The Scars of Child Labor: Links with Youth Employment and Earnings

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ERSA working paper 930

May 2026

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April 30, 2026

Abstract

We use longitudinal panel data from the Young Lives study, which tracks individuals from childhood into adulthood, to examine the effects of involvement in child labor at age twelve on subsequent labor market outcomes. Our results suggest that an additional hour of child labor participation at age twelve increases the probability of employment later in life by 10.7 percent, indicating, at least in part, an early labor market entry advantage. However, we also find that individuals who participated in child labor are more likely to work in hazardous jobs in adulthood. Using earnings as an outcome measure, we further show that involvement in child labor at age twelve has a significant negative effect on earnings fourteen years later, at age twenty-six. We argue that a key mechanism through which child labor affects later labor market outcomes is its persistent negative impact on educational attainment. Overall, our findings highlight the long-term costs of child labor and underscore the potential social benefits of policies that reduce child labor and mitigate its adverse effects on human capital formation through targeted safety nets.

Keywords: Child labour, youth employment, earnings.
JEL Codes: D13, I31, J22, J28, J31, O15

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1. Introduction

Events experienced in individuals' early lives have long-term consequences on health, human capital formation, and wealth accumulation (Heckman, 2006; Almond and Currie, 2011). This is particularly true in developing countries, where households are subject to considerable risk and shocks, but most do not have access to formal financial institutions to cope with them (Bardhan and Udry, 1999; Dercon et al., 2005; Manccini and Yang, 2009; Currie and Vogl, 2013; Adhvaryu et al., 2019; Carrillo, 2020; Adhvaryu et al., 2023). Child labor is a notable early life shock in the context of developing countries, often implemented by households as a coping strategy to covariate and idiosyncratic shocks (Beegle et al., 2006; Kruger, 2007; Duryea et al., 2007; Björkman-Nyqvist, 2013) and as a source of livelihood due to extreme intergenerational poverty (Emerson and Souza, 2003). At the start of 2020, the year the world experienced the COVID-19 pandemic, globally 160 million children (39.4% girls) were in child labor, and half of them engaged in hazardous jobs that directly risk their health, safety, and long-term development (ILO and UNICEF, 2021).

In this paper, we investigate the impact of working in child labor in early life on youth labor market outcomes using four rounds of the Young Lives (YL) panel data from Ethiopia. The YL panel data, initiated by the Department of International Development (ODID) of the University of Oxford, is a rich panel data that collects information on child labor for two cohorts of children (the old and young cohorts) spanning two decades. We exploit exogenous variation in the prevalence of natural shocks to instrument for child labor and assess its impact on two youth labor market outcomes—employment and earnings—using the probit instrumental variables and the fixed effects filtered instrumental variables estimators, respectively. We utilize the older cohort data, which documents child labor information at age 12, collected in the 2006 survey, and link it with labor market outcomes at ages 19, 22, and 26, collected in 2013, 2016, and 2020, respectively. The availability of panel data collected on the same individuals from childhood to youth and adulthood offers a significant opportunity to investigate the adverse long-term consequences of child labor.

We find a robust effect of working in child labor around the age of 12 on youth labor market outcomes. Marginal effects from an instrumental variables probit regression suggest that a one-hour increase in daily child labor at age 12 increases the probability of youth employment by 10.2%. This finding is consistent with previous literature, which suggests that child labor leads to early labor market entry (Edmonds, 2006; Kassouf et al., 2001; Ilahi et al., 2000) and that early labor market entry leads to greater employment opportunities (Sanders et al., 2020; Howieson and Iannelli, 2008; Reid, 1972). However, drawing on detailed youth occupational data, we demonstrate a strong correlation between participation in child labor and employment in hazardous jobs. We show that a one-hour increase in child labor at age 12 is associated with a 1.4% higher risk of being employed in hazardous jobs. The estimated effects of child labor on youth employment remain robust when using the control function approach - an alternative instrumental variables estimator.

We also find a strong negative effect of child labor on earnings at age 26, but not at ages 19 and 22. Fixed effects filtered instrumental variables (FFE-IV) results suggest that a one-hour increase in child labor reduces earnings at age 26 by approximately 23.1%. This indicates that the effect of child labor on earnings is strong at a later stage, which is likely to persist into adult life. We demonstrate that the key pathway through which involvement in child labor reduces earnings during adulthood is through its effect on human capital formation and, more importantly, education. Using exogenous variation in the prevalence of shocks as an instrument for child labor, we find that a one-hour increase in child labor at age 12 reduces education by 0.77 years at a later age. Those with a lower level of education are also more likely to work in hazardous jobs that put their safety at risk. Taken together, the results suggest that child labor indeed hurts human capital formation and labor market status in adulthood. Thus, putting safety net initiatives in place to protect vulnerable children from exploitation and child labor would not only be welfare-enhancing to the children but also improve the overall productivity of the working force.

This paper contributes to the development literature on the long-term impact of early life events. Three strands of literature in development economics study child labor and poverty. The first set of studies (e.g., Beegle et al., 2006; Kruger, 2007; Duryea et al., 2007; Björkman-Nyqvist, 2013) investigate the causes of child labor and document that vulnerable households with limited or no access to formal financial institutions use child labor to cope with idiosyncratic and covariate shocks. The second strand of literature, which our paper builds on, investigates the negative impact of child labor on school participation and educational outcomes (Beegle et al., 2009; Zabaleta, 2011), self-reported health (Lee and Orazem, 2010), adulthood income (Emerson and Souza, 2011), and test scores (Emerson et al., 2017). The third strand of literature investigates the effectiveness of different safety net interventions in reducing the incidence of child labor (e.g., Gertler et al., 2014; Edmonds and Shrestha, 2014; Edmonds and Theoharides, 2020), and in helping children who faced disadvantage or trauma early in life (Adhvaryu et al., 2023).[1]

However, the literature on the long-term effects of child labor is very limited. To the best of our knowledge, the three papers that investigate the long-term impact of child labor are Emerson and Souza (2011), Emerson et al. (2017) and Piza et al. (2024) conducted using data in Brazil. Emerson and Souza (2011) use retrospective data on involvement of child labor and document that working before the age of 13-14 years of age affects income in adult ages negatively but the effect turns positive when children start working at the age of 14. Emerson et al. (2017) use fixed effects regressions on panel data from Brazil and find that involving in child labor while in school negatively affects test scores of children leading to significant loss of average year of learning. More recently, Piza et al. (2024) use repeated cross-sectional data in a regression discontinuity setup and investigate the 1998 legislation to increase the minimum employment age to 16 in Brazil. These authors document that the minimum age legislation led to a persistent 35 percent decrease in paid labor among

[1]While almost all of these studies find significant positive effects of safety nets in reducing child labor, Edmonds and Theoharides (2020) find the opposite. These authors find that the 2016 Government of the Philippines' child labor elimination program, which offered a one-time productive asset grant, led to an increase in child labor because households relied on family labor to work the asset.

urban boys. We contribute to this limited literature by drawing on insights from rich data that track the same individuals from childhood to adulthood over nearly two decades in a Sub-Saharan context.

Our paper also contributes to the microeconomics literature on the long-term impacts of early-life shocks on human capital formation and labor market outcomes. A strand of applied economics literature (e.g., Heckman, 2006; Cunha and Heckman, 2007) models skill formation in life as a dynamic process in which early investments have a strong impact on later inputs. Investments and interventions made during early periods of child development result in more significant returns (Gertler et al., 2014; Aizer et al., 2016; Chetty et al., 2016; Hoynes et al., 2016; Hjort et al., 2017). The literature also documents that the converse is true, i.e., lack of investment during critical periods leads to long-term adverse effects. Previous studies in different contexts document how early life shocks affect long-term outcomes, e.g., adverse events experienced in utero on fatal mortality and early life mortality (Almond and Currie, 2011), exposure to drought on health, education, and socioeconomic outcomes (Manccini and Yang, 2009), and income shocks on psychological wellbeing (Adhvaryu et al., 2019). Previous research also documents that the long-term effects of early-life health shocks are larger in developing countries than in developed countries due to lower living standards (Currie and Vogl, 2013). Using long panel data that track the same individuals from childhood to youth and adulthood, we demonstrate the impact of child labor, a negative early life experience, on labor market outcomes and human capital formation. The findings are insightful for formulating appropriate interventions that mitigate the effects of early-life negative events.

While we acknowledge these contributions, we also recognize some limitations of our identification strategy in establishing a causal relationship between child labor and labor market outcomes, which we discuss in detail in Section 5 and leave for future research to address. Nevertheless, even if our findings are interpreted as correlations between involvement in child labor and long-term labor market outcomes (and not as causation), the fact that we use information on the participation in child labor at age 12 and link it with labor market outcomes of the same individual years later using detailed labor market data spanning two decades is insightful.

The rest of the paper is organized as follows. Section 2 describes the data and provides descriptive statistics of key variables. Section 3 presents the identification strategies. Section 4 presents the results from alternative instrumental variables estimators, robustness checks, and mechanisms analysis. Section 5 discusses some of the caveats of our analysis. Section 6 concludes the paper.

2. Data, Variables and Descriptive Statistics

2.1. Data and Variables

Our analysis is based on the Ethiopian Young Lives Survey data, an international longitudinal study initiated by the University of Oxford's Department of International Development (ODID). The survey spans four low-income countries, Ethiopia, India, Peru, and Vietnam, and aims to capture changes in childhood poverty by collecting data at both the household and child levels. The Ethiopian version of the data was implemented in 2002, 2006, 2009, 2013, 2016, and 2020. In the first round of the survey (2002), data was collected from 2,000 one-year-old children, referred to as the "young" cohort, and 1,000 eight-year-old children, referred to as the "old" cohort. Subsequent rounds of the survey tracked and surveyed the same children. The samples were drawn from 20 specific locations within Ethiopia's five major regional states: Amhara, Oromia, Southern Nations, Nationalities, and Peoples (SNNP), Tigray, and Addis Ababa, which collectively make up 96% of the national population. The attrition rate measured from the first wave in 2002 to the final wave in 2020 was 15.7% for the young cohort and 21.6% for the old cohort. We conduct a formal attrition test in the "Robustness Checks" section, and show that attrition is unlikely to bias the results.

Our empirical analysis for the outcome variables of interest is undertaken at the individual youth level using the most recent three waves (2013, 2016, and 2020) of the old cohort of children. However, we extracted information on child labor from the second round of the survey (2006) and integrated it with data from the most recent three waves excluding the 2009 wave when the children were not yet 18. We limit our sample to the older cohort since the sample has three rounds of labor market information for youths aged 18 to 26 in the 2013, 2016 and 2020 rounds. After excluding 286 (10.3%) observations with missing relevant information, we had 2,502 observations (2,405 observations surveyed at least in two of the three waves).

The primary focus of this paper is investigating the impact of involvement in child labor on the labor market outcomes of youth. According to the official United Nations definition, youth are 15 to 24 years old. However, the operational definition of youth (or young people) differs greatly among countries. The Ethiopian National Youth Policy (Ministry of Youth, Sports and Culture, 2004) defines youth as members of society aged 15-29 years. On the other hand, the ILO definition of child labor considers children aged 5 to 17 years (ILO and UNICEF, 2021). To establish a fairly clearer relationship between child labor and youth labor market outcomes, we focus on youths over 17. Information on child labor was collected when the respondents were 12 years old in round 2 of the survey, 2006. Empirical research (Seid and Gurmu, 2015; Haile and Haile, 2012; Basu and Van, 1998) shows that child labor exploitation peaks around this age.

We use employment, earnings, and unemployment to capture labor market outcomes. We constructed a dummy variable for employment status with a 1 if the youth worked for at least one hour the previous week and 0 otherwise. We consider youth who did not work the previous week but have a job in the week of the survey as employed. The employment might be in one's own business, for a family member, or someone else. The second outcome variable, earnings, is calculated as the net yearly monetary value (in Ethiopian Birr - ETB) of compensations from employment paid in cash or kind. We used net profits or self-determined wages to capture earnings from one's own firm. In addition to employment and earnings, we also use a dummy variable for unemployment status coded 1 for youth who did not work for more than one hour in the previous week but were available for and actively seeking work and 0 otherwise.

The key explanatory variable of interest, child labour, is measured as the total daily hours spent on unpaid and/or paid activities at and/or outside home by the child at the age of 12. The activities include time spent on household care, domestic tasks, unpaid work on the farm and/or family business, and paid work. In addition to this measure, we also consider the time spent on economic activities only (both unpaid work on the farm and/or family business and paid work) by the child, providing an alternative perspective.

2.2. Summary Statistics

Table 1 presents the summary statistics of the key variables. Column (1) displays the pooled data, column (2) presents the sample of youth observed at least twice, and columns 3 - 5 present data for the 2013, 2016 and 2020 rounds respectively. We note that the average rate of youth employment and unemployment during the 2013-2020 period are 58% and 14%, respectively. The youth unemployment rate in 2013 recorded in the Young Lives survey (10%) is equivalent to the youth unemployment rate reported in the 2013 National Labour Survey (9.2%) (Central Statistical Agency, 2014). However, the 2020 youth unemployment rate (21%) reported in column (3) is greater than the country' level youth unemployment rate of 11.8% reported in the 2021 Ethiopian Labour Force and Migration Survey (Central Statistical Agency and IOM, 2021). The higher youth unemployment in the Young Lives data might be because the survey round in 2020 overlapped with the COVID-19 epidemic, which affected labour markets globally. The average yearly earnings from work in the three rounds is around ETB 17,351 (USD 774.21) with a lower average earnings at the age of 19 (2013) and higher earnings at the age of 26 (2020).[2] Finally, we note that the mean values reported in columns 1 and 2 are very similar, which suggests that exclusion of those who were observed only once is unlikely to bias the sample.

Child labour is prevalent in Ethiopia. Table 1 shows that on average, each child at the age of 12 spends 4.5 hours per day on unpaid and/or paid tasks at home and/or outside home. This figure is comparable with previous research on child labor in Ethiopia. For example, Haile and Haile (2012) and Colmer (2021) document 34.21 and 27.55 hours of child labour per week, respectively, corresponding to 4.9 and 3.9 hours per day. Comparing child labour between non-economic activities (home care and/or housework) and economic activities (unpaid employment on a farm and/or family business and paid work) shows that the former constitutes (63%). The child labour dummy created following UNICEF's standard metric presented in Table 1 shows that 78% of the sample children involve in child labour by the age of 12 years. However, a child labour dummy based on at least one hour of daily time spent on economic activities reduces the proportion to 48%. The distribution of the sample of youth by gender and location of residence (rural/urban) are in equal proportion. The average respondent in the sample has 9.4 years of schooling, and reports subjective wellbeing about 5.1 measured in a scale of 1 to 9, lives in a household with 4.8 people, and a wealth index of 0.5 on a scale of 0 to 1. Finally, we note that 43% of the households the youth live with experienced at least one natural shock, such as drought, floods, or frost in the year the children involved in child labor.

[2] 1 USD = 22.41 ETB in 2016/17.

Table 1: Summary Statistics

	(1) Pooled Data	(2) $\geq$ 2 Waves	(3) 2013	(4) 2016	(5) 2020
Labour Market Outcomes (2013 - 2020)					
Employed, dummy	0.578	0.578	0.581	0.660	0.487
	(0.494)	(0.494)	(0.494)	(0.474)	(0.500)
Unemployed, dummy	0.137	0.138	0.100	0.108	0.209
	(0.344)	(0.345)	(0.300)	(0.311)	(0.407)
Earnings (Annual in Birr)	17351.0	17492.7	6489.6	13923.5	36393.3
	(28703.7)	(29101.9)	(12364.5)	(16766.5)	(44266.0)
Child Labour Indicators (2006)					
Child labour - all activities (hrs/day)	4.513	4.542			
	(2.412)	(2.415)			
Child labour - care & chores (hrs/day)	2.849	2.862			
	(1.890)	(1.894)			
Child labour - farm & paid (hrs/day)	1.665	1.681			
	(2.156)	(2.169)			
Child labour, dummy (UNICEF)	0.785	0.789			
	(0.411)	(0.408)			
Child labour, dummy ($\geq$1hr on farm & paid)	0.478	0.480			
	(0.500)	(0.500)			
Other Controls and Instrument					
Female, dummy	0.467	0.464	0.463	0.475	0.464
	(0.499)	(0.499)	(0.499)	(0.500)	(0.499)
Rural, dummy	0.505	0.511	0.572	0.526	0.406
	(0.500)	(0.500)	(0.495)	(0.500)	(0.491)
Child's age (in months)	266.3	267.3	228.7	264.3	312.3
	(34.43)	(34.36)	(3.908)	(3.737)	(3.783)
Education level	9.412	9.429	8.112	9.529	10.80
	(3.842)	(3.868)	(3.136)	(3.993)	(3.923)
Subjective well-being (9-step ladder)	5.093	5.101	5.182	5.406	4.661
	(1.546)	(1.546)	(1.546)	(1.617)	(1.362)
Family size	4.770	4.774	5.374	4.598	4.240
	(2.394)	(2.393)	(2.294)	(2.265)	(2.488)
Wealth index	0.514	0.514	0.427	0.461	0.669
	(0.191)	(0.192)	(0.169)	(0.165)	(0.142)
Weather shock, dummy (2006)	0.427	0.433			
	(0.495)	(0.496)			
Observations	2502	2405	908	814	780

Notes: This table reports descriptive statistics of key variables over time. Column (1) presents the mean values of the pooled sample. Column 2 presents the mean values of youth observed at least in two of the three rounds. Columns (3) - (5) present descriptive statistics for the respective three rounds. Child labour and weather-shock are variables capturing the respondents' exposure to child labor and shocks when they were 12 years old (in round 2). Standard deviations reported in parentheses.

3. Empirical Strategy

To investigate the impact of being exposed to child labor on long-term labor market outcomes (employment, unemployment, and the log of earnings), we primarily exploit plausibly exogenous variation in exposure to shocks in an instrumental variable setup. We draw on human capital theory (Becker, 1962; Schultz, 1961) and the Mincerian earning function (Mincer, 1974) and specify the basic empirical framework for estimating labor market outcomes as follows:

$$Y_{it} = \alpha + X_{it}\beta + Q_i\gamma + \delta C_i + \theta_t + \eta_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is the labour market outcome of youth i in period t. X_{it} is a vector of time-varying individual and household-specific covariates of youth i at time t. Q_i is a vector of time-invariant observable youth characteristics such as gender. C_i represents the key explanatory variable of interest - an individual's exposure to child labor at age 12. θ_t is a time specific fixed effect, η_i is a term capturing unobserved individual heterogeneity, and ε_{it} is an idiosyncratic error term. α, β, γ and δ are parameters to be estimated.

δ can be interpreted as the causal effect of exposure to child labor in a static regression framework only if child labor is exogenous. However, child labor is unlikely to be exogenous for several reasons, including due to the correlation of child labor with observable and unobservable factors. We attempt to identify the impact of child labor on youth labor market outcomes using exposure to natural shocks at the time of child labor as an instrument to child labor in an instrumental variables regression setup. We argue that exposure to natural shocks is a plausibly valid IV for child labor because shocks experienced at the age of 12 affect the likelihood of participating in child labor, but they are unlikely to affect the outcome variables of interest directly, labor market outcomes at later age (age 19, 22, and 26). The literature offers strong evidence on the relationship between child labor and shocks, more importantly, weather shocks (e.g., Beegle et al., 2006; Duryea et al., 2007; Björkman-Nyqvist, 2013; Guarcello et al., 2010; Colmer, 2021). In different developing country contexts, previous studies suggest that when shocks hit households, they respond by increasing child labor.[3] Given this, we construct an index of exposure to extreme weather shocks (more specifically drought, floods, erosion, and frost), to serve as instrument. The index constitutes a minimum value of 0 if the child's household encountered none of the shocks and a maximum value of 4 if the household experienced all shocks between the round before and at the age of 12. We discuss the potential issues related to the use of natural shocks and provide more motivation in section 5, Caveats.

Although we argue that exposure to natural shocks is a relevant instrument to child labor and offer empirical evidence in the results section, one could challenge the exclusion restriction because natural shocks may affect the outcome variables (youth labor market outcomes) via channels other than the treatment variable (child labor).

[3] Some research suggests that households use child labor during positive economic shocks as well. For e.g., Kruger (2007) shows that households in coffee-producing areas of Brazil increase child labor (more importantly, child labor of boys) in response to positive coffee production shock.

Alternative labor market theories contend that labor market outcomes such as employability and earnings are mostly determined by an individual's human capital or acquired skills and that human capital is mostly built through investment in health, education, and work experience (Becker, 1962; Schultz, 1961; Mincer, 1974). As child labor involves missing school and study time, it is expected to have a negative effect on education, but it will have a positive effect on work experience. This implies that child labor instrumented using weather shocks explains a portion of the variation in labor market outcomes ascribed to differences in education and experience. Weather shocks, however, may alter health outcomes and, thereby, human capital accumulation and labor market outcomes, in which case the exclusion restriction won't hold. Moreover, it is plausible to argue that weather extremes may displace households to other locations, thereby shaping the long-term outcomes of children.

We checked for these two possible channels using two specifications. First, we regress weather shocks on alternative health indicators, including the child's experience of serious injury or illness since the last survey round, the presence of long-term health problems, the child's health status compared to peers, subjective well-being, and body mass index (BMI). Second, we regressed weather shocks on migration. The regression results in columns 1 - 5 of Table A.1 in the appendix suggest no statistically significant relationship between household exposure to shocks on the alternative health indicators and migration. These findings, therefore, suggest that the exclusion restriction likely holds, and we can identify the impact of child labor on labor market outcomes by instrumenting it using exposure to shocks.

Given that our first outcome variable of interest (employment) is binary, we estimate two versions of instrumental variable regressions - an instrumental variable probit (iv-probit) and a control function (CF) estimator - for the main specification. The iv-probit estimator fits a model with a binary dependent variable and an endogenous regressor(s) in a maximum likelihood framework. The exogeneity of the endogenous regressor can be checked using the Wald test, which tests the null hypothesis of no endogeneity. As a robustness check, we also run the random effects probit estimator.

On the other hand, the control function estimator is a two-stage estimator that generates the residual by running the reduced form of the endogenous explanatory variable on all exogenous variables, where at least one exogenous variable is excluded from the main structural equation. The structural equation is then estimated with the new error term as an extra explanatory variable. Using fitted values for endogenous explanatory variables is often inconsistent in generating structural parameters and average partial or marginal effects (Wooldridge, 2015, 2014). This method has also been validated for estimating the binary response model of panel data (Tiwari, 2021). The CF approach is preferred over other estimators of similar structures because it accounts for unobserved heterogeneity. We, therefore, specify a binary choice regression for employment status with a single continuous endogenous explanatory variable as follows:

$$E_{it} = 1\{X_{it}\beta_1 + Q_i\gamma_1 + \delta C_i + \mu_i + \epsilon_{it} \geq 0\} \tag{2}$$

$$C_i = X_{it}\beta_2 + Q_i\gamma_2 + \phi Z_{ic} + \alpha_i + v_{it} \tag{3}$$

where E_{it} is the employment status of youth i at time t, taking a value of 1 if employed and 0 otherwise. Z_{ic} is an instrument for the endogenous explanatory variable C_i, child labor at age 12. μ_i and α_i are unobserved time-invariant individual effects of the structural and reduced form equations, respectively. v_{it} is an idiosyncratic error term of the reduced equation. The remainder of the terms are as described in equation 1.

For the second outcome variable of interest - youth's annual earnings - we use the Fixed Effect Filtered Instrumental Variable (FEF-IV) estimator proposed by Pesaran and Zhou (2018). The estimator is suitable for panel data where the explanatory variable of interest (child labor) is time-invariant and endogenous. The standard fixed effects (FE) estimator offers consistent parameter estimates for time-varying regressors under the strict exogeneity assumption. However, it eliminates all coefficients of time-invariant regressors.[4] Consequently, in FEF-IV, one can use an external instrument(s) to identify an endogenous variable's coefficient consistently. For large N and small T, the FEF-IV estimator is proven to be unbiased and consistent, as well as robust to residual serial correlation and heteroskedasticity (Pesaran and Zhou, 2018). We therefore specify a FEF-IV version of the earnings equation stated in equation 1 with a time-invariant endogenous regressor and other time-varying and time-invariant regressors as follows:

$$W_{it} = \alpha_i + X_{it}\beta + Q_i\gamma + \delta C_i + \theta_t + v_{it} \tag{4}$$

where $\alpha_i = \alpha + \mu_i$ and there exist an instrument Z_{ic} for C_i such that Z_{ic} is distributed independently of μ_j and $\bar{v}_j$ for all i and j, and satisfy the moment condition $E||Z_i - \bar{Z}||^4 < K < \infty$. W_{it} is annual earnings of individual i in period t. μ_i is the individual fixed effect, and v_{it} is an idiosyncratic error term. The remainder of the terms are as defined in equation 1.

4. Results

4.1. First Stage Results

We begin our discussion of the effect of child labor on the first outcome variable (employment) by presenting the first-stage results from the instrumental variables probit estimator in Table 2. Column 1 reports the results from a simple specification, where our instrument variable, weather shock, is the only explanatory variable. In this simple specification, weather shock is a strong and statistically significant predictor of child labor, with an F-statistic of 215.61. In Column 2, we report results for the specification, including relevant household characteristics and time-fixed effect as additional controls. The magnitude of the coefficient for the instrument declines,

[4]Another estimator used widely when the explanatory variable of interest is endogenous and time-invariant is the Hausman and Taylor (1981) two-stage estimator. The estimator generates internal instruments to address endogeneity. However, to do so, the model needs a subset of as many exogenous regressors as the endogenous estimators.

but it remains large and statistically significant, with an F-statistics of 61.94. Exposure to a weather shock leads to a large increase in child labor, which suggests that households use child labor as a coping strategy to an income shock triggered by a weather shock.

Table 2: First-Stage Regression Results

	(1) CL	(2) CL
Weather Shock	0.747***	0.422***
	(0.051)	(0.054)
Time Fixed Effects		✓
Controls		✓
Observations	2405	2385
F-stat	215.61	61.94

Notes: This table reports the first stage regression results from the instrumental variables probit estimator. Column (1) controls for the instrument (weather shock) only. Column (2) controls for a set of household controls and time fixed effects. Robust standard errors reported in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

4.2. Main Results

Table 3 presents regression results on the effect of child labor on the likelihood of employment later in life. Columns (1) and (2) report marginal effects from baseline random-effects probit models without and with controls, respectively. The control variables include gender, subjective well-being, household size, household wealth index, and location of residence.

The random-effects probit estimates indicate that participation in child labor during childhood is positively and significantly associated with subsequent employment. Specifically, an additional hour of child labor per day at age twelve increases the probability of youth employment by 3 percent in column (1) and by 2.4 percent in column (2).

A key limitation of the estimates in columns (1) and (2) is their reliance on the assumption that child labor is exogenous. As discussed earlier, child labor is likely endogenous due to unobserved household characteristics and selection into work. To address this concern, we re-estimate the employment regressions using an instrumental variables probit estimator and a control function (CF) approach. The corresponding marginal effects are reported in columns (3) and (4) of Table 3.

The IV probit estimates in column (3) suggest that an additional hour of child labor per day at age twelve increases the probability of employment by 10.2 percent, with the estimate statistically significant at the 1 percent level. Relative to the random-effects probit estimates, the magnitude of the effect increases by nearly threefold once endogeneity is accounted for. The CF estimates presented in column

(4) yield a similar result, indicating that an additional hour of child labor per day increases the likelihood of youth employment by 10.7 percent.

In the CF specification, the heteroskedasticity-robust coefficient on the residual term ($\hat{v}$) provides a formal test of the exogeneity of child labor. As shown in column (4) of Table 3, we reject the null hypothesis that child labor is exogenous, lending support to the instrumental variables approach. The estimates are robust to alternative instrument constructions; using a weather shock dummy instead of a weather shock index yields similar results (see Table A.2 in the online appendix).

Table 3: The Effect of Child Labour on Employment-Marginal Effects

	(1) xtPr	(2) xtPrCon	(3) Prob_IV	(4) CF
Child labour (Hrs/day)	0.030***	0.024***	0.102***	0.107***
	(0.005)	(0.005)	(0.036)	(0.031)
$\hat{v}$				-0.085***
				(0.031)
Time Fixed Effects		✓	✓	✓
Controls		✓	✓	✓
Observations	2405	2385	2385	2385
Mean	0.578	0.578	0.578	0.578

Notes: This table reports regressions on the impact of child labor on employment. Columns (1) and (2) present random effects probit regression results without and with controls, respectively. Column (3) presents results from the instrumental variables probit estimator. Column (4) presents results from the control functions estimator. The controls include gender, location of residence, subjective well-being, household size, and household wealth index. Standard errors reported in parenthesis in columns (1) - (3) are clustered at the individual level, while bootstrap standard errors are reported under column (4). ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Taken together, the results suggest that participation in child labor during childhood is associated with a higher likelihood of employment later in youth. This finding is consistent with previous studies emphasizing the role of early work experience and early labor market entry in shaping employment outcomes (Emerson and Souza, 2011; Bhukuth, 2008; Ilahi et al., 2000; Mincer, 1974; Edmonds, 2006; Kassouf et al., 2001).

At the same time, child labor may adversely affect labor market outcomes through its negative impact on education. A substantial body of evidence documents that child labor is associated with higher school dropout rates (Edmonds and Theoharides, 2021; DeGraff et al., 2016; Beegle et al., 2009), lower school attendance (Dinku et al., 2019), and poorer academic performance (Heady, 2003; Zabaleta, 2011; Emerson et al., 2017; Dinku and Fielding, 2021; Gunnarsson et al., 2006), which may translate into diminished long-run labor market prospects. We will discuss this issue more in the "Mechanisms" section.

4.3. Child Labor and Hazardous Employment

While child labor appears to increase employment probabilities, it may also affect the types of jobs youth enter. Prior research suggests that children engaged in labor are more likely to work under vulnerable conditions and may remain trapped in hazardous employment later in life (Burrone and Giannelli, 2020; Bridges et al., 2017). We investigate this phenomenon using detailed job characteristics from the Young Lives data.

The survey records whether respondents' main jobs involve hazardous or risky conditions, information available in two of the three survey rounds. Table A.6 in the appendix lists the types of hazardous jobs considered. Using this information, we construct binary indicators of hazardous employment and estimate random-effects probit models with these outcomes. The corresponding marginal effects are reported in Table 4.

Column (1) uses an indicator for employment in any hazardous job, while column (2) focuses on hazardous economic activities. The results indicate a strong positive association between child labor participation at age twelve and subsequent hazardous employment. A one-hour increase in child labor per day is associated with a 1.4 percent higher probability of working in any hazardous job and a 1.1 percent higher probability of employment in hazardous economic activities.

These findings suggest that the employment advantage associated with child labor may come at the cost of increased exposure to risky and vulnerable forms of work during adolescence and early adulthood.

Table 4: Employment in Hazardous Jobs

	(1) HazTot_xtPr	(2) HazEco_xtPr
Child labour (h/d)	0.014^{***}	0.011^{**}
	(0.005)	(0.005)
Time Fixed Effects	✓	✓
Controls	✓	✓
Observations	1270	1269
Mean	0.866	0.866

Notes: This table reports regression results on the impact of child labor on the probability of working in hazardous jobs. Columns (1) and (2) reports marginal effects from a random effects probit estimator on the probability of working in any hazardous job and hazardous economic job, respectively. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

4.4. Child Labor and Youth Earnings

We next examine the impact of child labor on youth earnings, our second labor market outcome of interest. The effect on earnings is theoretically ambiguous. Early labor market entry and lower reservation wages may facilitate employment, while reduced educational attainment associated with child labor may depress earnings.

Table 5 reports regression results from alternative estimators. Columns (1) and (2) present random-effects estimates without and with controls, respectively. The baseline estimate in column (1) indicates a statistically significant negative relationship between child labor and earnings. However, this association becomes statistically insignificant once controls and time fixed effects are included in column (2).

Table 5: The Effect of Child Labor on Earnings

	(1) RE	(2) RECon	(3) FEF_IV
Child labour (Hrs/day)	-0.049**	-0.017	-0.067
	(0.020)	(0.019)	(0.078)
Time Fixed Effects		✓	✓
Controls		✓	✓
Observations	1057	1052	1052
Mean Annual Earnings (Birr)	17493	17493	17493

Notes: This table reports regression results on the impact of child labor on earnings. Columns (1) and (2) report results from the random effects estimator without and with controls, respectively. Column (3) reports results from the Fixed Effects Filtered - Instrumental Variable (FEF-IV) estimator. The control variables include gender, place of residence, subjective well-being, age, and age-squared. Robust standard errors reported in parenthesis. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

As with the employment regressions, the random-effects models treat child labor as exogenous. To address endogeneity and time-invariant individual heterogeneity, we estimate the Fixed Effects Filtered Instrumental Variable (FEF-IV) estimator proposed by Pesaran and Zhou (2018). The results in column (3) suggest a negative but statistically insignificant effect of child labor on youth earnings. The findings are robust to alternative instrument definitions (Table A.2 in the online appendix).

The absence of statistically significant effects at early youth ages may reflect low earnings upon labor market entry, consistent with evidence that wage penalties from early labor market experiences often materialize later in adulthood (Burdett et al., 2011; Emerson and Souza, 2011; Ilahi et al., 2000).

4.5. Heterogeneity by Age

Figure 1 illustrates age-specific effects of child labor using coefficients from the CF and IV estimators. Because the Young Lives survey follows cohorts of the same age, survey rounds correspond to youth aged 19, 22, and 26.

The left panel presents CF estimates of the effect of child labor on employment by age group, while the right panel presents IV estimates for earnings. The CF estimates indicate positive and statistically significant effects on employment at ages 19 and 26, but not at age 22.

One potential explanation for the finding that child labor has a statistically significant positive effect on youth employment at all ages except age 22 relates to

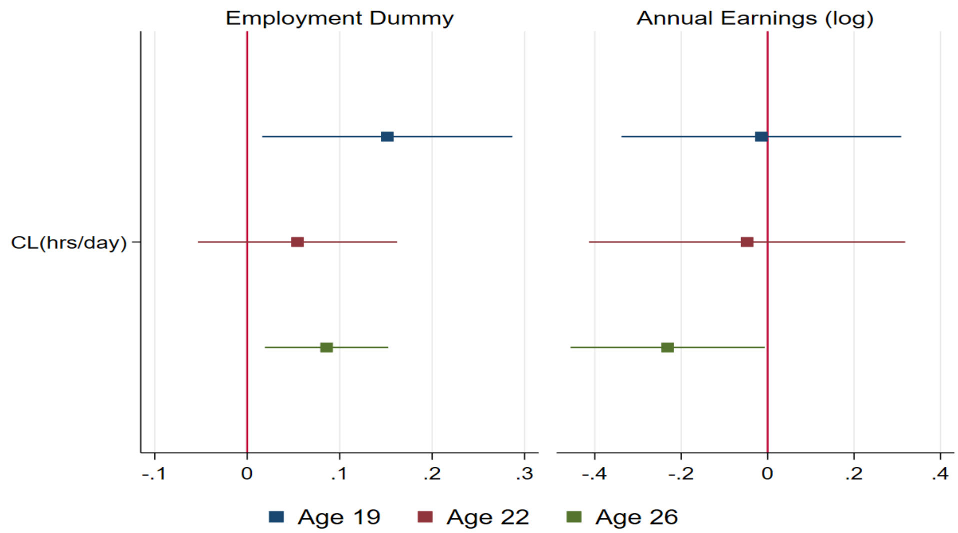

Figure 1: Child Labour and Labour Market Outcomes by Age
The graph depicts the coefficient estimate of the impact of child labour on the likelihood of employment (right panel) and annual earnings (left panel) by the age group of the youth. Robust standard errors are used with a 95% CI.

differences in schooling trajectories and the timing of labor market entry. Individuals who did not engage in child labor are more likely to remain in school for longer periods. Consequently, by age 19, a large share of these individuals may still be enrolled in school or only beginning to enter the labor market, whereas former child laborers tend to enter employment earlier. This dynamic may generate an "early entry advantage," reflected in higher employment rates at younger ages among those who worked as children.

By age 22, however, many individuals who pursued extended schooling—having completed secondary or tertiary education—begin to enter the labor market, narrowing earlier differences in employment outcomes. This convergence may explain the absence of a statistically significant effect at this age. By age 26, employment differentials may re-emerge, reflecting differences between accumulated work experience and educational attainment, particularly in labor markets with limited capacity to absorb new graduates.

Although the data do not provide sufficiently detailed information on schooling trajectories to directly test these mechanisms, we examine school enrollment patterns using data from survey rounds 4 and 5 at ages 19 and 22, conditional on child labor participation at age 12. The results, presented in Figure 2, provide suggestive evidence consistent with these hypotheses. At age 19, a relatively small proportion (26.1%) of children who did not engage in child labor are out of school and potentially competing for jobs, compared to 41.1% of those who participated in child labor—indicating an early labor market entry advantage and a competition ratio of approximately 3:5. However, by age 22, the share of non–child labor participants who are out of school rises to 51.8%, narrowing the job competition ratio to about 4:5.

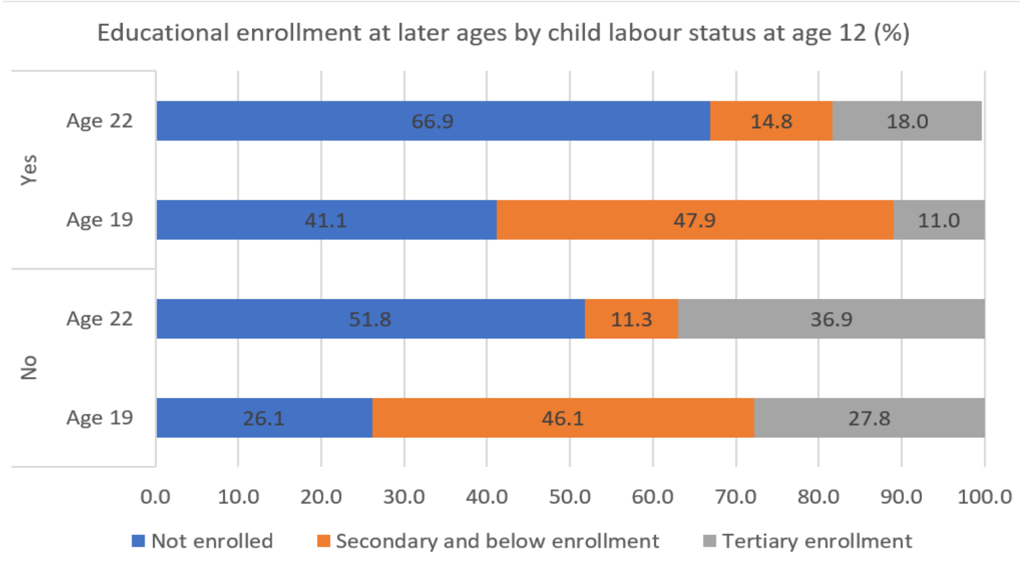

Figure 2: Educational Enrolment at Later Ages by Child Labor Status
The graph depicts educational enrolment at later ages by child labor participation as reported in rounds 4 and 5 of the YoungLives survey.

Consistent with the regression results, IV estimates indicate that child labor has no statistically significant impact on earnings at ages 19 and 22 but has a statistically significant negative effect on annual earnings at age 26, suggesting that earnings penalties emerge later in the life cycle. Full regression results are reported in Table A.3 in the online appendix.

4.6. Heterogeneity by Gender and Location

Figure 3 presents heterogeneous effects of child labor on youth employment by gender and place of residence. Table A.4 in the online appendix reports the full regression estimates. The results indicate substantial heterogeneity across groups.

Participation in child labor increases the probability of employment in rural areas by 11.2 percent, compared to 7.4 percent in urban areas. Gender-based heterogeneity is also pronounced: child labor increases the probability of employment among female youth by 34.3 percent, while the corresponding increase for male youth is 7.3 percent.

The lower likelihood of employment among male and urban youth is consistent with previous evidence from Ethiopia and other low-income countries. For example, Berhe (2021) and Serneels (2007) document longer unemployment durations in urban Ethiopia, particularly among relatively educated male youth. Similarly, Egessa et al. (2021) find that male urban youth are more likely to be unemployed than their female counterparts in Uganda.

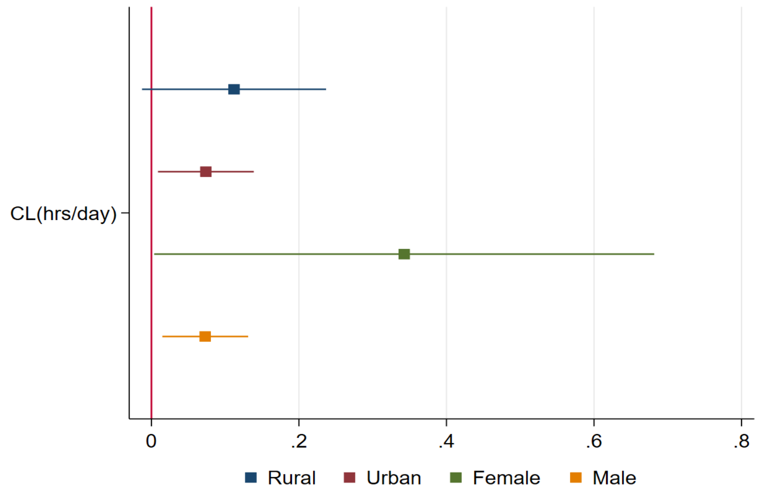

Figure 3: Likelihood of Employment by Place of Residence and Gender
The graph depicts the coefficient estimate of the impact of child labour on the likelihood of employment categorized by place of residence and gender. Robust standard errors are used with a 95% CI.

4.7. Robustness Checks

We conducted several robustness checks related to the measurement of our first outcome variable (youth employment), the key explanatory variable of interest (child labor), the instrumental variable (weather shocks), and attrition. First, using a binary indicator for employment may be problematic because youth less involved in child labor are likely to pursue higher education. As a result, comparing employed youth with the other aggregated categories of youth, including unemployed and economically inactive youth, could be misleading. We, therefore, consider the likelihood of being unemployed as an alternative outcome variable, as this category includes individuals who are unemployed but are actively looking for jobs. Table 6 presents the regression results. The control function regression results in column (1) suggest that participation in child labor significantly negatively affects the likelihood of youth unemployment. On average, a one-hour per day involvement in child labor at the age of 12 reduces the likelihood of youth unemployment by 7.8%.

Second, we consider a different measure of child labor. The definition of child labor differs based on contexts and country laws. According to the International Labor Organization (ILO), child labor is work that deprives children of their childhood, potential, and dignity and is harmful to their physical and mental development (ILO and UNICEF, 2021). However, for measurement reasons, the 18th International Conference of Labour Statisticians in 2008 endorsed a resolution that converts legal child labor requirements into statistical terms. According to this criteria, child labor includes work performed by children in any employment, except permitted light work and work that is not classified as one of the worst forms of child labor. According to the definition, employment primarily refers to work in economic activities such as production for market or personal use, as well as domestic tasks performed on an employment basis outside one's own home (ILO and UNICEF, 2021). Given this, we redefined child labor as total hours spent on productive activities (such as non-pay farm and family business work and paid jobs) and re-estimated the main regression results.

Column (2) presents regression results from the CF estimator for the probability of employment as a function of child labor in economic activities. The results remain robust, showing that child labor has a statistically significant and positive effect on the likelihood of youth employment. Specifically, a one-hour increase in child labor on productive activities per day increases the probability of employment by 10.2%. Column (3) also confirms that child labor in economic activities has a negative impact on youth unemployment. However, we don't find a significant effect of child labor on youth earnings from the fixed effects filtered instrumental variables estimator (column 5) when child labor is measured as time spent only on economic activities. Taken together, these checks suggest that the main results are robust to changes in the measurement of the labor market status of youth and child labor.

Table 6: Robustness Checks - Alternative Labour Market and Child Labour Indicators

	(1) CF_Unemp	(2) CF_EmEA	(3) CF_UnemEA	(4) CF_Attr	(5) FEF_IV_EarEA	(6) FEF_IV_Attr
Child labour (h/d)	-0.078***	0.102***	-0.073***	0.108***	-0.081	-0.075
	(0.023)	(0.031)	(0.021)	(0.033)	(0.095)	(0.081)
N_w				-0.025		0.169
				(0.037)		0.345
Time Fixed Effects	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	2385	2383	2383	2385	1052	1052
Mean	0.138	0.578	0.138	0.578	17493	17493

Notes: This table reports robustness checks on the impact of child labor on labor market outcomes. Column (1) presents control function estimates on the impact of child labor (measured as total child labor hours worked) on unemployment. Column (2) and (3) present control function estimates on the impact of child labor (measured as child labor on economic activities only) on employment and unemployment, respectively. Column (4) presents control function estimates on the impact of child labor on employment controlling for the number of subsequent waves (N_w) after each period to test for attrition. Columns (5) and (6) report fixed effects filtered instrumental variables estimates on the impact of child labor on earnings, without and with the number of subsequent waves (N_w) respectively. The control variables include gender, location of residence, subjective well-being, wealth index, family size, age, and age squared. Standard errors reported in parentheses under columns (1) - (4) are bootstrapped, while those under columns (5) and (6) are robust. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Third, following the Wooldridge method, we conducted an attrition test in the main regressions (the control function and the fixed effects filtered instrumental variables estimators). The method involves controlling for the number of subsequent waves after each wave in the main regressions. The results reported in columns 4 and 6 of Table 6 indicate that the subsequent waves after each period do not have a statistically significant effect on the key outcome variables of interest, which suggests that attrition is unlikely to bias our results.

Finally, the control function estimation reported in Columns (4) of Table 3 involves a non-linear second-stage estimation. Using non-linear second-stage estimators can be criticized based on the efficiency of the standard errors (Newey, 1987; Terza, 2016), and checking for the robustness of the results using linear second-stage estimators is warranted. We conduct these robustness checks and report the results in Table A.5 in the online appendix. Reassuringly, the results remain robust, as child labor affects the likelihood of employment almost to the same magnitude.

4.8. Mechanisms

Can poor educational outcomes be a key mechanism through which participation in child labor leads to adverse labor market outcomes and entrapment in hazardous jobs? Previous studies document a strong association between low educational attainment and employment in precarious or hazardous work (e.g., Papadakis et al., 2022; Kalleberg, 2009; Vono de Vilhena et al., 2016). We therefore argue that one of the primary mechanisms driving the disadvantaged labor market outcomes observed among individuals who participated in child labor is its negative impact on educational attainment.

To examine this mechanism, we investigate the effect of child labor participation on years of schooling using an instrumental variables (IV) regression framework, in which child labor is instrumented by exposure to natural shocks. Table 7 presents the corresponding regression results.

Column (1) reports the IV estimates of the impact of overall child labor participation on educational attainment, while column (2) reports the effect of participation in economic child labor activities. The results from both specifications indicate that child labor has a statistically and economically significant negative effect on educational outcomes later in life, measured at ages 19, 22, and 26. On average, a one-hour increase in child labor per day at age twelve reduces completed schooling by approximately 0.77 years (column (1)). Similarly, a one-hour increase in child labor in economic activities is associated with a 0.81-year reduction in years of schooling (column (2)).

Taken together, these findings suggest that reduced educational attainment is a key pathway through which involvement in child labor adversely affects the labor market outcomes of youth and young adults, increasing their likelihood of entering—and remaining in—low-quality and hazardous forms of employment.

5. Caveats and Scope for Future Research

Using the prevalence of weather shocks as an instrument for child labor in an instrumental variables regression framework, we show that participating in child labor at the age of 12 leads to a higher likelihood of employment later in life. However, this may not be considered a positive phenomenon because those who participated in child labor are more likely to work in hazardous jobs. We also find that participating in child labor at the age of 12 hurts earnings at the age of 26. The key pathway through which participation in child labor affects the outcome variables of interest is through its adverse effect on education. While we believe that our results are robust and novel in demonstrating the long-term effects of involvement in child labor, using the same cohort of respondents over a decade, we acknowledge some limitations

Table 7: Mechanisms - Child Labor and Education

	(1) EdTot_IV	(2) EdEco_IV
Child labour (h/d)	-0.774***	-0.805***
	(0.228)	(0.238)
Time Fixed Effects	✓	✓
Controls	✓	✓
Observations	2368	2366
Mean	9.429	9.429

Notes: This table reports regression results on the impact of child labor on education (measured in years of schooling). Columns (1) and (2) present panel instrumental variables regressions on the impact of total and economic child labor on years of schooling, respectively. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

related to identification, estimation, and measurement issues that we believe future research can address.

First, we used the occurrence of weather shocks as an instrument for child labor to establish a causal relationship between child labor at age 12 and labor market outcomes later in life. We pointed out and checked for two possible identification challenges: i) the likelihood that weather shocks may directly affect labor market outcomes in addition to through child labor (the treatment variable), and ii) the possibility that weather shocks may displace households to other locations, thereby shaping the long-term outcomes of children. We attempted to provide some evidence (see Table A.1 in the appendix) that these issues are unlikely to be of concern. However, weather shocks may still not pass the exclusion restriction criteria, which could compromise the causal relationship between child labor and labor market outcomes that we attempted to estimate. Weather shocks also likely affect educational outcomes; in such cases, the mechanisms we outlined may not be comprehensive. Consequently, the overall estimates of the impact of child labor may be biased.

Second, because we wanted to capture all possible natural shocks that affect the likelihood of participating in child labor (drought, floods, erosion, and frost), we used self-reported measures. While we acknowledge that self-reported information may be subject to measurement bias, previous studies in various contexts have shown that subjective (reported) and objective measures of shocks are highly correlated. For example, in a similar context, Abebe and Alem (2025) shows that subjective drought reported by households was strongly correlated with objective measures of drought computed using 30-year-long rainfall data, and the impact of drought on the outcome variables did not differ much when using both measures.

Finally, while estimating treatment effects using data collected from clusters (such as villages), clustering the standard errors at the village level is warranted. Clustering is essential to account for the correlation of outcome variables between respondents living in the same geographical areas, which may occur due to unobserved, village-specific factors that affect all households within that village. Consequently, if one fails to cluster the standard errors, the computed standard errors may be underestimated, leading to type I error (rejecting the null hypothesis when it should not be rejected or incorrectly estimating statistically significant results) (Abadie et al., 2022). The YoungLives data tracks children (not households). As a result, many children moved from one household to another, located in a different village, which made clustering the standard errors at the village level difficult. Instead, we clustered the standard errors at the child level to account for potential correlation among observations within the same child.

Child labor is a harmful early life event that affects the long-term well-being of the victims. Given one can not identify the impact of harmful life events like child labor on labor market outcomes through experimental methods, we believe that future research that exploits exogenous variation in child labor laws (e.g., legislations on minimum working age) and other events that directly affect involvement in child labor and identifies the impact on labor market outcomes later in life using a similar panel data to the one we used would be highly insightful in showing the actual effect of child labor and the possible means to address it.

6. Conclusion

In this paper, we draw on the Young Lives panel data from Ethiopia, which spans nearly two decades, and investigate the impact of child labor on labor market outcomes later in life. We specifically examined the effect of engaging in child labor at the age of 12 on labor market outcomes of the same children at the ages of 19, 22, and 26. We use exogenous variation in the prevalence of natural shocks as an instrument for child labor and estimate the impact on two key labor market outcome variables - the probability of employment and earnings. Using a reasonable identification strategy and quantifying how child labor affects long-term labor market outcomes by tracking the same individuals from childhood to adulthood is the key contribution of our paper.

We find that child labor has a significant positive effect on the probability of employment but a significant negative effect on earnings at age 26. While the positive effect of participation in child labor on the probability of being employed may seem a positive outcome at face value, we show that the vast majority of child labor participants work in hazardous jobs during their youth and adulthood, which puts their wellbeing and safety at risk. The fact that we find a strong negative impact of child labor on earnings at age 26 suggests that the effects of child labor on earnings will likely persist for a long time. We also find that the key pathway through which child labor affects earnings negatively is education. Instrumental variables regression results suggest that participation in child labor has a strong and significant negative effect on education.

We provide insights into the harmful effects of child labor in Ethiopia, Africa's second most populous country, where youth make up more than 22% of the population, and the youth unemployment rate is 12.5% (ILO, 2022). However, child labor and youth unemployment are widespread in many developing countries, and the existing youth employment is mostly in non-standard, informal, and precarious occupations, perpetuating poverty and poor wellbeing. For example, more than 95% of employed youth in Sub-Saharan Africa (SSA) work in informal jobs with little income stability and no social security coverage. As a result, roughly 42% of the continent's young workers were living in extreme poverty in 2019, while 27.2% were living in moderate poverty (ILO, 2020). Therefore, our findings have significant implications for social support and safety net initiatives that target children vulnerable to child labor in Ethiopia and other similar developing countries. Recent experimental studies demonstrate the importance of safety nets in helping tackle child labor and those who have experienced early life trauma. These interventions range from training parents on how to interact with children (Gertler et al., 2014), to scholarships for school-related expenses (Edmonds and Shrestha, 2014), and conditional cash transfers (Edmonds and Shrestha, 2014; Adhvaryu et al., 2023).

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The Scars of Child Labour: The Impact on Youth Employment and Earnings
(Online Appendix)

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A. Appendix Additional Tables

Table A.1: Weather shocks, health and migration

	(1) Injury/Ill	(2) Health_LT	(3) Health_Peer	(4) Well-being)	(5) Migration	(6) BMI
Weather Shock	0.012	-0.005	-0.010	0.084	-0.001	-0.106
	(0.013)	(0.007)	(0.025)	(0.059)	(0.001)	(0.072)
Observations	977	978	975	977	979	977

Notes. This table reports regression results on the effect of weather shocks on alternative child health outcomes and migration. Columns (1) to (4) report OLS results on the effect of weather shock on health indicators, child's experience of serious injury or illness, long-term health problem, relative health status compared to peers, and overall subjective well-being, respectively. Column (5) present OLS results on the effect of weather shocks on resettlement or forced migration of child's household. Robust standard errors reported in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A.2: The impact of child labor on labour market outcomes (weather shock dummy as an IV)

	(1) CF	(2) FEF-IV
Child labour (Hrs/day)	0.114^{***}	-0.086
	(0.043)	(0.085)
$\hat{v}$	-0.091^{**}	
	(0.043)	
Time Fixed Effects	✓	✓
Other controls	✓	✓
N	2385	1052
Mean	0.578	17493

Notes. This table reports regression results on the impact of child labour on labour market outcomes using weather shock dummy. Column (1) reports the results from the control functions estimator on the effect of weather shocks on the likelihood of employment. Column (2) presents results from the Fixed Effect Filtered - Instrumental Variable (FEF-IV) estimator on the impact of weather shocks on earnings. The control variables include gender, location of residence, subjective well-being, wealth index, family size, age, and age squared. Standard errors reported in parentheses under column (1) are bootstrapped, while those under column (2) are robust. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A.3: Child Labour and Labour Market Outcomes by Age and Survey Rounds

	(A): Employment - CF(dy/dx)			(B): Earnings (in log) - IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	19/2013	22/2016	26/2020	19/2013	22/2016	26/2020
Child labour (h/d)	0.151^{**}	0.054	0.086^{**}	-0.015	-0.048	-0.231^{**}
	(0.067)	(0.058)	(0.036)	(0.165)	(0.187)	(0.115)
Other controls	✓	✓	✓	✓	✓	✓
N	827	796	762	343	422	287
Mean	0.585	0.661	0.484	6009	13967	36467

Notes. This table reports regression results on the impact of child labour on labour market outcomes by age and survey rounds. Columns (1) to (3) present control function results on the impact of child labour on the likelihood of employment for three consecutive age ranges or survey rounds, respectively. Columns (4) - (5) report linear instrumental variables estimator results on the impact of child labour on earnings for the three consecutive age groups or survey rounds, respectively. The control variables include gender, location of residence, subjective well-being, wealth index, family size, age, and age-squared. Standard errors reported in parentheses under columns (1) to (3) are bootstrapped, while those under columns (4) to (6) are robust. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A.4: Heterogeneity Analysis by Place of Residence and Gender

	(A): CF - Employment (dy/dx)				(B): FEFIV - Earnings (in log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rural	Urban	Female	Male	Rural	Urban	Female	Male
CL(h/d)	0.112^{*}	0.074^{**}	0.343^{**}	0.073^{**}	-0.130	-0.098	0.113	-0.163^{*}
	(0.064)	(0.032)	(0.168)	(0.0302)	(0.196)	(0.069)	(0.185)	(0.085)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
N	1228	1157	1112	1273	499	553	377	675
Mean	0.655	0.498	0.457	0.683	11599	22803	13803	19555

Notes. This table reports regression results on the heterogeneous impact of child labour on labour market outcomes disaggregated by place of residence and gender. Columns (1) to (4) presents control function estimators on the impact of child labour on employment by place of residence (rural and urban) and gender (female and male), respectively. Columns (5) to (8) report FEF-IV estimators on the impact of child labour on earnings by place of residence (rural and urban) and gender (female and male). The control variables include gender, location of residence, subjective well-being, wealth index, family size, age, and age squared. Standard errors reported in parentheses under columns (1) to (4) are bootstrapped, while those under columns (5) to (8) are robust. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A.5: The effect of child labour on employment status - Linear Second Stage

	(1)
	CF(a)
Child labour (Hrs/day)	0.100***
	(0.028)
$\hat{v}$	-0.079***
	(0.028)
Time Fixed Effects	✓
Other controls	✓
N	2385
Mean	0.578

Notes. This table reports regression results on the impact of child labour on employment using a linear second stage regression. Columns (1) presents control function results with a linear second stage estimator. The control variables include gender, location of residence, subjective well-being, wealth index, family size. Standard errors reported in parentheses are bootstrapped. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A.6: List of items that measures involvement of the youth in risk jobs

No.	Items
01	Carrying heavy loads
02	Using dangerous tools such as machetes and knifes
03	Handling chemicals such as fertilizers, pesticides, solvents or paints
04	Working under the hot sun or in the rain
05	Working with insufficient lighting
06	Working in very noisy environment
07	Working with fumes, gases, and dust
08	Being close to moving vehicles or driving (cars, tractors, motorbikes etc.)
09	Working in a smelly and/or dirty environment
10	Working in heights
11	Working in a risky or unsafe environments (e.g. bars, street)