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EMPOWERED BY ADVERSITY:
ECONOMIC SHOCKS AND NONCOGNITIVE SKILL DEVELOPMENT
IN ETHIOPIAN YOUTH

Leonard Wantchekon
Sally Zhang

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ABSTRACT

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Leonard Wantchekon
Department of Politics
Princeton University
321 Bendheim Hall
Princeton, NJ 08544
and NBER
lwantche@princeton.edu

Sally Zhang
Tufts University
160 Packard Ave
Medford, MA 02155
sally.zhang@tufts.edu

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Leonard Wantchekon[†] Sally Zhang[‡]

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Abstract

Despite the widespread economic shocks faced by children in developing countries, the factors that contribute to resilience remain poorly understood. In this paper, we present three novel facts on the development of noncognitive skills using a longitudinal dataset from Ethiopia. First, we observe a weak correlation between parental wealth and noncognitive skills. Second, we find that while adverse weather shock cause a slight decline in cognitive test scores, they boost noncognitive skills, including generalized self-efficacy, self-esteem, and internal locus of control. Lastly, we show that past exposure to adverse weather shocks is correlated with better mental health during the COVID-19 pandemic. We rationalize these surprising findings within a model of cognitive and noncognitive skill development, where child agency serves a key role. In this model, when a child chooses to exert effort during a particular period, they not only increase their immediate consumption, but it also enhances their noncognitive skills through “learning by doing.” Incorporation of child agency in human capital development result in model predictions that are consistent with the empirical results, and highlights the policy relevance of improving child agency.

1 Introduction

“The challenges have helped me to be a hard worker. For instance, when the drought happened, I came to learn that I must be a hard worker to cope with such issues . . . [T]he challenges helped me become stronger.”

- Mesih, age 19 (excerpt from Crivello et al. (2021))

Growing up in the developing world, children and adolescents frequently encounter challenges such as natural disasters, conflicts, political unrest, and fluctuating economic conditions (Lundberg and Wuermli, 2012). Remarkably, many of these children not only survive these adversities but also thrive amidst them. Stories of resilience are not limited to personal anecdotes but are also evident at the national level. For instance, Burundi has similar harmonized learning outcomes to Ecuador and Colombia—countries whose GDP per capita is 20 times higher—and even surpasses the learning outcomes of Saudi Arabia and Kuwait, whose GDP per capita are up to 76 times higher (Altinok et al., 2018). This strongly suggests that children

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[†]Department of Politics, Princeton University; lwantche@princeton.edu

[‡]The Fletcher School, Tufts University; sally.zhang@tufts.edu

are capable of developing essential skills despite limited pecuniary resources or having encountered significant adversity.

This observation prompts us to consider an alternative perspective: could children actually develop certain skills when experiencing adversity? Personal stories of resilience, such as that of Mesih, often evince character strengths like grit, self-confidence, optimism, and hope (Duckworth, 2016; Werner and Smith, 2019; Crivello et al., 2021). These attributes, collectively known as “noncognitive skills” (or socio-emotional, character, or soft skills), have gained increasing recognition in the economics literature for their importance in achieving success in school, work, and life (Kautz et al., 2014; Heckman and Kautz, 2012; Borghans et al., 2008; UNICEF, 2019). In both developed and developing countries, noncognitive skills are highly valued by employers and are significant predictors of higher earnings (Bassi and Nansamba, 2022). However, there remains limited evidence on how these skills are formed and developed.

This paper presents three novel findings on noncognitive skill development in adolescence, using a longitudinal dataset from Ethiopia. First, we find that, in the cross-section, adolescent’s noncognitive skills do not show a statistically significant correlation with contemporaneous parental wealth, while their cognitive skills are positively correlated with contemporaneous and lagged parental wealth. Second, we show that adverse weather shocks cause a slight decrease in cognitive skills but a substantial short-term *increase* in noncognitive skills. Adolescents who experience a weather shock exhibit higher generalized self-efficacy, greater self-esteem, and a more internal locus of control. Third, we find that having experienced an adverse weather shock during adolescence is correlated with better mental health during the COVID-19 pandemic.

We explore the mechanisms underlying the observed increase in noncognitive skills during an economic shock. First, we find that adolescents often take on new work activities to support their families financially after an adverse weather shock, yet they are no less likely to remain enrolled in school. Specifically, they are more likely to engage in unpaid farm work and paid labor outside the home. Additionally, adolescents who experience weather shocks have stronger relationships with parents and peers, which are positively associated with noncognitive skills. Finally, we find little evidence to suggest that adolescents’ skill development is influenced by their parents’ coping strategies in response to the shock. These findings indicate that noncognitive skill development during an economic shock primarily occurs through adolescents’ agency, with parental investment playing a secondary role.

Inspired by the empirical findings, we develop a model of noncognitive skill development during economic shocks, with child agency playing a central role. While a child’s cognitive skills are typically developed through schooling—decisions often made by their guardians—noncognitive skills are cultivated through “learning by doing.” In each period, the child decides whether or not to exert effort. If they choose to exert effort, they not only attempt to increase their immediate consumption but also enhance their noncognitive

skills through their successes. During exogenous economic shocks, children exert additional effort, as the opportunity to increase consumption becomes more valuable, leading to an increased likelihood of noncognitive skill development in the aftermath of such shocks. This model illustrates how children employ various coping strategies during economic shocks. It also shows that, if they succeed in these efforts, they can enhance noncognitive skills such as self-confidence and self-esteem.

This model generates predictions that align with the empirical results: on average, noncognitive skills increase following an economic shock, while cognitive skills do not. Additionally, cognitive skills are strongly correlated with family wealth and education, whereas this correlation is weaker for noncognitive skills. In fact, the impact of parental wealth on noncognitive skills is ambiguous, as an over-protected child may have fewer opportunities to develop these skills through experimentation.

Our findings highlight the remarkable resilience of Ethiopian adolescents, who actively contribute to their families' coping strategies during an adverse weather shock while simultaneously acquiring vital life skills. Perhaps counterintuitively, it uncovers that crises can foster knowledge and resiliency. Based on these insights, we advocate for a shift in perspective: rather than focusing solely on the vulnerabilities of children and adolescents, we should also explore their potential for growth and adaptation in the face of adversity. This perspective shift is not intended to diminish the challenges children face, nor do we suggest burdening them with additional responsibilities. On the contrary, policies that empower children and increase their agency (Alan and Kubilay, forthcoming; Bandura, 2006) can foster resilience and benefit youth from various backgrounds, including out-of-school and displaced children, by enabling them to adapt and thrive in new environments.

Our paper contributes to three key strands of literature. First, we add to the literature on the impacts of economic shocks in developing countries by emphasizing the potential for skill development during such events. While numerous studies have explored children's vulnerabilities to economic shocks (Lundberg and Wuermli, 2012), few have examined the factors that foster resilience and capacity building in these contexts. A large body of literature has documented the detrimental short- and long-term effects of shocks on child nutrition (Rosales-Rueda, 2018; Tiwari and Zaman, 2010), health (Rocha and Soares, 2015), human capital (Shah and Steinberg, 2017; Almond et al., 2015; Majid, 2015; Barreca, 2010), child labor (Duryea et al., 2007), early marriages (Corno et al., 2020), and lower adult earnings (Karbownik and Wray, 2019; Almond, 2006). We contribute to the smaller body of research on resilience (Iwo et al., 2024; Frankenberg and Thomas, 2017) and social cohesion (Gordon et al., 2011; Bertinelli et al., 2023) in the aftermath of such shocks. Notably, most of the aforementioned studies focus on shocks experienced in utero or during early childhood (see Almond and Currie, 2011, and Almond et al., 2018 for excellent reviews of the evidence), a period when opportunities for child agency and active coping strategies are limited. In contrast, our study

examines shocks occurring during adolescence, a time when children can more actively shape their own coping strategies.

Moreover, we contribute to the growing literature on the importance of noncognitive skills by examining how these skills are formed in adolescence. A growing body of empirical research, pioneered by Heckman and Rubinstein (2001), has shown that noncognitive skills are strong predictors of both educational achievement and labor market success, with their role in life rivaling that of cognitive skills (Kautz et al., 2014; Heckman and Kautz, 2012; Borghans et al., 2008; Amornsiripanitch et al., 2023). For individuals grappling with poverty, the absence of these skills can create “internal constraints to economic mobility” (Sen, 1999; Bossuroy et al., 2022). Recent research has further highlighted the potential for enhancing noncognitive skills in developing country contexts. Interventions focusing on aspirations (Bernard et al., 2014; Orkin et al., 2023; Ashraf et al., 2022), self-image (Ghosal et al., 2022), hope (Rojas Valdes et al., 2021), and generalized self-efficacy (McKelway, 2023) have all demonstrated positive impacts on economic outcomes. Despite the growing recognition of the importance of noncognitive skills, much remains unknown about how these skills are cultivated and developed. Building on previous research showing that aspirations can be influenced by local policy changes, such as quotas for women in leadership positions (Beaman et al., 2012), social welfare policies like conditional cash transfers (García et al., 2019), and international child sponsorships (Wydick et al., 2013), we show that one key way adolescents cultivate noncognitive skills is by actively confronting economic hardships.

Additionally, our paper emphasizes the importance of individual agency, a factor that remains understudied in the economic literature. Hussam et al. (2022) finds that in Rohingya refugee camps in Bangladesh, providing employment significantly improves the psychosocial well-being of recipients, with the increase being higher than the effect of receiving cash of equal value. Similarly, Alan and Kubilay (forthcoming) shows that interventions that increase adolescents’ agency lead to better educational outcomes and social behavior. In our study, we find that child agency drives the increase in noncognitive skill development following an economic shock. Using a dynamic human capital production model, we demonstrate that incorporating child agency leads to greater noncognitive skill development during economic shocks, whereas a model that excludes child agency would predict the opposite. Our model builds on existing research that characterizes skill formation as a dynamic process exhibiting self-productivity and dynamic complementarity (Attanasio et al., 2020; Aucejo and James, 2021; Cunha et al., 2010; Cunha and Heckman, 2007). While retaining these essential characteristics, we expand the model by incorporating children’s own decisions into the development of noncognitive skills.

The remainder of the paper is organized as follows. Section 2 describes the empirical data, defines the relevant variables, and outlines the identification strategy. Section 3 presents the empirical results and

discusses the mechanisms underlying the findings. Section 4 develops a model of cognitive and noncognitive skill development in the context of economic shocks. Finally, Section 5 discusses the policy implications and concludes.

2 Data and Empirical Methodology

2.1 Young Lives Data

Young Lives is an ongoing longitudinal data set that has tracked two cohorts of youth over the past two decades (University of Oxford, 2019). In Ethiopia, this survey collected data on 2,000 individuals born in 2001 and 1,000 born in 1994. From 2002 to 2016, Young Lives gathered comprehensive data through five rounds of child, household, and community surveys, covering measures such as school attendance, health, household demographics, income, consumption, and both cognitive and noncognitive skills. An additional phone survey round was conducted in 2020, specifically to assess the impact of the COVID-19 pandemic on the lives of respondents.

For our analysis, we focus on the younger cohort in rounds 4 and 5, as these rounds include measures of noncognitive skills (Duc et al., 2022; Sanchez et al., 2022). In round 4, the younger cohort was approximately 12 years old, and in round 5, they were approximately 15 years old.

The sampling methodology for Ethiopia followed a multi-stage procedure. First, a set of sentinel sites was selected to capture cultural and geographic diversity, as well as urban and rural differences, with a focus on a pro-poor bias. These sentinel sites were chosen from five regions of Ethiopia: Addis Ababa, Amhara, Oromiya, SNNP, and Tigray. Once the sentinel sites were identified, a village was randomly selected within each site, and all households on the periphery of the village were interviewed until a target number of households had been included (Outes-Leon and Sanchez, 2007).

Summary statistics for the analysis sample are presented in Table A1. Within our sample, 55% are from rural areas. The sample is fairly evenly split by gender, with 53% boys and 47% girls. In round 4, all children are between 11.5 and 13 years old, while in round 5, they are between 14.5 and 16 years old. The most common ethnic groups in the sample are Amhara (34%), Tigrian (28%), and Oromo (23%). The most common religion is Orthodox Christian (82%), followed by Muslim (10%) and other Christians, including Protestant, Catholic, and Evangelist (6.55%).

The average household had six members, and each child had, on average, one brother and one sister. The average age of fathers was 35 years, and the average age of mothers was 26 at the time of the child's birth. The median father's education level was 8 years, while the median mother's education level was 4

years. Additionally, 14% of fathers and 35% of mothers had no formal schooling.

While a high proportion of children in the sample are enrolled in school, their educational paths are often characterized by delayed starts and frequent interruptions. The school enrollment rate exceeds 95%, but absences are relatively common, with 12% of children missing school for a week or more in the year before the survey. Children started school at a wide range of ages; while it is most common to begin grade one at age 6 or 7 (accounting for just over 60% of children), 28% started after age 8. Moreover, 32% of children had repeated at least one grade. As a result, when interviewed at ages 12 and 15, these children were enrolled in various grades, ranging from first grade in primary school to eleventh grade in secondary school. On a typical day, the average child spends 6 hours in school and another 2 hours studying outside of school. Most children (92%) reported no difficulty getting to school, and the mean average commuting time was 21 minutes.

In addition to attending school and studying, young adolescents also routinely engage in unpaid household work. Overall, 63% of the children reported working at home, 10% reported working outside the home, and 18% reported working on their family farm. On average, children spend over 2 hours per day on household chores and taking care of others. Among those who reported working on their family farm, the median child spends 3 hours per day on farm-related tasks. Among those who reported working outside of their home, the median child spends 2 hours on work activities in a typical day. Working for pay is less common than unpaid work: 6% of the sample reported working for pay, and less than 1% reported receiving in-kind payment for their labor.

2.2 Measures of Shocks

Our primary measure of economic shocks is whether the household identified an adverse weather event as one of the three most important factors negatively impacting their economic situation since the last round of data collection.

Although the Young Lives survey meticulously collected data on various types of economic shocks, we focus specifically on adverse weather shocks—such as droughts, floods, erosion, and frost—because to their plausible exogeneity and significant impact on households. Notably, 92% of households that reported experiencing an adverse weather shock considered it one of the three most important negative events affecting their economic situation since the last survey round. Among these households, 66% reported that the economic loss from the weather shock exceeded half of their annual income for at least one year.

Within our analysis sample, 22% of households reported being affected by adverse weather shocks. In round 4, 20% of households experienced such shocks, including 10% of households impacted by frost, 10%

impacted by droughts, 3% impacted by floods, and 2% impacted by soil erosion. In round 5, 24% of households reported being affected by adverse weather shocks, with 3% experiencing frost, 19% affected by droughts, 2% by floods, and less than 1% by soil erosion.

Households adopt a range of coping strategies in response to adverse weather shocks. The most common coping strategies include receiving help from the government or an NGO (42%) and reducing food consumption or other household expenditures (39%). Additionally, 24% of the households reported that they sold assets or animals, 21% reported working more or seeking additional employment, and 4% reported using savings. Among the less common coping methods, 5% of the households reported receiving help from communities, relatives, or friends, 3% sent children to work or removed them from school, and 2% migrated in response to the shock. Simultaneously, 23% of households reported “doing nothing” as their coping strategy.

Notably, most weather shocks are not large-scale natural disasters. While adverse weather events are common and can significantly impact household income, they typically do not result in grim consequences for children, such as malnutrition or dropping out of school. As shown in Table A3, adverse weather shocks do not increase the likelihood of a child being stunted, underweight, ill, or injured. Additionally, we find that these shocks do not affect the probability of a child being enrolled in school.

2.3 Measures of Cognitive and Noncognitive Skills

Adolescents’ cognitive skills are measured through tests of reading comprehension, receptive vocabulary, and mathematics. All adolescents, regardless of whether they are enrolled in school, complete these cognitive skill tests as part of the survey. The reading comprehension test includes questions on literacy and paragraph comprehension. The receptive vocabulary test is a translated and modified version of the Peabody Picture Vocabulary Test (PPVT), which is administered orally to assess children’s understanding of vocabulary. The mathematics achievement test focuses on numeracy. In the main specification, we standardize each test score to have a mean of 0 and a standard deviation of 1 within each cohort-survey round. In additional specifications, we use raw test scores as well as the percentage of correct answers on each test.

Noncognitive skills are measured using a series of items on a Likert scale, with adolescents’ responses ranging from “strongly disagree” to “strongly agree.” We aggregate these responses into three scales: generalized self-efficacy (GSE), self-esteem, and internal locus of control. Each scale is constructed as averages of z-scores.

GSE refers to individuals’ beliefs in their ability to succeed and achieve goals in life (Sherer et al., 1982). The GSE scale used in this study is adapted from Schwarzer and Jerusalem (1995) and consists of 10 questions from the Young Lives survey. One example item from the GSE scale is: “I can always manage to

solve difficult problems if I try hard enough.”

Self-esteem refers to an individual’s subjective evaluation of their own worth as a person (Trzesniewski et al., 2013). The self-esteem scale is constructed from eight questions in the Young Lives survey, based on the original self-esteem scale developed by Rosenberg (1965). An example item from the self-esteem scale is “In general, I like being the way I am.”

An internal locus of control is defined as the belief that one has control over life events, rather than attributing outcomes to fate, luck, or other external forces (Findley and Cooper, 1983). Our measure of internal locus of control is based on three items from the Young Lives survey, capturing children’s sense of how their own efforts can influence outcomes in schooling, work, and life in general. An example item from the locus of control scale is: “If I try hard, I can improve my situation in life.”

These psychosocial scales are constructed using the following procedure. First, responses for each item are standardized within each cohort-survey round to have a mean of 0 and a standard deviation of 1. Items coded as “I don’t know” and “I don’t want to answer” are treated as missing values and were thus excluded from the analysis.¹ After standardization, the averages of the z-scores are computed. This procedure follows established methods used in previous studies with Young Lives data (Ogando and Yorke, 2017; Hossain and Jukes, 2022), allowing for comparisons between groups. Higher values on the indices correspond to higher levels of GSE, self-esteem, and internal locus of control. The full list of survey questions used to construct the GSE, self-esteem, and locus of control scales is provided in Table A4. The reliability of the psychosocial scales is shown by the average inter-item correlations, which fall within the recommended range, and by high Cronbach’s alpha coefficients Ogando and Yorke (2017). These analyses are reported in Table A5.

We assume that the measurements of cognitive and noncognitive skills follow a dynamic factor model, similar to the one proposed by Cunha et al. (2010).

$$Y_{jt}^k = \alpha_{jt}^k \theta_t^k + \epsilon_{jt}^k \tag{1}$$

where $k \in \{C, N\}$, and $j = \{1, \dots, m_t^k\}$, with m_t^k representing the number of measurements of cognitive skills and noncognitive skills in period t . In our data, $m_t^k = 3 \forall t, k$, as we have three measurements for cognitive skills (math, reading, and PPVT scores) and three measurements for noncognitive skills (GSE, self-esteem, and locus of control).

We construct the dynamic cognitive and noncognitive factors using principal component analysis. For both cognitive and noncognitive measurements, the first principal component explains over 64% of the vari-

¹At the item level, responses coded as “I don’t know” or “I don’t want to answer” generally account for fewer than 1% of all responses, with the exception of the item “Other people think I am a good person,” which has a higher rate of responses claiming “I don’t know.” At the individual level, 3.09% of observations have at least one item coded as “I don’t know” or “I don’t want to answer.”

ance and exhibits positive loadings of roughly equal size across all measurements. Moreover, the eigenvalue of the first principal component is more than double that of the second and third components, confirming the unidimensionality of our measurements. In the subsequent analysis, we define this first principal component as the cognitive/noncognitive factor. The results of the principal component analysis are reported in Table A6.

2.4 Secondary Outcomes: Aspirations and Social Capital

The Young Lives survey collects data on both children's educational and career aspirations, as well as those reported by their caregivers. Educational aspirations are defined as the level of formal education that adolescents or their parents would desire, assuming there were no constraints and the adolescent could return to school if they had already left. Generally, educational aspirations in this sample are high, with 77% of the adolescents aspiring to complete a university degree or above, and 80% of the parents desiring the same outcome for their children. Educational expectations are similarly high, with 73% of adolescents and 74% of parents expressing the belief that not only do they desire a college education or higher for themselves/their children, but they also expect to be able to achieve that level of education.

College aspirations and expectations are consistent across boys and girls, but are lower for adolescents in rural areas and positively correlated with wealth. While the majority of adolescents and parents share high educational aspirations, there is some discordance between the two. In particular, 12% of child-parent pairs report a situation in which parents aspire for their children to attend college, but the child does not share this goal. Conversely, in 10% of households, adolescents aspire to complete a college degree, but their parents do not have similar aspirations for them. Interestingly, adolescents' educational aspirations tend to increase between the ages of 12 and 15; while parents' aspirations for their children tend to decrease over the same period.

In terms of career aspirations, we categorize them into four groups: professionals (e.g., doctors, engineers, accountants, or lawyers), public servants (e.g., teachers, politicians, or civil servants), agricultural/trade workers (e.g., agriculture, fishery, construction, or trade), and creatives (e.g., artists, athletes, or religious leaders).

When asked about their desired job at approximately 25 years old, the majority of adolescents (54%) aspire to become professionals. The second most common career aspiration (25%) is to work as a public servant. Approximately 13% of adolescents express an interest in careers within the agricultural or trade sectors, while the smallest group of adolescents (4%) aspire to become creatives. The remaining 4% of adolescents either indicate that they hope to be university students at age 25, do not know, or refuse to

answer the question.

Girls are more likely than boys to aspire to become professionals or public servants, while boys are more likely to aim for careers in the agricultural or trade sectors. Additionally, the aspiration to become a professional is positively correlated with living in an urban household, having higher parental wealth, more years of formal schooling, and stronger cognitive and noncognitive skills. In contrast, aspirations to become a civil servant or teacher are more common among adolescents from rural households, with lower parental wealth, and those possessing lower cognitive and noncognitive skills.

Average parental aspirations for their children’s careers closely mirror those of the adolescents’ themselves. The largest group of parents (49%) aspire for their children to become professionals, followed by public servants (39%), agricultural or trade sector workers (8.7%), and creatives (1.5%). However, while the average aspirations between the two generations are similar, there were notable differences between parents’ and children’s career aspirations. Exactly half of the adolescents share the same career aspirations as their parents, while the other half do not.

Regarding adolescents’ social capital, we assess their relationships with peers and with their parents. Similar to the scales for GSE, self-esteem, and locus of control, we construct peer relations and parent relations scales based on Likert-scale responses. Each of the peer relations and parent relations scales is a composite of 8 items, with each item standardized into z-scores. For example, one item in the peer relations measure is, “I make friends easily,” and an example item in the parent relation scale is, “I get along well with my parents.” The inter-item correlations and Cronbach’s alpha values for these scales are computed and reported in Table A5.

2.5 Secondary Outcomes: Mental Health During the COVID-19 Pandemic

Between 2020 and 2021, the Young Lives team conducted five rounds of short phone surveys with the respondents. In survey rounds 2 and 5, subjective well-being is assessed by asking the respondents to place themselves on a ladder, where the first step represents the worst possible life for them, and the ninth step represents the best possible life. The average response is the fifth step of the ladder.

In survey rounds 2, 3, and 5, symptoms of anxiety and depression are measured using the Generalized Anxiety Disorder-7 (GAD-7) scale and the Patient Health Questionnaire Depression scale-8 (PHQ-8). For each item in the GAD-7 and PHQ-8, respondents are asked whether the symptom had been experienced within the past 2 weeks. A score of 5 or above on the GAD-7 and PHQ-8 questionnaires indicates at least mild anxiety and depression, while a score of 10 or above indicates at least moderate anxiety and depression, respectively. Among the responses from all participants across the three rounds of the survey, 82% show no

or minimal anxiety (53% had a score of 0), 18% show at least mild anxiety, and 3% show at least moderate anxiety. Moreover, among all participants, 83% show no or minimal depression (50% have a score of 0), 17% show at least mild depression, and 2% show at least moderate depression.

2.6 Identification Strategy

Our main empirical specification is a fixed-effect (FE) regression:

$$y_{it} = \alpha + \beta Shock_{it} + \gamma_{it} + \rho_i + \delta_t + \epsilon_{it} \quad (2)$$

where y is the dependent variable in question, $Shock$ is an indicator of whether the household experienced an adverse weather shock, γ is a vector of household characteristics and child observable characteristics, ρ_i is a child fixed effect, and δ is a time fixed effect.

The observable characteristics we control for are children’s gender, age in months, age in months squared, ethnicity, religion, native language, household size, household lagged wealth index, rural indicator, survey cluster fixed effect, region fixed effect, and survey round fixed effect.

Assuming that any unobservable child characteristics affecting the dependent variables are time-invariant, the coefficient β can be interpreted as the causal effect of experiencing an economic shock. For instance, if more pessimistic parents are more likely to self-report adverse weather shocks, this would not bias our estimate because such time-invariant characteristics are controlled for by individual fixed effects. Moreover, suppose that parents are more likely to self-report adverse weather shocks during periods when they are more pessimistic, and that this pessimism lead to lower noncognitive skills in their children during that period (e.g., children having reduced self-confidence). In this case, our results would provide a lower bound of the true positive effect of the adverse weather shock. However, if more pessimistic parents are more likely to self-report adverse weather shocks, and if their pessimism boosts their children’s noncognitive skills (e.g., by making children more confident), this would be a confounder to our results. In such a scenario, we are unable to determine whether the observed positive effect reflects the causal impact of the adverse weather shock or the effect of parental pessimism. In section 3.5, we present suggestive evidence that parental coping strategies generally do not affect children’s noncognitive skill development after an adverse weather shock, which alleviates the concern that our results were primarily driven by parental characteristics that covary with reported adverse weather shocks.

Additionally, we present ordinary least squares (OLS) regression results, where we omit ρ_i from equation 2.

3 Empirical Results

In this section, we uncover three novel facts about noncognitive skill development in adolescents. First, we examine the descriptive correlations between skills, schooling, and parental wealth. We find that parental wealth and formal schooling are strongly correlated with cognitive skills but less so with noncognitive skills. Specifically, current household wealth is not correlated with noncognitive skills.

Next, we examine the causal effects of experiencing an adverse weather shock. We find that adverse weather shocks cause a decrease in adolescents' cognitive skills. Adolescents who experience an adverse weather shock are also less likely to aspire to complete a university degree compared to their peers who have not experienced such a shock. In contrast, adverse weather shocks lead to a large and statistically significant *increase* in noncognitive skills.

During the COVID-19 pandemic, we find that adolescents who have experienced an adverse weather shock have better mental health as young adults than their counterparts who did not report experiencing such a shock. While this set of results is merely suggestive, it further underscores the resiliency of Ethiopian adolescents who faced multiple shocks during their youth.

3.1 Skills, Schooling, and Household Wealth

In the first section, we examine the empirical correlation between skills, schooling, and household wealth. For formal schooling, we use an indicator of whether the adolescent is enrolled in school, and for those enrolled, the grade that the adolescent is enrolled in. For household wealth, we use the household wealth index from both the current and prior rounds. The household wealth index ranges from 0 to 1, with higher values indicating greater household wealth. It was constructed by averaging the household's housing quality, access to services, and ownership of consumer durables (Briones, 2017).

We find that formal schooling is significantly correlated with both cognitive and noncognitive skills. In contrast, household wealth shows a strong correlation with cognitive skills, but its correlation with noncognitive skills is not statistically significant. These results are reported in Table 1.

Adolescents who are enrolled in school exhibit significantly higher cognitive skills. Among those enrolled, cognitive skills increase with grade level. Specifically, current school enrollment is correlated with a 0.41 standard deviation increase in cognitive skills. It is also correlated with a 0.36 standard deviation increase in math scores, a 0.15 standard deviation increase in receptive vocabulary scores, and a 0.45 standard deviation increase in reading scores. Lagged school enrollment is correlated with a 0.31 standard deviation increase in cognitive skills, as well as a 0.25 standard deviation increase in math scores, a 0.20 standard deviation increase in receptive vocabulary scores, and a 0.28 standard deviation increase in reading score. Additionally,

conditional on school enrollment, being one grade higher is associated with a 0.23 standard deviation increase in cognitive skills and a 0.12–0.23 standard deviation increase in math, vocabulary, and reading scores. The OLS regressions controlled for child gender, age, ethnicity, religion, language, household size, rural indicator, survey cluster, region, and round fixed effects.

Although formal schooling also significantly correlates with noncognitive skills, the magnitude of the correlation is smaller compared to that of cognitive skills. Current school enrollment is associated with a 0.39 standard deviation increase in noncognitive skills. Specifically, it is correlated with a 0.12 standard deviation increase in GSE, a 0.16 standard deviation increase in self-esteem, and a 0.35 standard deviation increase in internal locus of control. In contrast, lagged school enrollment shows no statistically significant correlation with noncognitive skills. Conditional on being enrolled in school, each increase in grade level is associated with a 0.06 standard deviation increase in noncognitive skills. Furthermore, it is correlated with a 0.03 standard deviation increase in GSE, a 0.02 standard deviation increase in self-esteem, and a 0.05 standard deviation increase in internal locus of control.

Regarding the household wealth gradient, both the current and lagged household wealth indices are statistically significantly correlated with cognitive skills. A 1 standard deviation increase in the household wealth index is correlated with a 0.17 standard deviation increase in cognitive skills. In contrast, the correlation between current household wealth and noncognitive skills is not statistically significant. The correlation between lagged household wealth and noncognitive skills is only statistically significant in some specifications, but not others.

3.2 The Effect of Adverse Weather Shocks on Skill Formation

Table 2 presents the effects of adverse weather shocks on cognitive and noncognitive skills. We find that adverse weather shocks lead to a decrease in cognitive skills but increase noncognitive skills. In the preferred fixed-effects specifications, exposure to adverse weather shocks reduces cognitive factor by 0.08 (0.055 standard deviations), a decrease that is statistically significant at the 10% level. In contrast, exposure to adverse weather shocks increase the noncognitive factor by 0.437 (0.31 standard deviations), an increase that is statistically significant at the 1% level.

Examining the individual components that comprise cognitive skills (Panel A of Table 2), we find that exposure to adverse weather shocks have negative effects on the receptive vocabulary scores but do significantly impact math or reading scores. Specifically, adolescents exposed to adverse weather shocks score 0.23 standard deviations lower on the receptive vocabulary test, while their scores on the mathematics and reading tests are either similar or slightly higher. ²

²The main specification uses the z-scores of the corresponding test scores. In alternative specifications, we use raw scores and

Table 1: Schooling, Family Wealth, and Skills

	Cognitive Factor		Math Score		PPVT Score		Reading Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male	0.00973 (0.0412)	0.0999** (0.0398)	0.0274 (0.0321)	0.0813** (0.0317)	0.0612** (0.0243)	0.103*** (0.0241)	-0.0707** (0.0313)	-0.0185 (0.0309)
Age in Months	0.0923* (0.0479)	0.0695 (0.0453)	0.0637* (0.0376)	0.0458 (0.0365)	0.0292 (0.0280)	0.0253 (0.0277)	0.0578 (0.0367)	0.0425 (0.0357)
Age in Months Squared	-0.000225 (0.000145)	-0.000206 (0.000138)	-0.000169 (0.000115)	-0.000148 (0.000112)	-0.0000647 (0.0000856)	-0.0000712 (0.0000848)	-0.000133 (0.000111)	-0.000117 (0.000109)
School Enrollment	0.588*** (0.0896)		0.364*** (0.0625)		0.148** (0.0736)		0.447*** (0.0677)	
Lagged School Enrollment	0.448*** (0.0809)		0.250*** (0.0589)		0.201*** (0.0602)		0.284*** (0.0610)	
Grade Enrolled		0.338*** (0.0170)		0.225*** (0.0128)		0.116*** (0.0109)		0.211*** (0.0129)
Household Wealth Index	1.406*** (0.222)	1.073*** (0.213)	0.505*** (0.171)	0.306* (0.168)	1.075*** (0.133)	0.943*** (0.133)	0.739*** (0.163)	0.523*** (0.161)
Lagged Household Wealth Index	1.277*** (0.218)	0.782*** (0.215)	0.958*** (0.168)	0.645*** (0.167)	0.719*** (0.128)	0.529*** (0.128)	0.420*** (0.159)	0.114 (0.162)
Household Size	-0.0298*** (0.0114)	-0.0223** (0.0113)	-0.00843 (0.00866)	-0.00317 (0.00877)	-0.0389*** (0.00710)	-0.0356*** (0.00721)	-0.00247 (0.00887)	0.00134 (0.00886)
Rural	-0.558*** (0.169)	-0.612*** (0.164)	-0.344*** (0.118)	-0.384*** (0.118)	-0.303*** (0.108)	-0.325*** (0.107)	-0.269** (0.127)	-0.296** (0.125)
Observations	2656	2533	2656	2533	2656	2533	2656	2533

	Noncognitive Factor		Generalized Self-Efficacy		Self Esteem		Internal Locus of Control	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Male	0.0496 (0.0529)	0.0755 (0.0541)	0.0337 (0.0222)	0.0410* (0.0228)	0.0170 (0.0229)	0.0251 (0.0233)	-0.00446 (0.0271)	0.00915 (0.0278)
Age in Months	-0.0106 (0.0641)	-0.0224 (0.0650)	-0.00728 (0.0268)	-0.0102 (0.0273)	-0.00942 (0.0269)	-0.0121 (0.0274)	0.00952 (0.0336)	0.00110 (0.0339)
Age in Months Squared	0.0000161 (0.000193)	0.0000380 (0.000196)	0.0000218 (0.0000810)	0.0000265 (0.0000827)	0.0000123 (0.0000807)	0.0000132 (0.0000825)	-0.0000270 (0.000102)	-0.00000470 (0.000102)
School Enrollment	0.545*** (0.119)		0.118** (0.0492)		0.162*** (0.0539)		0.350*** (0.0703)	
Lagged School Enrollment	0.0983 (0.114)		0.0522 (0.0475)		0.0361 (0.0485)		0.00860 (0.0560)	
Grade Enrolled		0.0875*** (0.0226)		0.0305*** (0.00962)		0.0207** (0.00940)		0.0475*** (0.0113)
Household Wealth Index	0.110 (0.274)	0.103 (0.281)	0.0361 (0.115)	0.0397 (0.119)	-0.0226 (0.122)	0.00203 (0.126)	0.133 (0.142)	0.0832 (0.144)
Lagged Household Wealth Index	0.564** (0.282)	0.415 (0.290)	0.203* (0.118)	0.134 (0.123)	0.220* (0.119)	0.196 (0.122)	0.170 (0.143)	0.0976 (0.148)
Household Size	0.0338** (0.0148)	0.0342** (0.0153)	0.0139** (0.00610)	0.0138** (0.00636)	0.0227*** (0.00618)	0.0231*** (0.00639)	-0.00602 (0.00787)	-0.00603 (0.00808)
Rural	-0.126 (0.213)	-0.140 (0.222)	-0.0343 (0.0895)	-0.0478 (0.0936)	-0.0702 (0.0865)	-0.0828 (0.0887)	-0.0231 (0.107)	-0.00498 (0.112)
Observations	2656	2533	2656	2533	2656	2533	2656	2533

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variables in columns (3) to (8) are z-scores of the mathematics, receptive vocabulary, and reading comprehension tests, and dependent variables in columns (1) and (2) are the principal factors derived from the z-scores of the three cognitive tests. Dependent variables in columns (11) to (16) are psychosocial scales, which are calculated as the averages of the within-cohort-round z-scores of Likert scale responses. Dependent variables in columns (9) and (10) are the principal factors of the three psychosocial scales. “In school” is an indicator that takes the value of 1 if the child is currently enrolled in school. “Grade” refers to the child’s current grade level if the child is enrolled in school. “Wealth index” is an index between 0 and 1 that reflects household wealth using components of housing quality, access to services, and ownership of consumer durables (Briones, 2017). All regressions control additionally for child ethnicity, religion, language, survey cluster, region, and round fixed effects.

Table 2: Adverse Weather Shocks and Skills

	Cognitive Factor		Math Score		PPVT Score		Reading Score	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE	(7) OLS	(8) FE
<i>Panel A: Cognitive Skills</i>								
Adverse Weather Shocks	-0.0637 (0.0608)	-0.0797* (0.0474)	0.00988 (0.0436)	0.0142 (0.0433)	-0.208*** (0.0386)	-0.229*** (0.0352)	0.0878* (0.0461)	0.0770* (0.0426)
Observations	2656	2656	2656	2656	2656	2656	2656	2656
	Noncognitive Factor		Generalized Self-Efficacy		Self Esteem		Internal Locus of Control	
	(9) OLS	(10) FE	(11) OLS	(12) FE	(13) OLS	(14) FE	(15) OLS	(16) FE
<i>Panel B: Noncognitive Skills</i>								
Adverse Weather Shocks	0.370*** (0.0700)	0.437*** (0.0958)	0.191*** (0.0295)	0.251*** (0.0406)	0.100*** (0.0309)	0.102** (0.0419)	0.0914** (0.0379)	0.0950* (0.0504)
Observations	2656	2656	2656	2656	2656	2656	2656	2656

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variables in columns (3) to (8) are z-scores of the mathematics, receptive vocabulary, and reading comprehension tests, and dependent variables in columns (1) and (2) are the principal factors derived from the z-scores of the three cognitive tests. Dependent variables in columns (11) to (16) are psychosocial scales, which are calculated as the averages of the within-cohort-round z-scores of Likert scale responses. Dependent variables in columns (9) and (10) are the principal factors of the three psychosocial score z-scores. “Adverse weather shocks” is an indicator that takes the value of 1 if the household reports having a drought, flood, erosion, or frost as one of the three most important events that negatively affected the household’s economic condition. Columns (1), (3), (5), (7), (9), (11), (13), (15) control for gender, age in months, age in months squared, household size, rural indicator, child ethnicity, child religion, child language, lagged household wealth index, survey cluster, region, and round fixed effects. Robust standard errors are reported in parentheses. Columns (2), (4), (6), (8), (10), (12), (14), (16) additionally control for child fixed effects.

Adolescents who experienced an adverse weather shock in their household display higher generalized self-efficacy, higher self-esteem, and a stronger internal locus of control (Panel B of Table 2). Exposure to adverse weather shocks in the family increase adolescent GSE by 0.25 standard deviations, while self-esteem and internal locus of control increase by 0.10 standard deviations. All of these effects are statistically significant at the 5% level and are also economically meaningful. Notably, the magnitudes of these coefficients are similar to the correlation between school enrollment and noncognitive skills.

In addition to influencing adolescents’ skill formation, adverse weather shocks can also impact their aspirations. We find that experiencing adverse weather shocks leads to a decrease in adolescents’ academic aspirations but does not affect their career aspirations. Adolescents who experienced an adverse weather shock are less likely to aspire or expect to go to university, being 12 percentage points (or 15%) less likely to aspire to complete at least a university degree. Similarly, parents show lower educational aspirations for their children after such shocks, with a decrease of 8.8 percentage points (or 10.6%) in the likelihood that they aspire their children to pursue a university degree or higher. Meanwhile, adverse weather shocks do not significantly affect children’s career aspirations. Specifically, adverse weather shocks do not affect the likelihood that adolescents aspire to work in the agricultural/trade or creative sectors, or as a public servant or professional, when they are 25 years old. This highlights that adolescents who experience an adverse

percentages of correct answers as dependent variables. The decrease in PPVT score is statistically significant at the 1% level across all specifications. However, the increase in math and reading scores is not statistically significant in most specifications.

Table 3: Economic Shocks and Aspirations

	Child Aspires University Degree		Child Expects University Degree		Parent Aspires University Degree		Parent Expects University Degree	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE	(7) OLS	(8) FE
<i>Panel A. Educational Aspirations</i>								
Adverse Weather Shocks	-0.0776*** (0.0245)	-0.123*** (0.0285)	-0.0768*** (0.0256)	-0.119*** (0.0298)	-0.0344 (0.0242)	-0.0876*** (0.0274)	-0.0501** (0.0254)	-0.103*** (0.0298)
Dep. Var. Mean	0.77	0.77	0.73	0.73	0.80	0.80	0.74	0.74
Observations	2656	2656	2639	2622	2656	2656	2656	2656
	Child Aspires Agriculture/Trade Sector		Child Aspires Public Servant		Child Aspires Professional		Child Aspires Creative	
	(9) OLS	(10) FE	(11) OLS	(12) FE	(13) OLS	(14) FE	(15) OLS	(16) FE
<i>Panel B. Child Career Aspirations</i>								
Adverse Weather Shocks	0.00331 (0.0179)	0.0349 (0.0229)	-0.0124 (0.0260)	-0.0287 (0.0276)	0.0116 (0.0274)	-0.00639 (0.0336)	0.00243 (0.00712)	-0.00157 (0.0133)
Dep. Var. Mean	0.13	0.13	0.25	0.25	0.54	0.54	0.04	0.04
Observations	2656	2656	2656	2656	2656	2656	2656	2656
	Parent Aspires Agriculture/Trade Sector		Parent Aspires Public Servant		Parent Aspires Professional		Parent Aspires Creative	
	(17) OLS	(18) FE	(19) OLS	(20) FE	(21) OLS	(22) FE	(23) OLS	(24) FE
<i>Panel C. Parent Career Aspirations</i>								
Adverse Weather Shocks	-0.0302** (0.0134)	-0.0241 (0.0195)	0.0550** (0.0267)	0.0713** (0.0304)	-0.0287 (0.0263)	-0.0480 (0.0329)	0.000902 (0.00431)	-0.00686 (0.00831)
Dep. Var. Mean	0.09	0.09	0.39	0.39	0.49	0.49	0.01	0.01
Observations	2656	2656	2656	2656	2656	2656	2656	2656

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variables in Panel A are indicators that take the value of 1 if the child aspires to complete at least an undergraduate degree and expects to achieve this goal, or if the parent aspires for their child to complete at least an undergraduate degree and expects the child to reach their aspiration. The dependent variables in Panel B are also indicators. “Child Aspires Agriculture/Trade Sector” takes the value of 1 if the child would like to become a farmer, construction worker, laborer, driver, pilot, conductor, security guard, mason, mechanic, tailor, domestic worker, carpenter, or computer operator at age 25. “Child Aspires Professional” takes the value of 1 if the child would like to become a doctor, dentist, nurse, engineer, accountant, lawyer, scientist, manager, or journalist when at age 25. “Child Aspires Public Servant” takes the value of 1 if the child would like to become a teacher, civil servant, fireman/woman, district collector, policeman/woman, politician, president, or agricultural/health extension worker at age 25. “Child Aspires Creative” takes the value of 1 if the child would like to be an artist, musician, actor, sportsman/woman, or religious leader when at age 25. The dependent variables in Panel C reflect parental career aspirations for their child. “Adverse weather shocks” is an indicator that takes the value of 1 if the household reported experiencing a drought, flood, erosion, or frost as one of the three most important events that negatively affected their economic condition. OLS specifications control for gender, age in months, age in months squared, child ethnicity, child religion, household size, lagged family wealth index, survey cluster, region, and round fixed effects. Robust standard errors. Additionally, FE specifications control for child fixed effects.

weather shock are just as likely to aspire to become teachers, doctors, artists, or farmers. In contrast, parents are more likely to aspire for their children to become public servants after experiencing an adverse weather shock. These additional results are presented in Table 3.

3.3 Heterogeneity Analysis

We find no strong evidence of heterogeneity in the effects of adverse weather shocks based on gender or household wealth. While the positive effects of these shocks on noncognitive skills are larger for girls, the gender differences are not statistically significant. Similarly, there were no significant gender differences in the effects of adverse weather shocks on cognitive skills, educational aspirations, or career aspirations.

The results also show little variation across adolescents from different wealth terciles. Regarding the type of shock (drought, flood, erosion, or frost), we observed no heterogeneity in terms of skill accumulation or educational aspirations. However, the results show that erosion did have a significant impact on adolescents' career aspirations, as it decreased the likelihood that adolescents would aspire to become professionals and increased the probability that they would aspire to become public servants.

The effects of adverse weather shocks on cognitive and noncognitive skills vary depending on the severity of the shocks. In particular, when weather shocks affected more than half of the households' annual income, they result in a larger increase in noncognitive skills. These results are presented in Table A7. However, more severe shocks do not have an additional impact on the decrease in cognitive skills.

Finally, we examine the impact of adverse weather shocks on the distribution of cognitive and noncognitive skills using quantile regressions. We find that the coefficients for adverse weather shocks are positive and statistically significant across all points of the distribution (25th, 50th, and 75th percentiles) for noncognitive skills. Moreover, the magnitude of the effect increase when moving to the upper end of the distribution. In contrast, the coefficient of adverse weather shocks on cognitive skills is not statistically significant at any point in the distribution (25th, 50th, and 75th percentiles). A limitation of this analysis is that by excluding individual fixed effects, we do not account for any unobservable child characteristics that may influence both skill accumulation and the likelihood of experiencing adverse weather shocks. These results are reported in Table A8.

3.4 Adolescents' Continued Resilience During COVID-19 Pandemic

In the final section of the results, we provide suggestive evidence on how adolescents fare several years after the adverse weather shock. In 2020 and 2021, the Young Lives team conducted a series of phone surveys with the respondents. These surveys provide insights into what the adolescents were doing immediately before the pandemic occurred and how they are coping with the new life challenges.

Among our analysis sample of 1,328 adolescents, 1,230 (93%) are surveyed at least once during the COVID-19 phone surveys. Just before the pandemic began, 42% of the respondents reported having worked in the week prior to the survey. Although Young Lives team did not collect data on whether respondents were enrolled in any form of education prior to the COVID-19 pandemic, they did ask whether respondents planned to enroll in full-time education once schools re-opened. In August and September 2020, 73% of respondents indicated that they either planned to enroll in full-time education in the fall or had already enrolled for the new academic year. Since schools remained closed during this period, these reports reflect the respondents' educational plans and previous grade progressions rather than their current educational

status. At the time of the survey, only about 1% of respondents had attended an in-person class since March 2020, and fewer than 3% of respondents had attended a class online.

In this section, we compare respondents who reported experiencing an adverse weather shock in 2016 to those who did not. We control for factors including child gender, age in months, age in months squared, household size, ethnicity, religion, language, rural status, and fixed effects for region and survey round. Nevertheless, these results are descriptive in nature.

First, we find that adolescents who encountered an adverse weather shock a few years prior are just as likely to be studying or working as those who did not experience the weather shock. Both groups had similar rates of university enrollment, and among the adolescents who are enrolled in primary or secondary education, those who encountered an adverse weather shock are attending comparable grade levels as those who did not. Moreover, there was no significant difference in their likelihood of having worked during the week preceding the phone survey. Taken together, the adolescents who experienced an adverse weather shock prior to the 2016 survey round did not fall behind in their education or work in subsequent years.

In the previous sections, we find that adolescents increase noncognitive skills after encountering adverse weather shocks. Do these newly acquired skills help adolescents handle future challenges? Our findings suggest that adolescents who experienced an adverse weather shock exhibit higher subjective well-being and better mental health during the COVID-19 pandemic. First, they reported higher levels of well-being on a nine-step ladder, although the difference is not statistically significant at conventional levels. Moreover, these adolescents have lower anxiety and depression. They are more likely to respond negatively to all questions on the anxiety scale and are less likely to meet the criteria for having moderate or severe anxiety. Similarly, they are also more likely to respond negatively to all questions on the depression scale, though they are not less likely to meet the criteria for moderate or severe depression. These results are presented in Table 4.

3.5 Mechanisms

Why might economic shocks increase noncognitive skills among Ethiopian adolescents, despite much of the existing literature suggesting the opposite? This paper differs from prior research on economic shocks by focusing on young adolescents. Unlike the effects of shocks that occur in utero (Almond and Currie, 2011) or during early childhood (Maccini and Yang, 2009; Andrabi et al., 2023), adolescents are distinct in that they have greater agency. During times of economic stress, they are able to actively cope with shocks alongside other members of their household.

We propose and test three potential empirical mechanisms to explain this finding. First, adolescents may engage in new activities during an economic shock. Second, they may improve their noncognitive

Table 4: Adverse Weather Shocks and Mental Health During the COVID-19 Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	University	Worked Past Week	Subjective Well-being	Zero Anxiety Score	Mild Anxiety	Moderate Anxiety	Zero Depression Score	Mild Depression	Moderate Depression
Lagged Adverse Weather Shock	-0.000695 (0.00558)	0.00565 (0.0349)	0.165 (0.105)	0.0564* (0.0312)	-0.0643*** (0.0248)	-0.0167* (0.0100)	0.0842*** (0.0285)	0.0283 (0.0251)	0.00170 (0.00897)
Lagged School Enrollment	0.00803** (0.00378)	-0.0923* (0.0485)	0.297** (0.146)	-0.0165 (0.0508)	-0.0322 (0.0414)	-0.0229 (0.0176)	-0.0154 (0.0443)	-0.0266 (0.0365)	-0.00101 (0.0107)
Lagged Household Wealth Index	0.0849*** (0.0221)	-0.376*** (0.0928)	1.487*** (0.298)	0.0154 (0.0856)	-0.0405 (0.0722)	-0.0464 (0.0290)	0.167** (0.0805)	-0.00829 (0.0729)	-0.00248 (0.0288)
Observations	3946	1957	1952	1954	1954	1954	1953	1953	1953

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in column (1) is self-rated subjective well-being on a ladder from 1-9. Dependent variables in columns (2) to (4) uses the Generalized Anxiety Disorder Assessment (GAD-7) score, which ranges from 0 to 21. “Zero Anxiety Score” is an indicator that takes the value of 1 if the GAD-7 score is zero. “Mild Anxiety” is an indicator that takes the value of 1 if the GAD-7 score is greater than or equal to 5, which indicates at least symptoms of mild anxiety. “Moderate Anxiety” is an indicator that takes the value of 1 if the GAD-7 score is greater than or equal to 10, which indicates at least symptoms of moderate anxiety. Dependent variables in columns (5) to (7) uses the Patient Health Questionnaire depression scale (PHQ-8) score, which ranges from 0 to 24. “Zero Depression Score” is an indicator that takes the value of 1 if the PHQ-8 score is zero. “Mild Depression” is an indicator that takes the value of 1 if the PHQ-8 score is greater than or equal to 5, which indicates at least symptoms of mild depression. “Moderate Depression” is an indicator that takes the value of 1 if the PHQ-8 score is greater than or equal to 10, which indicates at least symptoms of moderate depression. “Lagged adverse weather shock” is an indicator that takes the value of 1 if the household reports having a drought, flood, erosion, or frost as one of the three most important events that negatively affected the household’s economic condition during the 2016 survey. All regressions additionally control for gender, age in months, age in months squared, child ethnicity, child religion, household size, lagged family wealth index, survey cluster, region, and survey round fixed effects.

skills through role modeling, particularly by seeing how their parents cope with adversity. Third, verbal encouragement from interactions with parents and peers may help adolescents develop their noncognitive skills. These hypotheses are grounded in the psychological literature on the development of GSE (Bandura et al., 1999).

First, we examine adolescents’ work and school activities following an adverse weather shock. We find that adolescents who encountered an adverse weather shock are just as likely to be enrolled in school as those who did not, and they are more likely to engage in work activities. Specifically, the likelihood that they engage in work activities increases by 18 percentage points (or 24%) following the shock, compared to their peers who did not experience it (Table 5). Work activities, in this context, refer to tasks that the adolescent undertakes to “get money or things for [themselves] or for [their] family” (University of Oxford, 2019). Notably, the increase in work participation by adolescents is not associated with school dropout. Adolescents who experienced the shock are equally as likely to be enrolled in school and no more likely to have missed more than a week of school. They also do not appear to have been enrolled in lower grades than they would have been otherwise.

Engaging in work activities, in turn, is associated with an increase in noncognitive skills. Among all children, participation in work activities correlated with a 0.28 standard deviation increase in noncognitive skills after controlling for child fixed effects. This correlation is statistically significant at the 1% level. At the same time, engaging in work is associated with a 0.06 standard deviation decrease in cognitive skills

after controlling for child fixed effects. This correlation is statistically significant at the 10% level.

Regarding the type of work that adolescents are engaging in, adverse weather shocks increase the likelihood of both working at home and working outside of the home (Table 5). Adolescents are 14 percentage points (22%) more likely to work at home, 4 percentage points (38%) more likely to work outside the home, and 8 percentage points (45%) more likely to work on the family farm. Additionally, they are 4 percentage points (or 69%) more likely to work for pay. The increase in work activities after an adverse weather shock is greater for girls, and this difference is statistically significant. Much of the gender difference is driven by work at-home, such as household chores and caregiving responsibilities.

The positive correlation between work and higher noncognitive skills highlights the importance of distinguishing between child labor and children’s work. While many forms of exploitative, harmful, and dangerous work are unequivocally harmful to children’s development, not all types of children’s work should be viewed in the same light. As Liebel (2004) eloquently argued, children often view work as a way to gain self-confidence, contribute to their families and society, socialize, and learn skills beyond those taught in school. This perspective emphasizes the agency of children, standing in contrast to much of the existing literature, which tends to frame children’s work as a decision made solely by parents to supplement family income, often at the expense of child development (Basu and Tzannatos, 2003). Therefore, the policy implication is not to condone child labor, but rather to acknowledge the agency of children and the valuable skills they can acquire through a wide range of activities, both within and outside of formal schooling.

In addition to taking on new activities, adolescents may also enhance their noncognitive skills through role modeling, learning from how their parents cope with the shock. However, we find little evidence supporting such an effect. Specifically, we find that adolescents’ cognitive and noncognitive skill responses to shocks appear largely independent of the coping strategies their parents employed, whether those strategies involved using savings, seeking help from others, reducing expenditures, or increasing work. The only exception was when the parent reported “doing nothing” as their coping strategy, which is correlated with a smaller increase in adolescents’ noncognitive skills. In fact, we cannot reject the hypothesis that adolescents’ noncognitive skills do not increase when the parent cited “doing nothing” as their coping strategy.

Finally, adolescents may develop noncognitive skills through encouragement from others, such as their parents, siblings, peers, teachers, relatives, and neighbors. Indeed, we find that adolescents who experience an economic shock tend to report better relationships with their parents and peers, and these improved relationships are positively linked with their noncognitive skills (Table A9). Our findings provide individual-level evidence that aligns with recent literature suggesting that natural disasters, such as earthquakes, can improve mental health indicators and decrease suicide rates at the community level (Bertinelli et al., 2023). Gordon et al. (2011) argues that this counterintuitive outcome arises from communities coming together and

Table 5: Economic Shocks, Schooling, and Working

	Enrolled in School		Missed School		Grade Enrolled		Worked	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE	(7) OLS	(8) FE
Adverse Weather Shocks	0.0214 (0.0134)	-0.00216 (0.0139)	-0.0231 (0.0193)	-0.0679*** (0.0230)	-0.0473 (0.0763)	-0.0291 (0.0313)	0.110*** (0.0160)	0.183*** (0.0264)
Dep. Var. Mean	0.95	0.95	0.12	0.12	6.31	6.31	0.77	0.77
Observations	2656	2656	2642	2628	2533	2434	2656	2656
	Working At Home		Working Outside Home		Working on Family Farm		Working for Pay	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE	(7) OLS	(8) FE
Adverse Weather Shocks	0.122*** (0.0246)	0.137*** (0.0323)	0.0135 (0.0159)	0.0388* (0.0212)	0.0389* (0.0201)	0.0812*** (0.0252)	0.0189 (0.0152)	0.0413** (0.0164)
Dep. Var. Mean	0.63	0.63	0.10	0.10	0.18	0.18	0.06	0.06
Observations	2656	2656	2656	2656	2656	2656	2656	2656

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. “Enrolled in School” is an indicator that takes the value of 1 if the child is currently enrolled in school. “Missed School” is an indicator that takes the value of 1 if the child has missed school for a week or more in the last 12 months. “Grade Enrolled” is the current grade that the child is enrolled in. “Worked” is an indicator that takes the value of 1 if the child engaged in any activity to get money or things for themselves or for their family in the last 12 months. “Working At Home” is an indicator that takes the value of 1 if the child reports at least one job in the last 12 months where the job activity is working for the household (e.g. domestic chores). “Working Outside Home” is an indicator that takes the value of 1 if the child reports at least one job in the last 12 months where the job activity is working outside of the household (e.g. selling goods, farm work for other households, wage work). “Working on Family Farm” is an indicator that takes the value of 1 if the child reports at least one job in the last 12 months where the job activity is farm work and they worked for the household. “Working for Pay” is an indicator that takes the value of 1 if the child reports having at least one job in the last 12 months where they received or expected to receive payment in money. “Adverse weather shocks” is an indicator that takes the value of 1 if the household reports having a drought, flood, erosion, or frost as one of the three most important events that negatively affected the household’s economic condition. OLS specifications control for gender, age in months, age in months squared, child ethnicity, child religion, household size, rural indicator, lagged household wealth index, survey cluster, region, and round fixed effects. Robust standard errors are reported. FE specifications control additionally for child fixed effects.

supporting one another in the aftermath of a natural disaster, which enhances a collective sense of belonging.

Taken together, the results in this section suggest that parental investment plays a secondary role in the noncognitive skill development of adolescents, with the child’s own effort taking a central role. During periods of economic shocks, children actively engage in coping strategies by attempting new activities, and they develop noncognitive skills through these experiences. Furthermore, strong social support during such shocks contributes to the development of adolescents’ noncognitive skills. In the next section, we develop a model of cognitive and noncognitive skill development with child effort, and show that this model generates predictions that are consistent with the empirical results.

4 Model: Noncognitive Skill Development Through “Learning-by-Doing”

In this section, we demonstrate that a model of noncognitive skill development based on “learning by doing” can explain the empirical results. Building on the work of Cunha and Heckman (2007) and Attanasio et al. (2020), we conceptualize the formation of both cognitive and noncognitive skills in children as a multistage process characterized by self-productivity and dynamic complementarity. Our primary innovation lies in incorporating the child’s own decisions into the development of noncognitive skills. While Cunha and Heckman (2007) suggests that both the development of both cognitive and noncognitive skills primarily depend on endowments and parental investment, we argue that noncognitive skills are largely developed through children’s active engagement in “learning by doing.”

In our model, the child decides whether or not to exert effort in each period. By exerting effort, they aim to increase their immediate consumption. Importantly, the probability of success in this endeavor depends on their existing cognitive and noncognitive skills. When the child exerts effort and succeeds in increasing consumption, their noncognitive skills improve as well. This process exemplifies “learning by doing,” which posits that the only way to enhance noncognitive skills is through exerting effort.

Noncognitive skills in this model exhibit both self-productivity and dynamic complementarity. The higher a child’s initial noncognitive skills, the greater their probability of success in increasing consumption. This enhanced self-belief encourages the child to likely exert more effort, which in turn leads to further improvements in their noncognitive skills.

Economic shocks are exogenous events that affect a child’s baseline consumption (i.e., consumption without exerting effort) and their probability of enrolling in school. Parental wealth also serves a role in determining the child’s baseline consumption and the likelihood of school enrollment. Since cognitive skills

are largely developed through school attendance, they are directly influenced by parental investment.

Economic shocks influence noncognitive skill development by altering the child's incentives. While a child may choose to exert effort in any period, their incentive to do so is stronger during times of economic shock, because their baseline consumption is lower. This leads to the key empirical prediction of the model: economic shocks have a positive effect on noncognitive skill development but a negative effect on cognitive skill development.

4.1 Model Setup

The Child's Problem In each period, a child decides whether to exert effort. The child's utility function depends on their consumption and effort cost.

$$\max_{e_t} u_t(e_t) = v(c_t(e_t)) - e_t \rho \quad (3)$$

Utility function is twice differentiable in consumption and $v' > 0$, $v'' < 0$. $e(t)$ is an indicator of whether the child exerts effort, and ρ is the utility cost associated with exerting effort.

The child can exert effort in an attempt to increase their consumption by one unit, but their attempt may not be successful. The probability of their success γ_t is determined by their cognitive skills $\theta_t^C \in [0, 1]$ and noncognitive skills $\theta_t^N \in [0, 1]$.

$$E[c_t] = \bar{c}_t + e_t \gamma_t (\theta_t^C, \theta_t^N) \quad (4)$$

where \bar{c}_t represents the child's baseline consumption, or consumption when they do not exert effort.

Economic shocks, schooling and baseline consumption In each period, economic shock happens with probability p . We denote the state of the world as $i \in \{L, H\}$. L is the state of the world where there is an economic shock, and H is the state of the world where there is no economic shock. An economic shock affects the child's baseline consumption and the probability that the child goes to school. The child's baseline consumption and probability of attending school are endogenous to parental characteristics. In particular, we assume that baseline consumption and schooling increases in parental wealth w_t , that is, $\frac{\partial \bar{c}_i}{\partial w_t} \geq 0$, $\frac{\partial s_i}{\partial w_t} \geq 0$, for $i \in \{L, H\}$. Moreover, the child's baseline consumption and probability of attending school is exogenously affected by economic shocks, that is, $\bar{c}_L \leq \bar{c}_H$, and $E[s_L] \leq E[s_H]$. Both baseline consumption and schooling are taken by the child as exogenous.

Evolution of cognitive and noncognitive skills The child's cognitive skills increase if the child goes to

school in period t .

$$\theta_{t+1}^C = f(\theta_t^C, \theta_t^N, s_t) \quad (5)$$

where $f(\theta_t^C, \theta_t^N, 0) = \theta_t^C$, $f(\theta_t^C, \theta_t^N, 1) > \theta_t^C$.

The child's noncognitive skills increase if the child exerted effort in period t and was successful in increasing their consumption.

$$\theta_{t+1}^N = g(\theta_t^C, \theta_t^N, e_t \gamma_t) \quad (6)$$

where $f(\theta_t^C, \theta_t^N, 0) = \theta_t^N$, $f(\theta_t^C, \theta_t^N, 1) > \theta_t^N$.

4.2 Model Solution

Solving the child's problem, we find that the child exerts effort in period t , $e_t = 1$, if and only if

$$\gamma_t(\theta_t^C, \theta_t^N) > \frac{\rho}{v(\bar{c}_i + 1) - v(\bar{c}_i)} \quad (7)$$

The child's effort choice depends on its likelihood of success, the effort cost, and the baseline consumption. Since γ_t increases in θ_t^C and θ_t^N , those with higher cognitive and noncognitive skills coming into the peiod are more likely to exert effort. Furthermore, because $v'' < 0$ and $\bar{c}_L \leq \bar{c}_H$, the child is weakly more likely to exert effort if there is an economic shock. In particular, we can calculate two thresholds, $\theta_L \leq \theta_H$, defined as follows:

$$\gamma_t(\theta_t^C, \theta_H) = \frac{\rho}{v(\bar{c}_H + 1) - v(\bar{c}_H)} \quad (8)$$

and

$$\gamma_t(\theta_t^C, \theta_L) = \frac{\rho}{v(\bar{c}_L + 1) - v(\bar{c}_L)} \quad (9)$$

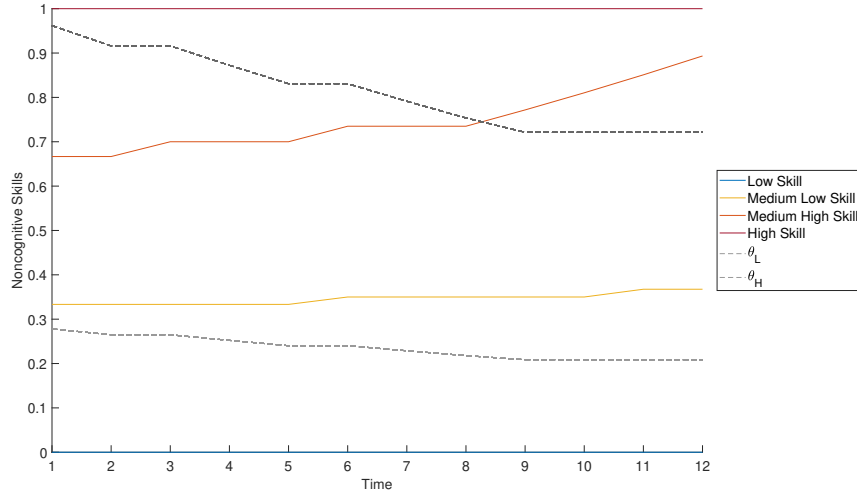
If $\theta_t^N > \theta_H$, child exerts effort in both states of the world. If $\theta_t^N \leq \theta_L$, child exerts effort in neither state of the world. If $\theta_L < \theta_t^N \leq \theta_H$, child exerts effort only when there is an economic shock.

The evolution of non-cognitive skills over time can be illustrated by figure 1, generated through model simulation³. When the child's initial non-cognitive skills are below θ_L , they never exert effort, and their non-cognitive skills do not increase. The fact that low noncognitive skills persist over time is consistent with the literature that has proposed concepts such as "aspiration trap" (Genicot and Ray, 2017) and "GSE trap" (McKelway, 2023). When the child's non-cognitive skills are between θ_L and θ_H , they exert effort during

³Simulation parameters: $v(c) = \log(c)$, $\bar{c}_L = 0.1$, $\bar{c}_H = 1$, $E[s_L] = 0.5$, $s_H = 1$, $p = 0.5$, $\rho = 0.5$, $\gamma_t = \theta_t^N \theta_t^C$. Non-cognitive skill production: $\theta_{t+1}^N = \min(\theta_t^N(1 + 0.05\gamma(t)e(t)), 1)$. Cognitive skill production: $\theta_{t+1}^C = \min(\theta_t^C(1 + 0.05s(t)), 1)$. Initial cognitive skills: $\theta_0^C = 0.75$. The simulation is run for 12 periods with four types of initial non-cognitive skill levels: low skill ($\theta_0^N = 0$), medium low skill ($\theta_0^N = 0.3333$), medium high skill ($\theta_0^N = 0.6667$), and high skill ($\theta_0^N = 1$).

periods of economic shock, and their non-cognitive skills increase if their effort is successful. A child with medium high initial skills increases their non-cognitive skills faster than one with medium low initial skills because, although both exert effort at the same rate, the former succeeds more often. Lastly, when a child's non-cognitive skills are above θ_H , they always exert effort, and their effort always succeeds. This simulation illustrates the self-productivity and dynamic complementarity of non-cognitive skills, where initial skills lead to increased effort and further skill development over time.

Figure 1: Model Simulation: Evolution of Noncognitive Skills Over Time



4.3 Model Predictions

The model generates five predictions that are consistent with the empirical results in Section 3.

First, the models predict that economic shocks have different implications for cognitive and noncognitive skill accumulation. A shock causes average cognitive skills to weakly decrease and average noncognitive skills to weakly increase.

Prediction 1. *An economic shock causes an expected weak increase in average noncognitive skills.*

Proof. If the child's initial skills θ_t^C, θ_t^N are such that $\gamma_t(\theta_t^C, \theta_t^N) > \frac{\rho}{v(\bar{c}_L+1)-v(\bar{c}_L)}$, the child exerts effort when there is an economic shock, $e_t = 1$, and their noncognitive skills increases in the next period with probability γ_t , since $\theta_{t+1}^N = g(\theta_t^N, \gamma_t) \geq \theta_t^N$. If the child's initial skills θ_t^C, θ_t^N are such that $\gamma_t(\theta_t^C, \theta_t^N) \leq \frac{\rho}{v(\bar{c}_L+1)-v(\bar{c}_L)}$, the child does not exert effort when there is an economic shock, $e_t = 0$, and their noncognitive skills do not increase in the next period, since $\theta_{t+1}^N = g(\theta_t^N, 0) = \theta_t^N$.

If the initial skill distribution includes a positive density of children with cognitive and noncognitive skills

above the threshold, an economic shock is expected to increase average noncognitive skills. Otherwise, an economic shock is expected to leave average noncognitive skills unchanged. \square

Prediction 2. *An economic shock causes an expected weak decrease in average cognitive skills.*

Proof. This follows directly from cognitive skill evolution, where cognitive skills are increasing in school attendance: $\theta_{t+1}^C = f(\theta_t^C, \theta_t^N, s_t)$, and $\frac{\partial \theta_{t+1}^C}{\partial s_t} > 0$. Moreover, economic shocks decrease probability of school attendance, $E[s_L] \leq E[s_H]$. \square

Moreover, the model predicts heterogeneity in the impacts of economic shocks on non-cognitive skills. First, these impacts depend on the child's initial skills. If a child's initial skills are too low, they may not exert effort due to a low probability of success, resulting in no increase in non-cognitive skills following an economic shock. Additionally, the effects of economic shocks are influenced by the child's baseline consumption. Lower baseline consumption can motivate the child to exert more effort, increasing the likelihood of gaining non-cognitive skills. Therefore, a shock that significantly affects the child's baseline consumption is more likely to prompt active coping and enhance non-cognitive skills. However, this assumption relies on the model's premise that the utility cost of exerting effort is constant and does not vary with external conditions. In reality, natural disasters could increase the cost of exerting effort, as children may experience decreased nutrition or heightened stress. We anticipate that these types of shocks will have different implications for the human capital production process, which are beyond the scope of this paper.

Prediction 3. *The increase in noncognitive skills after an economic shock increases with initial cognitive and noncognitive skills, and decreases with baseline consumption.*

Proof. The first part of the prediction states that the increase in noncognitive skills after a shock increases with initial noncognitive skills. This directly follows from Prediction 1. If the child's initial skills θ_t^C, θ_t^N are such that $\gamma_t(\theta_t^C, \theta_t^N) \leq \frac{\rho}{v(\tilde{c}_L+1)-v(\tilde{c}_L)}$, the child does not exert effort when there is an economic shock and their noncognitive skills do not increase in the next period.

The second part of the prediction, that increase in noncognitive skills decreases with baseline consumption, also follows from Prediction 1. Let $\tilde{c}_L < \hat{c}_L$, then $\frac{\rho}{v(\tilde{c}_L+1)-v(\tilde{c}_L)} < \frac{\rho}{v(\hat{c}_L+1)-v(\hat{c}_L)}$. In both cases, when initial skills θ_t^N are such that $\gamma_t(\theta_t^C, \theta_t^N) > \frac{\rho}{v(\tilde{c}_L+1)-v(\tilde{c}_L)}$, children exert effort during an economic shock. When initial skills θ_t^N are such that $\gamma_t(\theta_t^C, \theta_t^N) \leq \frac{\rho}{v(\tilde{c}_L+1)-v(\tilde{c}_L)}$, children do not exert effort during an economic shock. When initial skills θ_t^N are such that $\frac{\rho}{v(\tilde{c}_L+1)-v(\tilde{c}_L)} < \gamma_t(\theta_t^C, \theta_t^N) \leq \frac{\rho}{v(\hat{c}_L+1)-v(\hat{c}_L)}$, children exert effort during an economic shock when the baseline consumption is low (\tilde{c}_L) but not when the baseline consumption is high (\hat{c}_L). If the initial skill distribution includes a positive density of children with cognitive and noncognitive skills where $\frac{\rho}{v(\tilde{c}_L+1)-v(\tilde{c}_L)} < \gamma_t(\theta_t^C, \theta_t^N) \leq \frac{\rho}{v(\hat{c}_L+1)-v(\hat{c}_L)}$, an economic shock that leads to

lower baseline consumption, is expected to increase average noncognitive skills. Otherwise, an economic shock is expected to leave average noncognitive skills unchanged. \square

Lastly, the model predicts correlations between children's skills, schooling, and parental wealth. Schooling is expected to positively correlate with both cognitive and non-cognitive skills. In contrast, parental wealth is anticipated to have a positive correlation with cognitive skills, while its correlation with non-cognitive skills remains ambiguous. Wealthier parents increase their children's cognitive and non-cognitive skills through greater parental investment. However, these children might have less incentive to exert effort due to their high baseline consumption, leading to reduced opportunities for experimentation and consequently lower non-cognitive skills.

Prediction 4. *Both cognitive skills and noncognitive skills are positively correlated with schooling.*

Proof. Schooling affects cognitive skills directly. By the evolution of cognitive skills, $\frac{\partial \theta_{t+1}^C}{\partial s_t} = f^2(\theta_t^C, s_t) > 0$. Iteratively, $\frac{\partial \theta_{t+1}^C}{\partial s_{t-1}} = f^1(\theta_t^C, s_t) f^2(\theta_{t-1}^C, s_{t-1}) > 0$, $\frac{\partial \theta_{t+1}^C}{\partial s_{t-k}} = f^1(\theta_t^C, s_t) \prod_{j=1}^k f^2(\theta_{t-j}^C, s_{t-j}) > 0$.

Schooling affects cognitive skills indirectly through cognitive skills. By the evolution of noncognitive skills, $\frac{\partial \theta_{t+1}^N}{\partial s_t} = 0$. Iteratively, $\frac{\partial \theta_{t+1}^N}{\partial s_{t-1}} = g^2(\theta_t^N, e_t \gamma_t) \frac{\partial e_t \gamma_t}{\partial \theta_t^C} \frac{\partial \theta_t^C}{\partial s_{t-1}} > 0$, $\frac{\partial \theta_{t+1}^N}{\partial s_{t-k}} = g^2(\theta_t^N, e_t \gamma_t) \frac{\partial e_t \gamma_t}{\partial \theta_t^C} \frac{\partial \theta_t^C}{\partial s_{t-k}} > 0$. \square

Prediction 5. *Parental wealth is positively correlated with cognitive skills. Conditional on lagged parental wealth, current parental wealth is negatively correlated with noncognitive skills. The effect of lagged parental wealth on noncognitive skills is ambiguous.*

Proof. As per Prediction 4, cognitive skills are positively correlated with schooling in every period. Since schooling is positively correlated with parental wealth, cognitive skills are positively correlated with parental wealth in every period. By evolution of cognitive skills, $\frac{\partial \theta_{t+1}^C}{\partial w_t} = \frac{\partial \theta_{t+1}^C}{\partial s_t} \frac{\partial s_t}{\partial w_t} > 0$. Iteratively, $\frac{\partial \theta_{t+1}^C}{\partial w_{t-j}} = \frac{\partial \theta_{t+1}^C}{\partial s_{t-j}} \frac{\partial s_{t-j}}{\partial w_{t-j}} > 0 \forall j \leq t$. In other words, cognitive skills are positively correlated with both current parental wealth and lagged parental wealth.

In contrast, parental wealth affects noncognitive skills in two opposing channels. First, it affects noncognitive skills positively through schooling (Prediction 4). However, it affects noncognitive skills negatively through increasing baseline consumption (Prediction 3).

Conditional on lagged parental wealth, current parental wealth has a *negative* correlation to noncognitive skills in the next period because it disincentivizes effort. By the evolution of noncognitive skills, $\frac{\partial \theta_{t+1}^N}{\partial w_t} = \frac{\partial \theta_{t+1}^N}{\partial e_t \gamma_t} \frac{\partial e_t \gamma_t}{w_t} < 0$.

For lagged parental wealth, lagged parental wealth positively affects current cognitive skills, which positively affects noncognitive skills in the next period. At the same time, lagged parental wealth neg-

atively affects current noncognitive skills, which negatively affects noncognitive skills in the next period.

$$\frac{\partial \theta_{t+1}^N}{\partial w_{t-1}} = \frac{\partial \theta_{t+1}^N}{\partial \theta_t^C} \frac{\partial \theta_t^C}{\partial w_{t-1}} + \frac{\partial \theta_{t+1}^N}{\partial \theta_t^N} \frac{\partial \theta_t^N}{\partial w_{t-1}},$$

where the first term is positive, and the second term is negative. \square

5 Discussion: Agency Transforms Vulnerability into Possibility

In developing countries, children face numerous challenges to academic learning. In addition to idiosyncratic shocks within the family that we studied in this paper, school attendance is also disrupted by society-wide shocks such as the COVID-19 pandemic (World Bank et al., 2022) and regional violence (United Nations Children’s Fund , UNICEF). Two groups of particular concern are refugee and out-of-school children. An estimated 47 million forcibly displaced people, or 40 percent of the total, are children under the age of 18 (UNHCR, 2024). Moreover, 250 million school-age youth globally are out of school (United Nations, 2023). Innovative solutions are urgently needed to address the unique challenges faced by children living in prolonged uncertainty (Dryden-Peterson, 2016).

Much of the existing literature has focused on the vulnerability of children and learning losses, which is typically measured by standardized test scores (UNICEF, 2021). However, our findings suggest that this approach may be too narrow. Learning losses, while significant, do not capture the full picture of children’s capabilities. Many children who score lower on standardized tests may possess strong noncognitive skills that these tests cannot measure. These children possess substantial human capital due to their maturity, resourcefulness, and resiliency.

Our research suggests that children who score lower on cognitive measures may nonetheless possess significant noncognitive skills. Improving how noncognitive skills are measured, both within and beyond formal education systems, could lead to more holistic assessments of students, particularly in the wake of economic shocks. Moreover, improved measurement of noncognitive skills can lead to higher labor market earnings by allowing individuals with high human capital to credibly signal their capabilities to employers (Bassi and Nansamba, 2022).

Moreover, our research underscores the crucial role that child agency and gainful work play in fostering resilience and skill development. In this context, there could be substantial returns to policies that reduce barriers and expand educational and professional opportunities for disadvantaged youth. Currently, more than 70 million young people in Africa are not in employment, education, or training International Labour Organization (2023). Much of this phenomenon may be due to *restrictions* on education and employment: an estimated 55% of refugees reside in countries where access to formal employment is restricted or effectively nonexistent UNHCR (2023), and over six million pregnant and parenting girls are out of school UNESCO (2024). These restrictions not only perpetuate individual cycles of poverty but also hinder economic devel-

opment at the national level due to the misallocation of talent and the failure to fully realize individuals' potential. Greater emphasis on removing barriers for individuals with high skills and potential, rather than solely focusing on social protection, has the potential to be highly effective for skill development (Alan and Kubilay, forthcoming) and improving well-being (Hussam et al., 2022).

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