Adverse climate variability and child school absenteeism Intra-child gender evidence in Ethiopia

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Abstract

Ethiopian rural children aged 7 to 18 navigate a complex balance between leisure, schooling, and work, shaped by family decisions and constrained by time availability. This interplay significantly influences child welfare outcomes, particularly in education, leisure, and labor engagement. Studies reveal an inverse relationship between child labor and schooling, primarily driven by household income rather than direct correlations with child work. However, challenges persist due to endogeneity concerns, such as the complex interplay between productive asset ownership and child labor demand.

This paper examines the impact of adverse climate shocks on child school absenteeism in rural Ethiopian households, specifically exploring potential gender biases. Employing the random effects probit estimation technique on longitudinal data, the study evaluates these relationships with a focus on child school absenteeism as the outcome. Findings indicate that adverse climate shocks disproportionately affect younger children's school attendance, demonstrating universal impacts irrespective of gender.

Furthermore, maternal education levels, serving as a proxy for empowerment, show a significant inverse association with school absenteeism. Policy implications underscore the need for equitable interventions to mitigate climate-related impacts, emphasizing the role of maternal education and productive household structures in enhancing educational outcomes and alleviating child labor pressures. Future research should prioritize gender-equitable strategies and targeted interventions to foster human capital investment at the household level.

Keywords*:* Child school absenteeism; Random effects Probit; Climate shock; Gender.

1 Introduction

Rural children in Ethiopia aged 7 to 18 navigate a complex balance between leisure, schooling, and work, shaped by family decisions and constrained by time availability (Haile, G. and Haile, B., 2012; Orkin 2012; Tafere & Pankhurst, 2015). This interplay significantly influences child welfare outcomes, particularly in education, leisure, and labor engagement (Belete, A., 2019; Eriksen, S.H. and Mulugeta, E., 2021). Studies reveal an inverse relationship between child labor and schooling primarily driven by household income rather than direct correlations with child work. However, challenges persist due to endogeniety concerns, such as the complex between productive asset ownership and child labor demand (Haile, G. and Haile, B., 2012; Orkin 2012; Tafere & Pankhurst, 2015; Belete, A., 2019; 5Eriksen, S.H. and Mulugeta, E., 2021).

The rapid expansion of access to education in Ethiopia, combined with increasing economic opportunities involving child labor, has led to a situation where many children are engaged in both schooling and work. This raises important questions about the quality of education available to children living in poverty, the risks associated with the expansion of paid work, and the strains on children trying to combine school and work (Eriksen, S.H. and Mulugeta, E., 2021)

Many studies on the economics of child labor, which emphasize the link between poverty and child-time use, taking per capita income as a poverty indicator, confirm the existence of an inverse association of child labour and child schooling (Basu & Van 1998; Baland & Robinson 2000; Ravallion & Wodon 2000; Cockburn & Dostie 2007).

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Income is found to be the main factor that affects schooling, although empirical works failed to show a clear relationship between child work and income (Behrman & Knowles 1997; Behrman 1997).

One of the critical challenges for per capita analysis is the problem of endogeneity because of the correlation between asset productivity and child labor. For instance, owning land, livestock, and family enterprises increases child labor participation. The correlation between productive assets and child labor demand creates ambiguity; there is no clear-cut link between them.

Besides the problems discussed thus far, school absenteeism, schooling quality, school governance in the education sector, and child malnutrition from outside the education sector are among others affecting schooling outcomes (Glewwe 2002; Miguel & Kremer 2004; Chaudhury et al. 2006; Edmonds 2007).

From another perspective, differential power over control of resources at the household level has its own influence on children's well-being, particularly on schooling achievements (Thomas 1990; Behrman 1997; Quisumbing & Maluccio 2003; Chaudhury et al. 2006; Alkire et al. 2013). Thomas (1990) indicated that mothers prefer to devote resources to improving the nutritional status of daughters more than fathers do for their sons.

Other evidence by Quisumbing and Maluccio (2003) shows that women's asset ownership increases expenditure shares on education in Bangladesh and South Africa, while men's control of assets increases the expenditure share on son's education in Ethiopia.

A study by Chaudhury et al. (2006) examined the impact of shock against investment in education and confirmed the existence of a strong bias against investments in female education in rural Ethiopia.

Thus far, the empirical evidence confirms that resource control at the household level influences the allocation decision among members of the household. A work by Malapit et.al (2015) in Bangladesh examined the impact of Women's Empowerment in Agriculture (WEA) on child nutrition and education indicators. They confirmed that WEA and education have a significant positive correlation. The departure from this work is the reason that they did not consider child school absenteeism because once enrolled, numerous household situations can affect school attendance, which obviously affects schooling outcomes inversely. On top of this, it is important to raise the question of whether bargaining power (empowerment) affects school absenteeism of boys and girls equally within a household.

These questions are even more complicated when there is climate shock at the household level (Dillon 2012). So, incorporating the climate shock variable in the analysis can help to identify the decision-making behavior of the household during bad events.

Till now, the discussion has involved the concept of bargaining power in the decision-making process. Women empowerment in this aspect is a legitimate power that enables them to participate in planning and decision-making and to contribute to development programs and activities. Most of the time, per capita income and expenditure, are taken as excellent indicators for empowerment but criticized for their limitations in capturing the heterogeneity of preference in the decision-making process.

Using control over income and productive assets as a proxy variable to empowerment has noticeable endogeneity problems. To the best of the researcher's knowledge, there is no empirical work that simultaneously addresses empowerment, measured with per capita expenditure, and its endogeneity problems during child welfare analysis, and so its welfare differential effects on boys and girls within the household.

As a remedy, the decision maker's level of education is used as a proxy variable for empowerment. Level of education is the means and the outcome of empowerment in household decision-making.

Here, because the dependent variable is binary and values of all regression coefficients vary randomly over individuals, the random effects probit estimation technique is applied to the three-wave dataset so that it addresses the problem of endogeneity owing to unobserved individual effects, and endogeneity because of individual-level heterogeneity that is orthogonal to the independent variables (Wong & Mason 1985).

To have only children who were enrolled in school in the analysis, the school enrolment dummy is truncated from below at zero. Therefore, the analysis is focused on examining child school absenteeism and its determining factors. To see whether the adverse climate shock index effect on child school absenteeism varies with gender, the interaction variable is used (shock index with child gender dummy). Child gender dummy and father-mother education differences were taken to examine whether empowerment had a gender differential effect on school absenteeism. In addition, an interaction variable (age with shock index) is included in the regression to identify whether older or younger children are affected by the adverse climatic shock.

The results show that the adverse climate variability index has a negative effect on the outcome variable while the effect of the interaction term (shock index with gender dummy) does not vary with gender. Similarly, the climatic variability index affects younger school attendance negatively more than the older ones.

2 Review Literature

2.1 Child labor: A Factor of school absenteeism

Human capital development is about the development of a society in the long run, which usually correlates with the quantity and quality of the welfare given to nurture children from their childhood to adolescence. Children in developing countries are thought to be secure for old age, to provide labor, and to be a source of insurance against income instability. But human capital development in the long run and income fluctuations are contesting decisions of the household, which initiates the question of whether child labor displaces schooling (Ravallion & Wodon 2000). Child work in whatever type of employment endangers the health, safety, and morals of children. Sending a child to work is competing with the time in which the primary emphasis of the child should be learning, training, and socialization, which encourages him or her to accumulate knowledge so that the child can participate in decision-making in adolescence.

A study (Akabayashi & Psacharopoulos 1999), investigated the degree of trade-off between child labor and human capital formation using time-lag data of children from a Tanzanian household survey confirmed that hours of work and study hours correlate negatively: hours of work are affected by social conditions more than hours of study. This negative correlation, which is caused by a parent's decision, affects human capital development. That means that the allocation of welfare – child time in this case – is affected by the trade-off decisions made by parents.

The argument about the trade-off between child labor and child schooling is at the center of many empirical examinations. Ravallion and Wodon (2000) investigated whether there are incomes and child labor demand trade-offs and found no relationship between income and child labor hours. A targeted school prices subsidy increased school enrollment but was ambiguous about child labor. That is, the subsidy increased schooling but proved less significant in reducing child labor.

The expectation that child labor would fall with income increases is related mainly to the association between poverty and child labor. Unlike this expectation, an article in rural Ethiopia, which aimed to identify determinants of child labor along with the weak effect of poverty on child labor, confirmed that demand for child labor differs, depending on asset profiles and household composition. Demand-side analysis of this work suggests a weak link between poverty and child labor (Cockburn & Dostie 2007).

A later study by Edmonds (2006) found the same result, which confirmed the weak relationship between poverty and income. Anticipated changes in income should have no effect on child labor and schooling if households can borrow against permanent income. However, an increase in permanent income because of social pension eligibility showed a reduction in child labor and an increase in school attendance, which suggests that temporary income increases, have no effect. This can lead to the conclusion that the relationship between income and child labor is contextual.

The usual argument about poverty and child labor is that public works reduce the demand for child labor and increase child schooling. Gilligan et.al (2009) tested whether participation in public work in Ethiopia's Productive Safety Net Programme intervention induced the replacement of a child for adult labor at home and in informal employment to generate income. Using matching estimators to identify program impacts, their findings showed that participation in public work reduced labor hours for boys in both agricultural and domestic labor. The results for girls showed weaker evidence, though younger girls experience the worst outcome of public works. This finding supports the argument that public works reduce demand for child labor for boys, but if public works are coupled with agricultural packages, it does not confirm the positive correlation between public work and child schooling.

Contrary to Gilligan et.al (2009), a study by Psacharopoulos (1997) in Bolivia and Venezuela found that working children lag in their school years. Grade repetition, which is closely associated with child labor, is a common phenomenon in these study areas.

The contextual association of poverty and income is examined by Ray (2000) in Peru and Pakistan. The result shows hours of child labor and poverty, and child schooling and poverty are confirmed in Pakistan, but not in Peru.

Child income contributes to poverty reduction in Pakistan more than the Peruvian result shows. Yamano et al. (2005) also found that food aid compensated for the negative effects of shocks.

The hypothesis that argues the association between poverty and child labor demand is supported by some researchers, while others reject it. Similarly, the effect of income increase shows different effects between boys and girls in different economic contexts.

2.2 2.2 Gender disparity in child education investment

According to Alderman and King (1998), the gender gap in schooling is puzzling in relation to the expected returns, because an increase in schooling because of proportional wage increments does not differ between genders. Their findings indicated gender gaps in investment in child education due to differences in expected returns by parents. A similar finding in Côte d'Ivoire showed that costs and returns and the parents' preference and heterogeneity in decision-making are some of the determinants of disparity in the number of years of education for male and female children (Pasqua 2005).

Intra-household resource allocation analysis in Brazil regarding the influence of fathers and mothers on education investment and decisions on child labor demand found differences between spouses. This was due to differences in preferences or differences in the ways in which additional schooling affected the acquisition of human capital by sons and daughters. The level of a parent's education on the participation in the labor market and school attendance of their sons and daughters confirmed that the father's education had a greater negative impact than the mother's education on the labor status of sons (Emerson & Souza 2002).

Food aid in the form of free distribution and food for work has a positive effect on child nutritional status, estimated on whz06. Food aid in the form of free distribution in particular improved the nutrition of girls, while food for work improved nutrition for boys (Quisumbing 2003). Similarly, Dercon and Singh (2012) studied the presence of a gender gap across indicators of nutrition, education, aspirations, subjective well-being, and psychosocial competencies in Ethiopia, India, Peru, and Vietnam and found different results across countries, ages, and sexes. In Ethiopia, the nutritional status of girls is better than that of boys, while there is an institutionalized gender bias against girls. The non-competitive cognitive skill of a child is also a means of gender bias, due mainly to poorer market outcomes. Gender bias, which was also found to be affected by social institutions, and gender inequality are linked to female education, child mortality, fertility, and governance (Branisa et.al. 2015).

The heterogeneity of parental preferences, the cost of education, and the cognitive skills of a child are the main factors that affect child welfare distribution. However, some of the empirical findings show demand for child labor increases due to the substitution effect for an adult in domestic and unpaid agricultural activities. In many situations, parents fail to understand the negative effect of child labor on child welfare, and as a result decisions on child time allocation may result in disequilibrium despite parents' altruism and although child labor is socially inefficient. Cultural capital creates social differences in terms of parental investment in children's schooling.

3 Decision on child schooling

In most cases, children's responsibilities outside schooling are quite different from those of adults. In rural Ethiopia, the basic activities of children out of school time are collecting firewood, fetching water, herding, helping parents in agriculture, and carrying out domestic work (most of the time, girls are assigned to these activities) (Haile & Haile 2012). Child schooling achievements depend on household investment decisions on human capital, which is at the opportunity cost of child labor. Most often poor achievements in child schooling are associated with children from poor families (Ravallion & Wodon 2000; Morduch 2000; Ray 2002).

Assuming altruistic arrangements, parents decide on how to allocate their child's unit time endowment mainly between schooling and child labor. In other terms, the household maximization problem is dependent on the joint decision of the household on child schooling and child labor. Contextualizing Rosati and Rossi's (2003) human capital maximization problem, it is formulated as:

(3.13) $$S_{it} = h(C, x_{it},\ X, L_{it},), where\ S_{it} = h(0, L_{it}) = 0 \text{ , and } \frac{\partial S_{it}}{\partial L_{it}} < 0$$

Where S_it, C, x_it,X,and L_it denote child schooling attendance, household consumption, individual covariates, household and community level covariates, and labor supply of individual i at time t. Here, child labor is an endogenous variable (i.e. schooling attendance predictor), which can be expressed as the following scenarios:

If a family sends the child to school, then child labor supply and child schooling attendance, respectively, are

(3.14) $L_{it} = 1 - s_{it}$ and $s_{it} = 1 - L_{it}$

If the family does not send a child to school, the child labor supply is

(3.16) $L_{it} = 1$

The household maximization problem is over the current consumption and future consumption of children subject to the following constraints:

(3.15) $C_{1s} = \mu L_{it} + Y_t - Q_{it}$ and $C_{2s} = K + H$, here K and H are exogenous child endowment resources and child human capital where Y_t, μ, Q_it denotes parents' income, average child wage rate, and child cost of schooling, respectively, and subscripts 1 and 2 represent current and future consumption, respectively.

On the other hand, if parents do not send a child to school, the household's current consumption constraint becomes

(1) $C_{1L} = L_{it} + Y_t$ and $C_{2L} = K$

Then, based on the choice variables ofS_it, and L_it, parents' utility maximization problem is stated as:

(2) $MaxU(S_{it}, x_{it},\ X, L_{it})$

Then, the parents' optimal decisions to send their child to school,S_it given these current utilities in equation (2) are:

(3) $S_{it} > 0$ if $U'(S_{it}) >\ U'(L_{it})$ and

(4) $S_{it} < 0$ if $U'(S_{it}) <\ U'(L_{it})$.

In other terms, parents send their child if $\frac{\partial(U(S_{it}))}{\partial(L_{it})} > \frac{\partial(U(L_{it}))}{\partial(L_{it})}$.

To this end, it is apparent that the decision is based on the utility gained from these two endogenous variables and neglects the influences of decision heterogeneity and empowerment of decision-makers in the decision-making process. The influences of decision heterogeneity and household-level climate shock are introduced in the maximization problem in equation (2) as the determining factors for the outcome variables. X in equation (2) comprises the effects of parents' decision heterogeneity and a household-level climate shock and other covariates on child schooling absenteeism.

4 Data and descriptive results

The dataset used in this article came from three-round panel data from the Living Standard Measurement Study (LSMS Integrated Surveys on Agriculture (ISA) in 2011/12 (3969 households), 2013/14 (5262 households), and 2015/16 (4954 households). (See Table 1 for the demographic composition.)

In these surveys, these aspects were elicited: household demographics; dwelling characteristics; household expenditure; education; agricultural productivity and input use; crop utilization; agricultural extension; technology and information networks; livestock ownership

and income from livestock and livestock products; shocks; non-farm income and business activities – own business activities; off-farm employment; credit; trust; control and agency; household assets (non-land); transfers, gifts, and remittances; aspects of market supply and access.

For the study's purpose, the dataset was reduced to include only households with at least a boy and a girl. Further eliminating all individual respondents who were not in round 1 reduced the household size to 3969, and 13 678 individuals are included in the estimation.

Despite the scope of the study being limited to addressing the household decision heterogeneity on sending children to school, looking at the association of off-farm activities, and regional differences based on crops they grow such as cash-crop and child school absenteeism would have been worth enough to benefit this work.

Summary statistics in Table 3 describe the variables that are included in the regression estimation. From 13 678 (after truncating using a school enrolment dummy) children in the 7–18 age group are included in the sample, of whom about 51.4% are male (Table 3). The number of members in a household in this sample population is 5.8, which is close to the national household size reported by the CSA (2012) in which the average age of child respondents from 7 to 18 years old is 12.09 years. On average, the hours worked in the past seven days by a child were 9.520.

Table 1 Demographic characteristics: Average household size, dependency ratio, and age group by place of residence

	Average household size	Dependency ratio	Percentage of population by age group				
			0-5	0-9	0-14	15-64	65+
Tigrai	4.6	0.83	14.1	25.2	40.5	53.5	5.9
Amhara	4.2	0.75	13.2	24.2	31.1	55.9	5.1
Ormiya	5.2	0.97	16.0	28.6	46.0	50.3	3.7
SNNP	5.2	0.97	16.9	29.5	46.3	50.4	3.3
Addis Ababa	4.2	0.42	9.9	15.9	24.9	70.3	4.8
Other regions	5.0	0.96	18.7	31.7	46.8	50.4	2.8
Rural	5.2	1.00	16.1	29.1	46.4	49.3	4.3
Small town(urban)	4.3	0.69	12.2	23.0	38.1	58.6	3.4
Large town(urban)	3.7	0.48	12.7	19.2	29.4	67.2	3.4
Country	4.8	0.88	15.3	27.2	43.3	52.7	4.1

Source: Adapted from the LSMS-Integrated Surveys on Agriculture Ethiopia Socioeconomic Survey (ESS) report, 2017, p. 8.

The household dependency ratio in the current study is 51%, which is below many of the average regional dependency ratios, except in Addis Ababa (Table 1). School enrolment is about 64.7%, which is closely equal to the report in Table 5, of whom 6.09% were absent for a week or more in the last month of the survey (see also absenteeism rate in Table 2 for regional report).

Table 2: Reasons for absenteeism by gender and place of residence, Ethiopia 2015/16

Regions	Percentage of enrolled students absent	Reasons for being absent		
		work	Illness or death in the family	Other
Tigrai	6.8	(25.0)	(70.6)	(4.4)
Amhara	14.3	(17.2)	(72.8)	(10.0)
Oromiya	18.9	(28.5)	(56.3)	(16.2)
SNNP	4.3	(63.4)	(35.9)	(0.7)
Addis Ababa	2.2	(67.4)	(0.0)	(32.6)
Other Regions	4.8	(61.5)	(37.9)	(0.6)
Rural	14.4	27.5	60.9	11.6
Small town(urban)	9.8	(41.9)	(55.3)	(2.8)
Large town(urban)	3.3	(66.0)	(27.1)	(7.0)
Country	12.6	30.3	58.8	11.0

Source: A Adopted from the LSMS-Integrated Surveys on Agriculture Ethiopia Socioeconomic Survey (ESS) report, 2017, p. 13; values in parentheses are based on fewer than 100 observations

The effect of climate shock on child schooling absenteeism is estimated via random-effect probit regression where other indicator variables are included on the right-hand side.

The main explanatory variables that are included in the regression are household size, climate shock index, child gender dummy, age of a child in years, children's hours worked in agricultural activities in the last seven days, household dependency ratio, and mother's education level. The adverse climate shock index variable is expected to have a direct correlation with the outcome variable.

Table 3: Summary statistics of the covariates used in the random effect probit estimation

VARIABLES	(1) mean	(2) sd	(3) N	(4) min	(5) max
Household size	5.80	2.169	2.169	1	17
Hours in agricultural activities in the last seven days?	9.520	16.25	16.25	0	26
Own age	12.09	3.356	3.356	7	18
Number of children in the household	4.307	1.830	1.830	2	12
One if currently attending school, zero otherwise	0.647	0.478	0.478	0	1
One if one week absent from school last month	0.0609	0.239	0.239	0	1
Household dependency ratio	0.510	0.184	0.184	0	1
Mother's education linked to a child	0.466	0.849	0.849	N/A	N/A
Father's education linked to a child	1.434	1.571	1.571	N/A	N/A
Household school assistance linked to a child	0.0525	0.223	0.223	0	1
Mother's occupation linked to a child	5.236	5.940	5.940	N/A	N/A
Time to school for a child	1.073	1.336	1.336	0	6
Climate shock index	0.494	0.116	0.116	0	1
One if male, zero otherwise	0.514	0.500	0.500	0	1
One if father’s education > mother’s	0.531	0.499	0.499	0	1
Number of uniqui_id	8,096	8,096	8,096	8,096	8,096

Source: Author’s summary estimation result, 2021

As depicted in Table 4, the household level shock index is derived from the response of subjects who asked “During the last 12 months, was your household affected by any of the following shocks? Here climate shocks such as drought, flood, land-slid, heavy rain, and other crop damages are purposefully selected as significant climatic household shocks. The shock-index is the average of shocks that occurred. The frequency of any of the climatic shocks explained in the three rounds is taken there by the mean of all the five variables is the ‘Shock-index’ variable. The shock index ranges from zero to three (zero represents the lowest index while 3 shows five of the shocks that occurred in three of the rounds). Therefore, the values under the year’s column are the number of households that experience household-level climatic shocks in each of the years.

Table 4: Frequency of household level average shock occurrences

Average Shock-index	Date of First Interview (Year of interview) 2011/2012	2013/2014	2015/2016	Total
1	0	0	4	4
1.2	13	6	13	32
1.4	102	30	50	182
1.6	785	330	1302	2417
1.8	3780	2841	6262	12883
2	16269	17477	16854	50600
Total	20949	20684	24485	66118

Source: Author’s calculation from the LSMS three round dataset in Ethiopia.

Table 5: School enrolment by gender, level, region, and place of residence (age 7-18)

	Male (%)			Female (%)		
Region	**Not enrolled**	**Primary**	**Secondary**	**Not enrolled**	**Primary**	**Secondary**
Tigrai	26.9	65.5	7.6	22.7	67.9	9.5
Amhara	27.5	67.5	5.0	23.4	69.0	7.6
Oromiya	32.9	63.1	4.1	34.6	61.1	4.2
SNNP	29.9	64.9	5.2	29.1	66.4	4.5
Addis Ababa	(11.6)	(61.5)	(26.9)	15.0	66.6	18.4
Other regions	33.8	58.2	8.0	38.1	55.5	6.4
Rural	32.5	64.8	2.7	33.0	64.4	2.6
Small town(urban)	19.0	63.1	18.0	16.4	68.9	14.7
Large own(urban)	16.4	61.1	22.5	17.7	60.7	21.7
Country	30.2	64.3	5.5	30.0	64.2	5.8

Source: Adapted from the LSMS-Integrated Surveys on Agriculture Ethiopia Socioeconomic Survey (ESS) report, 2017; values in parentheses are based on fewer than 100 observations

Note: SNNP stands for Southern Nations Nationalities People while LSMS stands for Living Standard Measurement Survey

5 Empirical strategy

The household decision whether to send a child to school (the child is absent from school) is a binary outcome. The outcome variable is child school absenteeism. In a sense, once a child has been enrolled, many household circumstances influence school attendance, such as resource shortages due to climate shock to the household. By truncating the use of a school enrolment dummy, absenteeism is regressed on covariates so that it helps to identify the determinants of absenteeism.

A random effects probit model is applied to the panel dataset described in section 4. Random effects probit models are useful in analysing panel data with a binary dependent variable, and individual-level heterogeneity orthogonal to the independent variables.

Child school absenteeism is the outcome variable and the latent variable representation of the random effect probit is stated as:

$$S_{it}^{*} = \alpha_0 + \beta_{it}X_{it} + \tau_{it}\theta_{it} + u_i + \varepsilon_{it} \quad (5)$$

$$S_{it} = \begin{cases} 1 & if \;\; S_{it}^{*} \geq 0 \\ 0 & if \; S_{it}^{*} < 0 \end{cases} \quad (6)$$

Where S_it^* is the unobserved latent variable, S_it is the observed binary outcome variable. X_it is 1x K household, community, and individual characteristics. θ_it is the household-level climate shock index while β_it and τ_it are both K x 1 vector of coefficients for X_it and θ_it , respectively. ε_it, and u_i represent an idiosyncratic error term, and a mean-zero error term specific to the individual level of the panel, respectively.

The primary purpose was to investigate whether household decision-making agents are gender biased when they allocate child time within a household's activity during a bad event to the household. For this reason, an interaction between the climate shock index and the gender of a child is included in the regression.

Because this model is a nonlinear model, random effect probit model estimation outputs are not simply regression coefficients, so they are reported alongside the standard regression outputs. The marginal effects communicate the economic significance of the random effects probit result.

6 Results and discussion

The results of the estimates of school absenteeism dummy on covariate with and without interaction are presented in Model 3 and Model 1 in Table 6, respectively. The interaction of climate shock index and gender, age of the child, and gender with father-mother education difference allowed analysis of the combined effect on the outcome variable. Average marginal effect models after the random effect probit technique are presented in Table 7.

The primary point of interest here is the effect of adverse climate shock on child school absenteeism. The household's livelihood fluctuation due to climate shock, such as shortage of rainfall, forces a household to use child labor as a buffer to smooth consumption. Consistent with the empirical literature, the current result confirmed that adverse climate shock is one of the determining factors for an increase in school absenteeism (see for example Chuta 2014; Fabre & Pallage 2015; Guarcello et.al. 2010).

Truncating using the child schooling enrolment dummy, school absenteeism (the outcome variable), and climate shock index variable indicates a significant positive correlation with a very small rate of change (Table 6).

To examine the intra-children time allocation decision-making in bad times, the child gender variable is interacted with the climate shock index. Contrary to the evidence that confirmed that boys are favoured over girls in welfare allocation, the researchers found that there is no varied significant effect of the negative climate shock index on child school absenteeism (Table 6).

This indicates that an increase in climate shock index does not have any gender discrepancy on school absenteeism, but its occurrence increases school absenteeism in both sexes.

Another angle to examine whether a household's resource allocation decision-making is gender biased or not concerns the bargaining power of the decision-making agents, which requires identifying a proxy variable for empowerment because individuals do not necessarily pool resources or share the same preferences (Haddad et al. 1997).

In effect, men and women may have differences in preferences over a decision on children's human capital investment and may use different coping strategies when climate shock occurs to the household.

Table 6: Random effect probit with and without interaction estimation result

VARIABLES	(Model 1) Random effect probit without interaction	(Model 2) lnsig2u (VRE[3])	(Model 3) Random effect probit with interaction	(Model 4) lnsig2u (VRE)
One if male, zero otherwise	-0.007		-0.156	
	(0.033)		(0.552)	
Climate shock index	0.004		1.137*	
	(0.143)		(0.600)	
Household Size	-0.033**		-0.034**	
	(0.015)		(0.015)	
Own-age	0.004		0.194**	
	(0.005)		(0.090)	
Education difference b/n mother and father	-0.118***		-0.092*	
	(0.034)		(0.048)	
1.gender#c.shock_index			0.091	
			(0.284)	
c.age#c.shock_index			-0.097**	
			(0.046)	
1.gender#c.Father-mother education diff			-0.053	
			(0.066)	
Hours spent on household agricultural activities in 7 days?	0.005***		0.005***	
	(0.001)		(0.001)	
Household dependency ratio	0.365***		0.360***	
	(0.118)		(0.118)	
Number of children in the household	-0.003		-0.002	
	(0.020)		(0.020)	
Mother's education = max primary	-0.032		-0.032	
	(0.040)		(0.040)	
Mother's education = junior	-0.078		-0.078	
	(0.087)		(0.088)	
Mother's education = senior[4]	-0.375***		-0.374***	
	(0.085)		(0.085)	
Mother's education = other[5]	-0.766***		-0.769***	
	(0.264)		(0.264)	
Constant	-1.388***	-1.760***	-3.597***	-1.753***
	(0.307)	(0.28804)	(1.172)	(0.286)
Observations	13,678	13,678	13,678	13,678
Number of uniqui_id	8,096	8,096	8,096	8,096

Source: Author's estimation, 2021, standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

[3] lnsig2u (VRE) in models 2 and 4 refers to the (logged) variance of the random effect probit. Sigma_u is the SD and if it takes the log of sigma_u squared, it gives the same result. It is equivalent to 2 times the log of the SD.
[4] Senior school is high school above grade nine and above.
[5] 'Other' in this case refers to education level above senior school

Mother’s education level, one of the main predictors of child schooling outcomes, is an excellent proxy variable for women's bargaining power. Therefore, the mother’s education level and mother-father education-level gap variables are included in the estimation as bargaining power factors.

The results in Table 7 indicate that a mother’s education level above senior school affects school absenteeism compared with the non-educated ones with a 1% level of significance. An increase in the one-unit category of mothers’ education level gives a 4.76 percentage point decrease in school absenteeism.

Similarly, a mother’s education level above senior school level has a 1% level of negative significance on school absenteeism, highlighting that an increase by one category level in a mother’s education results in a significant decline of school absenteeism by approximately 7.59%.

The other variable that is a good proxy for bargaining power, that is, the difference in education level between mothers and fathers, indicates a negative significant correlation with the outcome variable at a 1% level of significance. A dummy is 1 if the father’s education category level is greater than the mother’s. Therefore, if the dummy for education category level difference is 1, school absenteeism declines by 1.82 percentage points.

Agricultural activity, one of the child time competing activities, that is, hours spent on agriculture, is negatively correlated with child schooling (Patrinos & Psacharopoulos 1997; Baland & Robinson 2000; Glewwe & Muralidharan 2016). Consistent with the literature, a positive significant correlation is found between child agricultural activity and the outcome variable at a 1% level of significance, which shows that if child agricultural activities increase by one hour, it results in a 0.08 percentage point increase in absenteeism, a negative effect on the child welfare.

The dependency ratio is also a determining factor that increases the child burden at the household. The more dependants in the household, the more child time is turned to non-school activities such as domestic and agricultural activities (Alvi & Dendir 2011).

Table 7: Average marginal effects after random effects Probit estimation result

Variables	**Delta method**			
	Average marginal effects	**Std. Err.**	**z**	**P>|z|**
Gender	-0.001	0.005	-0.21	0.833
Climate shock index	0.001	0.021	0.03	0.073
Household size	-0.005	0.002	-2.12	0.034
Own age	0.001	0.001	0.71	0.479
Education difference b/n mother and father	-0.018	0.005	-3.49	0.000
Hours spent on household agricultural activities in 7 days	0.001	0.0001	5.22	0.000
HH dependency ratio	0.055	0.018	3.09	0.002
Number of children in the household	-0.001	0.003	-0.16	0.870
Mother's education level				
Mother's education max primary	-0.005	0.006	-0.82	0.412
Mother's education junior	-0.011	0.012	-0.93	0.354
Mother's education senior	-0.047	0.008	-5.48	0.000
Mother's education other	-0.075	0.013	-5.53	0.000

Source: Author's estimation, 2021

The current result is in line with this empirical evidence. Its positive correlation between the dependency ratio and the outcome variable at a 1% level of significance indicates that a unit increase in the dependency ratio in the household gives about a 5.60 percentage point increase, which is an inverse implication for child welfare.

Here, the result for household size shows a negative 5% level of significance. A unit increase in the household size results in a 0.52 percentage point decrease in the outcome variable. This hints that if the increase in household size is in the non-dependent members' age group, it will have an inverse impact on school absenteeism.

The interaction between age and the climate shock index variable in Table 6 shows an interesting coefficient, namely that age has a negative effect on school absenteeism in the sense that older children attend class more than their younger siblings in the household.

7 Summary and conclusion

There is a critical need to reduce the amount of time that children spend on household chores, family farming, and other child time competing activities. The empirical results in this work employed the random effects probit estimation technique. The positive correlation between the adverse climate shock index and the child school absenteeism dummy is a clue that a negative shock forces children to divert their time from school to support the household. That is, during household-level adverse climate shock, households send their children to work so that the household can smooth consumption. In this situation, both boys and girls are forced to work.

To see whether the shock had a gender differential effect, the study looked at the interaction terms between gender dummy and adverse climate shock index. The interaction terms result indicates that there are no negative associations between the interaction variable (gender-adverse climate shock index interaction) and absenteeism within a household.

This suggests that policies that are devised to mitigate the impact of adverse climate shock on absenteeism should not be gender biased as there is no gender-discriminatory effect of the shock. Measures should be gender equitable so that gender welfare equity is maintained. The result also suggests possible interventions that

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compensate for incomes generated by children in bad times so that the policy intervention can minimize the burden on children and tackle the negative effects of lack of school attendance.

The results of family education level on absenteeism could lead to the conclusion that educated parents send their children to school more than uneducated ones. Mothers with senior education levels and above are more aware of the expected benefits of child school investment than those with zero education. Therefore, educating mothers should be the policy priority because it enhances the child's education and reduces child school absenteeism.

Another point is the issue that child time is employed in agricultural activities. The current result is in line with the empirical evidence that confirms the existence of the negative impact of child labor on absenteeism. This invites a measure to correct and look at another alternative solution that replaces child labor in agriculture.

The effect of dependency ratio at the household level on absenteeism is also grounds to conclude that dependents are the reason for child burdens in the household. The findings on household size support this conclusion in the sense that a large household that is productive reduces child absenteeism. Therefore, a possible suggestion is to make every capable household member productive or to help those dependants with government programs so that the child burden is minimized.

Finally, these findings should be set as priority agendas by stakeholders, so that investment in human capital at the household level should be promoted with due attention to gender even-handedness.

8 Limitations

The study is restricted by its reliance solely on datasets gathered from three rounds of research conducted within Ethiopia, potentially limiting the comprehensiveness and depth of insights that could have been attained with the inclusion of data from a fourth round.

CRediT authorship contribution statement

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