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Persistent Agricultural Shocks and Child Poverty: Evidence from Ethiopia

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Abstract

This study shows how persistent agricultural shocks in Ethiopia affect education, health and labor outcomes through a time-use study of young people, aged 0-22. Leveraging five rounds of the Young Lives Study from 2002-2016, we use dynamic panel instrumental variable regressions to account for the unobserved heterogeneity and serial correlation in the estimation of persistent shocks. Agricultural shocks significantly reduce schooling participation and time spent in schooling, deteriorate health, and increase both labor force participation and labor time. Household wealth acts as a buffer and mitigates the adverse effects of shocks on schooling. Interestingly, children from wealthier households have a higher likelihood of joining agricultural labor during shocks, but their intensity of child labor is significantly lower compared to the poorer households. The study recommends agricultural insurance for the poor and incentives for school participation in areas susceptible to agricultural shocks.

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1 Introduction

The adverse impact of agricultural shocks and its threat to household and child welfare in the developing world has been documented for over four decades.[1] However, the persistent nature of agricultural shocks (flood, drought, pests, soil erosion and frosts among others) has brought into question the estimation techniques from previous research, underscoring the issues of endogeneity and serial correlations. Households living in areas with recurring agricultural shocks might be adjusting their consumption behavior and time-use accordingly. For instance, in areas with recurring agricultural shocks, households may be stocking more and selling less of the yields, saving more and spending less on consumption and child education, and members may have higher migration rates to seek better economic opportunities [Giles and Yoo, 2007]. These adaptive behaviors are bound to change the time-use patterns of household members. In this context, a longitudinal and causal study of how recurring agricultural shocks affect child education, health, labor, and the time use dynamics has remained elusive.

In low income countries, a large proportion of the population depends on subsistence agriculture, cash crop production or hired farm labor as primary means of economic support.[2] Therein, rainfall and agricultural shocks have kept the agricultural yield and demand for agricultural labor low, thus negatively affecting the economic conditions of agricultural households. Ethiopia is one such country, where about 85% of the population live in rainfed rural areas, and have been unable to protect themselves from rainfall failure that occurs, on average, every five years [Porter, 2012]. Ethiopia is heavily reliant on small-scale rainfed agriculture systems, highly localized agricultural markets, erratic climatic conditions, weak storage capacity, and high yield transportation costs. These structural and systematic failures are argued to be the cause of recurrent agricultural shocks and food insecurity [Miller, 2017; Rijkers and Söderbom, 2013; Durevall et al., 2013; Shah and Steinberg, 2017]. Although Ethiopia has made consistent progress in improving development indicators, vulnerability to extreme weather events, such as the El Nino in 2015-2016, is a continuing concern, especially for people reliant on agriculture for their livelihoods [Koo et al., 2019].

[1] For more details, see Beegle et al. [2006]; Singh and Vennam [2016]; Jensen [2000]; Zimmermann [2012]; Adhvaryu and Nyshadham [2016]; Andalón et al. [2016]; Currie and Hyson [1999]; Buckles and Hungerman [2013]; Cornwell and Inder [2015]; Feeny et al. [2021]; Agamile and Lawson [2021]; Giles and Yoo [2007]; Shah and Steinberg [2017].

[2] In 2016, around 65% of poor working adults made a living through agriculture. In 2018, agriculture accounted for 4% of global gross domestic product, and in some least developing countries, it accounts for more than 25% of GDP (World Bank, 2022).

In addition, more recently, growing scarcity of land for agricultural production has restricted younger generations in investing their time in agriculture, and has disincentivized knowledge creation and transmission for improving agricultural output in Ethiopia [Bezu and Holden, 2014].

To the extent that agricultural households are often geographically isolated in regions where there are few off-farm employment opportunities or other mechanisms for coping with agricultural risk, precautionary under-investments in education and health may reinforce poverty traps [Giles and Yoo, 2007; Shah and Steinberg, 2017]. Observers have also concluded that poor children suffer from "double jeopardy" as they are both more likely to suffer negative education and health shocks, and are less likely to be able to recover from them [Currie and Hyson, 1999; Becker and Tomes, 1986]. Early research on household consumption responses to agricultural risks has not allowed for updating of risk perceptions with changes in household wealth due to lack of dynamic panel data, or have introduced the impact of changes to expected wealth in an ad-hoc manner using constant absolute risk preferences or short panel surveys which do not allow for dynamic risk updating [Campbell, 1987; Jalan and Ravallion, 1999]. More recent studies have shown that wealth indicators such as land size, assets and livestock holding play a significant role in explaining changes in household consumption and child labor [Bhalotra and Heady, 2003; Amare et al., 2018].

Obscured from the public domain and policy discussions, a recent report by the ILO and UNICEF in 2020[3] finds that since 2016, global child labor has increased for the first time in two decades. According to the report, the number of children in child labor has risen to 160 million worldwide – an increase of 8.4 million children in the last four years. A vast majority of these children are engaged in agricultural labor, and predominantly work on family farms [Bhalotra and Heady, 2003]. In this context, examining how children reallocate their time and responsibilities in the event of agricultural shocks can provide us with a clearer picture of the costs of recurring agricultural shocks on human development, as schooling lost in formative years has been found to be a significant deterrent to quality of life in later years [Das et al., 2022; Huebner et al., 2014].

Risk exposures and smoothing behaviors could evolve with changes in household wealth. In the context of agricultural economies in Africa, the impact of household land ownership on child education has been found to be fairly positive [Jensen, 2000; Charles and Hurst, 2003]. However, its impact on child labor has also been found to be positive (more agricultural

[3]Link to the report: International Labor Organization, 2020. The report states that, "agriculture sector accounts for 70 per cent of children in child labour (112 million) globally".

land leading to more child agricultural labor force participation) in developing economies such as Ghana, Pakistan and Burkina Faso, and has been regarded as the 'wealth paradox' [Dumas, 2007; Basu et al., 2010; Bhalotra and Heady, 2003]. However, thus far, the analysis of the impact of wealth on child outcomes has focused on land ownership as an indicator of wealth, but not on wealth in general—housing quality, consumer durables and access to services. Focusing on only land as natural capital has geographical limits, therefore, there is a need to examine the impact of physical capital as a buffer against agricultural shocks to inform more sustainable and resilient development. This is especially important in the Ethiopian context where the state controls the distribution of land and the allocation of land for agricultural purposes is increasingly becoming difficult due to limited availability [Bezu and Holden, 2014]. Therefore, analyzing non-land based wealth for agricultural households and its impact on child outcomes during an agricultural shock provides alternative evidence on wealth as a buffer, and acts as a test for the land based 'wealth paradox'. In addition, understanding whether household wealth acts as a cushion against agricultural shocks in a dynamic context is crucial given the improvements in living standards overtime and relatively low levels of wealth inequality and high degree of imperfection in credit and labor markets in Ethiopia [Thiede, 2014; Ali et al., 2016].

This study provides a longitudinal time-use analysis of the costs of agricultural shocks on education, health and labor force participation for young people, and the role of wealth in mitigating the adverse impacts of recurring agricultural shocks. The study fills several gaps in the literature on education, health and labor responses to agricultural shocks: (i) we use an exogenous proxy for recurring agricultural shocks by using a dynamic instrumental variables approach, (ii) we examine child labor and household investment in child education and health as agricultural uncertainty becomes predictable in a dynamic setting, (iii) we account for the role of non-land based household wealth in responding to agricultural shocks in a dynamic set-up, and (iv) we analyze agricultural shocks and time-use dynamics of young people.

We leverage five rounds of the Young Lives Study (YLS) to conduct dynamic panel data based instrumental variable regressions to tease out the causal effects of recurring agricultural shocks on outcomes of human development for children [Blundell and Bond, 1998; Blundell et al., 2001]. Since the YLS has repeated rounds of data on the same child over fifteen years, the dynamic panel data estimation uses generalized method of moment conditions with lagged differences of the dependent variables as instruments for the difference equation, and the lagged treatment variable as an instrument for the level equation, thereby eliminating the potential serial correlation in the outcome variable in previous and current periods, and the error correlations between the treatment and outcome variables in the current period. We begin our estimation with linear ordinary least squares (OLS) regression, then test its coefficients with two-way fixed effects (FE) regressions which controls for time-invariant unobserved heterogeneity. Finally, we compare the OLS and FE estimates with the causal estimates of the GMM-IV model to examine the nature of the selection bias in the coefficients of interest.

Results from OLS, FE and GMM-IV models show that agricultural shocks have a significant negative (positive) impact on the extensive margin of schooling (labor) for children aged 6 months to twenty-two years, that is agricultural shocks lead to children dropping out of school and joining the labor force. Agricultural shocks significantly reduce the reported health condition of children even after controlling for the body mass index of the child. In terms of the intensive margin of time use, agricultural shocks significantly reduce the time spent by children in school, and more than proportionally increases the time spent by the child in agricultural labor. Agricultural shocks also reduce leisure (play time) for children both at the extensive and intensive margins. In addition, higher incidents of agricultural shocks imply higher increases in child labor and reductions in child education and leisure time.

Wealth acts as a buffer against agricultural shocks on the intensive margin for schooling and labor. Wealthier households are able to mitigate the adverse impact of agricultural shocks on child's time spent in schooling and labor. However, wealth does not seem to buffer schooling at the extensive margin (schooling participation of children is not significantly different between wealthier and poorer households). Children from wealthier households are more likely to start working in response to a shock. Wealth appears to buffer the intensive margin for schooling more for younger children (age<15) than older children. Wealth buffers the intensive margin for labor for older children more than younger children. We find that younger wealthy children are induced to join labor force by a shock, driven mostly by farm labor. This result highlights the substitution of labor from hired to own household labor for wealthy households. However, there is a decline in the number of hours spent in labor activities with agricultural shocks for children from wealthy households relative to poorer households highlighting the wealth cushion effect at the intensive margin.

The positive and significant interactive effect of wealth and agricultural shocks on the use of child labor though initially surprising (since child labor is often portrayed as being negatively associated with household wealth) is not unexpected. In agricultural settings, a positive association between agricultural land holding and child agricultural labor has been previously noted in Pakistan and Ghana underscoring the failures in credit and labor markets in developing economies [Bhalotra and Heady, 2003; Beegle et al., 2006]. We do not find a significant difference in health outcomes based on wealth.

2 Data

We use data from the YLS, which started conducting surveys for 2,000 children born between May 2001 and May 2002, and 1,000 children born between Jan 1994 and Jan 1995 in twenty sites across Ethiopia [Outes-Leon and Sanchez, 2008]. The surveys are sponsored by the Department for International Development (DfID) and collected by the Young Lives team at Oxford University. Data is available from five rounds of surveys conducted in 2002, 2006, 2009, 2013 and 2016 — when children were approximately one, five, eight, twelve and fifteen–years old (younger cohort), and eight, twelve, fifteen, eighteen and twenty-two year old (older cohort). Each survey round was conducted every three or four years, which means that children from both cohorts were interviewed at similar ages. The study collected information on child time use in education, labor and leisure, and categorical variables for general health.[4]

Our outcome variables, derived from the relevant data at the child level, are the extensive margins of education and labor, and general health, and intensive margins of education, labor and leisure. The extensive margin for education is 1 if any time has been spent on school and study activities, 0 otherwise. The extensive margin for labor is 1 if any time has been spent on farming, farm business and paid market activity, 0 otherwise. The intensive margins are based on at least some time spent on education and labor. Our categorical measure of child health is based on five relative states of health: very good, good, average, poor and very poor, and we code the first three states of health as 1, and the last two as 0.[5] While poor and food-poor areas were over-sampled by the study, the communities

[4] In terms of labor force participation, YLS collected data on time spent in household tasks of farming and farm business, and paid market activity. We sum the time spent in both these activities to arrive at the outcome variable, 'labor', for our analysis. Children were sampled from 20 clusters in Ethiopia. Even though the samples are not statistically representative of the national population – as poorer regions were over-sampled – comparisons with nationally representative data sets (DHS, LSMS, and so on) show that they reflect the heterogeneity of ethnicity and religion as well as living standards in each of the study countries [Outes-Leon and Sanchez, 2008].

[5] The data on child health is only available for the last three waves of the survey, that is 2009, 2013 and 2016. All other measures of health, except anthropometric measures are available less frequently as

span Ethiopia geographically and are contained in the regions where almost 97% of the population reside [Miller, 2017].

Our exposure measure of agricultural shock is constructed both at the extensive and intensive margin on the basis of the household survey questionnaire which asks whether the household experienced any of the following agricultural shocks: droughts, flooding, erosion, frost, pests on crops, crop-failure, pests on storage, pests on livestock and natural disasters during the time since the previous survey.[6] We first create a categorical variable which takes the value 1 if there has been any one of the above shocks to the household since the last survey round, 0 otherwise. At the intensive margin, we sum all the shocks and create a variable which takes on the value from zero to eight depending on the number of shocks experienced by the household.

The control variables included in our analysis are: the wave intercepts for all survey rounds that are available, child age in months, household size, household head's education and the Body Mass Index (BMI) of the child. The focus of our analysis is mainly on education and labor force participation of the child, and the examination of household wealth as a buffer against agricultural shocks, therefore we control for the channel of health in examining the effect of agricultural shocks by including child's BMI as a covariate.[7] Lastly, YLS provided a constructed wealth index based on sub-indices of housing quality, access to services, and consumer durables (for details, see Briones [2018]).[8] We used the constructed household wealth index for each of the survey rounds to examine if wealth acts as a cushion for the impact of agricultural shocks.

Insert Table 1 about here

Table 1 shows the descriptive statistics for households with and without agricultural shocks

compared to the general health status of the child.

[6]The effects estimated in the paper are on shocks that occur sometime over the previous 4 years (roughly).

[7]Note, we do not control for BMI in analyzing the effects of agricultural shocks on child health as BMI is a critical determinant of child health, and is strongly correlated to pre-natal conditions such as mother's BMI, food security and obesity [Kedir, 2009; Kassie and Workie, 2020; Dinku et al., 2020].

[8]Housing Quality index (HQ index) that takes values from zero to one. The HQ index constructed by the YLS survey team is based on crowding (rooms per person) and quality of materials used for the walls, roof, and floor. The Consumer Durable index (CD index) provided by the YLS team takes values from zero to one. The CD index is based on the number of non-productive assets owned by the household. The Access to Services index (AS index) is constructed by taking a simple average of the following four dummy variables: safe drinking water, clean cooking fuel, electricity, sanitation facilities, it also takes the value from zero to one.

for the five rounds of the surveys combined. For households with agricultural shocks, the average number of shocks experienced is almost two shocks (i.e., 1.84) since the last survey. At the extensive margin, there is a significantly higher likelihood, 9.5 percentage points (pp), of a child going to school for households without agricultural shocks as compared to households with agricultural shocks. Similarly, it is 19.2 pp less likely that a child from a household without any agricultural shocks will join the labor force in farming activities. Children from households experiencing agricultural shocks reported poorer general health levels as compared to their counterparts (7 pp less likely of reporting good health). At the intensive (time-use) margin as shown in the third panel of Table 1, children in households without agricultural shocks spent 0.88 more hours on education and 0.70 less hours in the labor force compared to households with agricultural shocks. As expected, households without agricultural shocks are more wealthy and their children have higher body mass index (BMI) than households with agricultural shocks. Figure A1 shows the kernel densities (with epenechnikov bandwidth=1) of the time spent in various activities for children with and without agricultural shocks.[9] As evident from the figure, there is a substantially less school and study time of children with agricultural shocks to the households. There is also a substantially more time spent on farming activities and farm business for children with household agricultural shocks.

3 Empirical Framework

Our estimation of exposure effects to agricultural shocks on child education, labor and health begins with the two-way individual fixed effects specification, proposed by Imai and Kim [2021] and contended by De Chaisemartin and d'Haultfoeuille [2020].[10] The benchmark fixed effect estimator is as follows:

$$Y_{it} = \beta_0 + \beta_1 \text{Shock}_{it} + \gamma \mathbf{X}_{it} + \eta_i + \delta_t + \epsilon_{it} \tag{1}$$

Here Y_{it} represents the outcome of interest: education, labor force participation, health and leisure for child i in survey year t. Shock_{it} indicates agricultural shocks in the time between survey waves. $\mathbf{X}'_{it}$ is a vector of household and child level observable socioeconomic and

[9]The vertical line is the mean of the distribution, conditional on non-zero value of the activity (some time spent in the activity), and at baseline with no agricultural shocks.

[10]The estimator assumes that the treatment effect is constant across groups and over time, and estimates that effect under the standard "common trends" assumption.

demographic characteristics which could potentially affect the outcome variables of interest. These include child's age, household size, child's BMI and household head's education. η_i and δ_t are child and time fixed effects (accounting for major macroeconomic trends). Finally ϵ_{it} is the error term. Our primary interest is on the effect of agricultural shocks on measures of child's welfare, i.e., our focus is on β_1.

If agricultural shocks were randomly occurring across time and space, then the estimated $\hat{\beta}_1$ from equation (1) would provide causal estimates of the impact of agricultural shocks on the relevant outcome variable of interest. However, in practice, agricultural shocks in the Ethiopian context are recurring and not random [Porter, 2012; Gebremariam and Tesfaye, 2018; Debebe, 2010]. There is self-selection and sorting involved based on income, ethnicity, household size and knowledge of the neighborhood. Households might be adjusting their consumption, patterns of savings, division of labor and time-use in anticipation of recurring agricultural shocks, as also argued by [Giles and Yoo, 2007]. All these are hard to account for using observational data. These issues lead to potential endogeneity, resulting in bias in estimated effects.

Our regressions control for an extensive set of household and individual observable characteristics that could also be driving child outcomes. Important time-invariant characteristics such as ethnicity, religion, and geography are also controlled for by the child fixed effect η_i, which also captures any time-invariant unobserved characteristics of the child. The time fixed effect δ_t further controls for aggregate time trends. That being said, the fixed effect model's assumption of common trends [De Chaisemartin and d'Haultfoeuille, 2020] does not strictly apply in the case of agricultural shocks in Ethiopia, as for instance, the effect of agricultural shocks on schooling, health and labor may vary geographically across survey areas, and may change over time. Also, fixed effect estimates are weighted sums of the average treatment effects (ATE) in each group (child in our study) and period, where weights that may be negative, which potentially presents an underestimation bias in the coefficients [De Chaisemartin and d'Haultfoeuille, 2020]. We therefore use a dynamic panel data instrumental variables approach to examine the robustness of our benchmark model. The GMM-IV model is as follows:

$$Y_{it} = \sum_{j=1}^{\rho} \alpha_j Y_{i,t-j} + \beta_1 \mathbf{Shock}_{it} + \gamma \mathbf{X}_{it} + \eta_i + \epsilon_{it} \tag{2}$$

Where, the $\alpha_1, ...\alpha_\rho$ are the ρ parameters of the lagged values for the dependent variables. $Y_{i,t-j}$ is the lag of the dependent variable, the order of which is determined by j. $\mathbf{X}_{it}$ is a $1{*}k_2$

vector of covariates in the model viz: age of the child in months, the waves of the survey, BMI of the child, household size and head's education. $\mathbf{Shock}_{it}$ is a $1 * k_1$ vector of the strictly endogenous agricultural shocks. As in our benchmark model, β_1 is the parameter of interest in our analysis. The above linear dynamic panel data model uses generalized method of moment conditions (GMM) in which lagged differences of dependent variables are used as instruments for the differenced equation (GMM type: two lags of dependent variables) along with standard differences of the covariates. In addition, the model also uses moment conditions in which lagged levels of the agricultural shocks are instruments for the level equation (GMM type: LD.agricultural shocks) [Blundell and Bond, 1998; Blundell et al., 2001]. η_i are the panel-level effects (which may be correlated with $\mathbf{Shock}_{it}$ or $\mathbf{X}_{it}$), and ϵ_{it} are independent and identically distributed over the whole sample with variance σ_ϵ^2. In all our specifications, we use the standard two lags of the dependent variables as instruments for the difference equation.[11]

3.1 Model for Wealth Effects

In order to analyze household wealth as a potential mechanism for heterogeneous effects of agricultural shocks on child welfare, we also estimate an extended version of equation (1) where we interact household wealth with the dummy for agricultural shock in a two-way fixed effect model:[12]

$$\begin{aligned} Y_{it} = \beta_0 &+ \beta_1 \text{Shock}_{it} + \beta_2 \text{Wealth} \\ &+ \beta_3 (\text{Shock}_{it} \times \text{Wealth}) \\ &+ \gamma \mathbf{X}_{it} + \eta_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

This specification is used to test our hypothesis that household wealth acts as a cushion against child poverty during agricultural shocks. $\hat{\beta}_1$ gives us the estimated effect of agricultural shocks for households with a low wealth index, while $\hat{\beta}_3$ is the additional effect of agricultural shocks on child welfare for households that have a high wealth index. So $\hat{\beta}_1 + \hat{\beta}_3$ is the total effect of agricultural shocks on child welfare for households that have a high wealth index.

[11] See Stata's xtdpd command for further details on the linear dynamic panel estimation.

[12] Since we do not have a continous IV for wealth and not enough lagged outcome and treatment variables to use as instruments, we do not carry out a GMM-IV model to examine the wealth effect.

4 Results

Reporting of our empirical analysis is divided into two parts. First, we examine the impact of agricultural shocks on the extensive margins of schooling, labor and general health, and intensive margins of time-spent in schooling, labor and leisure. The second part examines the role of wealth in mitigating the impact of agricultural shocks on child welfare (both at the extensive and intensive margin). The Sargan test for over-identification shows that the dynamic model we use for our analysis is exactly identified (fail to reject the null hypothesis that the overidentifying restrictions are valid, with $Prob > \chi^2 > 0.100$). In other words, rejection of the null hypothesis that the overidentifying restrictions are valid implies that the GMM instruments are valid. In addition, since we test the point estimates for multiple hypotheses, we use the Anderson [2008] two stage q-values to reduce the likelihood of false rejection.

Table A1 in the appendix gives the correlations of agricultural shocks with lagged agricultural shocks, lagged wealth, and lagged time-use variables such as hours of schooling, farm & business labor, unpaid care & chores. The predictions of the occurrence of agricultural shocks in Ethiopia using a maximum likelihood estimation technique shows that lagged variables have a significant prediction probability of agricultural shocks. However, as we move from the parsimonious specification to the ones including more variables, the predictive power reduces though remaining significant. For instance, holding the other coefficients at their respective means, previous wealth and previous agricultural shock have lower mean predicted probability of agricultural shock of 0.687 and 0.182, respectively (column 3) compared to 1.125 in the parsimonious specification (column 1). Similarly, time-use variables also have significantly significant predictive probability for agricultural shock i.e., school and study (0.081), unpaid care & chores (0.012) and leisure (0.022) [column 3]. However, previous period farm labor is not a significant predictor for agricultural shocks. Most importantly, in column 3, we see the previous period agricultural shock is a significant positive predictor of current period agricultural shock which is the underlying reason why we argue that agricultural shocks are persistent.

4.1 Agricultural Shocks: Schooling, Labor and Health

Table 2 shows the analysis from OLS, FE, and the GMM-IV models in three panels with the count of the shock variables as the treatment. Panel (a) shows the causal point estimates of the GMM-IV model. At the extensive margin, a one unit increase in agricultural shock (one more agricultural shock) significantly reduces the likelihood of school participation by 3 pp (column 1), increases the likelihood of joining farm labor and family business by 1.7 pp (column 2) and reduces the status of general health by 2.4 pp (column 3). At the intensive margin, a one unit increase in agricultural shock significantly reduces school and study time by 0.27 hours (column 4) and increases farm labor and business activity by 0.65 hours (column 5). Overall, supporting the previous findings in Africa, our results from dynamic panel instrumental variable regression show that agricultural shocks are detrimental to child welfare, and a deterrent to human capital formation in Ethiopia.

Insert Table 2 about here

In panel (b), we show the two-way fixed effects model which accounts for time-invariant heterogeneity and any macroeconomic trends in Ethiopia between 2002-2016. Results for the fixed effects analysis corroborates the findings from the GMM-IV regressions with the same signs and significance for all outcome variables. However, the magnitude of impact with the fixed effects is lower for schooling (both at the extensive and intensive margins) and for labor at the intensive margin underscoring the negative selection as there could be unobservable time-varying heterogeneity strongly correlated with more schooling hours and less agricultural shocks. Results suggest a bias towards zero in the fixed effects regressions compared to our GMM-IV estimate consistent with households updating their behavior in response to persistent agricultural shocks. Fixed effects model produce the estimates from the switch in shock from one period to another while not accounting for the updating of household behavior in response to shock prior to the period in consideration, this may lead to the estimates being smaller when considering any two periods within the time frame of the survey [De Chaisemartin and d'Haultfoeuille, 2020]. In addition to the issue of treatment effects being heterogeneous (vary across different units or exhibit dynamics or change across different time periods), the five time periods of the YLS survey pose a methodological issue that leads to under-estimation of the two-way fixed effects, that is, the model fails to compare newly treated units (at time t) to already treated units at time periods $t-2$,3 & 4 [Callaway and Sant'Anna, 2021]. Therefore, we argue that the GMM-IV model provides a robust estimation of the point estimates after taking into account the exposure to treatments in periods before $t-1$. The OLS model in panel (c) also shows similar signs and significance as the GMM-IV model albeit with expectantly higher magnitude of coefficients due to negative bias, except for labor at the intensive margin.

Overall, we can infer that our results are robust to changes in econometric models. In all results in Table 2 (except the health result in column 3), we control for the BMI of the child to control for the health effect of agricultural shock on schooling and labor outcomes.

Table 3 shows the GMM-IV analysis of unconditional and conditional results for the outcome variables of interest: schooling, labor and leisure. Here unconditional time spent in the activity is irrespective of any non-negative time spent (any positive time spent including zero minutes) in the activity, while conditional restricts to only positive time (greater than zero minutes) spent on said activity. The analysis shows non-linear results by examining any shock (dummy: 0/1) faced by the household, more than one shock faced by the household, and more than two shocks faced by the household. The first three columns (unconditional effects) in panel (a) show that any agricultural shock (0/1) faced by the household reduces the time spent in schooling activities by 0.70 hours (42 minutes), increases the time spent in labor activity by 0.47 hours (28 minutes) and reduces time spent in leisure activities by 0.22 hours (13 minutes). The last three columns (conditional effects) show that any agricultural shock faced by the household reduces the time spent in schooling activities by 0.47 hours (28 minutes), increases labor time by 1.12 hours (72 minutes) and reduces leisure time by 0.19 hours (12 minutes). Comparing the unconditional and conditional effects shows the impact of the switch from any time spent (including zero minutes) to at least some time spent in the activity. As expected, conditional effects on schooling are smaller than unconditional effects, given the significant categorical effect of a shock on dropping out of school, whereas the conditional effects for labor is stronger than unconditional effects underscoring the increased labor input for individuals already in the labor force. There is no statistically significant difference between unconditional and conditional effects of shocks on leisure as we expect minimal switching effects from leisure to no leisure.

Insert Table 3 about here

Results in panel (b) (more than 1 shock) and (c) (more than 2 shock) show that the effects of agricultural shocks are non-linear in nature. For schooling and labor, the impact of higher order shocks in both conditional and unconditional margins show that a higher order of shock leads to higher reductions in school participation and time spent in schooling, and higher increases in labor force participation and time spent in the labor market. The unconditional results for labor is mainly driven by the switch from not being in the labor force to joining the labor force (with 77% of the control mean having zero minutes of labor activity), highlighting the push factor for children to join the labor force during times of economic hardship created by higher level of shocks. This can be understood through the lens of weak labor and credit markets in developing African countries, such as the case of Ghana [Bhalotra and Heady, 2003]. Higher agricultural shocks reduce employment opportunities due to lower economic activity in the community and create hardship in finding non-agricultural employment, due to lower overall labor demand, and credit for alternate forms of income generating opportunities. Hence, households seek to employ children in farming activities to compensate for the lost labor. Overall, when household wealth is unaccounted for, persistent agricultural shocks in Ethiopia reduce school participation and schooling time for children while increasing labor force participation and labor time.

4.2 Wealth: Buffer for Agricultural Shocks

As the state owns all land in Ethiopia, rural residents have been guaranteed access to land through a law that grants them a right to obtain agricultural land for free. However, it has become increasingly more difficult to fulfill this right for the younger generation. Ethiopia currently faces severe land scarcity in parts of the highlands where population densities have become very high and farm sizes have become very small. As a result, land as a safety net is eroding and landlessness is emerging among the youth who are unable to stay on their parents' land. This is particularly true in parts of Southern Ethiopia where the majority of farmers cultivate less than one hectare of land [Bezu and Holden, 2014]. In this context, examining the non-land based environmental resilience of household wealth is a critical determinant of child poverty in Ethiopia.

Insert Table 4 about here

Table 4 illustrates an analysis of whether household wealth has any significant dynamic impact on the observed relationship between environmental shocks and child poverty for all ages. Table 4 shows the results of two-way fixed effects regressions: the interactive impact of agricultural shocks and household wealth on children's time use vis-à-vis schooling and labor. The analysis shows schooling, labor, and health results at the extensive margins, while the intensive margin results are shown for schooling and labor. The analysis portrays the impact of an agricultural shock as households get wealthier. The linear combination (i.e., $\hat{\alpha}_1 + \hat{\alpha}_3$) shows the total effect of agricultural shocks depending on the level of wealth of the household.

At the extensive margin, for poorer households, an agricultural shock insignificantly reduces children's schooling and general health by 0.7 pp (column 1) and 2.4 pp (column 3), respectively, but it significantly reduces child labor by 12.1 pp (column 2). At the intensive margin, for poorer households, agriculture shock significantly reduces schooling by 22.62 minutes (37% of an hour) (column 4) and increases child labor by 45 minutes (75% of an hour) (column 5). For wealthier households, agricultural shock insignificantly increases schooling by 2.9 pp (column 1), insignificantly decreases general health by 4.9 pp (column 3) but significantly increases the switch to child labor by 43.7 pp (column 2). At the intensive margin, for wealthier households, agriculture shock has insignificant impact on schooling, but it significantly reduces child labor by 102 minutes (column 5). The total effect of the agricultural shocks shows that they insignificantly increase schooling by 2.2 pp (column 1), insignificantly decreases general health by 7.2 pp (column 3) but significantly increases the switch to child labor by 31.6 pp (column 2). At the intensive margin, agriculture shock is not significant for schooling, but it significantly reduces child labor by 58 minutes (column 5).

Households in the sample are found to be using non-land-based wealth as a buffer against the negative impact of agricultural shocks on child education and health. However, at the extensive margin of joining the labor force, we find that wealthy households are more likely to have their child join the agricultural business. These results are consistent if persistent agricultural shocks can introduce a distortion in the land, labor and credit market. In the context of Ghana where land, labor and credit markets are imperfect, Bhalotra and Heady [2003] hypothesize and empirically show that households with land to farm have an incentive to employ child labor; this is what they call the "wealth paradox".

Insert Table 5 about here

A similar analysis of the interactive impact of agricultural shock and household wealth is done in Table 5 except in this analysis, the age of children is restricted to those below 15 years old to focus on the minimum age for employment under the 2019 Labour Proclamation.[13] At the extensive margin, the outcomes are schooling, labor, farming, and paid work[14] while at the intensive margin, the outcomes are schooling and labor. When the household is poorer, the extensive margin results show that an agriculture shock is not significant for schooling and child paid work but significantly reduces the switch to child

[13] Link to the proclamation.

[14] Here, labor is the sum of children's farming and paid work below the age of 15.

labor by 13.4 pp (column 2). On the other hand, at the intensive margin, for poorer households, agriculture shock significantly reduces schooling by 26 minutes (column 5) and is not significant for child labor. Results for poorer households highlight the constrained labor market impact of agricultural shock; lack of employment opportunities in farming when an agricultural shock occurs. On the other hand, for wealthier households, the effect of agricultural shock insignificantly reduces schooling by 5.3 pp (column 1) while the switch to child labor increases significantly by 55.4 pp (column 2).[15] However, at the intensive margin, wealth acts as a buffer against agricultural shocks by increasing schooling by 50 minutes (84% of an hour, column 5), and the impact is not significant for child labor. The linear combination indicating the total effect shows that agricultural shocks increase the switch to child labor by 41.6 pp (column 2). On the other hand, the total effect at the intensive margin shows that agricultural shocks have insignificant impact on schooling and labor. Thus, wealth plays a critical role as a buffer against agricultural shock. Overall, the extensive (switching) and intensive (time-use) analysis show the differential impact of wealth on child labor, and calls for more detailed surveys encompassing elements of time-use (intensity of labor) for children in developing economies.

5 Discussion & Conclusion

The persistence of agricultural shocks, though pervasive, has been under-examined in the literature, especially in the context of how these shocks affect child poverty outcomes in developing economies. With persistent agricultural shocks, household members can make adjustments in consumption, savings and investments as a coping mechanism. In such contexts, household wealth becomes a critical buffer against the negative impacts on schooling, labor, and health of children. Using two-way individual fixed effects and dynamic panel instrumental variable regressions, we examined the impact of agricultural shocks on education, child labor, and general health in a longitudinal study of young lives aged between 6 months and 22 years old. The study contributes to this literature in understanding the effect of recurring agricultural shocks in several ways. Firstly, we use an exogenous proxy for recurring and persistent agricultural shocks through a GMM-IV estimation model. Secondly, we examine household decisions as agricultural uncertainty becomes predictable in a dynamic setting. Thirdly, we consider the role of non-land-based household wealth in deciding household investments in child education, general health, and

[15]The main child labor impact for wealthier household is driven by farming and not paid work.

labor in a dynamic environment. Finally, as a unique contribution, we examine the effects of persistent agricultural shocks on the intensity of child education and labor through a time-use study.

Using the five survey waves over two age cohorts of children in Ethiopia, we find that agricultural shocks lead to children dropping out of school and joining the labor force. Agricultural shocks significantly reduce general health condition of children, even when we control for their body mass index. Agricultural shocks significantly reduce the time spent by children in school and leisure (playtime), but increase the time spent on child labor. Interestingly, there is a significant positive likelihood that children from wealthy households join the household tasks of farming and farm business when there is an agricultural shock, corroborating with the 'wealth paradox' [Bhalotra and Heady, 2003], but the positive child labor effect is reversed at the intensive margin, with regards to labor time, highlighting the issues with dichotomous measures of labor for children. Overall, wealthy families can mitigate the impact of agricultural shocks on the welfare of their children. Our findings point to the resilience of an economy, and underscores how wealth makes a difference in cushioning the anticipated adverse effects of shocks.

Notwithstanding the findings, the study has some limitations. In YLS surveys, poor areas were oversampled [Barnett et al., 2013], which raises internal and external validity concerns. Nonetheless, despite oversampling poor areas, the sample is representative of regions, policy contexts, living conditions, and rural and urban areas in Ethiopia. The Demographic and Health Survey, 2000, and the Welfare Monitoring Survey, 2000, also corroborated the representativeness of the YLS sample. Also, the comparisons of several living standard indicators showed that the samples in YLS were similar to those nationally representative in Ethiopia [Barnett et al., 2013]. In addition, in a longitudinal survey there is bound to be some level of attrition of participants either because of death[16], relocation, lack of formal addresses, or even a waning of interest from respondents. This loss of participants can lead to bias in the inferential results because of possible correlations with observable characteristics and sample selection [Outes-Leon and Dercon, 2009]. However, due to maintaining the same field supervisors over all rounds[17], the attrition rates were kept very low in Ethiopia at 5.3% for the younger cohort and 17.7% for the older cohort from round one to five, with the main reason for attrition being international migration (for 22-year-olds) and the sheer

[16]For instance, between Rounds 1 and 3 in the younger cohort, 72 children died in Ethiopia [Barnett et al., 2013].

[17]Having the same field supervisors for the 15 years cultivated cordial and stable relations with respondents [Lives, 2018].

impossibility to track some children [Barnett et al., 2013; Lives, 2018].

The implication of this study for future research is cross-cutting in both academia and policy circles. Firstly, the methodological approaches to understanding the impacts of agriculture shocks or similar persistent shocks should appreciate the fact that such shocks are mostly not exogenous and should thus be modeled accordingly. The persistent nature of agricultural shocks such as floods, droughts, pests, soil erosion, and frosts highlight their endogenous nature and the potential for biasing estimation results. Estimation approaches such as the dynamic panel data model (GMM-IV method) use lagged difference of dependent variables and lagged agricultural shock as instruments for resolving potential endogeneity and serial correlations. Secondly, in terms of policy, it is imperative to acknowledge that persistent agricultural shocks lead to the habit of adaptation, especially when wealth variation is present. Policymakers should form informed expectations about potential child outcomes wherever agricultural shocks are likely to be persistent, and the role that wealth, income, wage or insurance might have in mitigating the impact of such shocks on child outcomes. Agricultural shocks can hamper life-long outcomes for children, especially from non-wealthy households, hence appropriate incentives and fall-back options through insurance and educational subsidies should be in place where agricultural shocks are perennial.

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Table 1: Descriptive Statistics, Ethiopia, YLS, 2002-2016

Variable	Obs	Mean	Min	Max	Obs	Mean	Min	Max	t test
	No Agricultural Shock				Agricultural Shock				
No. of. Ag. Shocks	9013	0.00	-	-	5,892	1.844	1	8	
						(1.164)			
Dummy Variables (0/1)									
Schooling	9,103	0.600	0.00	1	5,892	0.505	0.00	1	0.095***
		(0.496)				(0.500)			
Labor	9,103	0.238	0.00	1	5,892	0.430	0.00	1	-0.192***
		(0.426)				(0.495)			
Gen. Health	5,083	0.842	0.00	1	3,178	0.772	0.00	1	0.070***
		(0.364)				(0.419)			
Time Use in Hours									
Hours of School & Study	9,103	4.464	0.00	19.00	5,892	3.579	0.00	16.00	0.885***
		(4.236)				(3.704)			
Hours of Farm Labor & Paid Work	9,103	1.087	0.00	20.00	5,892	1.790	0.00	16.00	-0.703***
		(2.524)				(2.630)			
Hours of Leisure	6,309	4.352	0.00	16.00	4,259	4.362	0.00	17.00	-0.010
		(2.819)				(3.147)			
Control Variables									
Wealth Index (0-1)	8,260	0.419	0.01	0.92	5,880	0.237	0.00	0.82	0.182***
		(0.194)				(0.147)			
Age in months/12	8,269	10.851	0.50	23.08	5,878	9.670	0.33	22.75	1.181***
		(6.070)				(5.609)			
Household Size	8,302	5.616	0.00	16.00	5,892	6.340	1.00	16.00	-0.725***
		(2.148)				(2.002)			
Body Mass Index	8,145	16.076	1.76	36.56	5,754	15.318	4.95	39.95	0.757***
		(2.732)				(2.293)			
Household Head's Education	8,092	7.646	0.00	30.00	5,782	6.994	0.00	29.00	0.651***
		(8.378)				(10.471)			

Significance $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. 't-test' is t-test for mean difference between the variables for households with and without agricultural shocks. Standard deviations are in the parentheses below the mean values. The variable General Health is coded as 0 for very poor, poor and OK health, and 1 for good and very good health, and the data for the same is available in round 3, 4 and 5 only.

Table 2: Dynamic GMM-IV, Fixed Effects and OLS: Impact of Agricultural Shocks on Time Use in Schooling, Labor and Health. YLS, Ethiopia, 2002-2016

	(1)	(2)	(3)	(4)	(5)
	Dummy			Time Use	
Variables	Schooling	Labor	Gen Health	Schooling	Labor
Panel (a) GMM-IV					
Ag. Shocks	-0.030***	0.017**	-0.024***	-0.269**	0.653**
	(0.006)	(0.007)	(0.005)	(0.135)	(0.313)
Two stage q values	0.001	0.034	0.006	0.104	0.022
Sargan-overidentification	0.417	0.312	0.536	0.160	0.441
Observations	13,571	13,571	7,925	7,998	4,690
Number of individuals	2,981	2,981	2,836	2,847	2,032
Panel (b) Fixed Effects					
Ag. Shocks	-0.009**	0.012***	-0.024***	-0.100***	0.133***
	(0.004)	(0.004)	(0.006)	(0.020)	(0.036)
Two stage q values	0.013	0.001	0.006	0.004	0.011
Observations	13,571	13,571	7,925	7,998	4,690
Number of individuals	2,981	2,981	2,836	2,847	2,032
Panel (c) OLS					
Ag. Shocks	-0.037***	0.083***	-0.031***	-0.330***	0.163***
	(0.003)	(0.003)	(0.005)	(0.015)	(0.025)
Two stage q values	0.001	0.004	0.003	0.007	0.007
Observations	13,571	13,571	7,925	7,998	4,690

Note: The treatment variable represents agricultural shocks to the household. Control variables include age and BMI of the child, household head's education, household size and the wave intercept for the 5 rounds, 2002, 2007, 2009, 2012, 2016. Labor includes time spent in household task of farming and and farm business, and paid market work activity. Columns 1,2, and 3 have dummy variables as outcome variables with the coefficients of β being interpreted as percentage point changes. Columns 4 and 5 have outcomes conditional on a positive time spent in the said activity, the β coefficient are interpreted in percent of hours. Dynamic panel data based over-identifications criteria are met in all specifications [Chao et al., 2014]. Standard errors are clustered at the individual level. The sharpened two stage q-values are derived from Anderson [2008] to reduce the likelihood of false rejections when testing multiple hypotheses. Significance $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3: GMM-IV: Effects of Ag. Shocks on Children Time Use in Schooling, Labor and Leisure at the Intensive Level. YLS, Ethiopia, 2002-2016

	(1)	(2)	(3)	(4)	(5)	(6)
	Unconditional			Conditional		
	Schooling	Labor	Leisure	Schooling	Labor	Leisure
Panel (a)						
Any Ag. Shock (0/1)	-0.707***	0.472**	0.158	-0.475*	1.122*	0.147
	(0.178)	(0.202)	(0.131)	(0.263)	(0.612)	(0.137)
Two stage q values	0.002	0.021	0.045	0.067	0.079	0.033
Sargan over-identification	0.447	0.928	0.564	0.137	0.338	0.421
Observations	13,571	13,571	10,229	7,998	4,690	10,126
Number of individuals	2,981	2,981	2,879	2,847	2,032	2,879
Panel (b)						
More than 1 Shock	-0.849***	0.557***	-0.319***	-0.549**	0.744*	-0.222**
	(0.170)	(0.162)	(0.103)	(0.255)	(0.316)	(0.095)
Two stage q values	0.003	0.007	0.006	0.033	0.118	0.028
Sargan over-identification	0.471	0.916	0.490	0.110	0.282	0.342
Observations	13,571	13,571	10,229	7,997	4,684	10,126
Number of individuals	2,981	2,981	2,879	2,847	2,030	2,879
Panel (c)						
More than 2 Shocks	-1.407***	0.594***	-0.104	-0.989***	0.166	-0.068
	(0.239)	(0.200)	(0.130)	(0.214)	(0.490)	(0.123)
Two stage q values	0.003	0.004	0.329	0.006	0.877	0.991
Sargan over-identification	0.656	0.889	0.530	0.100	0.229	0.352
Observations	13,571	13,571	10,229	7,997	4,684	10,126
Number of individuals	2,981	2,981	2,879	2,847	2,030	2,879

Note: Dynamic panel instrumental variable regressions with Generalized Methods of Moments in all specifications [Andrews and Lu, 2001]. Treatment variable is more than one and two agricultural shocks to the household since the past survey. Control variables include wave intercept for the 5 rounds, 2002, 2007, 2009, 2012, 2016. Age of the child, household head's education, household size and the Body Mass Index (bmi) for the child. Labor includes time spent in household task of farming and and farm business. Unconditional regressions are irrespective of time spent in the said activity, while, conditional regressions are conditional on a positive time spent in the said activity. Standard errors are clustered at the individual level. The sharpened two stage q-values are derived from Anderson [2008] to reduce the likelihood of false rejections when testing multiple hypotheses. Significance $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Fixed Effects: The Interactive Impact of Agricultural Shock and Household Wealth on Child's Time Use in Schooling, Labor and Leisure. YLS, Ethiopia, 2002- 2016

	(1)	(2)	(3)	(4)	(5)
	Dummy			Time Use	
Variables	Schooling	Labor	Gen Health	Schooling	Labor
Ag. Shock (0/1)	-0.007	-0.121***	-0.024	-0.377***	0.751***
	(0.016)	(0.017)	(0.029)	(0.124)	(0.241)
Wealth Index	-0.082*	-0.134***	0.099	0.319	2.875***
	(0.046)	(0.046)	(0.065)	(0.312)	(0.673)
Wealth*Shock	0.029	0.437***	-0.049	0.526	-1.712**
	(0.048)	(0.052)	(0.080)	(0.353)	(0.746)
$\hat{\alpha}_1 + \hat{\alpha}_3$	0.022	0.316***	-0.072	0.149	-0.961*
	(0.035)	(0.039)	(0.055)	(0.247)	(0.540)
Observations	13,524	13,524	7,912	7,986	4,682
R-squared	0.518	0.266	0.014	0.085	0.215
Number of individuals	2,980	2,980	2,836	2,828	1,997

Robust standard errors in brackets, clustered at the individual level. Significance $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: Fixed Effects: The Interactive Impact of Agricultural Shock and Household Wealth on Time Use in Schooling and Labor for age less than 15, YLS, Ethiopia, 2002-2016

	(1)	(2)	(3)	(4)	(5)	(6)
	Dummy (0/1)				Time-use	
Variables	Schooling	Labor	Farming	Paid Work	Schooling	Labor
Ag. Shock (0/1)	0.011	-0.134***	-0.130***	-0.003	-0.433***	-0.131
	(0.016)	(0.020)	(0.021)	(0.012)	(0.138)	(0.244)
Wealth Index	0.077*	-0.160***	-0.141**	-0.005	0.308	1.164
	(0.043)	(0.054)	(0.058)	(0.034)	(0.346)	(0.808)
Wealth*Shock	-0.053	0.551***	0.514***	-0.004	0.841**	0.196
	(0.050)	(0.061)	(0.066)	(0.038)	(0.398)	(0.751)
$\hat{\alpha}_1 + \hat{\alpha}_3$	-0.041	0.416***	0.384***	-0.007	0.408	0.064
	(0.038)	(0.046)	(0.051)	(0.028)	(0.281)	(0.550)
Two stage q values	0.209	0.001	0.002	0.593	0.119	0.933
Observations	10,294	10,294	10,294	10,294	5,527	2,861
Number of individuals	2,978	2,978	2,978	2,978	2,777	1,638

Robust standard errors in brackets, clustered at the individual level. Significance ***$p <$ 0.01, **$p < 0.05$, *$p < 0.1$. Here, labor is the sum of farming and paid work activity for the child below 15 years.

Online Appendix

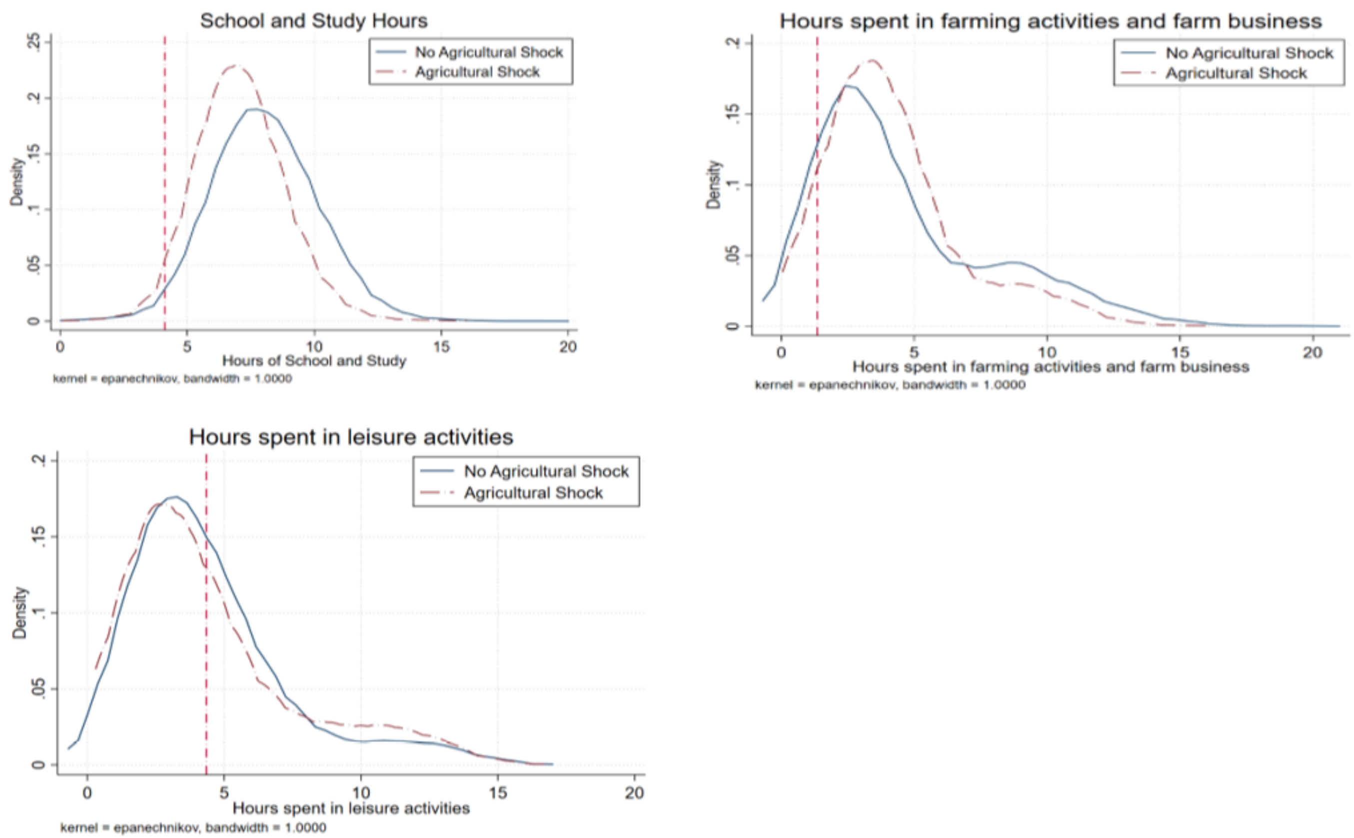

Figure A1: Kernel densities with and without agricultural shocks in Ethiopia, YLS, 2002-2016

Note: vertical dashed lines are the mean values of hours spent on different activities irrespective of the presence (or lack there of) of agricultural shocks.

Table A1: Predicting the occurrence of agricultural shocks in Ethiopia using Probit regressions, YLS, 2002-2016.

	(1)	(2)	(3)
Variables	Agricultural Shock		
	Probit	Probit	Probit
Lag Wealth Index	-1.125***	-0.892***	-0.687***
	(0.017)	(0.025)	(0.028)
Lag Hours of School & Study		-0.028***	-0.081***
		(0.003)	(0.003)
Lag Farm-Labor & Business		-0.003	-0.004
		(0.003)	(0.003)
Lag Unpaid Care & Chores		-0.015***	-0.012***
		(0.003)	(0.003)
Lag Leisure		-0.027***	-0.022***
		(0.004)	(0.004)
Lag Agricultural Shock			0.182***
			(0.009)
Observations	11,483	7,925	7,925

Control variables include the wave intercept for the 5 rounds, 2002, 2007, 2009, 2012, 2016. Coefficients are interpreted as average marginal effects. Significance $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors derived from the delta method and clustered at the individual level.