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HOW DO IDIOSYNCRATIC AND COVARIATE SHOCKS AFFECT HUMAN CAPITAL OUTCOMES FOR ETHIOPIAN CHILDREN

MOHAMMAD ALI [a] AND JANAK JOSHI [b]

[a] *Centenary College of Louisiana, U.S.A*
[b] *Hood College, U.S.A*

Previous literature has mostly looked at the impact of singular shocks on children's human capital. In this paper, we explore how disparate idiosyncratic and covariate shocks affect the cognitive, health and time allocation outcomes for a sample of Ethiopian children during the later stages of childhood. We also examine how these relationships differ based on rural/urban location and age groups. Employing a fixed effects panel model, we find that loss of employment, theft, damage to home, and pests affecting crops have the highest negative impact on multiple dimensions of human capital. Moreover, we also find that monetary shocks, especially in rural areas, affect children's human capital more than natural disasters in Ethiopia. Finally, the relationship between shocks and human capital changes based on the location and age group of the child.

Keywords: Shocks, Human Capital, Cognition, Health, Time Allocation
JEL Classification: D13, I14, J22, J24, Q54

1. INTRODUCTION

Recent medical and economics research has shown that genetics alone does not determine the production of human capital for children. This strand of research has highlighted the role that household investments and the social environment can play in affecting human capital outcomes (Barker, 1995; Gluckman and Hanson, 2005; Rosales-Rueda, 2018; Akresh et al., 2021; Ali and Villa 2023). On the other hand, shocks experienced during childhood may negatively impact human capital outcomes throughout its lifecycle of production (Cunha and Heckman, 2007; Heckman, 2007; Almond and Currie, 2011). These shocks range from natural disasters (Almond et al., 2010; Dercon and Porter, 2014; Rabassa et al., 2014) and pandemics (Kelly, 2011) to wars (Agüero and Deolalikar, 2012; Akresh et al., 2021; León, 2012) and man-made disasters (Black et al., 2019). In the existing literature, most of these shocks have been studied in the context of their relationship with health outcomes. However, there is a growing literature which looks at their impact on cognitive, and time allocation dimensions of human capital for children. This paper contributes to this branch of literature.

In this paper, we examine how disparate idiosyncratic (which affect specific households) and covariate (which affect the community) shocks affect multiple dimensions of human capital outcomes for a sample of Ethiopian children. We divide the idiosyncratic shocks into monetary and household composition shocks. The covariate shocks are divided into two main subgroups of natural disasters and economic shocks. We look at how these different types of shocks impact three separate dimensions of human capital: cognitive, health, and time allocation. We rely on the data from the Ethiopian younger cohort from Young Lives (YL) dataset to investigate the relationship between the above-mentioned shocks and human capital outcomes. More specifically, we look at which shocks affect human capital outcomes the most. We also look at whether idiosyncratic or covariate shocks have a more negative impact on children’s human capital. Furthermore, we extend our analysis to see if children from rural and urban areas respond differently to shocks. Finally, we attempt to find if idiosyncratic and covariate shocks affect human capital outcomes differently during distinct stages of childhood. These research questions have the potential to inform policy making, pointing out the specific shocks and time periods which pose the most risk to children’s human capital outcomes.

We contribute to the existing literature in multiple ways. First, most of the previous research based on the YL dataset has focused on the effect of shocks on a single dimension of human capital (Galab and Outes-Leon, 2011; Dung, 2013; Berhane et al., 2015). More specifically, most of the existing literature on developing countries has focused on children’s health outcomes with a limited number of studies focusing on cognitive and time allocation outcomes (Shah and Steinberg, 2012; Aguilar and Vicarelli. 2018). In this paper, we look at the effect of shocks on multiple variables within the three (cognitive, health, and time allocation) human capital dimesnsions as well as examine whether shocks affect human capital differentially by their dimension. Second, we include a variety of idiosyncratic and covariate shocks in our analysis which gives a more complete picture of which shocks affect human capital outcomes the most. Most of the previous literature on human capital formation often looked at extreme covariate shocks which are comparatively rare than idiosyncratic shocks (Ampaabeng and Tan, 2013; Bundervoet and Fransen, 2018; Rosales-Rueda, 2018; Akresh et al., 2021). Exploring the effects of both idiosyncratic and covariate shocks separately is also important as the former have been found to have a smaller negative impact on human capital. This is because in response to idiosyncratic shocks, pooling of risks at the community level can occur (Townsend, 1994; Pan, 2009). Third, we rely on the geographic variation provided in our sample and examine the effect of shocks on children from rural and urban households separately. Shocks are likely to have different effects on rural versus urban children because of differences in social safety nets, access to food and health etc. Finally, most of the previous literature has highlighted the first four years of children's lives as the most important for human capital development (Cunha et al., 2010; Victoria et al., 2010; Almond and Currie, 2011; Currie, 2011; Lynch and Gibbs, 2017). This mitigates the potential negative impact that shocks might have during the later stages of childhood. Therefore, we focus on the later stages of childhood and look at the effect of shocks at distinct stages of later childhood separately.

The results from the fixed effects panel estimation suggest that loss of employment, theft, damage to home, and pests affecting crops have the greatest negative impact on different dimensions of children's human capital. Overall, monetary shocks, especially in rural areas, seem to affect human capital outcomes more than natural disasters. We also find that the health outcomes are generally more resilient in the face of shocks compared to cognitive and time allocation outcomes. This resiliency of health outcomes increases as the children grow older. Moreover, results from the separate samples from children at different age groups shows that when 5 to 8 years old children are faced with a shock, they become part of the child labor force and remain there. Finally, household composition shocks and natural disasters have a lower impact on human capital outcomes at ages 8 to 12 in comparison to at ages 5 to 8.

2. LITERATURE REVIEW

The impact of covariate shocks especially natural disasters in relation to health outcomes has been well-investigated in the previous literature, with a relatively lesser focus on the relationship with cognitive and schooling outcomes (Baez et al., 2010). Although, the majority of the evidence points to covariate shocks affecting the human capital outcomes negatively by decreasing investments in children's human capital as well as households resorting to sub-optimal coping mechanisms (Escobal et al., 2005; Beegle et al., 2006; Dung, 2013; Berhane et al., 2015), there is some evidence to the contrary where covariate shocks seem to positively impact human capital outcomes (Black and Sokoloff, 2006; Boo, 2012; Shah and Steinberg, 2012; Baloch and Behrman, 2014; Dornan et al., 2014). The latter likely results from the substitution effect of the shock dominating the income effect. Further discussion on this can be found in the Methodology section.

Idiosyncratic shocks including monetary shocks e.g. loss of employment, theft, long-term unemployment etc., and household composition shocks e.g. death of a household member are shown to cause a significant reduction in household income and even lead to poverty (Acs et al., 2009; Acs and Nichols, 2010; Zedlewski and Nichols, 2012). Thus, idiosyncratic shocks can lead to less access to healthcare (Mills and Amick, 2011), food insecurity (Coleman-Jensen et al., 2012), and school absenteeism (Alaimo et al., 2001; Cook and Frank, 2008; Ramsey et al., 2011) exacerbating the human capital outcomes for children. Although, pooling of resources at the community-level can occur, idiosyncratic shocks can have a larger impact in developing countries where the governmental support for households is lacking in the face of such shocks (Mani et al., 2013; Bogliacino et al,. 2017; Kampfen et al., 2022).

As mentioned above, previous literature on shocks in developing countries has indicated that compared to covariate shocks, the negative effects of idiosyncratic shocks are sometimes insured by pooling the risk at the community-level (Townsend, 1994; Pan, 2009). Some of the coping strategies against idiosyncratic shocks that have been seen in developing countries include strategic storage of grains for the next growing season, ownership of assets such as cattle, availability of credit from informal sectors, as well as direct transfers from familial and community linkages (Townsend, 1994).

When it comes to the timing of shocks, there is a general consensus in the existing literature that shocks experienced during the first four years of a child's life have the largest negative influence on their human capital outcomes (Cunha et al., 2010; Victoria et al., 2010; Almond and Currie, 2011; Currie, 2011; Lynch and Gibbs, 2017). This time period has been referred to as a "sensitive period" because of its relative importance for the development of human capital (Cunha and Heckman, 2007; Almond and Currie, 2011). But there is a growing literature that points to the importance of later stages of childhood (after age four) and adolescence by concluding that shocks experienced in these time periods can also negatively impact human capital outcomes (Case and Paxson, 2008; Agüero and Deolalikar, 2012; Akresh et al., 2021).

Idiosyncratic and covariate shocks in Ethiopia have been found to worsen the already high rates of malnutrition, child labor and primary school dropout (Woldehanna, 2012). As Ethiopia does not have specific social programs targeting the welfare of children, shocks deteriorate their human capital outcomes in the short and long run (Berhane et al., 2017). Shocks in Ethiopia have been mostly found to affect children's outcomes through the income channel. Since an average Ethiopian household spends two-thirds of its income on food, any shocks have the potential to reduce the food supply of the households, in turn affecting the nutritional, cognitive, and time allocation outcomes for children (Berhane et al., 2012). The above-mentioned problems faced by Ethiopian children provide a unique opportunity to explore the patterns of human capital formation in the face of exogenous shocks within a developing country setting.

3. METHODOLOGY

3.1. Theoretical Framework

As mentioned in the previous section, there is a general consensus that shocks experienced during childhood affect human capital outcomes. What is less clear is how much do different types of shocks affect the diverse dimensions of human capital. In this paper, we explore how a variety of idiosyncratic and covariate shocks affect the cognitive, health and time allocation dimensions of human capital for Ethiopian children.

Looking at a list of shocks rather than a singular shock will highlight the shocks that have the potential to affect the children's human capital the most. Moreover, exploring the effect of shocks on the multiple dimensions of human capital will reveal whether specific shocks affect all aspects of human capital equally or differentially. Both of the above approaches will better inform future policymaking by highlighting where scarce resources should be directed at the time of shocks. Finally, we also examine whether the effect of shocks is different for rural versus urban children, and for different stages of childhood.

We broadly consider two categories of shocks in our analysis: idiosyncratic and covariate. Idiosynncratic shocks are those which are localized, for example a household suffering from theft or a death in the family is said to have experienced an idiosyncratic shock. On the other hand, covariate shocks are experienced at the community-level, for example a flood affecring many households at the same time is termed as a covariate shock. We further divide the idiosyncratic shocks into two subcategories of monetary and household composition shocks. The former comprises of loss of employment, theft, and damage to home while the latter is made up of whether the household suffered from the father's or mother's death. We also divide the covariate shocks included in our analysis into two subcategories of natural disasters and economic shocks. The natural disasters are made up of drought, flooding, pests affecting crops, and crop failures while the economic shocks consist of forced taxation, input price increase, and output price increase.

Including a variety of idiosyncratic and covariate shocks lets us observe their heterogeneous effects on human capital. This is important because idiosyncratic and covariate shocks are fundamentally very different from each other. First, covariate shocks in addition to having the income effect are also likely to exhibit a substitution effect through the depressed opportunities in the post-shock labor market. For example, a natural disaster affecting an entire community will reduce the households' disposable resources. Taking study time as an example, this negative income effect will reduce investment in schooling, ultimately decreasing the allocation of study time. However, the substitution effect will work in the opposite direction as the opportunity cost of studying decreases due to lesser employment opportunities. Whichever of the two effects dominates will determine the total effect of a covariate shock. A similar logic applies to how covariate shocks affect health outcomes for children, where depending on the post-shock labor market opportunities, more of the parental time might be allocated towards cooking healthy food and gathering clean drinking water (Ferreira and Schady 2009). If more parental time is allocated for these activities, the substitution effect might outweigh the income effect.

Second, idiosyncratic and covariate shocks are also intrinsically different from each other as the former may be better cushioned by pooling of resources at the community-level. This is less likely in response to covariate shocks as the resources of the whole community are negatively affected. On the other hand, in a developing country, the governmental response to covariate shocks might outweigh that for individual households suffering an idiosyncratic shock (Mani et al., 2013; Bogliacino et al., 2017; Kampfen et al., 2022). Thus, it would be interesting to ascertain which of the two responses (community pooling and governmental assistance) or both are effective in the face of shocks in Ethiopia.

It is also important to include multiple dimensions of human capital in our analysis. We include three broad dimensions of human capital namely cognitive, health, and time allocation. The cognitive dimension is made up of two separate measures: Peabody Picture Vocabulary Test (PPVT) scores and mathematics test scores. These tests measure receptive vocabulary and mathematics skills respectively (Paxson and Schady, 2007) and use different parts of the brain (Sousa, 2011). It might be possible that specific shocks affect separate parts of the brain having differential impacts on vocabulary and mathematics skills.

We also include two separate mesures of health namely height-for-age z-scores (HAZ) and body mass index for age z-scores (BMI) in our analysis. Both these measures are widely accepted as better measures of nutrition than those derived from food consumption data (Ali and Villa, 2022). HAZ can be thought of as a cumulative measure of health meaning that it is less susceptible to changes in the short-run. On the other hand, because BMI is affected by weight, which can vary in the short-run, it can be thought of as a short-run measure of health. Overall, HAZ and BMI can be considered as measures of the stock and flow of wealth respectively. Thus, examining both these measures in relationship to shocks will reveal how shocks affect health outcomes differently in the short- and long-run.

Finally, it is important to include both study time and work time in the time allocation dimension for human capital. Increases in study time can generally affect children's human capital outcomes positively. But if this increase is accompanied by increases in work time, the directional effect of shocks on human capital might not be very straightforward. In fact, previous literature has shown that climatic shocks can leave school enrolment unaffected but the children end up learning less due to some of their time being allocated for fetching water and farm work (Lewis and Serna, 2011; Colmer, 2013).

We explore the relationship between shocks and human capital outcomes by utilizing data at ages 5, 8, and 12. These stages of childhood cover the Piaget's pre-operational (5 to 8) and concrete operational (8 to 12) stages of cognitive development. The former is marked by the recognition and representation of events and objects, while the latter signifies the formal start of the use of inductive logic (Wadsworth, 2004). Thus, the impact of shocks might reveal the different levels of children's resiliency at critical stages of development.

When it comes to the question of whether the shocks analyzed in this paper can truly be considered exogenous, it would be reasonable to think that covariate shcoks e.g. droughts and floods would be exogenous. However, the exogeneity of household-level idiosyncratic shocks might be harder to justify. For example, job loss could be related to undisciplined and less responsible parents, theft and damage to home could be related to neighborhood characteristics. If this was the case we should expect to see a high correlation between all the household-level idiosyncratic shocks that are employed in the paper. Tables A1, A2, and A3 in the appendix present the correlation matrices between all shocks from the three rounds of data collection. All three tables generally show a low level of correlation between the different idiosyncratic shocks with the highest correlation coefficient being 0.11 (between father's and mother's death at age 5). Magnitudes of coefficients this small show little or no linear correlation. Moreover, the resulting coefficients of determination are also small enough to not explain much variation in an idiosyncratic shock that results from variation in another idiosyncratic shock. Thus, the overall small magnitudes of the correlation coefficients makes us confident in the exogeneity of idiosyncratic shocks used in the paper.

Another concern is that the household-level idiosyncratic shocks might be endogenous to the occurrence of some of the covariate shocks. For instance, job loss and theft might occur along with natural disasters. Tables A1, A2, and A3 again reveal low magnitudes of correlation coefficients between the idiosyncratic and covariate shocks. We see some of these coefficients of correlation as being statistically significant at 1% level of significance. However, the small magnitudes of the coefficients of determination imply that these are cases of weak correlations that are statistically significant.

The only place where we see some albeit low level of correlation in Tables A1, A2, and A3 is between covariate shocks. But these can be explained through the fact that some of the covariate shocks can occur together. For example, droughts and flooding can result in crop failures. Similarly, natural disasters can lead to input price increase. Thus, it can be expected that some of the covariate shocks would overlap with each other. This makes us more confident in the exogeneity of drought and flooding compared to other covariate shocks as the former can cause the latter to occur. Nevertheless, the low levels of correlation resulting in low coefficients of determination between drought and flooding with other covariate shocks implies that the overlap between shocks is not considerable.

3.2. Empirical Model

Empirically, we Estimate equation (1) to explore how idiosyncratic and covariate shocks affect the different dimensions of human capital. HC_{jt}^{k} is the kth dimension of human capital for the child in household j at time t, that is affected by S_{jt}^{m}, the idiosyncratic/covariate shock m suffered by the child in household j at time t. Lastly, X_{jt}, and V_{jt} are vectors of household- and community-level control variables respectively.

$$HC_{jt}^{k} = \beta_0^{km} + \beta_1^{km} S_{jt}^{m} + \beta_2^{km} X_{jt} + \beta_3^{km} V_{jt} + \alpha_j^{km} + \varepsilon_{jt}^{km}, \tag{1}$$

In Equation (1), α_j^{km} is the unobserved time-invariant household effect in the relationship between shocks and human capital, ε_{jt}^{km} is the error term. X_{jt} includes the sex of the child, whether the household had access to health and food aid, strength of social network, dietary diversity, indices for wealth, housing quality, housing services, and consumer durables, both parent's level of education, parental aspirations, whether the child is currently in school and in private school, household size, ethnicity, religion, as well as whether the household head is the mother. Finally, V_{jt} consists of whether the household is rural or urban, and the cluster location of the household. S_{jt}^{m} takes the value of 1 when the child suffered from the shock and 0 if the shock did not affect the child at time t. When consistently estimated, β_1^{km} will provide the effect of idiosyncratic and covariate shocks on the different dimensions of human capital included in the empirical model. The coefficient β_1^{km} is estimated with clustered standard errors at the primary sampling unit (PSU).

Equation (1) is also estimated separately for children from rural and urban households because of differences in social safety nets, access to food and health etc. We also estimate equation (1) separately for children when they were between ages 5 to 8, and 8 to 12 years as these ages coincide with Piaget's stages of childhood development. Hence, there might be different dynamics at play during each of these distinct stages of childhood development. For the total sample, rural and urban subsamples, as well as subsamples with different age groups, Equation (1) is estimated using a fixed effects panel model.

4. DATA

4.1. Dataset

To explore the impact of idiosyncratic and covariate shocks on children's human capital outcomes, we use panel data from the Ethiopian module of the YL dataset. The YL dataset is collected and compiled by University of Oxford's Department of International Development and tracks two separate groups of 2000 younger and 1000 older children. Data from these two groups was collected in 2002, 2006, 2009, and 2013. We only employ the data from the last three rounds of the younger cohort as the children are 5, 8, and 12 years old at the time of data collection. These ages correspond to the later stages of childhood as well as Piaget's pre-operational and concrete operational stages of childhood development, which is the focus of our study.

The YL data sampled poor households, as the aim of data collection was to understand how the dynamics of poverty affect children. With this aim in mind, the YL project collected data on the economic, social, psychosocial, health, and environmental characteristics at the child, household, and community level. These data came from the four major regions of Ethiopia: Amhara, Oromia, SNNP, and Tigray that comprise approximately 78% of the overall Ethiopian population. Thus, the collected sample is well representative of the Ethiopian population (City Population, 2015). Twenty districts (woredas) were selected from the above-mentioned regions, and one community was selected from each district. The final sample comprised 100 randomly chosen households from each selected community where the households selected had at least one child born between 2001 and 2002 (Morow, 2009). For more information on the YL's data collection methodology refer to Outes and Sanchez (2008).

4.2. Key Variables

The data for idiosyncratic and covariate shocks in our analysis comes from the "Economic History and Recent Life History" module of the YL dataset's child questionnaire. A separate question was asked by the data collectors for each shock to ascertain whether the household suffered from the shock since the last round of data collection. For example, the question recording the data for drought in round two of the YL dataset went as follows: "Have you experienced drought in the last four years?". The shock variables take the value of one if the household suffered from the shock and zero if it did not.

The data for the cognitive dimension of human capital comes from the PPVT and mathematics test scores conducted during the second, third, and fourth rounds of data collection. Both these tests have been commonly used measures of cognition in previous literature (Paxson and Schady, 2007). During the PPVT test, children chose one out of four pictures that best represented the meaning of the words presented to them by the data collectors. On the other hand, the mathematics test mostly consisted of basic mathematical skills such as addition, subtraction etc. with the level of difficulty varying by the age of children during different rounds. The mathematics test conducted in the second round was the Cognitive Development Assessment Quantity Test while in the third and fourth rounds was the Mathematics Achievement Test. We standardize the PPVT and mathematics test scores to make sure that comparison between rounds is possible. The YL data collectors measured and recorded the data for HAZ and BMI for all three rounds of data used in our analysis.

Finally, we constructed the study time and work time variables from the data on time allocation available in the YL dataset. The YL data collectors gathered data on how many hours the child spent during a typical day in the last week for different activities. We constructed the study time variable by adding the number of hours spent at school and studying outside of school. We created the work time variable by adding the number of hours spent on paid activities, unpaid work on family farm/business, and domestic activities (fetching water, fetching firewood, cooking, washing, etc.).

We observe some sample loss after combining the data from the three separate rounds in our analysis. For example, with PPVT scores as the dependent variable, the sample size comes out to be 4,808, with 1,649, 1,684, and 1,475 from rounds two, three, and four respectively. This sample size is out of a possible maximum of 6,000 observations from the three rounds. The sample loss becomes higher for mathematics test scores, and study time/work time because of greater number of missing observations in the fourth and second rounds for these variables respectively. However, looking at the socioeconomic variables of the missing versus non-missing observations seems to suggest that the sample loss is not systematic.

Table 1 provides the summary statistics for the key variables used in our empirical model with means and standard deviations at different ages as well as for the overall sample. PPVT and mathematics test scores have means and standard deviations close to 0 and 1 respectively at all ages. This is purely because we are using standardized cognition scores for the purposes of comparison across rounds. The mean for HAZ is less than -1 and greater than -2 at all ages which denotes that on average children in the sample are mildly stunted (WHO, 2008). BMI on average shows a gradual decline from ages 5 to 12 with a mean of -1.804 at age 12. Thus, as the children grow, they are getting closer to the World Health Organization's (WHO) range for "wasted" which starts below a BMI of -2 (WHO, 2008). The mean for study time increases steadily as children grow older and start formal school education. Work time increases sharply from ages 5 to 8 and then remains roughly the same on average. This implies that on average children start school and increasingly become part of the child labor force around the same time.

Table 1. Summary Statistics

	Overall		Age 5		Age 8		Age 12	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
PPVT	-0.038	0.984	-0.039	0.974	-0.032	0.981	-0.045	0.999
Math	-0.006	0.982	-0.002	0.977	-0.037	0.978	0.027	0.991
Height for Age	-1.353	1.056	-1.425	1.103	-1.224	1.069	-1.42	0.97
BMI for Age	-1.236	1.105	-0.66	1.063	-1.301	0.952	-1.804	0.993
Study Time	5.299	3.572	2.113	3.55	5.845	3.055	7.156	2.262
Work Time	2.769	2.399	1.244	2.091	3.214	2.312	3.448	2.194
Loss of Employment	0.101	0.301	0.101	0.302	0.112	0.316	0.087	0.282
Theft	0.064	0.244	0	0	0.1	0.3	0.093	0.291
Damage to Home	0.008	0.088	0.001	0.025	0.017	0.128	0.005	0.073
Father's Death	0.022	0.148	0.028	0.166	0.023	0.149	0.016	0.124
Mother's Death	0.015	0.12	0.019	0.136	0.017	0.128	0.007	0.086
Drought	0.27	0.444	0.289	0.454	0.354	0.478	0.151	0.358
Flooding	0.126	0.332	0.149	0.356	0.138	0.345	0.088	0.284
Pests affecting Crops	0.071	0.257	0.073	0.261	0.072	0.258	0.068	0.251
Crop Failures	0.235	0.424	0.22	0.414	0.271	0.444	0.211	0.408
Forced Taxation	0.032	0.177	0.027	0.163	0.042	0.2	0.027	0.162
Input Price Increase	0.289	0.454	0.303	0.46	0.389	0.488	0.161	0.367
Output Price Decrease	0.049	0.216	0.059	0.236	0.053	0.225	0.032	0.176

From the monetary shocks, roughly 10% of the households suffered from loss of employment in each round. Comparatively, fewer households suffered from theft and damage to home. Household composition shocks (father's death and mother's death) comprised of less than 3% of the sample in each round. Households that suffered from drought peaked at age 8 (in 2006) with 35.4% but came down to 15.1% at age 12 (in 2009). This might be the result of the major drought suffered by Ethiopia in 2002-03 (De Waal et al., 2006). The other natural disasters in descending order of the number of households impacted were crop failures, flooding, and pests affecting crops. Finally, from the economic shocks category, at least 16% of the households suffered from an input price increase in each round, while less than 6% of the households suffered from forced taxation and output price decrease at any age.

5. RESULTS

Table 2 provides the results from the estimation of Equation (1) for the total sample. All the estimated coefficients in Table 2 are from separate regressions of Equation (1) with different combinations of human capital outcomes and shocks. In the case of monetary shocks, we find that PPVT scores have a negative and significant (at the level of 1%) relationship with theft in Ethiopia, where households that suffered theft had a reduction of 0.127 standard deviations in the child's PPVT scores. However, we find an insignificant relationship between PPVT scores and loss of employment and damage to home. This might be because, as indicated earlier, different cognition test scores might be measuring the cognitive ability of different parts of the human brain. Supporting this idea, we find a negative and significant relationship between mathematics test scores and all three monetary shock variables. This might also allude to the possibility of the existence of substitution effect between different kinds of cognitive abilities. For example, because of the post-shock time constraint a child in the sample might be allocating more time to a particular subject of study over others. This can ultimately result in a differential impact of shocks on PPVT and mathematics test scores as indicated by Zamand and Hyder (2016).

When it comes to the effect of monetary shocks on health outcomes, we find that apart from theft affecting BMI negatively, none of the monetary shocks have a significant relationship with HAZ and BMI. This shows that short- and long-term health, as denoted by BMI and HAZ, are generally more resilient to monetary shocks than cognitive outcomes. Moreover, health outcomes like HAZ and BMI are closely associated with food intake and people in the social network are more likely to provide assistance that alleviates any food shortage. This kind of assistance points towards a better pooling of resources at the community-level in Ethiopia for health outcomes in the face of monetary shocks.

Finally, all the monetary shocks increase work time significantly. Within monetary shocks, the coefficient for work time is the highest for damage to home (0.996). This is possibly because of the higher allocation of work time towards rebuilding the dwelling. However, for all the monetary shocks, the positive and significant coefficients for work time are accompanied by insignificant coefficients for study time. Moreover, the latter exist alongside negative and significant coefficients for cognition test scores. This possibly alludes to the fact that when Ethiopian households suffer from monetary shocks, children keep on attending school but learn less because of increased participation in child labor leading to lower attention spans in the classroom.

Table 2. Effect of Shocks on Human Capital Outcomes

	Human Capital Outcomes					
	PPVT	Math	Height for Age	BMI for Age	Study Time	Work Time
Idiosyncratic Shocks						
Monetary Shocks						
Loss of Employment	-0.00268	-0.115**	-0.0464	-0.0231	0.125	0.273*
	(0.0547)	(0.0465)	(0.0303)	(0.0454)	(0.0799)	(0.145)
Theft	-0.127**	-0.157***	-0.0430	-0.141**	-0.133	0.653**
	(0.0505)	(0.0546)	(0.0432)	(0.0562)	(0.157)	(0.230)
Damage to Home	-0.112	-0.283***	0.102	0.161	-0.407	0.996*
	(0.114)	(0.0964)	(0.119)	(0.137)	(0.278)	(0.507)
Household Composition Shocks						
Father's Death	0.0334	-0.0415	0.0328	0.0458	0.102	0.132
	(0.133)	(0.0753)	(0.0778)	(0.0796)	(0.305)	(0.193)
Mother's Death	0.189	0.107	0.0217	0.0605	0.252	0.00373
	(0.126)	(0.140)	(0.0772)	(0.109)	(0.266)	(0.412)
Covariate Shocks						
Natural Disasters						
Drought	-0.0363	0.0136	0.0321	0.131	-0.0504	0.0743
	(0.0630)	(0.0621)	(0.0335)	(0.0788)	(0.169)	(0.183)
Flooding	0.0122	0.000912	0.0948	0.00850	0.00764	0.0439
	(0.0765)	(0.0763)	(0.0564)	(0.0390)	(0.109)	(0.156)
Pests affecting Crops	-0.0816	-0.0330	-0.0886***	-0.0477	-0.199	0.341**
	(0.0613)	(0.0639)	(0.0247)	(0.0473)	(0.154)	(0.155)
Crop Failures	-0.0267	0.0454	0.0102	0.0163	-0.00977	0.336
	(0.0702)	(0.0398)	(0.0352)	(0.0574)	(0.0668)	(0.204)
Economic Shocks						
Forced Taxation	-0.0339	0.0329	-0.102	-0.0216	-0.0910	0.322
	(0.0780)	(0.111)	(0.0676)	(0.128)	(0.166)	(0.343)
Input Price Increase	-0.0592	-0.0290	0.0592**	0.0925*	0.141	0.242*
	(0.0559)	(0.0478)	(0.0243)	(0.0500)	(0.160)	(0.125)
Output Price Decrease	-0.0751	0.0629	0.0347	0.0246	-0.0952	0.276
	(0.0675)	(0.0777)	(0.0520)	(0.0564)	(0.203)	(0.314)
Observations	4,808	4,584	4,808	4,808	4,307	4,305

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Effect of Shocks on Human Capital Outcomes for Rural Households

	Human Capital Outcomes					
	PPVT	Math	Height for Age	BMI for Age	Study Time	Work Time
Idiosyncratic Shocks						
Monetary Shocks						
Loss of Employment	-0.00895	-0.141**	-0.0396	-0.0805	0.254*	0.750***
	(0.0634)	(0.0610)	(0.0622)	(0.0629)	(0.129)	(0.232)
Theft	-0.129*	-0.139*	-0.0288	-0.160**	-0.140*	0.995***
	(0.0664)	(0.0705)	(0.0573)	(0.0636)	(0.0760)	(0.226)
Damage to Home	-0.195	-0.297**	0.210	0.196	-0.532	1.314*
	(0.135)	(0.110)	(0.145)	(0.213)	(0.341)	(0.648)
Household Composition Shocks						
Father's Death	0.179	0.0738	0.00159	0.0565	-0.129	0.309
	(0.139)	(0.165)	(0.139)	(0.142)	(0.271)	(0.401)
Mother's Death	0.0600	-0.117	0.0103	0.153	0.0746	0.0232
	(0.119)	(0.175)	(0.102)	(0.148)	(0.180)	(0.620)
Covariate Shocks						
Natural Disasters						
Drought	-0.0488	-0.0275	0.0317	0.132	0.0117	0.0971
	(0.0710)	(0.0466)	(0.0340)	(0.0805)	(0.139)	(0.196)
Flooding	0.0153	-0.00937	0.107	0.0153	0.0325	0.0797
	(0.0767)	(0.0793)	(0.0635)	(0.0374)	(0.149)	(0.162)
Pests affecting Crops	-0.0730	-0.0149	-0.0748**	-0.0596	-0.206**	0.344*
	(0.0631)	(0.0579)	(0.0269)	(0.0518)	(0.0907)	(0.166)
Crop Failures	-0.0261	0.0439	0.00438	0.0126	-0.0121	0.400*
	(0.0747)	(0.0373)	(0.0376)	(0.0585)	(0.0649)	(0.221)
Economic Shocks						
Forced Taxation	-0.0642	0.0680	-0.100	0.0465	-0.0536	0.618
	(0.119)	(0.140)	(0.0986)	(0.194)	(0.121)	(0.497)
Input Price Increase	-0.0392	-0.00316	0.0469	0.105**	0.0980	0.429***
	(0.0603)	(0.0476)	(0.0280)	(0.0480)	(0.167)	(0.124)
Output Price Decrease	-0.0957	0.0292	0.0436	0.0253	-0.187	0.293
	(0.0732)	(0.0724)	(0.0582)	(0.0594)	(0.176)	(0.372)
Observations	2,941	2,747	2,941	2,941	2,630	2,629

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The household composition shocks tell an entirely different story. Father's and mother's death do not have a significant relationship with any of the human capital outcomes. This reveals the existence of coping mechanisms, possibly through familial and communal ties that help in alleviating the stresses related to the death of a parent. Thus, we can conclude that Ethiopian children's human capital outcomes are generally immune to parental death possibly because of efficient pooling of resources at the community-level.

Table 4. Effect of Shocks on Human Capital Outcomes for Urban Households

	Human Capital Outcomes					
	PPVT	Math	Height for Age	BMI for Age	Study Time	Work Time
Idiosyncratic Shocks						
Monetary Shocks						
Loss of Employment	0.0211	-0.0851	-0.0280	0.0321	0.0397	-0.0710
	(0.0823)	(0.0735)	(0.0287)	(0.0533)	(0.0844)	(0.108)
Theft	-0.0923	-0.160	-0.0288	-0.0523	-0.236	-0.121
	(0.0680)	(0.109)	(0.0386)	(0.0665)	(0.326)	(0.144)
Damage to Home	-0.00216	-0.355*	-0.132	0.0208	0.476	0.365
	(0.252)	(0.193)	(0.0876)	(0.139)	(0.337)	(0.748)
Household Composition Shocks						
Father's Death	-0.0131	-0.0912	0.0529	0.0510	-0.00718	-0.0476
	(0.231)	(0.0811)	(0.0960)	(0.0913)	(0.526)	(0.196)
Mother's Death	0.210	0.219	0.0198	-0.0666	0.607	-0.0680
	(0.160)	(0.129)	(0.147)	(0.174)	(0.479)	(0.254)
Covariate Shocks						
Natural Disasters						
Drought	-0.0783	0.264*	0.0126	0.0524	0.222	0.381*
	(0.117)	(0.134)	(0.0436)	(0.0597)	(0.798)	(0.204)
Flooding	-0.187	0.200	-0.0876	-0.100	-0.0690	-0.342
	(0.169)	(0.147)	(0.111)	(0.185)	(0.707)	(0.242)
Pests affecting Crops	-0.126	-0.219*	-0.304**	-0.0291	-0.195	0.149
	(0.121)	(0.114)	(0.113)	(0.122)	(0.494)	(0.293)
Crop Failures	0.0256	0.184**	0.0753	0.0233	-0.0875	-0.225
	(0.113)	(0.0741)	(0.0842)	(0.0730)	(0.578)	(0.182)
Economic Shocks						
Forced Taxation	0.0547	0.0190	-0.129*	-0.162***	-0.0677	-0.0861
	(0.0848)	(0.154)	(0.0633)	(0.0364)	(0.431)	(0.263)
Input Price Increase	-0.0549	0.0327	0.114**	0.0810	0.0256	-0.325*
	(0.0906)	(0.0768)	(0.0458)	(0.0850)	(0.349)	(0.175)
Output Price Decrease	-0.119	0.0672	-0.0638	-0.0410	1.484**	0.144
	(0.0900)	(0.200)	(0.0997)	(0.133)	(0.527)	(0.239)
Observations	1,867	1,837	1,867	1,867	1,677	1,676

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Looking at how natural disasters affect cognitive outcomes, we find that none of the natural disasters has any significant effect on cognition test scores in Ethiopia. This lack of significance indicates that the positive substitution effects (from reduced employment opportunities) and the negative income effects resulting from natural disasters cancel each other out. The insignificant relationship between natural disasters and cognition scores is seen alongside the insignificant coefficients for the effect of natural disasters on study time. This clearly shows that since study time does not decrease significantly in the face of natural disasters, children's learning is not hampered, resulting in a lack of impact of natural disasters on cognitive outcomes.

Table 5. Effect of Shocks on Human Capital Outcomes for Ages 5 to 8

	Human Capital Outcomes					
	PPVT	Math	Height for Age	BMI for Age	Study Time	Work Time
Idiosyncratic Shocks						
Monetary Shocks						
Loss of Employment	0.00827	-0.142*	-0.0545	-0.0418	0.256	0.417*
	(0.0845)	(0.0704)	(0.0478)	(0.0640)	(0.161)	(0.221)
Theft	-0.209**	-0.244**	-0.0915	-0.213**	0.215	1.260***
	(0.0894)	(0.0894)	(0.0547)	(0.0886)	(0.244)	(0.372)
Damage to Home	-0.112	-0.222	-0.0237	0.0364	0.693	1.105
	(0.158)	(0.171)	(0.120)	(0.147)	(0.467)	(1.116)
Household Composition Shocks						
Father's Death	0.0821	0.138	-0.152*	-0.244**	0.188	0.524*
	(0.209)	(0.113)	(0.0750)	(0.113)	(0.459)	(0.299)
Mother's Death	-0.00854	0.211	-0.180	-0.105	0.201	-0.520
	(0.152)	(0.222)	(0.109)	(0.141)	(0.581)	(0.321)
Covariate Shocks						
Natural Disasters						
Drought	-0.0294	0.00858	-0.0556	-0.0733	0.414	0.0396
	(0.0660)	(0.0886)	(0.0438)	(0.0602)	(0.252)	(0.334)
Flooding	0.0170	-0.0128	0.0521	-0.0464	0.0567	-0.345
	(0.0508)	(0.0864)	(0.0590)	(0.0554)	(0.166)	(0.225)
Pests affecting Crops	-0.0333	-0.00496	-0.0817**	-0.0310	-0.555**	0.220
	(0.0401)	(0.0813)	(0.0346)	(0.0498)	(0.219)	(0.210)
Crop Failures	-0.00635	0.0688	-0.0169	-0.0405	0.225	0.603**
	(0.0467)	(0.0718)	(0.0307)	(0.0265)	(0.166)	(0.239)
Economic Shocks						
Forced Taxation	-0.00995	0.0371	-0.0159	0.0790	0.107	0.337
	(0.147)	(0.166)	(0.0608)	(0.140)	(0.303)	(0.603)
Input Price Increase	-0.0424	-0.0278	-0.00448	-0.0240	0.480**	0.350*
	(0.0595)	(0.0731)	(0.0235)	(0.0628)	(0.205)	(0.200)
Output Price Decrease	-0.00169	0.0865	0.00897	-0.0639	-0.176	-0.263
	(0.0726)	(0.0950)	(0.0461)	(0.0618)	(0.370)	(0.566)
Observations	3,333	3,268	3,333	3,333	2,832	2,830

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Pests affecting crops is the only natural disaster with a negative and significant relationship with one of the health outcomes, HAZ. Thus, pests affecting crops can negatively affect children's long-term health in Ethiopia. This might be because of increased allocation of work hours in the face of pests affecting crops as shown by its positive and significant coefficient. All the other coefficients for the effect of natural disasters on health outcomes are insignificant implying that the substitution and income effects cancel each other out. These insignificant coefficients also point to the remedial role that assistance from governmental and international agencies might be playing after natural disasters.

Table 6. Effect of Shocks on Human Capital Outcomes for Ages 8 to 12

	Human Capital Outcomes					
	PPVT	Math	Height for Age	BMI for Age	Study Time	Work Time
Idiosyncratic Shocks						
Monetary Shocks						
Loss of Employment	0.0290	-0.129*	-0.0240	-0.0533	0.0618	-0.0601
	(0.0750)	(0.0718)	(0.0479)	(0.0822)	(0.0864)	(0.142)
Theft	-0.00461	-0.0305	-0.00524	0.00386	-0.176	0.0655
	(0.0725)	(0.0799)	(0.0392)	(0.0484)	(0.162)	(0.218)
Damage to Home	-0.169	-0.325**	0.0295	0.350**	-0.935***	0.0917
	(0.108)	(0.125)	(0.0953)	(0.131)	(0.278)	(0.427)
Household Composition Shocks						
Father's Death	-0.0695	-0.0229	0.0957	0.169*	-0.169	0.0807
	(0.127)	(0.142)	(0.111)	(0.0876)	(0.266)	(0.244)
Mother's Death	0.0397	0.0482	0.177*	0.113	-0.0374	0.279
	(0.182)	(0.109)	(0.0953)	(0.150)	(0.281)	(0.443)
Covariate Shocks						
Natural Disasters						
Drought	0.0126	-0.0189	0.0851*	0.217**	-0.120	0.120
	(0.0955)	(0.0711)	(0.0430)	(0.0802)	(0.121)	(0.135)
Flooding	-0.129	-0.0480	0.0677	0.0514	0.00604	0.225
	(0.130)	(0.0744)	(0.0558)	(0.109)	(0.121)	(0.202)
Pests affecting Crops	-0.0547	-0.0572	-0.0141	0.0697	0.0820	0.203
	(0.0697)	(0.0732)	(0.0477)	(0.0872)	(0.183)	(0.255)
Crop Failures	0.0185	0.0340	0.0290	0.0732	-0.153	0.0282
	(0.115)	(0.0320)	(0.0333)	(0.0824)	(0.100)	(0.156)
Economic Shocks						
Forced Taxation	0.000124	-0.0188	-0.0941	0.0244	-0.0264	0.329
	(0.0940)	(0.0818)	(0.0630)	(0.117)	(0.202)	(0.333)
Input Price Increase	-0.105	-0.0122	0.113***	0.187***	-0.128	0.0150
	(0.0802)	(0.0554)	(0.0373)	(0.0568)	(0.214)	(0.133)
Output Price Decrease	-0.269**	0.00547	0.0316	0.0966	0.0889	0.679**
	(0.112)	(0.0566)	(0.0733)	(0.0983)	(0.271)	(0.278)
Observations	3,159	2,936	3,159	3,159	3,159	3,158

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Within the subcategory of economic shocks, none of the shocks affect the cognition scores significantly. Also, the insignificant coefficients for economic shocks on study time reveal that for households that suffer from economic shcoks children might still be attending school without any gain or loss in learning. The allocation of work time increases for children from households suffering from input price increase. Thus, children are studying the same as before but working more. In the case of health outcomes, input price increase has a positive impact on both HAZ and BMI. This is an interesting finding and shows that in the face of input price increase, the positive substitution effect might outweigh the negative income effect for health. Such a scenario can occur if because of depressed labor market opportunities; there is a higher allocation of parental time towards cooking healthy food and gathering clean drinking water etc., which can ultimately contribute poisitively to children's health outcomes. Moreover, parents can think of such a reallocation of time as strategic investment in child's health in the hope of a better return in the labor market later. The rest of the coefficients of economic shocks on health outcomes are insignificant implying that the substitution and income effects nullify each other.

The results from Table 2 reveal several important findings. First, monetary shocks in general have a greater negative impact on multiple dimensions of human capital outcomes than natural disasters. This finding is dissimilar from the previous literature (Townsend, 1994; Pan, 2009) which revealed that idiosyncratic shocks are better insured against, compared to covariate shocks in developing countries through pooling of resources at the community-level. Second, the effect of shocks on health outcomes is ambiguous. Most of the shocks have an insignificant relationship with health outcomes followed by an equal number of coefficients having a positive and negative sign. Some previous literature has also found similar paradoxical findings in the case of shocks' effect on health outcomes (Baloch and Behrman, 2014; Tiwari et al., 2017). But overall we can conclude that health outcomes, including both short-term (denoted by BMI) and long-term health (denoted by HAZ), are generally immune to idiosyncratic and covariate shocks. Third, shocks have generally no effect on study time but affect work time positively. This reveals that households in response to shocks keep children in school but allocate higher work time for children. However, specially in the case of covariate shocks, this higher work time possibly constitutes largely of unpaid domestic work (fetching water, fetching firewood, cooking, washing, etc.) because of depressed labor market opportunities. Finally, loss of employment, theft, damage to home, and pests affecting crops seem to be the most important shocks for policymakers as these affect multiple dimensions of human capital negatively.

The results in Table 2 include the total sample and thus may mask important differences in how shocks affect human capital outcomes in rural and urban households. This is because food prices, market structures, access to healthcare and community networks etc. might be different in rural and urban households. Therefore, we estimate Equation (1) separately for both rural and urban households. The results are provided in Tables 3 and 4 respectively. Table 3 shows that the results from the main sample are primarily driven by rural households. However, the one main difference between the results from the overall and rural sample is that in the face of theft and pests affecting crops households reduce the allocation of study hours for the latter. For the overall sample, none of the shocks affected study time.

Moreover, Table 4 shows mostly insignificant relationships between monetary shocks and human capital outcomes (apart from damage to home affecting mathematics test scores) implying that urban households are more resilient to monetary shocks. This reveals a better coping mechanism of pooling of resources at the community-level in the face of monetary shocks for urban areas, possibly because of proximity of the households to each other. It might also be the case that whenever there is a monetary shock, alternatives to substitute the lost income are easier to find in urban areas. Turning to natural disasters, we find that drought and crop failures have a positive and significant relationship with mathematics test scores. These are accompanied by the positive coefficient for work time in the face of droughts. Thus, it shows that despite droughts increasing the allocation of work hours, the children are learning more in terms of mathematics alluding to the positive substitution effect outweighing the negative income effect of the shock. Another difference for the urban sample is that pests affecting crops affect mathematics test scores negatively while not impacting the allocation of study or work hours showing that children might still be attending school but learning less. Finally, when it comes to economic shocks, forced taxation affects both the health measures negatively for the urban sample. Moreover, input price increase affects work time negatively while output price decrease affects study time positively. Both outcomes might be because of reduced labor market opportunities because of these shocks in urban areas.

Tables 5 and 6 provide the results from the estimation of Equation (1) when children were between the ages 5 to 8 and 8 to 12 years respectively. During ages 5 to 8, theft has a negative and significant effect on human capital outcomes while loss of employment increases the allocation of work time and decreases mathematics test scores. On the other hand, loss of employment and damage to home affect mathematics skills during ages 8 to 12. Thus, mathematics scores are generally sensitive to monetary shocks during both stages of childhood. Moreover, damage to home reduces the allocation of study time during ages 8 to 12, which was not the case during ages 5 to 8. There is a strong relationship between shocks and work time during ages 5 to 8, which shows that once there is a higher allocation of work time in the face of shocks at this age, children remain in the child labor force.

Father's death affects both short- (BMI) and long-term health (HAZ) negatively during ages 5 to 8. This result is different from the results from the total sample where household composition shocks had no impact on human capital outcomes. Father's death also increases the allocation of work hours during ages 5 to 8. This shows that during ages 5 to 8, father's death affects multiple aspects of children's human capital negatively. On the other hand, father's and mother's death do not affect human capital negatively during ages 8 to 12. On the contrary, father's death increases BMI and mother's death increases HAZ during this age. This counterintuitive result possibly explains that coping mechanisms, such as familial and communal ties are better suited to working for children when one of their parents dies.

Turning our attention to natural disasters reveals that none of them affect human capital outcomes negatively during ages 8 to 12. Droughts affecting the health of the children positively during this age might be because of the positive substitution effect of the shock outweighing its negative income effect. However, during ages 5 to 8, pests affecting crops affect HAZ and study time allocation negatively while crop failures increase the allocation of work time. These results show that natural disasters have a relatively higher negative effect during ages 5 to 8 than at ages 8 to 12. However, we see no impact of natural disasters on cognitive outcomes for both age groups.

Input price increase seems to be the economic shock with the greatest impact on human capital outcomes during ages 5 to 8 as it increases the allocation of study and work time. This implies that children attend school but also face the pressures of higher work time. On the other hand, output price decrease affects PPVT scores negatively while increasing the allocation of work hours during ages 8 to 12. At this age, input price increase increases both BMI and HAZ showing the generally higher levels of resiliency of health outcomes against shocks compared to ages 5 to 8.

Tables 5 and 6 inform us about the different dynamics at play during the distinct stages of later childhood. First, while the overall sample shows the general resilience of health outcomes in the face of shocks, we find that health outcomes are more susceptible to the negative effects of shocks during ages 5 to 8. This is especially true in the case of household composition shocks. Thus, as children grow older their health becomes more resilient. Second, multiple shocks increase work time during ages 5 to 8 compared to during ages 8 to 12. This implies that once children become part of the child labor force early on in their childhood, they remain part of it even later. Hence, post-shock policies should be designed to guard against children becoming part of the child labor force. Finally, natural disasters have a greater negative impact on health and time allocation outcomes during ages 5 to 8 compared to ages 8 to 12.

6. CONCLUSION

Previous literature has shown that exogenous shocks can negatively affect human capital outcomes during childhood (Cunha and Heckman, 2007; Heckman, 2007; Almond and Currie, 2011). However, most of the existing literature has examined the effect of a single shock on a single dimension of human capital. This begs the question whether the same shock can have a differential impact on the multiple dimensions of human capital. In this paper, we explore how a variety of idiosyncratic and covariate shocks affect the cognitive, health, and time allocation outcomes for children in Ethiopia. Thus, we attempt to provide a more holistic picture of how a shock can affect human capital outcomes for children during later childhood. We do this by utilizing the YL panel data which provides data for the same set of children at ages 5, 8, and 12 years.

Our results from the overall sample reveal that loss of employment, theft, damage to home, and pests affecting crops negatively impact multiple dimensions of children's human capital outcomes. This disparate list of shocks shows that policymakers might overlook the damage caused to children's human capital outcomes by only focusing on either covariate or idiosyncratic shocks. The results also show that monetary shocks (subcategory of idiosyncratic shocks) have a greater negative effect on children's human capital outcomes than natural disasters (subcategory of covariate shocks). This finding is contrary to the general belief that idiosyncratic shocks have better insurance against them in the form of pooling of resources at the community-level. Covariate shocks do not have such an insurance mechanism as households in a particular community suffer from them collectively. Thus, we find a lack of pooling of resources at the community-level in the face of monetary shocks in Ethiopia. Moreover, natural disasters having a lower negative effect on human capital outcomes might also mean that there is greater governmental/international assistance for these shocks as result of greater attention in local and international media.

Results from the overall sample also show that health outcomes are generally immune to shocks compared to cognitive and time allocation dimensions of human capital. This result is similar to findings in the previous literature (Baloch and Behrman, 2014; Tiwari et al., 2017). However, looking at the age groups separately showed that the effect of shocks on health outcomes, especially household composition shocks, is relatively higher for ages 5 to 8 than for ages 8 to 12. This is an important finding for policymakers as scarce post-shock resources, especially for older children, can be better targeted towards other dimensions of human capital than health.

Separating the sample into subgroups also exposed further important information. We find that monetary shocks affect human capital outcomes more in rural areas than in urban areas. We surmise that this might be because of relatively better pooling of resources in urban areas as a result of greater proximity between households. The results from different age groups show that household composition shocks and natural disasters have a lower negative impact at ages 8 to 12 than at ages 5 to 8. Thus, policymakers should assign greater remedial resources to younger children and children from rural areas. The results from the subsamples of age groups also showed that when children at ages 5 to 8 are faced with shocks they become part of the child labor force and stay there.

More specifically, policymakers should place a greater emphasis on children who suffered from monetary and household composition shocks. Direct financial support to households might be helpful in compensating the losses in human capital outcomes of the affected children. But such a program will entail greater effort in identifying households that suffer from idiosyncratic shocks. Furthermore, policymakers should also try to avoid children becoming part of the child labor force during ages 5 to 8 of childhood. This can be done through strict enforcement of child labor laws. But if the incentives faced by the parents do not change, there is a chance that children might become part of the underground economy further worsening their working conditions. A better solution might be to employ a policy of conditional cash transfers to households where the parents have to keep their children in school to receive cash payments. Such a policy will change the incentives faced by the parents.

Lastly, we point out two limitations of our study as well as potential areas of future research. First, lack of data on the severity of idiosyncratic and covariate shocks means that the question that how much does the intensity of the shock affects human capital outcomes for children remains unanswered. If future data collection efforts can somehow accurately measure the severity of shocks, it can enhance the understanding of the relationship between shocks and human capital. Second, pre- and post-shock data on the measures of human capital outcomes is absent, limiting our ability to identify clear causal relationships. If such data is available, we would also be able to isolate the exact short- and long-run impacts of a particular shock on human capital outcomes.

APPENDIX

Table A1. Correlation Matrix at Age 5

Variables	Loss of Employment	Damage to Home	Father's Death	Mother's Death	Drought	Flooding	Pests affecting Crops	Crop Failures	Forced Taxation	Input Price Increase	Output Price Decrease
Loss of Employment	1.000										
Damage to Home	-0.008	1.000									
Father's Death	0.039	-0.004	1.000								
Mother's Death	-0.030	-0.003	0.110*	1.000							
Drought	-0.052	0.038	-0.023	-0.038	1.000						
Flooding	-0.031	0.060	-0.050	0.018	0.126*	1.000					
Pests affecting Crops	0.065*	-0.007	-0.020	0.012	0.200*	0.309*	1.000				
Crop Failures	-0.007	0.047	-0.020	-0.018	0.365*	0.171*	0.240*	1.000			
Forced Taxation	0.044	-0.004	-0.005	0.005	0.071*	0.055	0.135*	0.055	1.000		
Input Price Increase	-0.010	-0.016	-0.050	-0.032	0.184*	0.253*	0.191*	0.214*	0.098*	1.000	
Output Price Decrease	0.066*	-0.006	-0.027	0.003	0.094*	0.222*	0.221*	0.155*	0.067*	0.251*	1.000

Note: * p < 0.01

Table A2. Correlation Matrix at Age 8

Variables	Loss of Employment	Theft	Damage to Home	Father's Death	Mother's Death	Drought	Flooding	Pests affecting Crops	Crop Failures	Forced Taxation	Input Price Increase	Output Price Decrease
Loss of Employment	1.000											
Theft	-0.007	1.000										
Damage to Home	-0.032	0.047	1.000									
Father's Death	0.020	-0.011	0.010	1.000								
Mother's Death	-0.004	-0.028	-0.017	0.041	1.000							
Drought	0.006	0.044	-0.003	-0.023	-0.040	1.000						
Flooding	-0.001	0.056	0.027	-0.015	-0.039	0.280*	1.000					
Pests affecting Crops	0.017	0.115*	0.052	-0.027	-0.001	0.143*	0.149*	1.000				
Crop Failures	-0.054	0.045	0.002	0.022	-0.029	0.328*	0.161*	0.141*	1.000			
Forced Taxation	-0.009	0.068*	0.041	-0.032	0.018	0.023	-0.023	0.057	0.026	1.000		
Input Price Increase	-0.027	0.039	0.007	-0.025	-0.003	0.331*	0.150*	0.196*	0.218*	0.080*	1.000	
Output Price Decrease	0.032	0.045	-0.010	0.034	0.030	0.099*	0.105*	0.129*	0.058	0.043	0.112*	1.000

Note: * p < 0.01

Table A3. Correlation Matrix at Age 12

Variables	Loss of Employment	Theft	Damage to Home	Father's Death	Mother's Death	Drought	Flooding	Pests affecting Crops	Crop Failures	Forced Taxation	Input Price Increase	Output Price Decrease
Loss of Employment	1.000											
Theft	0.091*	1.000										
Damage to Home	-0.022	0.002	1.000									
Father's Death	0.010	-0.013	-0.010	1.000								
Mother's Death	-0.002	0.016	-0.007	-0.012	1.000							
Drought	-0.024	0.128*	0.014	-0.003	0.002	1.000						
Flooding	0.010	0.112*	0.033	0.055	-0.003	0.256*	1.000					
Pests affecting Crops	0.000	0.165*	0.013	-0.016	0.004	0.357*	0.317*	1.000				
Crop Failures	-0.010	0.125*	0.002	0.001	-0.011	0.413*	0.252*	0.301*	1.000			
Forced Taxation	0.115*	0.071*	-0.012	0.037	-0.014	0.086*	0.081*	0.123*	0.063*	1.000		
Input Price Increase	-0.002	0.032	0.004	-0.040	0.009	0.245*	0.175*	0.214*	0.227*	0.011	1.000	
Output Price Decrease	0.041	0.041	0.032	0.002	0.023	0.175*	0.190*	0.188*	0.146*	0.067*	0.173*	1.000

Note: * $p < 0.01$

REFERENCES

Acs, G., and A. Nichols (2010), "America Insecure: Changes in the Economic Security of American Families," Washington DC: Urban Institute.

Acs, G., P. J. Loprest and A. Nichols (2009), "Risk and Recovery: Documenting the Changing Risks to Family Incomes," Washington DC: Urban Institute.

Agüero, J.M., and A. Deolalikar (2012), "Late Bloomers? Identifying Critical Periods in Human Capital Accumulation: Evidence from the Rwanda Genocide," Ninth Midwest International Economics Development Conference, Minneapolis, MN, US, April, pp. 20-21), Minneapolis.

Aguilar, A., and M. Vicarelli (2018), "El Niño and Mexican Children: Medium-Term Effects of Early-Life Weather Shocks on Cognitive and Health Outcomes," Retrieved from Arturo A. Aguilar Esteva: http://www.aguilaresteva.com/wp-content/uploads/2012/09/2018_07_17_Article.pdf

Akresh, R., S. Bhalotra, M. Leone and U. Osili (2021), "First and Second Generation Impacts of the Bifarian War," *Journal of Human Resources*, 58(2), 488-531.

Alaimo, K., C.M. Olson and E.A. Frongillo (2001), "Food Insufficiency and American School-Aged Children's Cognitive, Academic, and Psychosocial Development," *Pediatrics,* 108(1), 44-53.

Ali, M. and K.M. Villa (2022), "We Are How Much We Eat: Nutrient-Specific Versus

Calorie-Based Adult-Equivalent Scales," *Agriculture and Food Sciences Research,* 9(1), 32-38.

______ (2023), "Persistence and Catch-Up in Mathematics Skills in Ethiopia: Evidence from Childhood and Adolescence," *Journal of African Development,* 24(2), 228-252.

Almond, D. and J. Currie (2011), "Human Capital Development before Age Five," *Handbook of Labor Economics*, 4(B), 1315-1486.

Almond, D., L. Edlund, H. Li and J. Zhang (2010), "Long-Term Effects of Early-Life Development: Evidence from the 1959 to 1961 China Famine," in Ito, T. and A.K. Rose (Eds), *The Economic Consequences of Demographic Change in East Asia,* Chicago Scholarship.

Ampaabeng, S.K. and C.M. Tan (2013), "The Long-Term Cognitive Consequences of Early Childhood Malnutrition: The Case of Famine in Ghana," *Journal of Health Economics,* 32(6), 1013-1027.

Baez, J., A. de la Fuente and I. Santos (2010), "Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence," Institute for the Study of Labor Working Paper No.5464.

Baloch, A.H. and J.R. Behrman (2014), "Climatic Shocks and Child Human Capital: Evidence from Ethiopia," *Journal of Asian and African Studies,* 51(5), 594-618.

Barker, D.J. (1995), "Fetal Origins of Coronary Heart Disease," *British Medical Journal,* 311(6998), 171.

Beegle, K., R.H. Dehejia and R. Gatti (2006), "Child Labor and Agricultural Shocks," *Journal of Development Economics,* 81(1), 80-96.

Berhane, G., M.H. Abay and T. Woldehanna (2015), "Childhood Shocks, Safety Nets and Cognitive Skills," IFPRI Ethiopia Strategy Support Program Working Paper 73.

Berhane, G., J.F. Hoddinott and N. Kumar (2017), "The impact of Ethiopia's Productive Safety Net Programme on the nutritional status of children: 2008-2012," Washington DC: Ethiopia: International Food Policy Research Institute (IFPRI). Retrieved from https://www.ifpri.org/publication/impact-ethiopias-productive-safety-net-programme-nutritional-status-children-20082012

Berhane, G., L. McBride, K.T. Hirfroft and S. Tamru (2012), "Patterns in Foodgrain Consumption and Calorie Intake," in Dorosh P.A. and S. Rashid, *Food and Agriculture in Ethiopia: Progress and Policy Challenges,* University of Pennsylvania Press.

Black, S.E. and K.L. Sokoloff (2006), "Long-Term Trends in Schooling: The Rise and Decline (?) of Public Education in the United States," in *Handbook of the Economics of Education*, 1, 69-105.

Black, S.E., A. Bütikofer, P.J. Devereux and K. Salvanes (2019), "This Is Only a Test? Long-Run and Intergenerational Impacts of Prenatal Exposure to Radioactive Fallout," *Review of Economics and Statistics,* 101(3), 531-546.

Bogliacino, F., G. Grimalda, P. Ortoleva and P. Ring (2017), "Exposure to and Recall of Violence Reduce Short-Term Memory and Cognitive Control," *Proceedings of the National Academy of Sciences,* 114(32), 8505-8510.

Boo, F.L. (2012), “In School or at Work? Evidence from a Crisis,” *Oxford Developmental Studies,* 40(3), 381-404.

Bundervoet, T. and S. Fransen (2018), “The Educational Impact of Shocks in Utero: Evidence from Rwanda,” *Economics and Human Biology,* 29, 88-101.

Case, A. and C. Paxson (2008), “Stature and Status: Height, Ability, and Labor Market Outcomes,” *Journal of Political Economy,* 116(3), 499-532.

City Population (2015), Retrieved from City Population at http://www.citypopulation.de/Ethiopia.html.

Coleman-Jensen, A., M. Nord, M. Andrews and S. Carlson (2012), “Household Food Security in the United States in 2011,” Washington DC: USDA.

Colmer, J. (2013), “Climate Variability, Child Labour and Schooling: Evidence on the Intensive and Extensive Margin,” Centre for Climate Change Economics and Policy Working Paper No.148.

Cook, J.T. and D.A. Frank (2008), “Food Security, Poverty, and Human Development in the United States,” *Annals of the New York Academy of Sciences,* 1136(1), 193-209.

Cunha, F. and J. Heckman (2007), “The Technology of Skill Formation,” *American Economic Review,* 97(2), 31-47.

Cunha, F., J.J. Heckman and S.M. Schennach (2010), “Estimating the Technology of Cognitive and Noncognitive Skill Formation,” *Econometrica,* 78(3), 883-931.

Currie, J. (2011), “Inequality at Birth: Some Causes and Consequences,” *American Economic Review*, 101(3), 1-22.

De Waal, A., A. Taffesse and L. Carruth (2006), “Child Survival During the 2002-2003 Drought in Ethiopia,” *Global Public Health,* 1(2), 125-132.

Dercon, S. and C. Porter (2014), “Live Aid Revisited: Long-Term Impacts of the 1984 Ethiopian Famine on Children,” *Journal of the European Economic Association,* 12(4), 927-948.

Dornan, P., M.J. Portela and K. Pells (2014), “Climate Shocks, Food and Nutrition Security: Evidene from the Young Lives Cohort Study,” Oxford: OXFAM Research Projects.

Dung, N.T. (2013), “Shocks, Borrowing Constraints and Schooling in Rural Vietnam,” Young Lives Working Paper 94.

Escobal, J., J. Saavedra and P. Suarez (2005), “Economic Shocks and Changes in School Attendance Levels and Education Expenditure in Peru,” University Library of Munich, Germany.

Ferreira, F.H. and N. Schady (2009), “Aggregate Economic Shocks, Child Schooling, and Child Health,” *World Bank Research Observer,* 24(2), 147-181.

Galab, S. and I. Outes-Leon (2011), “Siblings, Schooling, Work and Drought,” Young Lives Working Paper 73.

Gluckman, P. and M. Hanson (2005), *The Fetal Matrix: Evolution, Development and Disease*, Cambridge University Press.

Heckman, J. (2007), “The Economics, Technology and Neuroscience of Human Capability Formation,” *Proceedings of the National Academy of Sciences,* 104(33), 13250-5.

Kampfen, F., F. Zahra, H-P. Kohler and R. Kidman (2022), "The Effects of Negative Economic Shocks at Birth on Adolescents' Cognitive Health and Educational Attainment in Malawi," *SSM-Population Health*, 18, 101085.

Kelly, E. (2011), "The Scourge of Asian Flu: In utero Exposure to Pandemic Influenza and the Development of a Cohort of British Children," *Journal of Human Resources,* 46(4), 669-694.

León, G. (2012), "Civil Conflict and Human Capital Accumulation: The Long-term Effects of Political Violence in Perú," *Journal of Human Resources,* 47(4), 991-1022.

Lewis, B. and J. Serna (2011), "Impacts of the Drought in North East Kenya: Findings from Save the Children's Multi-Sector Needs Assessment, Aprill 2011" Child Rights Resource Center Working Paper, Save the Children.

Lynch, J.L. and B.G. Gibbs (2017), "Birth Weight and Early Cognitive Skills: Can Parenting Offset the Link?" *Maternal and Child Health Journal,* 21(1), 156-167.

Mani, A., S. Mullainathan, E. Shafir and J. Zhao (2013), "Poverty Impedes Cognitive Function," *Science,* 341(6149), 976-980.

Mills, G.B. and J. Amick (2011), "Can Savings Help Overcome Income Instability?" Washington DC: Urban Institute.

Morow, V. (2009), "The Ethics of Social Research with Children and Families in Young Lives: Practical Experiences," Oxford: Young Lives Working Paper No.53.

Outes, I. and A. Sanchez (2008), "An Assessment of the Young Lives Sampling Approach in Ethiopia," Oxford: Young Lives Technical Note No.1.

Pan, L. (2009), "Risk Pooling through Transfers in Rural Ethiopia," *Economic Development and Cultural Change,* 57(4), 809-835.

Paxson, C. and N. Schady (2007), "Cognitive Development among Young Children in Ecuador: The Roles of Wealth, Health, and Parenting," *Journal of Human Resources,* 42(1), 49-84.

Rabassa, M., E. Skoufias and H. Jacoby (2014), "Weather and Child Health in Rural Nigeria," *Journal of African Economies,* 23(4), 464-492.

Ramsey, R., K. Giskes, G. Turrell and D. Gallegos (2011), "Food Insecurity among Australian Children: Potential Determinants, Health and Developmental Consequences," *Journal of Child Health Care,* 15(4), 401-416.

Rosales-Rueda, M. (2018), "The Impact of Early Life Shocks on Human Capital Formation: Evidence from El Niño Floods in Ecuador," *Journal of Health Economics,* 62, 13-44.

Shah, M. and B.M. Steinberg (2012), "Could Droughts Improve Human Capital? Evidence from India," Retrieved from Federal Reserve Bank of San Francisco: https://www.frbsf.org/economic-research/files/Shah_Steinberg.pdf

Sousa, D.A. (2011), *How the Brain Learns: A Classroom Teacher's Guide* (4th Eds.). Corwin.

Tiwari, S., H.G. Jacoby and E. Skoufias (2017), "Monsoon Babies: Rainfall Shocks and

Child Nutrition in Nepal," *Economic Development and Cultural Change,* 65(2), 167-188.

Townsend, R.M. (1994), "Risk and Insurance in Village India," *Econometrica,* 62(3), 539-591.

Victora, C.G., M. de Onis, P.C. Hallal, M. Blossner and R. Shrimpton (2010), "Worldwide Timing of Growth Faltering: Revisiting Implications for Interventions," *Pediatrics,* 125(3), 473-480.

Wadsworth, B.J. (2004), *Piaget's Theory of Cognitive and Affective Development: Foundations of Constructivism* (5th Eds.), Pearson.

WHO (2008), *Training Course on Child Growth Assessment*, Geneva: World Health Organization.

Woldehanna, T. (2012), "Do Economic Shocks Have a Long-Term Effect on the Height of 5-Year-Old Children? Evidence from Rural and Urban Ethiopia," in Bourdillon, M., J. Boyden, R. Huijsmans, N. Ansell, *Palgrave Studies on Children and Development*, London: Palgrave Macmillan.

Zamand, M. and A. Hyder (2016), "Impact of Climatic Shocks on Child Human Capital: Evidence from Young Lives Data," *Environmental Hazards,* 15(3), 246-268.

Zedlewski, S. and A. Nichols (2012), *What Happens to Families' Income and Poverty after Unemployment?* Washington DC: Urban Institute.

Mailing Address: Mohammad Ali, the Frost School of Business, Centenary College of Louisiana, 2911 Centenary Blvd, Shreveport, LA 71104, E-mail: mali@centenary.edu.

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