** | -1.816*** | -0.384*** |
| | (0.26) | (0.25) | (0.05) | (0.39) | (0.37) | (0.04) | (0.27) | (0.27) | (0.05) |
| Education father (Illiterate) | | | | | | | | | |
| Literate | -0.089 | -0.142 | -0.025* | -0.382* | -0.419** | -0.024* | -0.092 | -0.127 | -0.018 |
| | (0.11) | (0.10) | (0.18) | (0.21) | (0.20) | (0.01) | (0.12) | (0.12) | (0.02) |
| Educ mother (Illiterate) | | | | | | | | | |
| **Literate** | -0.237 | -0.210 | -0.034 | -0.203 | -0.107 | -0.007 | -0.361** | -0.369** | -0.046** |
| | (0.14) | (0.14) | (0.02) | (0.27) | (0.27) | (0.02) | (0.17) | (0.17) | (0.03) |
| Wealth index (1st quartile) | | | | | | | | | |
| 2nd quartile | -0.306* | -0.287* | -0.048* | -0.759* | -0.786** | -0.041** | -0.141 | -0.109 | -0.015 |
| | (0.16) | (0.16) | (0.03) | (0.37) | (0.37) | (0.02) | (0.18) | (0.18) | (0.02) |
| 3rd quartile | 0.052 | 0.030 | 0.005 | 0.144 | 0.113 | 0.008 | 0.054 | 0.040 | 0.006 |
| | (0.12) | (0.11) | (0.02) | (0.20) | (0.20) | (0.01) | (0.13) | (0.13) | (0.02) |
| 4th quartile | 0.060 | -0.0527 | -0.010 | -0.245 | -0.214 | -0.014 | 0.014 | 0.016 | 0.002 |
| | (0.12) | (0.12) | (0.02) | (0.22) | (0.22) | (0.01) | (0.13) | (0.13) | (0.02) |
| Access weekly market | | | | | | | | | |
| **Yes** | -0.082 | -0.088 | -0.015 | -0.023 | -0.010 | -0.001 | -0.005 | -0.014 | -0.002 |
| | (0.09) | (0.09) | (0.02) | (0.17) | (0.17) | (0.01) | (0.11) | (0.11) | (0.02) |
| Access business opportunities | | | | | | | | | |
| **Yes** | 0.168 | 0.159 | 0.028 | 0.432* | 0.391 | 0.030 | -0.008 | -0.014 | -0.002 |
| | (0.16) | (0.15) | (0.03) | (0.26) | (0.26) | (0.02) | (0.18) | (0.18) | (0.03) |
| Access to MFIs services | | | | | | | | | |
| Yes | 0.087 | 0.076 | 0.015 | 0.339 | 0.301 | 0.023 | 0.222 | 0.217 | 0.034 |
| | (0.13) | (0.13) | (0.02) | (0.23) | (0.23) | (0.02) | (0.15) | (0.15) | (0.02) |
| **Year** | .0.170* | 0.124 | 0.021 | 0.317 | 0.123 | 0.006 | 0.015 | 0.051 | 0.007 |
| **1** | (0.10) | (0.09) | (0.02) | (0.18) | (0.17) | (0.01) | (0.11) | (0.11) | (0.02) |
| N | 2,765 | 2,765 | 2,765 | 2,197 | 2,221 | 2,221 | 2,565 | 2,565 | 2,565 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Sources: authors computation.

Gender emerges as a critical determinant, with females disproportionately represented in the NEET population, particularly in the inactive category, pointing to entrenched cultural and caregiving barriers. Age effects are also pronounced, with the 25–29 cohort facing the greatest risk, highlighting the challenges of the school-to-work transition. Education shows a dual effect: tertiary attainment reduces unemployed NEET but increases inactivity, suggesting a mismatch between higher education and labor market demands. Marital disruption significantly heightens NEET risk, while parental literacy provides a protective effect, emphasizing the importance of foundational skills.

Poor health substantially increases NEET vulnerability, and father's employment status is the most decisive factor, dramatically lowering NEET odds and reinforcing the stabilizing role of household employment. By contrast, contextual variables such as wealth quartiles, market access, and microfinance services show limited or mixed effects, while year dummies reveal a temporal rise in NEET risk linked to pandemic and conflict-related disruptions.

Taken together, these findings demonstrate that NEET outcomes are driven by a complex interplay of individual, household, and structural factors, with health, parental employment, literacy, and gender standing out as the most robust determinants.

### 5.2. Recommendation

The findings of this study point to several important policy directions. Given that inactivity accounts for more than 73% of the NEET population, interventions must go beyond job creation and incorporate motivational, psychosocial, and re-engagement strategies to encourage inactive youth to return to education, training, or employment. Gender disparities, with females disproportionately represented among inactive NEETs, call for gender-sensitive programs that address cultural norms, caregiving responsibilities, and limited opportunities, thereby unlocking women's participation in the labor market and education.

The decisive role of father's employment status in reducing NEET odds highlights the importance of expanding rural employment opportunities and strengthening household livelihoods, which can stabilize family income and provide role models for youth labor market participation. The strong effect of poor health on NEET risk underscores the need to integrate accessible and affordable health services into youth development strategies such as strengthening the health insurance policies in the country and ensuring that illness does not become a barrier to education or work.

The elevated risk among the 25–29 age cohort points to the necessity of targeted school-to-work transition initiatives, such as apprenticeships, internships, and career counselling, to ease entry into stable employment. The dual effect of tertiary education—reducing unemployed NEET but increasing inactivity—suggests reforms to align higher education curricula with labor market demands, strengthening employability and reducing skills mismatches. The protective role of parental literacy emphasizes the value of intergenerational education initiatives, while the temporal rise in NEET risk linked to COVID-19 and conflict disruptions highlights the urgency of resilience-oriented policies, including emergency employment schemes and flexible training programs, to buffer youth against external shocks. Strengthening the accessibility and affordability of rural health services, including through the expansion of national health insurance, would also be a vital step in reducing NEET vulnerability.

### 5.3. Limitations and Future Research

Although this study provides robust evidence on the determinants of NEET status among rural Ethiopian youth, certain limitations remain. The use of a PCA-based wealth index may obscure differences between variable and fixed assets, suggesting that future research should disaggregate household wealth to capture more nuanced effects. In addition, while the conditional fixed-effects logit model offered superior fit and reliability, time-invariant factors such as gender could not be fully incorporated, warranting methodological innovations to better integrate these dynamics. The two-wave dataset (2019 and 2022) also limits the ability to track long-term transitions into and out of NEET status, highlighting the need for extended panel data. Addressing these limitations will deepen understanding of NEET vulnerability and strengthen the evidence base for designing effective youth policies.

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# Appendix Tables

## Appendix Table 1. Summary of Translon of NEET youth

. tabulate year NEET_trans

| year | NEET_trans Entered.. | Exited .. | No Change | Total |
|---|---|---|---|---|
| 0 | 608 | 608 | 2,287 | 3,503 |
| 1 | 682 | 674 | 2,182 | 3,538 |
| Total | 1,290 | 1,282 | 4,469 | 7,041 |

. tabulate year unemployed_NEET_trans

| year | unemployed_NEET_trans Entered.. | Exited .. | No Change | Total |
|---|---|---|---|---|
| 0 | 0 | 0 | 3,503 | 3,503 |
| 1 | 32 | 29 | 3,477 | 3,538 |
| Total | 32 | 29 | 6,980 | 7,041 |

. tabulate year inactive_NEET_trans

| year | inactive_NEET_trans Entered.. | Exited .. | No Change | Total |
|---|---|---|---|---|
| 0 | 0 | 0 | 3,503 | 3,503 |
| 1 | 91 | 89 | 3,358 | 3,538 |
| Total | 91 | 89 | 6,861 | 7,041 |

# Appendix Table 2. Results of conditional FE and RE models of NEET

Conditional (fixed-effects) logistic regression

Number of obs = 2,765
LR chi2(18) = 166.14
Prob > chi2 = 0.0000
Log likelihood = -1440.6597 Pseudo R2 = 0.0545

| NEET | Odds Ratio | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| gen | 1 | (omitted) | | | | |
| age_cohort | | | | | | |
| 20-24 | 1.19275 | .1450858 | 1.45 | 0.147 | .9397443 | 1.513873 |
| 25-29 | 1.36654 | .1906966 | 2.24 | 0.025 | 1.039537 | 1.796409 |
| educ_level | | | | | | |
| Primary | .5882837 | .2076677 | -1.50 | 0.133 | .2945151 | 1.175077 |
| Secondary | .7176691 | .2582032 | -0.92 | 0.356 | .3545509 | 1.45268 |
| Tertiary | .460167 | .1649286 | -2.17 | 0.030 | .2279481 | .9289556 |
| mart_ss | | | | | | |
| married | 1.058965 | .147993 | 0.41 | 0.682 | .8052374 | 1.392641 |
| divor_separt_widow | 2.085709 | .5049162 | 3.04 | 0.002 | 1.297751 | 3.35209 |
| Health_st | | | | | | |
| sick | 2.417674 | .4402296 | 4.85 | 0.000 | 1.692014 | 3.454549 |
| employ_sf | | | | | | |
| employedf | .1213367 | .0315689 | -8.11 | 0.000 | .0728669 | .2020478 |
| educ_f_lit | | | | | | |
| Literate | .9149277 | .0963604 | -0.84 | 0.399 | .7442829 | 1.124697 |
| educ_m_lit | | | | | | |
| Literate | .7889834 | .1121567 | -1.67 | 0.095 | .5971269 | 1.042483 |
| wealth_quartile | | | | | | |
| 2 | .73668 | .1194898 | -1.88 | 0.060 | .5360604 | 1.012381 |
| 3 | 1.053248 | .1218359 | 0.45 | 0.654 | .8395888 | 1.321279 |
| 4 | .941366 | .110629 | -0.51 | 0.607 | .7476969 | 1.185199 |
| acces_markt_1 | | | | | | |
| yes | .9211026 | .0852721 | -0.89 | 0.375 | .768258 | 1.104356 |
| access_busin_opp_1 | | | | | | |
| yes | 1.183484 | .1851579 | 1.08 | 0.282 | .8709452 | 1.608179 |
| access_mfs_1 | | | | | | |
| yes | 1.090878 | .1454227 | 0.65 | 0.514 | .8400483 | 1.416603 |
| 1.year | 1.185727 | .114209 | 1.77 | 0.077 | .981741 | 1.432096 |

. estat ic

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 2,765 | -1523.731 | -1440.66 | 18 | 2917.319 | 3023.966 |

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Random-effects logistic regression Number of obs = 2,765
Group variable: serial_number Number of groups = 2,679

Random effects u_i ~ Gaussian Obs per group:
min = 1
avg = 1.0
max = 2

Integration method: mvaghermite Integration pts. = 12

Wald chi2(19) = 212.86
Log likelihood = -1485.0159 Prob > chi2 = 0.0000

| NEET | OR | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| gen | .4373677 | .0440974 | -8.20 | 0.000 | .3589424 | .5329281 |
| age_cohort | | | | | | |
| 20-24 | 1.226814 | .1455306 | 1.72 | 0.085 | .9723103 | 1.547933 |
| 25-29 | 1.343547 | .177982 | 2.23 | 0.026 | 1.036317 | 1.741859 |
| educ_level | | | | | | |
| Primary | .5975478 | .2075065 | -1.48 | 0.138 | .302539 | 1.180222 |
| Secondary | .7617829 | .2702306 | -0.77 | 0.443 | .380085 | 1.526798 |
| Tertiary | .4970161 | .1756868 | -1.98 | 0.048 | .2485908 | .9937012 |
| mart_ss | | | | | | |
| married | 1.098892 | .135399 | 0.77 | 0.444 | .8631273 | 1.399056 |
| divor_separt_widow | 2.082573 | .4974323 | 3.07 | 0.002 | 1.304028 | 3.325935 |
| Health_st | | | | | | |
| sick | 2.136558 | .3806616 | 4.26 | 0.000 | 1.506814 | 3.029492 |
| employ_sf | | | | | | |
| employedf | .1550503 | .03943 | -7.33 | 0.000 | .0941907 | .255233 |
| educ_f_lit | | | | | | |
| Literate | .8673729 | .0902387 | -1.37 | 0.171 | .7073747 | 1.06356 |
| educ_m_lit | | | | | | |
| Literate | .8103684 | .1136547 | -1.50 | 0.134 | .6156032 | 1.066754 |
| wealth_quartile | | | | | | |
| 2 | .7496751 | .1208839 | -1.79 | 0.074 | .5465353 | 1.028319 |
| 3 | 1.030147 | .1184045 | 0.26 | 0.796 | .8223611 | 1.290434 |
| 4 | .9485717 | .1106423 | -0.45 | 0.651 | .7547189 | 1.192216 |
| acces_markt_1 | | | | | | |
| yes | .9156861 | .0842531 | -0.96 | 0.338 | .7645868 | 1.096646 |
| access_busin_opp_1 | | | | | | |
| yes | 1.172519 | .1822136 | 1.02 | 0.306 | .8646497 | 1.590009 |
| access_mfs_1 | | | | | | |
| yes | 1.07886 | .1428051 | 0.57 | 0.566 | .8323273 | 1.398414 |
| 1.year | 1.132919 | .1049769 | 1.35 | 0.178 | .9447699 | 1.358537 |
| _cons | 5.200305 | 2.319365 | 3.70 | 0.000 | 2.169642 | 12.46435 |
| /lnsig2u | -4.299131 | 5.329286 | | | -14.74434 | 6.146078 |
| sigma_u | .1165348 | .3105236 | | | .0006285 | 21.60746 |
| rho | .004111 | .0218184 | | | 1.20e-07 | .9930028 |

LR test of rho=0: chibar2(01) = 1.9e-03 Prob >= chibar2 = 0.483

. estat ic

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 2,765 | . | -1485.016 | 21 | 3012.032 | 3136.453 |

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

# Appendix Table 3. Results of conditional FE and RE models of unemployed-NEET

Conditional (fixed-effects) logistic regression

Number of obs = 2,197
LR chi2(18) = 57.98
Prob > chi2 = 0.0000
Log likelihood = -511.51679
Pseudo R2 = 0.0536

| unemployed_NEET | Odds Ratio | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| gen | 1 | (omitted) | | | | |
| age_cohort | | | | | | |
| 20-24 | .9218437 | .21508 | -0.35 | 0.727 | .5835246 | 1.456315 |
| 25-29 | 1.103562 | .2828534 | 0.38 | 0.701 | .6677682 | 1.82376 |
| educ_level | | | | | | |
| Primary | .5380079 | .30704 | -1.09 | 0.277 | .1757963 | 1.646523 |
| Secondary | .616794 | .3592084 | -0.83 | 0.407 | .1969779 | 1.931358 |
| Tertiary | .3901765 | .227144 | -1.62 | 0.106 | .1246603 | 1.221221 |
| mart_ss | | | | | | |
| married | .9466399 | .235079 | -0.22 | 0.825 | .5818433 | 1.540152 |
| divor_separt_widow | 1.638049 | .7370058 | 1.10 | 0.273 | .6781822 | 3.956464 |
| Health_st | | | | | | |
| sick | 2.347505 | .6675181 | 3.00 | 0.003 | 1.344515 | 4.098713 |
| employ_sf | | | | | | |
| employedf | .1970598 | .0777376 | -4.12 | 0.000 | .0909515 | .4269593 |
| educ_f_lit | | | | | | |
| Literate | .6825132 | .1417529 | -1.84 | 0.066 | .4542792 | 1.025414 |
| educ_m_lit | | | | | | |
| Literate | .8158785 | .2208617 | -0.75 | 0.452 | .4799564 | 1.386913 |
| wealth_quartile | | | | | | |
| 2 | .4679973 | .1730166 | -2.05 | 0.040 | .2267555 | .9658929 |
| 3 | 1.154919 | .2348833 | 0.71 | 0.479 | .7752423 | 1.720545 |
| 4 | .7823809 | .1737007 | -1.11 | 0.269 | .5063354 | 1.208922 |
| acces_markt_1 | | | | | | |
| yes | .9769914 | .1678337 | -0.14 | 0.892 | .6976956 | 1.368093 |
| access_busin_opp_1 | | | | | | |
| yes | 1.54071 | .4012524 | 1.66 | 0.097 | .9247824 | 2.56686 |
| access_mfs_1 | | | | | | |
| yes | 1.4044 | .3291117 | 1.45 | 0.147 | .8871914 | 2.223126 |
| 1.year | 1.373085 | .2404599 | 1.81 | 0.070 | .9741632 | 1.935366 |

. estat ic

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 2,197 | -540.5057 | -511.5168 | 18 | 1059.034 | 1161.541 |

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Iteration 40: log likelihood = -542.96973

Random-effects logistic regression
Group variable: serial_number
Number of obs = 2,221
Number of groups = 2,171

Random effects u_i ~ Gaussian
Obs per group:
min = 1
avg = 1.0
max = 2

Integration method: mvaghermite
Integration pts. = 12

Wald chi2(19) = 16.00
Log likelihood = -542.96973
Prob > chi2 = 0.6572

| unemployed_NEET | OR | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| gen | .3548546 | .1269433 | -2.90 | 0.004 | .1760141 | .7154074 |
| age_cohort | | | | | | |
| 20-24 | 1.232175 | .4000331 | 0.64 | 0.520 | .6521154 | 2.328199 |
| 25-29 | 1.707454 | .6393401 | 1.43 | 0.153 | .8196431 | 3.556915 |
| educ_level | | | | | | |
| Primary | .3246922 | .2973541 | -1.23 | 0.219 | .0539435 | 1.954361 |
| Secondary | .5081139 | .4629202 | -0.74 | 0.457 | .0852057 | 3.030075 |
| Tertiary | .2664871 | .2518642 | -1.40 | 0.162 | .0418006 | 1.698909 |
| mart_ss | | | | | | |
| married | 1.383715 | .4513621 | 1.00 | 0.319 | .7301102 | 2.622437 |
| divor_separt_widow | 2.297395 | 1.576429 | 1.21 | 0.225 | .5986285 | 8.81686 |
| Health_st | | | | | | |
| sick | 4.048693 | 2.15006 | 2.63 | 0.008 | 1.429828 | 11.46425 |
| employ_sf | | | | | | |
| employedf | .1303985 | .098113 | -2.71 | 0.007 | .0298415 | .569802 |
| educ_f_lit | | | | | | |
| Literate | .548378 | .1748749 | -1.88 | 0.060 | .293519 | 1.024528 |
| educ_m_lit | | | | | | |
| Literate | .895124 | .3338477 | -0.30 | 0.766 | .4309401 | 1.8593 |
| wealth_quartile | | | | | | |
| 2 | .312247 | .179086 | -2.03 | 0.042 | .1014613 | .9609397 |
| 3 | 1.190197 | .3523631 | 0.59 | 0.556 | .6662192 | 2.126282 |
| 4 | .7329461 | .2352451 | -0.97 | 0.333 | .3907256 | 1.374904 |
| acces_markt_1 | | | | | | |
| yes | .9867805 | .2419823 | -0.05 | 0.957 | .6102186 | 1.595716 |
| access_busin_opp_1 | | | | | | |
| yes | 1.804097 | .7288837 | 1.46 | 0.144 | .8172612 | 3.982527 |
| access_mfs_1 | | | | | | |
| yes | 1.490441 | .5167667 | 1.15 | 0.250 | .7554146 | 2.940654 |
| 1.year | 1.260204 | .3172353 | 0.92 | 0.358 | .7694225 | 2.064032 |
| _cons | .4810277 | .5455989 | -0.65 | 0.519 | .0520843 | 4.442561 |
| /lnsig2u | 1.566761 | .7894329 | | | .0195011 | 3.114021 |
| sigma_u | 2.188859 | .8639787 | | | 1.009798 | 4.744616 |
| rho | .5928871 | .190547 | | | .2366117 | .8724919 |

LR test of rho=0: chibar2(01) = 2.03 Prob >= chibar2 = 0.077

. estat ic

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 2,221 | . | -542.9697 | 21 | 1127.939 | 1247.759 |

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

# Appendix Table 4. Results of conditional FE and RE models of inactive-NEET

Conditional (fixed-effects) logistic regression

Number of obs = 2,565
LR chi2(18) = 101.38
Prob > chi2 = 0.0000
Log likelihood = -1152.4759 Pseudo R2 = 0.0421

| inactive_NEET | Odds Ratio | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| gen | 1 | (omitted) | | | | |
| age_cohort | | | | | | |
| 20-24 | 1.406698 | .1939907 | 2.47 | 0.013 | 1.073534 | 1.843256 |
| 25-29 | 1.39161 | .2251996 | 2.04 | 0.041 | 1.013376 | 1.911017 |
| educ_level | | | | | | |
| Primary | .6720996 | .2800199 | -0.95 | 0.340 | .2970254 | 1.520805 |
| Secondary | .8110647 | .3442151 | -0.49 | 0.622 | .3530257 | 1.863394 |
| Tertiary | .5717388 | .2416834 | -1.32 | 0.186 | .2496783 | 1.309226 |
| mart_ss | | | | | | |
| married | 1.011966 | .1625561 | 0.07 | 0.941 | .7386422 | 1.386429 |
| divor_separt_widow | 1.810141 | .494888 | 2.17 | 0.030 | 1.059244 | 3.093348 |
| Health_st | | | | | | |
| sick | 1.931782 | .4023242 | 3.16 | 0.002 | 1.284346 | 2.90559 |
| employ_sf | | | | | | |
| employedf | .1436752 | .0393261 | -7.09 | 0.000 | .0840223 | .2456794 |
| educ_f_lit | | | | | | |
| Literate | .9117297 | .1090294 | -0.77 | 0.440 | .7212319 | 1.152543 |
| educ_m_lit | | | | | | |
| Literate | .6966442 | .1172543 | -2.15 | 0.032 | .5008904 | .9689008 |
| wealth_quartile | | | | | | |
| 2 | .8681895 | .1558915 | -0.79 | 0.431 | .6106234 | 1.234399 |
| 3 | 1.055488 | .14112 | 0.40 | 0.686 | .8121699 | 1.371703 |
| 4 | 1.014211 | .1355158 | 0.11 | 0.916 | .780537 | 1.317842 |
| acces_markt_1 | | | | | | |
| yes | .9954518 | .1055331 | -0.04 | 0.966 | .8086859 | 1.225351 |
| access_busin_opp_1 | | | | | | |
| yes | .9917424 | .1831567 | -0.04 | 0.964 | .6905538 | 1.424296 |
| access_mfs_1 | | | | | | |
| yes | 1.248716 | .185852 | 1.49 | 0.136 | .9327719 | 1.671675 |
| 1.year | 1.011603 | .1124829 | 0.10 | 0.917 | .81351 | 1.257933 |

. estat ic

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 2,565 | -1203.165 | -1152.476 | 18 | 2340.952 | 2446.247 |

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Random-effects logistic regression Number of obs = 2,565
Group variable: serial_number Number of groups = 2,492

Random effects u_i ~ Gaussian Obs per group:
min = 1
avg = 1.0
max = 2

Integration method: mvaghermite Integration pts. = 12

Wald chi2(19) = 125.87
Log likelihood = -1187.6734 Prob > chi2 = 0.0000

| inactive_NEET | OR | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| gen | .5357458 | .0613997 | -5.45 | 0.000 | .4279628 | .6706742 |
| age_cohort | | | | | | |
| 20-24 | 1.324558 | .176868 | 2.10 | 0.035 | 1.019553 | 1.720805 |
| 25-29 | 1.238816 | .1892968 | 1.40 | 0.161 | .9182048 | 1.671377 |
| educ_level | | | | | | |
| Primary | .73191 | .3010325 | -0.76 | 0.448 | .3268594 | 1.638907 |
| Secondary | .8736623 | .3670314 | -0.32 | 0.748 | .3834848 | 1.990394 |
| Tertiary | .6166786 | .2581224 | -1.15 | 0.248 | .2715017 | 1.400701 |
| mart_ss | | | | | | |
| married | .9911464 | .1408735 | -0.06 | 0.950 | .7501617 | 1.309546 |
| divor_separt_widow | 1.723939 | .4644834 | 2.02 | 0.043 | 1.016674 | 2.923226 |
| Health_st | | | | | | |
| sick | 1.762142 | .3615708 | 2.76 | 0.006 | 1.178648 | 2.634495 |
| employ_sf | | | | | | |
| employedf | .1626148 | .043341 | -6.81 | 0.000 | .096448 | .2741745 |
| educ_f_lit | | | | | | |
| Literate | .8805635 | .1040436 | -1.08 | 0.282 | .6985321 | 1.110031 |
| educ_m_lit | | | | | | |
| Literate | .6913012 | .1150605 | -2.22 | 0.027 | .4988763 | .9579475 |
| wealth_quartile | | | | | | |
| 2 | .8968036 | .1601633 | -0.61 | 0.542 | .6319435 | 1.272672 |
| 3 | 1.041042 | .1382717 | 0.30 | 0.762 | .8024375 | 1.350595 |
| 4 | 1.016178 | .135184 | 0.12 | 0.904 | .7829478 | 1.318884 |
| acces_markt_1 | | | | | | |
| yes | .9864162 | .1040157 | -0.13 | 0.897 | .8022369 | 1.21288 |
| access_busin_opp_1 | | | | | | |
| yes | .9864134 | .1813176 | -0.07 | 0.941 | .6880109 | 1.414238 |
| access_mfs_1 | | | | | | |
| yes | 1.242797 | .1840647 | 1.47 | 0.142 | .9296786 | 1.661375 |
| 1.year | 1.05228 | .1121573 | 0.48 | 0.633 | .8538977 | 1.296751 |
| _cons | 2.432408 | 1.238696 | 1.75 | 0.081 | .8965297 | 6.599456 |
| /lnsig2u | -10.08836 | 14.46532 | | | -38.43987 | 18.26315 |
| sigma_u | .0064467 | .046627 | | | 4.50e-09 | 9242.546 |
| rho | .0000126 | .0001827 | | | 6.15e-18 | 1 |

LR test of rho=0: chibar2(01) = 1.8e-04 Prob >= chibar2 = 0.495

. estat ic

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 2,565 | . | -1187.673 | 21 | 2417.347 | 2540.191 |

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Appendix Table 5. Results of the Principal Component Analysis (PCA)

```
                                                  Number of obs    =      7,041
                                                  Number of comp.  =         23
                                                  Trace            =         23
Rotation: (unrotated = principal)                 Rho              =     1.0000
```

| Component | Eigenvalue | Difference | Proportion | Cumulative |
|---|---|---|---|---|
| Comp1 | 1.48221 | .44897 | 0.0644 | 0.0644 |
| Comp2 | 1.03324 | .00170627 | 0.0449 | 0.1094 |
| Comp3 | 1.03154 | .000477387 | 0.0448 | 0.1542 |
| Comp4 | 1.03106 | .000553918 | 0.0448 | 0.1990 |
| Comp5 | 1.03051 | .000279407 | 0.0448 | 0.2439 |
| Comp6 | 1.03023 | .000226088 | 0.0448 | 0.2886 |
| Comp7 | 1.03 | .000342409 | 0.0448 | 0.3334 |
| Comp8 | 1.02966 | .000463199 | 0.0448 | 0.3782 |
| Comp9 | 1.02919 | .000109855 | 0.0447 | 0.4229 |
| Comp10 | 1.02909 | .0000809213 | 0.0447 | 0.4677 |
| Comp11 | 1.029 | .0000694638 | 0.0447 | 0.5124 |
| Comp12 | 1.02893 | .000564181 | 0.0447 | 0.5572 |
| Comp13 | 1.02837 | .000337207 | 0.0447 | 0.6019 |
| Comp14 | 1.02803 | .00020644 | 0.0447 | 0.6466 |
| Comp15 | 1.02783 | .000365893 | 0.0447 | 0.6913 |
| Comp16 | 1.02746 | .00025788 | 0.0447 | 0.7359 |
| Comp17 | 1.0272 | .00016587 | 0.0447 | 0.7806 |
| Comp18 | 1.02704 | .000282732 | 0.0447 | 0.8252 |
| Comp19 | 1.02675 | .00070094 | 0.0446 | 0.8699 |
| Comp20 | 1.02605 | .000607699 | 0.0446 | 0.9145 |
| Comp21 | 1.02545 | .473239 | 0.0446 | 0.9591 |
| Comp22 | .552207 | .163264 | 0.0240 | 0.9831 |
| Comp23 | .388943 | . | 0.0169 | 1.0000 |

Appendix Table 6. Results of the Variance Inflation Factor for regression model of NEET youth

. vif

| Variable | VIF | 1/VIF |
|---|---|---|
| gen | 1.19 | 0.840452 |
| age_cohort | | |
| 2 | 1.30 | 0.768677 |
| 3 | 1.76 | 0.567001 |
| educ_level | | |
| 1 | 17.81 | 0.056133 |
| 2 | 11.96 | 0.083643 |
| 3 | 14.25 | 0.070186 |
| mart_ss | | |
| 2 | 1.72 | 0.581386 |
| 3 | 1.07 | 0.934060 |
| 1.Health_st | 1.07 | 0.936689 |
| 1.employ_sf | 1.08 | 0.927726 |
| 1.educ_f_lit | 1.18 | 0.844352 |
| 1.educ_m_lit | 1.15 | 0.873029 |
| wealth~rtile | | |
| 2 | 1.14 | 0.878615 |
| 3 | 1.22 | 0.820828 |
| 4 | 1.22 | 0.818936 |
| 1.acces_ma~1 | 1.01 | 0.986781 |
| 1.access_b~1 | 1.02 | 0.984181 |
| 1.access_m~1 | 1.03 | 0.974102 |
| 1.year | 1.05 | 0.956877 |
| Mean VIF | 3.33 | |