Environmental Shocks and Child Labor: A Panel Data Evidence from Ethiopia & India

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ABSTRACT

Environmental shocks, particularly high impact natural disasters, force children into the labor market to meet the basic survival needs in straitened times. Currently India has the largest number of child labor in the world while disaster prone African economy of Ethiopia is experiencing a surge in child labor. Using Young Lives Longitudinal Survey Data on Ethiopia and India covering period 2002-2016, this paper examines the dynamics between child labor and environmental shocks, employing different panel data models of child labor supply. The paper has two notable features. First, it investigates the relationship between environmental shocks and child labor using the Young Lives Survey Datasets (2020), a data set rich on child welfare information not previously explored, to examine the links between climate shocks and child labor. Second, it employs the panel-data fix and random effects estimators to analyze the impact of environmental shocks on child labor, to our knowledge, a first tempt of its kind to deal with observable and unobservable endogenous time-invariant influences on child labor supply. We control for a relatively large set of child, household and community levels covariates, and obtain robust, statistically significant evidence of the positive impact of climate disaster on the incidence and amount of child labor in both Ethiopia and India and in all different models employed. We also report strong negative effects of link between child education and child labor, and some less clear evidence of the negative link between child health (stunning and obesity) and child labor. The evidence presented indicate that the traditional public policy devises like parents' education and social safety nets programs do not make statistically robust contribution to reducing child labor supply, suggesting income gains from such programs are not sufficient to meet the survival needs of poor households and hence to prevent child labor.

Keywords: Environmental Shocks, Child Labor, Panel Data

JEL Classification: C33, J13, Q54

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1 INTRODUCTION

Environmental shocks, particularly the high impact natural disasters, such as floods, hurricanes, droughts, earthquakes etc. affect an average of 224 million people worldwide per year (Samhsa, 2018). According to EM-DAT (2020), 6,681 environmental disasters over the last twenty years between 2000 and 2019 have claimed approximately 1.23 million lives, an average of 60,000 per annum, and affected a total of over 4 billion people (many on more than one occasion). Additionally, these environmental shocks led to approximately US$ 2.97 trillion in economic losses worldwide. In contrast, 3.2 billion people were affected and 995,330 people died by 3,656 environmental disasters (47% due to drought or flood) between period 1980-1999 with economic losses totaled US$ 1.63 trillion. The number of people affected by disasters, including injuries and disruption of livelihoods, especially in agriculture, and the associated economic damage are growing. In the meantime, effects of climate change are being evident in the increased frequency of extreme weather events including heatwaves, droughts, flooding, winter storms, hurricanes and wildfires (Currie & Deschênes, 2016).

Children differ from adults based on varied physiological, cognitive, and emotional developmental factors, making them more vulnerable to the damaging effects of natural disasters. In reality, children in less developing countries bear a disproportionate share of the burden of environmental shocks; affecting their wellbeing through many direct, indirect, and societal pathways (UNICEF, 2019). On the one hand, children are the most susceptible to diseases resulted from such shocks which increase their risk of malnutrition and death. One the other hand, environmental shocks disrupt food production and food access for rural families – with flood and drought causing 80 per cent of damage and losses in agriculture. In areas where people rely on a single staple crop like rice, wheat or maize, a shock to food production can wipe out the entire food supply. Increasingly, the disruption from such shock is forcing families to use the hands of children to earn money to cope up with the food insecurity, which is only exacerbating child labor. According to International Labor Organization (ILO, 2017), a total of 152 million children, 64 million girls and 88 million boys, are in child labor worldwide, accounting for almost one in ten of all children globally. Almost half of all 152 million victims of child labor are aged 5-11 years. 42 million (28%) are 12-14 years old; and 37 million (24%) are 15-17 years old. Nearly half of all them, 73 million children in absolute terms, are engaged in hazardous work that directly endangers their life. 58% of all children in child labor and 62% of all children in hazardous work are boys. Boys appear to face a greater risk of child labor than girls, but this may also be a reflection of an under-reporting of girls' work, particularly in domestic child labor. Child labor is concentrated primarily in agriculture (71%), which includes fishing, forestry, livestock herding and aquaculture, and comprises both subsistence and commercial farming; 17% in Services; and 12% in the Industrial sector, including mining.

The incidence of child labor is very high in lower middle-income countries (LMIC) and low-income countries (LIC). According to ILO (2017), almost half of child labor (72.1 million) is to be found in Africa; 62.1 million in the Asia and the Pacific; 10.7 million in the Americas; 1.2 million in the Arab States and 5.5 million in Europe and Central Asia (Figure-1). In terms of prevalence, the Africa region and the Asia and the Pacific region together host nine out of every ten children in child labor. Africa ranks highest both in the percentage of children in child labor – one-fifth – and the absolute number of children in child labor – 72 million. Asia and the Pacific ranks second highest in both these measures – 7 per cent of all children, 62 million in absolute terms, are in child labor in this region. India has the largest number of working children of any country in the world while Ethiopia is the key country with enormous child labor (Kim et al., 2020)

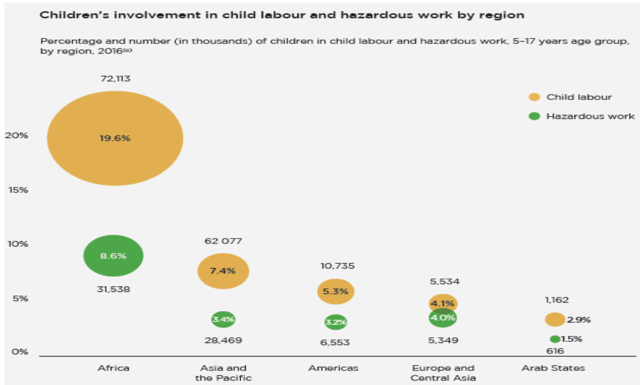

Figure 1: Distribution of Global Child Labor

(Source: International Labor Organization (ILO, 2017; page 29))

Child labor affects the current and future welfare of children in several ways (Vásquez & Bohara, 2010). Imprimis, child labor affects physical, physiological, and emotional developmental of children. Secondly, child labor also reduces the time available for school and the quality of schooling and hence hinders their cognitive and intellectual development (Binder and Scrogin 1999; Psacharopoulus 1997). Thirdly, hazardous child work exposes children to unsafe working environments which threaten their life and liberty and potentially leading to lifelong physical or moral damage. It is thus a violation human rights, brake on human capital promotion and sustainable development, and anathema to just societies. The Sustainable Development Goals (SDG) target 8.7 calls for immediate and effective measures to end child labor in all its forms by 2030 (United Nations, 2015). Thus, the elimination of child labor is a universal and fundamental value which requires special and exclusive efforts to explore the root causes of child labor and address them with public policy intervention in order to control child labor.

This paper aims to explore the dynamics between environmental shocks and child labor, focusing on India and Ethiopia to address this relatively neglected relationship. The original contribution of this paper is twofold. First, it investigates the relationship between environmental shocks and child labor using The Young Lives Survey Datasets (2020), a data series rich on child welfare information which is never being accomplished before. Secondly, it employs the panel-data fix and random effects estimators to analyze the impact of environmental shocks on child labor, to our knowledge, a first tempt of its kind that controls for observable and unobservable endogenous time-invariant influences on child labor supply.

The paper is organized as follows: next section summaries the existing literature on the definition and determinants of child labor and develops the conceptual framework for the study. Section 3 and its subsections discuss the empirical methods employed in the study. Section 4 provides the description of data and variables used in the study. Section 5 examines the results and findings. And finally, section 6 concludes the study with suggesting policy solutions.

2 LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

This paper deals with socioeconomic and econometric modeling of child labor. However, it will be helpful to examine the definition of child labor employed in most of the cited studies.

2.1 Definition of Child Labor

Given the widespread prevalence of literature on child labor, it is not surprising that there is no unique definition of child labor. There is enormous debate among economists, policy makers and human right activists about the definition of "child" with respect to age limits and the classification of functions as "labor". In general, a human person is designated as "child" if he or she is below the age of eighteen years of old (United Nations, 1989) whereas child work is classified as a "labor" if he or she is "economically active" (Ashagrie, 1993). Moreover, a person is supposed to be economically active if the person is "gainfully employed", that is, he or she works on a regular basis for remuneration.

According to the traditional definition of ILO (1973), child labor refers to any work performed by children under the age of 12, non-light work done by children aged 12–14, and hazardous work done by children aged 15–17. Hazardous child labor or hazardous work is the work which, by its nature or the circumstances in which it is carried out, is likely to harm the health, safety or morals of children. For instance, work which exposes children to physical, psychological or sexual abuse; work underground, under water, at dangerous heights or in confined spaces; work with dangerous machinery, equipment and tools, or which involves the manual handling or transport of heavy loads; work in an unhealthy environment which may expose children to hazardous substances, agents or processes, or to temperatures, noise levels, or vibrations damaging to their health; work under particularly difficult conditions such as work for long hours or during the night or work where the child is unreasonably confined to the premises of the employer. The updated and modern definition of ILO (2021) has broadened the scope of child labor as follow:

> "The term 'child labour' is defined as work that deprives children of their childhood, their potential and their dignity, and that is harmful to physical and mental development. It refers to work that:
>
> - is mentally, physically, socially or morally dangerous and harmful to children; and
> - interferes with their schooling by: depriving them of the opportunity to attend school; obliging them to leave school prematurely; or requiring them to attempt to combine school attendance with excessively long and heavy work."

Whether or not particular forms of work can be called child labor depends on the child’s age, the type and hours of work performed, the conditions under which it is performed and the objectives pursued by individual countries that varies from country to country and sectors to sectors. Children’s participation in work that does not adversely affect their health and personal development or interfere with their schooling, is generally regarded as being something positive. This includes activities such as helping their parents around the home, assisting in a family business or earning pocket money outside school hours and during school holidays. These kinds of activities contribute to children’s development and to the welfare of their families; they provide them with skills and experience, and help to prepare them to be productive members of society during their adult life.

2.2 Literature on Socio-Economic Determinants of Child Labor

The literature on the impact of non-climatic shocks on child labor is fairly extensive, here we select a few to highlight the relative absence of studies on child labor in relation to environmental shocks. Beegle et al. (2006) examines the relationship between household income shocks and child labor using data from a household panel survey in Tanzania, where they find that transitory income shocks lead to increases in child labor while household asset holdings mitigate the effects of these shocks. They argue from the household's point of view, child labor entails a trade-off between immediate benefits, that is, increased current income, and the accumulation of the child's human capital, and long-run costs of lower future earnings potential. Thus, when faced with a transitory shock, households would use asset holdings either as a buffer or as collateral against credit to offset the shock. However, if households do not succeed in smoothing their consumption profile, either because they lack buffer stocks or are credit constrained, then they are forced to resort to other mechanisms such as child labor to cope with income shocks. Alvi and Dendir (2011) maintain that child labor increases with the magnitude of the shock if households do not receive credit from the formal credit market. They argue child labor may be a response to non-availability of credit, specially, to the degree of access to consumption smoothing by agrarian households in absence of loans from the formal sources like microcredit organizations, forcing them to borrow money from the informal village or urban lenders tied to debt bondage. Chakrabarty (2015) finds empirical evidence in support of the "child bonded labor" hypothesis, situations where a child's labor services are offered in exchange for a loan. He argues that children enter into bondage in two main ways: (i) intergenerational bonded family: once a parent is no longer able to work, debts are inherited from parents or other family member; (ii) adult bonded laborers. The majority of bonded child laborers are found in the informal sector who are forced to work for substandard or no wages because their earnings are retained by the employer (or a middleman) to repay an outstanding debt. Additionally, credit-constrained farmer households might increase their demand for child labor for farming. Dowla and Barua (2006) show that microfinance corrects two type of market failure (i) prevent credit market failure, and (ii) create social capital as a public good that mitigates child bonded labor. Chakrabarty et al. (2011) finds that the improvement of the head of the household's educational status significantly decreases the probability of a child's employment in the labor market. Households with more children are much more likely to send their children to work than households with fewer children. Mother's job is also negatively related with child's employment, an employed mother is less likely to send her child to work. However, a female child is more likely to involve domestic work than a male child. Additionally, adult income has a significant positive influence on child schooling and therefore, negatively related with child labor. Likewise, Homaie Rad et al. (2015), using secondary data of population and housing census gathered by Iranian Statistical Center in 2011. on 14859 children of Iran, finds that the mothers' fertility rate and education are the strongest determinants of on child labor supply in the country. Additionally, Parents determine the child labor supply by weighing its harmful effects against its potential benefits. Moreover, Koohi-Kamali (2008) notes that the increase in the household size by newborn body may incite households to discriminate against older child in order to finance the additional costs. This is consistent with the view that the discrimination may take the form of greater increase in child labor supply.

The above selected survey from a vast literature on child labor reveals the surprising absence of any analysis of the specific impact of environmental shocks on child labor despite the increasing urgency of such a critical rule of climate change on the labor market. This study is addressed to this missing research area of child labor in the literature.

2.2 Conceptual Link between Environmental Shock & Child Labor

The United Nations International Strategy for Disaster Reduction (UNISDR, 2009) defines an environmental shock as a natural event that causes a serious disruption of the functioning of a community or a society and leads to one or more of the following: human, material, immaterial, natural and economic losses and impacts. Children are the most vulnerable in such shocks. Particularly, environmental disasters present a significant and growing threat to the well-being of children; 175 million children globally are affected by natural disasters, including floods, cyclones, droughts, heatwaves, severe storms, and earthquakes every year (Lai & Greca, 2020). Children are exposed to such experiences increased problems regarding their physical, mental, academic and economic outcome after exposure. Kousky (2016) delineates these three ways that environmental disasters affect children:

"First, disasters can damage children's physical health; disasters can cut off access to medical care, even for non-disaster-related illnesses. Second, disasters can cause mental health problems; from damage to their homes and possessions; from migration and from breakdowns in social networks, neighborhoods, and local economies. Third, disasters can interrupt children's education by displacing families, destroying schools, and pushing children into the labor force."

Carter et al. (2008) argues that environmental shocks test the boundaries of social resilience and vulnerability. Shocks, ranging from individual-specific like illness, theft or unemployment to economy-wide like droughts or recessions, have important implications for consumption and nutrition. The direct impacts of the droughts, hurricanes and other environmental shocks can be horrific, resulting in immediate increases in poverty and deprivation. If direct destruction of assets is modest, the income losses of repeated crop failures in some locations can still force households to choose between preserving assets, or selling them to maintain current consumption and health. Moreover, the longer-term effects of shocks can lead towards a "poverty trap"; if there is such a trap comes at the very high cost of immediately reduced consumption, there will be irreversible losses in child education and health and compel laboring child.

Bretschger & Vinogradova (2019) have discussed different kinds of environmental disasters can be modeled depending on their scales: (i) relatively small, random, and continuous shocks, (ii) discrete and recurring jumps with fixed or variable sizes, and (iii) so-called tipping points, leading to a very high damage or even an absorbing state with a total loss of productive capacity. Seddighi et al. (2021) maintains that most families affected by natural disasters, especially those in lower socioeconomic status, face greater social and economic pressures, and are more vulnerable to loss of food and shelter, and forced their child into food or cash earning activities. They also find children's rejection to do so are predictors of increased violence against children in emergency situations and present association between extreme weather events and aggravated food insecurity. Vásquez & Bohara (2010) employing National Survey of Standards of Living for Guatemala and find that households use child labor and schooling reduction as strategies to cope with socioeconomic shocks and natural disasters. Moreover, des Hommes (2017) reports five case studies in Nepal, India, Burkina Faso, Peru and Nicaragua that show environmental changes act as root causes or exacerbated existing roots of pushing children into working. This paper depicts how a combination of poor livelihood conditions, low quality education and lack of decent work opportunities as well as seasonal migration from three to six months in a year due to environmental stress in their home districts, denies the children access to quality education and increase child labor in the state of Odisha in India. Such outcomes are more likely in rural areas where families' livelihoods depend on the land are heavily impacted by flood, droughts, extreme temperatures and other environmental changes. Agricultural crops damage or productivity falls due to environmental disasters and extreme weather events lead families to migrate, either seasonally or permanently, to urban areas in search of food safety and employment; as this type of work is easy to access, children from the migrating families ultimately turn into urban waste pickers.

Webbink et al. (2013) have developed a new framework for analyzing child labor based on three foundations: (1) three multilayered levels of authorities affecting children: household, local, national; (2) three groups of explanatory variables: resources, structure and culture represents economics, sociology and anthropology respectively, (3) three concentric circles with the relevant group of explanatory factors at the inner or lower levels embedded within and affected by the outer or higher level decisions simultaneously. For instance, decisions regarding child schooling vs child labor are made at the household level by parents or by household head in absence of the parents. At the household level, resources and cultural characteristics influence child labor whereas structural characteristics have no effect. Cultural characteristics norms and values regarding child labor are expected to influence parent's attitudes towards child labor; in addition to the type of resources they hold like farmland, livestock and or their income etc. This paper incorporates environmental shocks into the model. Environmental disasters affect the resource base of the household by reducing their earning from resources in farm, land, crop, houses and so on. A disaster also affects the current earnings of the household, and thus enters into the household choice set between schooling or laboring child. Based upon the above literature, we can identify the major determinants of child labor presented in a framework below:

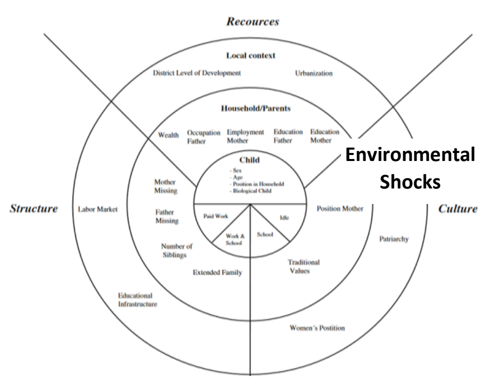

Figure 2: Conceptual Framework of the Determents of Child Labor
(Source: Adopted & Modified from Webbink et al. (2013))

DATA & EMPIRICAL METHODS

Below we describe the panel data we use and outline the econometric models we employ.

3.1 Data and Variables Description

This paper employs Briones (2018) *Young Lives Study of Childhood Poverty Dataset* which is a longitudinal panel dataset of four developing countries namely Ethiopia, India, Peru and Vietnam carried out over 15 years in five rounds between 2002–2016 sponsored by the UK Department for International Development and conducted by the *Young Lives* team based at the *University of Oxford*. In each round it covers approximately 13,000 children for each country. The purpose of the project is to improve understanding of the causes and consequences of childhood poverty and examine how policies affect children's well-being, in order to inform the development of future policy and to target child welfare interventions more effectively. The present study utilizes the constructed Young Lives dataset for Ethiopia and India covering all five rounds. The longitudinal study comprised of two cohorts of children–a younger cohort of 1999 children who were about 1 year old and an older cohort of 1000 children who were about eight years old at the start of the study in 2002 (Round 1). Both cohorts were followed for about 15 years in five rounds–Round 1 (2002), Round 2 (2006), Round 3 (2009), Round 4 (2013) and Round 5 (2016). The younger cohort was followed from 1 year to 15 years of age, while the older cohort was followed from 8 years to 22 years of age. The sample size is large enough for general statistical analyses such as modeling child welfare and its dynamics overtime. We note the longitudinal survey data is not nationally representative for India (for instance, it covers only the States of Andhra Pradesh and Telangana in case of India).

The dependent variable of this study is the supply of child labor. The definition of child labor in this paper includes 5-16 years children engaged in paid employment with payment being either in cash or in kind or unpaid domestic household works for more than an hour per day regarded as effecting child academic and physical development. Two different measures of child labor are also used. In quantitative terms, child labor is defined in terms of numbers of hours they work per day. The numbers of hour of child work as a laboring is generated by summing up the time child spends on (i) working outside household on paid activities, that is, the amount of time doing paid or remunerated work or activities outside of the household or for someone not in the household including travel time to and from work; (ii) working on household tasks, that is, the amount of time doing work inside the household which generated income including farming, cattle herding, shepherding, and other family businesses; and (iii) running household chores that includes work or task done to help at home such as fetching water, firewood, cleaning, cooking, washing, shopping, and so on but excludes daily care for others. In qualitative terms, child labor is defined in terms of their engagement in labor supply process using an indicator variable 1 if they are laboring or 0 otherwise.

The explanatory variables are classified into three groups namely, the “Child’s Characteristics”, “Household Head’s Characteristics” and “Socio-Economic-Environmental Characteristics” ; those are potential determinates of the child labor based upon the literature delineated above. The independent variables of child’s characteristics include child’s age in years. Though the dataset records age in terms of months, this study has converted them into years by diving with 12. Child Sex variable is defined as an indicator variable as 0=Male, 1=Female. The child’s history of illness and injury is included in the constructed data files. We use indicator variable on whether or not the child has had permanent disability that affects his/her work capacity as the measurement of child’s disability response (0=No, 1=Yes). The data file also includes anthropometric information on child’s weight, height, and body mass index (BMI), available in the constructed files for both cohorts in all rounds. We use the World Health Organization (WHO)’s BMI reference tables to classify the children health status into five categories: Stunning (BMI <12), Underweight (BMI 12.1-<18.5), Normal (BMI 18.5–24.9), Overweight (BMI 25–29.9) and Obesity (BMI > 30). The child’s time-allocation information is available in the ‘time use’ survey section that asks the amount of time (in hours) a child spends on eight activities during a typical day, where a typical day, defined as a weekday or a normal school day, excluding holidays, festivals, days of rest during the weekend, and so on. The variable is generated by adding the time a child spends at school, time used to get from home to school and from school to home and time child spends studying at home and doing homework or attending classes or tutorials outside school class hours.

Household head's characteristics include age measured in years and sex 0=Male, 1=Female. Based upon the 19 categories of data on household head's education level, we decompose them into five groups; (i) Illiterate: those who cannot read or write; (ii) Informal Education: who can read or write but have no formal training except adult literacy and religious education; (iii) Primary Education: who spent at least five years in schooling and pass primary grade; (iv) Secondary Education: who spent at least six to twelve years in schooling; and finally (v) Tertiary Education: who has vocational, technical or university bachelor or masters, or doctorate.

Area defines the household area of residence designated by a binary variable 0 for Rural and1 for Urban. Access to electricity is defined by a binary variable equal to 1 if household has electricity, 0 otherwise. This includes legal and illegal electricity connections and electricity coming from generators, including wind, solar, and biogas. It does not include electricity generated by car batteries. Similarly, availability of cooking energy is defined as dummy variable equal to 1 if the household uses kerosene, paraffin, gas, or electricity as fuel for cooking, 0 otherwise. If the household has multiple sources of fuel for cooking, the most frequent source is recorded by the dataset.

The wealth index is a powerful tool to explore changes to households' socio-economic status, poverty dynamics, and intra and intergenerational socio-economic mobility. Young Lives wealth index is intended to be the primary measure of socio-economic status of households. It is constructed from three indices: housing quality, access to services, and ownership of consumer durables (Briones, 2018a). With the assumption that the average of the three indices measures wealth; the average produces a value between 0 and 1, where a higher wealth index indicates a higher household wealth on a continuous scale. For our analysis, we divide child household into Five Wealth Quantile reflecting the income distribution from top to bottom.

$$\text{WEALTH INDEX} = \frac{\text{HOUSING QUALITY} + \text{ACCESS TO SERVICES} + \text{CONSUMER DURABLES}}{3}$$

The number of household members by sex and age groups are available in the constructed files. The size of the household is also available in the dataset. Dependence ratio is calculated by the authors here by taking the ratio of household size to the total numbers of earning members of the family between age 17-60.

In general, shocks are events with negative consequence on them. Socio-economic-environmental shocks are then derived from the different indicator of shocks data available in the datasets. In the constructed files, all shock-related variables are binary (the variable equals 1 when shock was reported during the period between rounds, 0 otherwise). Household Shock is defined by summing up the shocks generated within the family members as such death of father, death of mother, death of other earning household member, illness or disablement of father or mother or other earning household member, divorce or separation, imprisonment, victim of crime, conscription, abduction or draft, as well as political, ethnic and social discrimination. Food Shock is obtained by summing up the shock reported by the respondent due to increase in food prices or agricultural inputs or output prices or decrease in food availability. Income shock is generated by aggregating shocks reported by the respondent in terms of loss of job, source of income or family enterprise, industrial action, closure of employment place, contractual disputes in purchase of inputs or sale of output or disbanding credit, destruction or theft of tools for production, theft of cash or crops or livestock. The variable assets shock is computed by adding theft or destruction of housing or consumer goods, fire or collapse of building, land redistribution, resettlement or forced migration, forced contributions, eviction or invasion of property, confiscation of assets, disputes with family or neighbors about assets.

Environmental shock is calculated by combining shock felt due to drought, flooding, heavy rainfall, cyclone, tornado, hurricane, erosion, overflowing of rivers or surge of the sea frost, earthquake, forest fire, pollution caused by mining, storm, landslide, pests on crops or storage or livestock and crop failure due to any natural disaster.

Social security coverage is defined by the household’s participation in several country-specific public policy support programs. In case of Ethiopia, it is ranked by binary variable 1 if the household is receiving benefit from any one of the programs or zero otherwise: (i) Health Extension Program, (ii) PSNP-Public Works Program in the past 12 months, (iii) PSNP-Direct Support Program in the past 12 months (iv) Emergency Aid Program since the previous round. On the other case of India, it is ranked by binary digit 1 if the household is receiving benefit from any one of the programs or zero otherwise: (i)

Public Distribution System, (ii) a job card under the NREGS, (iii) Rajiv/NTR Arogyasri card, (iv) SABLA program and (v) REGSEAG/SABLA. The last variable, credit, indicates whether or not a household has obtained a loan or credit from banks, financial institutions, insurance companies, companies, municipal and rural banks, savings cooperatives, micro credit and so on.

3.2 Econometric Models

This paper employs irregular spacing panel data sets, in which the same children are observed in all periods surveyed (balanced panels), but for some periods (years in this study) we have missing data. Using i as subscript for the cross sectional unit of observation and t as subscript for the time-period and letting the data set contain N units and T time-periods, the coverage of a balanced panel data set can be denoted as i=1, . . . ,N and t=1, . . . , T with N>T as $N \rightarrow \infty$ (Mátyás and Sevestre, 2008). Panel data has several important advantages over data sets with only a temporal or longitudinal dimension, particularly, it has the ability to control possible error term correlated time-invariant heterogeneity. An additional advantage of panel data, compared to time series data, is the reduction in collinearity among explanatory variables and the increase in efficiency of econometric estimators. Below we discussed the various specifications of panel data used in this study.

3.2.1 Panel Logit Model

The first panel data model we employ is with a binary dependent variable using the panel logit model. Here, the probability of a positive outcome is assumed to be determined by the logistic cumulative distribution as a function of the factors affecting the probability of child labor, Pr (CL). The dependent variable is now a dichotomous form of child labor where CL=1 implies the children is involved in child labor and CL=0 otherwise.

$$\Pr(CL_{it}|0,1) = \alpha + X_{it}'\beta + u_i + \epsilon_{it} \;\; \forall\, i \,=\, 1,\ldots,N;\; t \,=\, 1,\ldots,T \qquad (1)$$

With panel data we can control for stable characteristics, i.e. characteristics that do not change across time, regardless of whether they are observable or not. These include such child features as sex, race, and ethnicity, as well as more difficult to measure variables such as intelligence, parents' child-rearing practices, and genetic makeup.

3.2.2 Pooled OLS

While (1) provides estimates of whether a child is active in the labor market, we are often interested in how many hours of work that activity entails. The Pooled Ordinary Least Squares (OLS) can offer estimates of the covariant when the dependent variable is a continuous one, the number of hours of labor preformed in this case. The pooled OLS estimator assumes that the intercepts are homogeneous, namely $\alpha_i = \alpha$, for all i (Greene, 2017). Given a panel sample of *N* child over *T* periods, the basic linear regression equation takes the form of Pooled OLS as:

$$CL_{it} = \alpha + X'_{it}\beta + e_{it} \qquad \forall \;\; i = 1, \ldots, N;\; t = 1, \ldots, T \qquad (2)$$

Here, CL stands for child labor, measured in numbers of hours of labor, is the dependent variable of the study covering *i*= 1, 2,…., *N* cross-sectional unit (child) at time *t* =1, 2, . . . , *T* (year). X_{it} is the vector of explanatory variables that includes environmental shocks and other socio-economic factors. Here, α accounts for any individual child specific effect that is not included in the regression and e_{it} is an error term, $iid.\sim(0, \sigma^2)$. α and β are to be estimated by the OLS procedure after pooling the panel data and the resultant estimators of β is known as the pooled OLS estimate. This approach, however, ignores potential unobservable child-specific effects, or cross-sectional heterogeneity; in addition to the non-constant error variance.

3.2.3 Fixed Effect Model

Fixed effect model rewrites pooled OLS model by introducing an unobservable child specific time-invariant effect, u_i. If individual effect u_i (cross-sectional or time specific effect) does not exist (u_i=0), pooled OLS produces efficient and consistent parameter estimates.

$$CL_{it} = \alpha_i + X'_{it}\beta + e_{it} \qquad \forall\ i = 1, 2, \ldots, N \ \&\ t = 1, 2, \ldots, T \qquad (3)$$

However, when individual effect is not zero ($u_i \neq 0$) in longitudinal data, heterogeneity (individual specific characteristics) yields biased estimators, that is, pooled OLS estimator is no longer blue. Moreover, disturbances may not have same variance but vary across individual (heteroscedasticity) or related with each other (autocorrelation) (Wooldridge, 2016). Fixed effect model models provide a way to deal with estimation biased that stems from heterogeneity problems. In order to ensure valid statistical inference based on robust standard errors, heteroskedasticity-consistent covariance matrix estimators have been developed by White (1980). Furthermore, cross-sectional dependence constitutes a problem for many microeconometric panel datasets (Hoechle, 2007). We use Driscoll and Kraay (1998) standard error estimates that are robust to both types of heteroscedasticity, cross-sectional and temporal.

3.2.4 Random Effect Model

Fixed effects estimator cannot provide estimation for the impact of time-invariant influences, for instance gender, on child labor, since it removes all such influences from the model. Random effects estimator retains estimates of time-invariants by splitting the heterogeneity intercept into a constant mean and a random cross-sectional part added to the fixed effects error term as a new component. That is,

$$CL_{it} = \alpha + X'_{it}\beta + [u_i + \epsilon_{it}] \quad \forall\ i = 1, 2, \ldots, N \ \&\ t = 1, 2, \ldots, T \qquad (4)$$

where now $\alpha_i = \alpha + u_i$. Here random effect is captured by the term u_i. However, should (4) exclude unobservable time-invariants, $[u_i + \epsilon_{it}]$ will be correlated with the explanatory variables if, as it is likely, any of the included are correlated with the excluded variables. Hence, unlike fixed effects model, random effects estimator cannot ensure consistency and must be tested for endogeneity in order to choose between the two estimators.

3.2.5 Choosing between Fixed Effect Model and Random Effect Model

The validity of fixed effects is tested by the F test, while presence of random effects is examined by the Lagrange multiplier (LM) χ^2 test (Breusch and Pagan, 1980). If the null hypothesis is not rejected in either test, the pooled OLS regression is favored. However, if null hypothesis is rejected in both tests, there is a dilemma in choosing the appropriate model. To resolve that, Hausman (1978) devised a specification test based on the difference between the fixed and random effects estimators. Using the results of the preceding example, we can retrieve the coefficient vector and estimated asymptotic covariance matrix, b_{FE} and V_{FE} from the fixed effects results and the elements of $\hat{\beta}_{RE}$ and V_{RE} (excluding the constant term). Hence, the null hypothesis of the test is

$$H_0 : (b_{FE} - \hat{\beta}_{RE})'(V_{FE} - V_{RE})^{-1}\left(b_{FE} - \hat{\beta}_{RE}\right) = 0 \qquad (5)$$

The Hausman specification test (H) examines if the individual effects are uncorrelated with other regressors in the model. If individual effects are correlated with any other regressor, the random effect model violates a Gauss-Markov assumption and is no longer blue (Park, 2011). It is because individual effects (u_i) are parts of the composite error term (ϵ_{it}) in a random effect model. Therefore, if the null hypothesis is rejected, a fixed effect model is favored over the random counterpart. In a fixed effect model, individual effects are parts of the intercept and the correlation between the intercept and regressors does not violate any Gauss-Markov assumption; such a model remains blue. If the null hypothesis is not rejected, we can conclude that there is a significant random effect in the panel data and such random effect model is able to deal with heterogeneity and offer consistent estimates of the time-invariants.

4. ESTIMATION RESULTS

We present the results from the models outlined in section 3 starting with the pooled least squares panel, logit, fix effects and random effects models.

4.1 Pooled OLS

Table1, the first column lists the explanatory variables of the model while column 2 and column 3 present the Pooled OLS results for Ethiopia and India respectively. For both countries, we find that environmental shocks are positively affecting child labor at 1% level of significance. In case of Ethiopia, the coefficient value is 0.16, suggesting that one additional environmental shock leads to more than 1-hour addition to child labor per week (0.16 hour per day *7 days a week=1.12 hours) holding all other factors constant. Additionally, age of children, area of living, food shock and income shock are positively correlated with the child labor at 1% level of significance in both countries. For instance, in case of India, an urban child is more prone to child labor than a rural child, holding all other factors constant. Moreover, hours spent on study, household head's age and sex, wealth and dependency ratio are negatively affecting the numbers of hours of child labor at the conventional level of significance. The female headed households are negatively and statistically related to the child labor hours at 1% level of significance implying that mothers are more reluctant to put their children into work than fathers. Additionally, the child living in the top quantile wealthy household are also found significantly absent the child labor cohort. An increase in the level of education of the household head beyond the primary level of education also reduces the child labor at the conventional level of significance particularly in case of Ethiopia, but not India. Social security programs appeared to statistically significant determinants of child labor at 1% level of significance, however, in case of Ethiopia, it is promoting child labor while it is contributing to child labor in case India. As discussed in the literature review, the outcome of social security programs on child labor depends on the nature of the program taken. For instance, in case of India, the data indicates the existence of school feeding program which is contributing to school attendance and reduce child labor. In contrast, in Ethiopian case, the data indicates the prevalent of public work aid program might have encourage child to work for food. In addition, obesity condition is found negatively affecting the child labor supply in case of Ethiopia merely whereas stunned, underweight and normal weight children are more likely supplying labor in case of India. Access to electricity and cooking energy availability near home are also statistically significantly reducing the child labor in case of Ethiopia. Furthermore, household shock, for instance death of the head, is a statistically significantly contributor to heightening child labor supply in Ethiopia while assets shock is doing the same in case of India.

It is notable that almost all of this long list of explanatory variables have the expected sign and often highly significant. We take that as preliminary evidence of the basic model's effectiveness.

4.-2 Panel Logit Random Effects

Table 2 reports the results of panel logit estimation. Here the dependent variable is binary measuring whether or not the child is engaged into the labor effort. When a binary outcome variable is modeled using logistic regression, it is assumed that the logit transformation of the outcome variable has a linear relationship with the predictor variables. This makes the interpretation of the regression coefficients somewhat tricky. For instance, child age, sex, health condition like disability and study time all have statistically significant effects on the chance of being in the child labor cohort at 1% level of significance. Disability coefficient (odds ratio) for Ethiopia is -1.758 which suggests that increases in the physical or psychological disability reduces the probability of child labor by [$e^{-.1758}/(1+ e^{-.1758})$]= 0.15 or by 15%, given all other factors remain unchanged. We also find that availability of nearby cooking facilities, dependency ratio, social security coverage, and household shocks affect the probability of child labor at 1% level of significance in both cases of Ethiopia and India, as do environmental shocks. For instance, in case of India, odds ratio of environmental shock is 0.126; that reveals an increase in an environmental shock increases the probability of child labor by [$e^{.126}/(1+ e^{.126})$=] 0.53 or by 53% given all other factors remain the same at 1% level of significance and so on. A likelihood-ratio (LR) test of this is included at the bottom of the output. This test formally compares the pooled estimator (logit) with the pooled panel estimator. LR test outcomes reject that null hypothesis that pooled logit estimator and the panel logit estimator are the same at 1% level of significance which justify the employment of panel analysis against simple pooled analysis in this present context.

4.3 Fixed & Random Effects

Table 3 reports the results of panel fixed effect and random effect analysis. We note that child gender variable is dropped from the fixed affect model since it is a time-invariant, however, household head's sex is kept in the fixed affect model since household head may be changing over time periods of the five rounds of the data collection due to demise or divorce of the previous head of household or so on. The analysis indicates children age, study hours, food shock, income shock and environmental shock are statistically significantly correlated with the child labor supply with conventional sign and level of significance for both Ethiopia and India irrespective of different specification chosen. Remaining results are the same as the pooled OLS findings discussed above with a few exceptions. We then conduct the Hausman speciation test to choose between the fixed effect and random effect models, the outcome statistically favors the random effect model over fixed effect model for both countries.

5. CONCLUSION

Child labor involves both formal and informal employment of the children which directly or indirectly poses danger to their physical, psychological, social, moral and intellectual development. Environmental shocks by natural disasters and climate change are becoming more prominent root causes of child labor. This paper has employed Young Lives Panel Survey Data on Ethiopia and India covering period 2002-2016 to analysis the interplay between child labor and environmental shocks. We have presented a range of evidence that the environmental shocks have statistically significant positive effect on child labor outcome. This conclusion is remarkably strong and robust irrespective of different model and country specifications examined, and after separately controlling for a relatively large number of children, household and community levels influences, including non-environmental shocks. Furthermore, the environmental shocks effects increase both the probability of being trapped into child labor and into facing conditions that undermine a wide range of child welfare determinants such as child and household specific characteristics, socio-economic and geographical welfare determinants. However, we regard our random effects estimates as the most reliable results in this paper; they are consistent in presence of time-invariant endogeneity and able to quantify the impacts of such variables on child labor supply. On caveats, we note that we have not yet addressed the potential joint variation of clime and non-climate shocks. The case for doing so stems from the possibility of some non-climate shocks, for instance, the head's unemployment, may also be the result of household climate shocks. We believe there are some potential instruments available to address this issue by a GMM estimator. The current analysis can also benefit from potential efficiency gains by exploring Bayesian estimation applications. We hope to address such issues in a revised version of this paper.

Policy recommendations usually consist of collaborative interventions, that is, public action which alters the economic environment so that parents would prefer to withdraw children from the labor force. The availability of good schools, the provision of free meals, and efforts to bolster adult wages are examples of collaborative interventions. However, in the presence of increasing environmental treats, these actions may not be feasible. This paper finds that parents' education (proxied by household head's education) and traditional social safety nets programs do not provide significant protection against climate-shock child labor. Our estimates suggest monetary gains from social safety nets programs are not enough to meet the survival needs of climate-shocked poor households and hence to stop child labor. Additionally, there may not be enough resources available in developing countries to provide sufficient amount of social security coverage to vulnerable children. Environmental protection policies that directly target climatic disasters have a better chance of protecting children against the short and long-run ravages of child labor.

Table1: Pooled OLS Estimation Results

Dependent Variable: Numbers of Hours Labored by Child Per Day		
Explanatory Variables	ETHIOPIA	INDIA
Child's Characteristics		
Age	0.391***	0.272***
	(0.008)	(0.008)
Sex (0=Male, 1=Female)	0.011	0.379***
	(0.038)	(0.039)
Disability (0=No, 1=Yes)	-0.612	-2.389***
	(0.385)	(0.570)
Health (0 = Stunning; BMI <12		
1 = Underweight; BMI 12.1-<18.5	0.008	0.130**
	(0.060)	(0.060)
2 = Normal; BMI 18.5–24.9	0.063	0.166***
	(0.074)	(0.061)
3 = Overweight; BMI 25–29.9	0.169	0.149
	(0.600)	(0.169)
4 = Obesity; BMI > 30	-0.711***	-0.724
	(0.137)	(0.679)
Study (Hours)	-0.112***	-0.598***
	(0.010)	(0.013)
Household Head's Characteristics		
Headage	-0.009***	-0.005**
	(0.002)	(0.002)
Sex (0=Male, 1=Female)	-0.488***	-0.169**
	(0.053)	(0.072)
Education (0= Illiterate)		
(1=Informal Education)	0.253***	-0.024
	(0.076)	(0.131)
(2= Primary Education ≤ 5 years)	-0.028	-0.113**
	(0.055)	(0.056)
(3=Secondary Education 5 to 12 years)	-0.227***	-0.067
	(0.060)	(0.058)
(4=Tertiary Education ≥ 12 years)	-0.459***	-0.034
	(0.098)	(0.077)
Socio-Economic-Environmental Characteristics		
Area (0=Rural, 1=Urban)	0.868***	0.234***
	(0.066)	(0.058)
Access to Electricity (0=No, 1=Yes)	-0.264***	-0.074
	(0.072)	(0.137)
Access to Cooking Energy (0=No, 1=Yes)	-0.366***	-0.089
	(0.066)	(0.056)
Wealth Quantile 1	-0.494***	-0.217**
	(0.104)	(0.105)
Wealth Quantile 2	0.145	-0.018

	(0.094)	(0.084)
Wealth Quantile 3	0.160**	-0.030
	(0.076)	(0.074)
Wealth Quantile 4	0.209***	0.002
	(0.059)	(0.052)
Dependence Ratio	-0.279*	-0.408**
	(0.145)	(0.159)
Household Shock	0.217***	-0.004
	(0.025)	(0.038)
Food Shock	0.231***	0.091**
	(0.041)	(0.037)
Income Shock	0.452***	0.148**
	(0.048)	(0.068)
Asset Shock	0.093	0.352***
	(0.061)	(0.122)
Environmental Shock	**0.160*** **	**0.107*** **
	(0.023)	**(0.029)**
Social Security Coverage	0.748***	-0.052**
	(0.056)	(0.021)
Credit	0.451***	0.044
	(0.069)	(0.029)
Constant	1.120***	4.134***
	(0.164)	(0.242)
Observations	12,364	12,652
F test	7899.61***	4335.87***
P-value	(0.000)	(0.000)

Notes: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table2: Panel Logit Random Effect Estimation Results

Dependent Variable: Child Labor (0=No, 1=Yes)

Explanatory Variables	ETHIOPIA	INDIA
Child's Characteristics		
Age	0.338***	0.377***
	(0.020)	(0.012)
Sex (0=Male, 1=Female)	0.251***	0.620***
	(0.066)	(0.054)
Disability (0=No, 1=Yes)	-1.758***	-1.050***
	(0.415)	(0.385)
Health (0 =Stunning; BMI <12		
1 = Underweight; BMI 12.1-<18.5	0.386**	-0.128
	(0.173)	(0.106)
2 = Normal; BMI 18.5–24.9	-0.015	-0.141
	(0.207)	(0.108)
3 = Overweight; BMI 25–29.9	-0.504	0.508
	(1.161)	(0.331)
4 = Obesity; BMI > 30	-2.179***	0.212
	(0.367)	(0.356)
Study (Hours)	0.265***	0.032***
	(0.013)	(0.007)
Household Head's Characteristics		
Headage	-0.003	-0.005
	(0.003)	(0.003)
Sex (0=Male, 1=Female)		
	-0.334***	-0.076
Education (0= Illiterate)	(0.089)	(0.103)
(1=Informal Education)	0.577***	0.326*
	(0.136)	(0.194)
(2= Primary Education ≤ 5 years)	0.152*	0.081
	(0.092)	(0.076)
	-0.152	-0.036
(3=Secondary Education 5 to 12 years)	(0.100)	(0.074)
(4=Tertiary Education ≥ 12 years)	-0.057	-0.302**
	(0.191)	(0.129)
Socio-Economic-Environmental Characteristics		
Area (0=Rural, 1=Urban)	1.675***	0.043
	(0.140)	(0.079)
Access to Electricity (0=No, 1=Yes)	-0.113	0.043
	(0.142)	(0.110)
Access to Cooking Energy	-0.790***	-0.271***
(0=No, 1=Yes)	(0.125)	(0.089)
Wealth Quantile 1	-1.042***	0.118
	(0.188)	(0.136)
Wealth Quantile 2	-0.179	0.234*
	(0.175)	(0.124)
Wealth Quantile 3	-0.040	0.122

	(0.148)	(0.117)
Wealth Quantile 4	0.201*	0.199**
	(0.118)	(0.091)
Dependence Ratio	-0.487**	-0.466**
	(0.242)	(0.234)
Household Shock	0.264***	0.234***
	(0.039)	(0.045)
Food Shock	0.046	0.246***
	(0.067)	(0.067)
Income Shock	0.355***	-0.059
	(0.080)	(0.095)
Asset Shock	0.126	0.446***
	(0.083)	(0.098)
Environmental Shock	0.182***	0.126***
	(0.037)	(0.037)
Social Security Coverage	0.775***	0.412***
	(0.116)	(0.075)
Credit	0.259	0.002
	(0.171)	(0.093)
Constant	-4.331***	-4.752***
	(0.389)	(0.255)
Observations	12,364	12, 652
F test	2964.48***	2398.52***
P-value	(0.000)	(0.000)
LR test	20.93 ***	25.30***

Notes: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3: Fixed Effect and Random Effect Estimation Results

Dependent Variable: Numbers of Hours Labored by Child				
Explanatory Variables	Fixed Effect Model		Random Effect Model	
	ETHIOPIA	INDIA	ETHIOPIA	INDIA
Child's Characteristics				
Age	0.432***	0.348***	0.390***	0.274***
	(0.012)	(0.011)	(0.008)	(0.008)
Sex (0=Male, 1=Female)	-	-	0.010	0.404***
			(0.038)	(0.042)
Disability (0=No, 1=Yes)	-0.609	-0.984***	-0.628	-1.876***
	(0.373)	(0.332)	(0.389)	(0.504)
Health (0 = Stunning; BMI <12				
1 = Underweight; BMI 12.1-<18.5	-0.013	0.208***	0.009	0.109*
	(0.067)	(0.061)	(0.061)	(0.060)
2 = Normal; BMI 18.5–24.9	0.103	0.275***	0.063	0.144**
	(0.085)	(0.078)	(0.074)	(0.062)
3 = Overweight; BMI 25–29.9	0.383	0.172	0.172	0.121
	(0.642)	(0.186)	(0.598)	(0.165)
4 = Obesity; BMI > 30	-0.873***	0.322	-0.698***	-0.582
	(0.169)	(0.231)	(0.138)	(0.578)
Study (Hours)	-0.079***	-0.268***	-0.115***	-0.594***
	(0.010)	(0.009)	(0.010)	(0.013)
Household Head's Characteristics				
Headage	-0.002	-0.002	-0.009***	-0.005**
	(0.004)	(0.002)	(0.002)	(0.003)
Sex (0=Male, 1=Female)	-0.335***	-0.017	-0.493***	-0.142**
	(0.085)	(0.078)	(0.053)	(0.072)
Education (0= Illiterate)				
(1=Informal Education)	0.330***	0.631***	0.248***	-0.041
	(0.106)	(0.178)	(0.076)	(0.134)
(2= Primary Education ≤ 5 years)	0.205**	0.210***	-0.033	-0.128**
	(0.084)	(0.065)	(0.055)	(0.059)
(3=Secondary Education 5 to 12	-0.170	0.194**	-0.226***	-0.070
years)	(0.112)	(0.081)	(0.060)	(0.062)
(4=Tertiary Education ≥ 12 years)	-0.982***	0.020	-0.443***	-0.046
	(0.170)	(0.123)	(0.097)	(0.083)
Socio-Economic-Environmental Characteristics				
Area (0=Rural, 1=Urban)	0.257	0.292***	0.855***	0.245***
	(0.208)	(0.098)	(0.065)	(0.060)
Access to Electricity (0=No, 1=Yes)	-0.076	0.246***	-0.272***	-0.006
	(0.089)	(0.081)	(0.072)	(0.144)
Access to Cooking Energy	-0.087	-0.353***	-0.374***	-0.103*
(0=No, 1=Yes)	(0.090)	(0.059)	(0.066)	(0.057)
Wealth Quantile 1	-0.767***	-0.020	-0.479***	-0.129
	(0.138)	(0.103)	(0.104)	(0.109)
Wealth Quantile 2	0.060	0.251***	0.147	0.011

	(0.119)	(0.084)	(0.094)	(0.087)
Wealth Quantile 3	0.195**	0.312***	0.156**	-0.012
	(0.096)	(0.074)	(0.076)	(0.075)
Wealth Quantile 4	0.253***	0.272***	0.206***	0.037
	(0.073)	(0.052)	(0.059)	(0.054)
Dependence Ratio	0.117	0.309*	-0.295**	-0.298*
	(0.173)	(0.163)	(0.146)	(0.160)
Household Shock	0.211***	-0.004	0.218***	-0.012
	(0.029)	(0.029)	(0.025)	(0.038)
Food Shock	0.297***	0.335***	0.230***	0.094**
	(0.044)	(0.041)	(0.041)	(0.037)
Income Shock	0.458***	0.201***	0.452***	0.129*
	(0.054)	(0.056)	(0.048)	(0.067)
Asset Shock	0.061	0.226***	0.095	0.344***
	(0.066)	(0.069)	(0.061)	(0.125)
Environmental Shock	0.142***	0.063**	0.159***	0.102***
	(0.028)	(0.027)	(0.023)	(0.029)
Social Security Coverage	-0.009	0.057***	0.770***	-0.053**
	(0.070)	(0.015)	(0.056)	(0.022)
Credit	0.850***	0.024	0.433***	0.039
	(0.076)	(0.066)	(0.069)	(0.029)
Constant	-1.912***	-1.177***	-1.067***	3.975***
	(0.268)	(0.177)	(0.165)	(0.245)
Observations	12,364	12,652	12,364	12,652
Fixed Effects	YES	YES	NO	NO
F test	478.5***	117.4***		
	(0.000)	(0.000)		
Wald chi2			17848.02***	4318.77***
P-value			(0.000)	(0.000)

Notes: Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1

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