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ORIGINAL RESEARCH

Household Shocks and Adolescent Well-Being in Peru

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Abstract

This paper explores the linkages between exposure to household shocks across early life and children's educational and well-being outcomes in Peru. We use longitudinal survey data for a sample of 1713 children from five rounds of the Young Lives Survey to investigate how exposure to shocks across early life is linked to test scores and well-being in adolescence and to determine the extent to which critical periods of shock exposure exist. We expand on prior work by assessing the relationship between early childhood shocks and broader metrics of adolescent well-being beyond cognitive outcomes and by evaluating the cumulative impact of shocks over the course of a child's early life. We find that exposure to a greater number of shocks across early life is negatively associated with reading and vocabulary test scores. In addition, shock exposure in adolescence—versus earlier in childhood—has the strongest negative association with testing and well-being outcomes, suggesting that older children's time and household resources may be diverted away from learning and well-being in response to shocks. In light of increasingly frequent and severe weather events associated with climate change, as well as recent large-scale economic and health crises, policies aimed at supporting the most vulnerable children should be considered to alleviate the negative consequences of shocks on children's educational outcomes and well-being.

Keywords Household Shocks · Education · Children · Peru

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Introduction

Household shocks experienced by children in early life can have dramatic consequences for learning, schooling, and well-being outcomes. Shocks such as income loss and family instability can strain economic resources, change demands on household member' time, and lead to food insecurity (Berhane, Abay, & Woldehanna, 2016; Gitter & Barham, 2007; Soares et al., 2012; Woldehanna & Hagos, 2015). In addition, extreme weather, coupled with large-scale shocks such as macroeconomic crises and Covid-19, can further exacerbate household vulnerability (Hallegatte & Rozenberg, 2017; Prime et al., 2020; Tran et al., 2020). This in turn can adversely impact the health and well-being of household members over both the short and long term (Akter & Basher, 2014; Duryea et al., 2007). Populations in low- and middle- income countries are particularly vulnerable to shocks given high levels of poverty, heavy reliance on agriculture, limited social safety net programs, and less resilient infrastructure (Akter & Basher, 2014; Baird et al., 2011; Cohn et al., 2017; Hanna & Oliva, 2016; Otto et al., 2017; Thorpe et al., 2020). For example, environmental shocks such as drought, flooding, or unseasonable frost can undermine crop and livestock production. Affected households—particularly the poorest—may face subsequent difficulties recovering due to lost assets, insecure market conditions, and limited alternate employment opportunities (Carter et al., 2007).

Interventions to improve children's long-term well-being in low- and middle-income countries often target learning outcomes, food security, and health, which offer the potential to boost labor-market opportunities, improve adult health, and increase socioeconomic status (Ahmad & Khan, 2019; Bayraktar-Sağlam, 2016). Though vast improvements in school attendance have been achieved over the past several decades, in 2018, nearly a 5th of the world's school-age children remained out of school (United Nations, 2020). Similarly, rates of stunting and malnutrition have declined dramatically over the past 2 decades, but as of 2020, 22% of children under five worldwide were stunted (low height-for-age) and 6.7% were wasted (low weight-for-age) (Global Change Data Lab & University of Oxford, 2021; UNICEF, 2021). The United Nations has focused two of its 17 Sustainable Development Goals on education and eradicating hunger and undernutrition, with targets including achieving universal primary and secondary education, promoting universal literacy and numeracy, and eliminating all forms of malnutrition by 2030 (United Nations, 2020). Access to high-quality schooling and food security are associated with poverty reduction and improved living standards (Ahmad & Khan, 2019; Bayraktar-Sağlam, 2016). Shocks experienced in childhood may be detrimental to such well-being outcomes if children's study time and nutritional needs are undermined by more immediate household needs (Bandara et al., 2015; Zimmermann, 2020).

Children are often the household members most vulnerable to shock exposure given their lack of agency over household decisions and coping strategies (Crivello et al., 2009). Young children are particularly vulnerable, as shocks experienced during the first few years of life can affect well-being across the life

course by impairing physical and cognitive development (Alderman et al., 2006; Bourdillon & Boyden, 2014). Further, older children from rural households in low- and middle-income countries face high vulnerability to environmental shocks, as agricultural losses may force them out of school to assist with household income generation (Bandara et al., 2015; Duryea et al., 2007; Zimmermann, 2020). As such, children's vulnerability to shocks may be reflected in schooling and testing outcomes as well as in broader measures of well-being (Berhane et al., 2016; Gitter & Barham, 2007; Randell & Gray, 2019; Rodríguez, 2016; Woldehanna & Hagos, 2015).

This study uses longitudinal data from Peru to understand the linkages between childhood shock exposure and schooling and well-being outcomes in adolescence. Peru is particularly vulnerable to shocks given high levels of poverty, inequality, and reliance on agriculture among a large portion of the population (World Bank, 2017). Prior studies on shock exposure and educational outcomes have found that environmental and family-related shocks are associated with adverse educational outcomes, such as lower educational attainment or dropping out of school (Randell & Gray, 2016; Woldehanna & Hagos, 2015). However, such studies have relied on cross-sectional data, or have focused on just one or two types of shocks (Berhane et al., 2016; Gitter & Barham, 2007; Randell & Gray, 2019; Woldehanna & Hagos, 2015; Zamand & Hyder, 2016). We build on this existing research by exploring linkages between multiple types of shocks experienced over the first 15 years of a child's life and several testing outcomes (reading, math, and vocabulary) as well as multiple indicators of youth well-being (food security, time use, and self-rated health). Further, we examine whether the timing of shock exposure is important. Understanding the relationship between household shock exposure and indicators of schooling and well-being is critical to inform policies aimed at improving well-being outcomes among children and adolescents amidst increasingly frequent and widespread environmental, economic, and health shocks.

Shocks, Schooling, and Well-Being in Low- and Middle-Income Countries

Household wealth is a key determinant of educational attainment and health in low- and middle-income countries (Filmer & Pritchett, 1999; Reynolds et al., 2017). Economic shocks—such as sudden unemployment—primarily operate by undermining resources available within a household to invest in schooling and food for children. Alternatively, economic shocks may lead children to miss or leave school in order to assist with income-generating activities (Berhane et al., 2016; Gitter & Barham, 2007; Woldehanna & Hagos, 2015). For example, Gitter and Barham (2007) found that among children exposed to Hurricane Mitch in Nicaragua, those from wealthier households were more likely to be in the appropriate grade for their age than those from poorer households, particularly if the households had access to credit. In Ethiopia, economic shocks including crop failure and livestock death were associated with dropping out of school, with the strongest effects on children exposed between the ages of 9 and 12 years (Woldehanna & Hagos, 2015).

In Brazil, economic shocks were found to be associated with increased child labor and declines in children's school attendance (Soares et al., 2012). Further, economic shocks can impact household food security, undermining children's learning, health and well-being (Berhane et al., 2016; Lazzaroni & Wagner, 2016). Berhane et al., (2016) found that food price increases were negatively correlated with cognitive testing outcomes among rural Ethiopian children, linking negative health and food security indicators with cognitive outcomes. In Senegal, household income shocks were found to be negatively associated with food security—reflected in significantly lower weight-for-age among exposed children (Lazzaroni & Wagner, 2016). This body of work suggests that household wealth is positively associated with schooling and testing outcomes and that economic shocks may undermine children's schooling, time use, and health.

Environmental shocks can also erode household resources, particularly among rural households reliant on agriculture. Shocks such as droughts and floods may adversely affect children's learning and schooling progress if households respond by redirecting resources for schooling toward more immediate household needs (Berhane et al., 2016; Shah & Steinberg, 2017). Similarly, children might stay home from school or spend less time studying in order to help their household with income generation activities in response to shocks (Marchetta et al., 2019). Further, adverse climatic conditions experienced in early life may impact child health and nutrition during critical periods of cognitive development, thereby affecting schooling outcomes in adolescence (Randell & Gray, 2019). For example, a prolonged drought during early childhood may reduce income and food security, leading to undernutrition and lower cognitive abilities in later childhood (Glewwe & King, 2001).

Indeed, a substantial body of work has emerged linking environmental conditions to children's well-being and educational outcomes (Gitter & Barham, 2007; Marchetta et al., 2019; Nguyen & Nguyen, 2020; Randell & Gray, 2016; Shah & Steinberg, 2017; Zamand & Hyder, 2016). For example, in Ethiopia, adverse rainfall conditions are associated with a lower likelihood of school enrollment by early adolescence as well as with lower cognitive test scores (Berhane et al, 2016; Randell & Gray, 2016). The context and the timing of environmental shocks in children's lives is associated with differential effects on learning and well-being. For example, young children in India and Indonesia who experienced greater rainfall had higher testing outcomes, better educational attainment and enhanced self-reported health and were more likely to stay on track in school in later childhood and early adulthood (Maccini & Yang, 2009; Shah & Steinberg, 2017). In contrast, high rainfall or cyclones experienced in adolescence in both Madagascar and India were linked to lower test scores, fewer years of schooling and a higher likelihood of leaving school to join the workforce (Marchetta et al., 2019; Shah & Steinberg, 2017). In Peru, drought had a significant negative impact on vocabulary testing outcomes and increased the likelihood of children being underweight for their age (Zamand & Hyder, 2016). This growing body of work suggests that environmental shocks can negatively impact children's schooling outcomes in a variety of geographic contexts, and that the timing of shock exposure is key.

In addition to economic and environmental shocks, experiencing parental separation or the illness or death of a family member at young ages has also been found to negatively impact children's psychological and social well-being, as well as cognitive outcomes (Berhane et al., 2016; Chae, 2016; Dhanaraj, 2016; Dinku, Fielding, & Genç, 2018; Woldehanna & Hagos, 2015). Family instability in early life may lead to psychological trauma for children, affecting their schoolwork, or may drive children to stay home from school to supplement shifting household needs. Parental divorce in early life has been linked to poorer vocabulary test scores, delayed school progression, and dropping out of school (Berhane et al., 2016; Chae, 2016). The illness or death of a parent has been associated with later school enrollment for younger children, delayed school progression for older children, and increased probability of a child dropping out of primary school (Dhanaraj, 2016; Woldehanna & Hagos, 2015). In India, parental illness in families with few resources led households to divert resources away from children's schooling (Dhanaraj, 2016). In Ethiopia, the illness or death of a family member acted as an economic shock, thereby impacting the household's ability to afford schooling for young children (Woldehanna & Hagos, 2015). Finally, children's time spent on school work, play, domestic tasks and income-generating work were found to be impacted by parental illness (Dinku et al., 2018). In sum, experiencing family shocks such as parental separation, death or illness has been found to impact children's well-being, particularly by undermining schooling and time use.

Taken together, this body of work suggests that economic, environmental, and family shocks can affect children's well-being and educational outcomes through multiple channels, including reallocating children's time spent in school or on school work, diverting resources for children's education and nutrition for more immediate household needs, or disrupting children's ability to concentrate and thrive by undermining mental and physical well-being. We build on this body of work in three important ways. First, we use five rounds of longitudinal survey data to evaluate the relationships between cumulative shock exposure from the 1st year of life through age 15 and three key cognitive outcomes among adolescents—reading, math, and vocabulary test scores. This builds upon prior work, much of which uses cross-sectional data (e.g., Zimmerman (2020)) or longitudinal data spanning a shorter time span (e.g., Berhane et al., 2016; Dornan et al., 2014; Dinku et al., 2018). Longitudinal data from a 15-year period provide unique insight into how children experience shocks across the early life course, with minimal risk of recall bias. Second, we examine whether critical time periods of shock exposure exist over the course of a young child's life. With few exceptions (Aurino, Schott, Behrman, & Penny, 2019), existing literature has focused primarily on the first 1000 days of a child's life. We expand on this by collectively considering exposures during early childhood, later childhood, and early adolescence to identify whether the sensitivity of testing and well-being outcomes to shocks varies based on the timing of exposure. Finally, we assess whether shock exposure influences other important metrics of child well-being including food security, time use, and self-reported health. The links between shocks and these outcomes are underexplored in the literature, and non-cognitive

indicators of well-being offer important insight into the possible pathways through which shocks might influence learning and later-life outcomes.

The Peruvian Context

Peru is a geographically and climatically diverse country comprised of three significant ecological zones—the Andean mountain region, the coast, and the jungle. Each region has a unique sociocultural history, which creates challenges for national-level policymaking. Climatic conditions vary across the country, ranging from coastal dry desert to Andean highland slopes, and each region experiences distinct vulnerabilities to abrupt weather events. For example, heavy rainfall on the coast is linked to flooding, while in the Andean region, it is associated with landslides and erosion (Oliver-Smith & Hoffman, 1999; Romero et al., 2007). Climate change in Peru is projected to lead to an increased intensity and frequency of extreme weather events, including droughts, floods, and frost (Heidinger et al., 2018; Obregón, G. et al., 2009). Environmental shocks may also affect livelihood strategies among agriculture-dependent households, undermining income and impacting the health and well-being of children (Carter et al., 2007; Sanabria et al., 2014). Exposure to repeated shocks has the potential to compound these negative impacts by delaying or impeding household recovery efforts.

Peru is considered an upper-middle-income country by the World Bank and has experienced steady economic growth over the course of the past decade (The World Bank, 2007). The country has seen rapid urbanization and succeeded in achieving nearly universal primary school enrollment by the late 1990s (Guzman et al., 1996). Economic growth has been accompanied by shifting family dynamics in which labor migration is increasingly common and households have focused greater attention on educational attainment for younger generations (Crivello, 2015; Vincent, 2000). However, national economic growth has not been felt evenly in the country, with 30% of the total population under the national poverty line in 2020 (World Bank Data, 2019). Forty-six percent of those in rural areas live in poverty, and 14% of the rural population experiences extreme poverty as measured by the Peruvian National Statistics Institute (INEI) (INEI, 2020). In addition, regional disparities exist between children from rural and urban areas, evident in a higher prevalence of stunting and food insecurity in rural areas (Dornan, 2010; Rossel, 2008).

Regional economic inequality manifests in children's educational attainment as well. Peru achieved nearly universal school enrollment by the early 2000s, with a primary school enrollment of children between the ages of 6 and 12 of 98% in rural and 99% in urban areas in 2013. However, enrollment discrepancies begin to emerge at the secondary level, with enrollment in 2013 at 75% in rural areas and 92% in urban areas (SEDLAC, 2015). Further, comparative international testing such as the Programme for International Student Assessment (PISA) reveals stark inequalities in academic achievement between rural and urban areas. PISA tests administered in 2012 to 15-year-old students, organized by the

OECD (Organization of Economic Cooperation and Development), found that the average rural student in Peru was 2 academic years behind urban students in terms of reading and math comprehension (Bos, Ganimian, Vegas, & Alfonso, 2014). Preliminary work emerging from the Young Lives study confirms such inequalities, revealing lower testing scores for children from rural areas compared to urban areas (Cuento & Felipe, 2018). However, the authors found children that migrate from rural to urban areas perform better on cognitive tests than those that remain in rural areas.

Data and Methods

To better understand the linkages between exposure to shocks and children's educational and well-being outcomes, we use data from the Young Lives Longitudinal Survey, which offers a unique dataset through which to explore the relationship between cumulative shocks and child well-being. A child-centered study to understand the impacts of poverty across four countries, the Young Lives survey follows two cohorts of children from Ethiopia, India, Vietnam, and Peru over the course of 15 years. The survey was coordinated by the University of Oxford's Department of International Development. Five rounds of data were collected in 2002, 2006, 2009, 2013, and 2016, when children from the younger cohort were approximately 1, 5, 8, 12, and 15 years old (Boyden, 2018). While the Young Lives survey is not intended to be nationally representative, the sampling strategy used nationally representative samples from the DHS and ENAHO (Living Standard Measurement Survey of Peru) to recruit children representative of the country's geographic, socioeconomic, and ethnic diversity. In Peru, the surveys were conducted in 20 communities throughout the coast, Andes, and Amazon regions. Poorer families were oversampled given the explicit goal of Young Lives to understand the impacts of childhood poverty (Crivello et al., 2009; Escobal & Flores, 2008). Families were recruited by in-person visits to homes in randomly selected neighborhoods within randomly selected population centers in the 20 pre-selected districts (for additional details about participant recruitment, see Escobal and Flores (2008) and Sanchez, Cueto, Penny, Miranda, & Melendez (2015)). In the first round, the Peruvian sample included 2052 children from the younger cohort (aged 6 to 18 months) and 714 in the older cohort (age eight), with attrition rates by the 5th round of 8.2% and 14.1%, respectively (*Young Lives Survey* Design & Sampling Round 5 Fact Sheet, 2018). In order to understand the effects of exposure to shocks during early life, we restrict the analytic sample to children from the younger cohort.

We utilize three key educational outcome variables: testing data assessing reading, math, and vocabulary administered by the Young Lives surveyors. In addition, we assess three indicators of well-being: food security, time use, and self-rated health. All outcome measures are drawn from the final round of the survey (round five) when the child is 15 years old. Testing questions were developed in conjunction with GRADE (Group for Analysis of Development).

The questions were determined after several rounds of pilot testing and were meant to reflect education and cognition appropriate for the age group based on widely used international evaluations (Guerrero, 2006). We describe the outcome measures in detail below.

Math

The math test outcome used in our models is based on a child's percentage correct out of 30 questions including 20 age-appropriate mathematical questions of addition, subtraction, division, and multiplication and 10 problem-solving questions drawn from two international comparison exams, TIMMS (Trends in International Mathematics and Science Study) and PISA (Guerrero, 2006).

Reading

To evaluate the student reading ability, a Cloze test was administered. Cloze tests are commonly used evaluations of language ability, asking children to fill in missing words from sentences of short paragraphs. Children were given 10 min to respond to 27 questions in their native language (Spanish or Quechua in the Peruvian context), and responses were coded by trained enumerators (Guerrero, 2006). The reading test outcome in our models measures the percent of reading questions answered correctly.

Vocabulary (PPVT)

Vocabulary comprehension was evaluated using the Peabody Picture Vocabulary Test (PPVT), a widely used tool developed in 1959. Children were asked to select a picture that best suits the situation or description offered by the oral examiner out of 125 possible questions. Once twelve increasingly difficult questions above a baseline are answered with no more than one error, the rest of the questions below the baseline level are assigned a value of 1, as they are presumed to be easier. In Peru, the test was administered in Spanish or Quechua (Guerrero, 2006). The vocabulary test outcome in our models consists of the percent of vocabulary questions answered correctly.

Table 1 Shock categories

Economic/agricultural shocks	Loss of job/source of income/family enterprise, pests on crops, crop failure, pests on storage, pests on livestock, death of livestock
Environmental shocks	Drought, flooding, erosion, frost, earthquake
Family shocks	Death of father or mother, divorce or separation, death of another household member

Food Security

Food security was assessed using a variable from the fifth survey round in which children were asked "Which of the following statements best describes the food situation at your home." Responses were recoded such that those who reported always getting enough to each were coded as 1, and children who do not always get enough to eat, sometimes do not eat enough or frequently do not eat enough were coded as 0.

Time Use

We assess two types of children's time surveyed at round 5 that have previously been found to be associated with shocks[1]—children's time spent studying and time spent on chores (Dinku et al., 2018). Hours studying is a continuous variable in which children were asked how many hours per day they spent studying at home or outside of class on a typical week day. Hours spent on chores is a continuous variable in which children were asked how many hours on a typical week day they spent on chores, including washing dishes or clothing, shopping, cleaning, collecting firewood, etc (Azubuike & Briones, 2018).

Self-Rated Health

At round five, children were asked to rank their general health on a scale from 1 (very poor) to 5 (very good) (Azubuike & Briones, 2018). Given the low frequency in each category, this variable was recoded to facilitate analysis into a binary variable in which 1 = good or very good health and 0 = very poor, poor, or average health.

The main predictor of interest is *exposure to shocks* between rounds one and five. We categorize shocks into three broad groups for descriptive purposes, displayed in Table 1: Economic/agricultural shocks, environmental shocks, and family shocks. In each survey, beginning in round 2, shocks that occurred since the prior survey round were self-reported by respondents. Children or a family member in the household

[1] We do not test children's time spent on income-generating activities due to the low number of children in the sample (3%) who reported 1 or more hours in income-generating activities outside of the household.

was asked if they experienced each type of shock since the last survey with yes/no response options (e.g., did you experience crop failure since the last survey round? Yes or no). Affirmative responses were coded with a one. Indices for each shock category were constructed by summing the total number of shocks experienced by a child over their lifetime (to assess cumulative exposure) and during each intra-round period (to assess timing of exposure).

Self-report of family and economic or agricultural shocks allows us to assess the impact of such shocks at the individual and household level. Self-reported environmental shocks, while less precise than meteorological data, offer unique contributions. First, they allow for within-community variation to distinguish the effects of shocks from other community effects. Households in the same community may experience environmental shocks differently based on where in the community they live, as well as by household characteristics such as wealth and livelihood type. As such, self-reports reflect whether or not a given shock is noteworthy and memorable at the time of the survey. Self-reported shocks suggest that household coping mechanisms are activated, as shocks are more likely to be reported if households had to respond or adapt (Zamand & Hyder, 2016).

In addition to shock exposure, we include a set of individual-, household, and community-level controls to account for other factors associated with the outcome variables. All baseline characteristics are drawn from the first round of the survey, when the average age of the child was 1 year old. At the individual level, controls measured at baseline include the child's gender, primary language spoken at home (Spanish or other), age in months, and whether the child is a biological child of the household head. Qualitative evidence in Peru suggests that migration of children to provide better educational opportunities is common (Leinaweaver, 2008). Therefore, we also include a migration variable from round 5 in which children were asked if they had ever moved to a different locality for more than 3 months. At the household level, we include baseline controls for wealth index, whether a member of the household is engaged in agricultural labor, mother's age and educational attainment, and whether or not the child lived in a female-headed household (Basu & Stephenson, 2005; Filmer & Pritchett, 1999; Guetto & Panichella, 2019; White & Masset, 2003). The wealth index, measured at baseline, serves as a proxy for household-level socioeconomic status, factoring in housing quality (home construction materials, number of rooms), access to services (electricity, source of drinking water and sanitation, cooking fuels) and consumer durables (ownership of common household items) (Briones & Lives, 2017). Additionally, we include controls for the caretaker (mother, father, or other) who responded to the survey on the child's behalf in rounds 2–3. At the community level, controls include geographic region (coast, Andes or jungle), whether the community was rural or urban, whether the community was accessible by paved road, and the predominant language spoken in the community (Spanish or other). Community characteristics are included to capture well-documented social determinants of education and well-being (Ames, 2013; INEI, 2020; OECD, 2017).

We then estimate a set of multivariable OLS, logistic, and Poisson regression models to analyze the relationship between shock exposure and measures of cognition and well-being. We conduct three analyses: First, we utilize OLS

regression to understand the cumulative effects of early life shock exposure on cognitive test scores based on the total number of shocks experienced across childhood; second, to assess whether timing of shock exposure is linked to educational outcomes, we test the correlation between the number of intra-period shocks and test scores; and third, we examine the links between shock exposure and additional well-being outcomes: food security, self-reported health, and children's time use. Food security and self-reported health are binary measures for which logistic regression models are used. For the two time use outcomes, we fit Poisson regression estimating the number of hours spent on each activity per day. For all models, standard errors are clustered at the baseline community level to account for non-independence among children from the same community. Young Lives datasets do not provide sampling weights (see: Sanchez et al. (2015)). Given that Young Lives oversampled children from poorer households, a lack of sampling weights means that our findings are not nationally representative.

Results

Table 2 provides descriptive statistics for the analytic sample of 1173 children. Nearly half of the children are girls and were 11 months old on average at baseline. Average testing outcomes reveal relatively high scores for reading and vocabulary, but low average math scores. Over 85% of children speak Spanish as their native language, though only 70% live in communities where Spanish is the predominant language spoken. At baseline, most children lived in urban areas in the Andean and coastal regions, and over half had mothers who completed secondary-level education. Nearly 12% of the sample lived in female-headed households and almost 17% reported living outside of their communities for at least 3 months. The standard deviation for household wealth at baseline reveals a wide range within the sample, with some children living in extremely impoverished conditions and others being well off.

Table 3 presents results from multivariable OLS models examining links between cumulative shock exposure across childhood and testing outcomes. Results reveal that exposure to a greater number of shocks was significantly associated with lower vocabulary and reading scores.[2] Each additional shock experienced during a child's life is associated with a 0.4 percentage point decline in vocabulary score and a 0.3 percentage point decline in reading score. A number of individual-, household-, and community-level variables were also associated with testing outcomes. On average, girls have significantly lower math and vocabulary scores than boys, and a mother's secondary or higher education is positively associated with all testing outcomes, consistent with previous studies (Doren & Grodsky, 2016; Harding, 2015). Children who speak Spanish at home have higher reading and vocabulary scores on average,

[2] Our findings were consistent when fractional logit models were estimated. Results of these models are presented in Table 9 of the Appendix.

Table 2 Descriptive Statistics

	Mean	Std. dev	Min	Max
Outcome variables				
Test score outcomes				
Math score	37.399	14.901	0.000	87.097
Reading score	62.931	14.705	7.407	100
Vocabulary score	77.300	13.560	1.600	100
Child always has enough to eat	0.398	–	0	1
Time use				
Chores (hours/day)	1.308	0.866	0	7
Studying (hours/day)	2.097	1.073	0	9
Self-rated health				
Very poor, poor or average health	0.291	–	0	1
Good or very good health	0.709	–	0	1
Shocks				
Cumulative number of household shocks	2.148	2.445	0	16
Number of shocks per round		–		
Round 2	0.463	0.849	0	6
Round 3	0.570	1.047	0	8
Round 4	0.561	0.911	0	6
Round 5	0.584	1.016	0	8
Child characteristics (measured at baseline)				
Gender (female)				
Female	0.497	–	0	1
Male	0.503	–	0	1
Age in months	11.524	3.527	5	22
Child's language				
Other (reference)	0.145	–	0	1
Spanish	0.855	–	0	1
Child has ever migrated between rounds 1–5	0.170	–	0	1
Relationship to household head (ref = other)				
Other (reference)	0.200	–	0	1
Biological child	0.800	–	0	1
Household characteristics (measured at baseline)				
Mother's age	26.942	6.707	14	49
Mother's education				
Primary or less (reference)	0.489	–	0	1
Secondary or more	0.511	–	0	1
Female-headed household	0.114	–	0	1
Wealth index	0.433	0.237	0.002	0.910
Household member engaged in agriculture	0.540	–	0	1
Household member responding to survey, round 2				
Mother	0.817	–	0	1
Father	0.152	–	0	1

Table 2 (continued)

	Mean	Std. dev	Min	Max
Other	0.031	–	0	1
Household member responding to survey, round 3				
Mother	0.894	–	0	1
Father	0.064	–	0	1
Other	0.042	–	0	1
Community characteristics (measured at baseline)				
Rural	0.308	–	0	1
Urban	0.692	–	0	1
Region				
Coast (reference)	0.356	–	0	1
Andes	0.498	–	0	1
Jungle	0.147	–	0	1
Paved road access to community	0.534	–	0	1
Predominant language in community				
Other (reference)	0.305	–	0	1
Spanish	0.695	–	0	1
N	**1713**			

and household wealth is positively associated with test outcomes (Dhanaraj, 2016; Woldehanna & Hagos, 2015).

In addition, we fit regression models for each cognitive outcome using a) a categorical variable of shock exposure (zero shocks, 1–2 shocks, 3 + shocks) and b) exposure to different categories of shocks (agricultural/income, environmental, or family shocks). We find that compared to children who experienced zero shocks, exposure to 1–2 shocks is significantly associated with lower math and reading scores and exposure to 3 + shocks is associated with significantly lower reading and vocabulary scores (see Appendix, Table 7). As expected, exposure to agricultural/income, environmental, and family shocks is negatively associated with nearly all of the testing outcomes, though only the relationship between environmental shocks and vocabulary scores is statistically significant (see Appendix, Table 6).

Table 4 presents results from models predicting test scores based on the number of shocks experienced during each intra-round period to evaluate whether critical time periods of exposure exist. We find that experiencing a greater number of shocks in later childhood, specifically between rounds four and five, is significantly associated with lower test scores. Each additional shock experienced by a child during the period directly prior to the final survey round is associated with a 0.95 percentage point decline in vocabulary scores and a 0.86 percentage point decline in math scores. Shocks experienced between rounds 4 and 5 are also found to predict lower reading scores, though this finding is marginally significant ($p < 0.10$).

Finally, we explore the extent to which shocks influence youth well-being, measured by food security, self-reported health, and time spent studying and on household chores. As indicated in Table 5, shock exposure across childhood is

Table 3 OLS regression examining the links between cumulative shocks and testing outcomes

	Math		Reading		Vocabulary	
	Model 1		Model 2		Model 3	
	B	SE	B	SE	B	SE
Cumulative number of household shocks	− 0.140	(0.124)	− 0.299*	(0.130)	− 0.390*	(0.138)
Child characteristics (measured at baseline)						
Gender (female)	− 3.237***	(0.696)	0.345	(0.784)	− 2.200***	(0.445)
Age in months	0.054	(0.087)	0.284*	(0.101)	0.260**	(0.068)
Child's language (ref = other)						
Spanish	4.606	(2.585)	5.243*	(2.411)	7.106***	(1.755)
Child has ever migrated between rounds 1–5	− 0.247	(1.101)	− 0.037	(0.964)	0.815	(0.618)
Relationship to household head (ref = other)						
Biological child	0.840	(1.087)	0.456	(1.028)	0.239	(0.835)
Household characteristics (measured at baseline)						
Mother's age	0.118*	(0.051)	0.021	(0.037)	− 0.005	(0.043)
Mother's education (ref = primary or less)						
Secondary or more	5.172***	(1.019)	4.339***	(0.611)	4.366***	(0.721)
Female-headed household	1.225	(0.808)	2.200*	(0.796)	1.643*	(0.586)
Wealth index	12.304***	(2.349)	12.673***	(2.699)	14.209***	(2.116)
Household member engaged in agriculture	1.057	(0.815)	2.541**	(0.827)	-0.187	(0.683)
Community characteristics (measured at baseline)						
Rural	− 1.077	(1.501)	− 1.734	(1.249)	− 0.625	(1.199)
Region (ref = coast)						
Andes	2.867	(1.562)	2.025*	(0.840)	2.095	(1.412)
Jungle	0.089	(1.553)	0.593	(0.935)	0.211	(1.398)
Paved road access to community	1.903	(1.325)	1.484	(0.825)	1.659	(1.017)
Predominant language in community (ref = other)						
Spanish	− 1.614	(1.346)	0.132	(1.277)	-0.773	(1.398)
Caretaker respondent, round 2 (ref = Father)						
Mother	− 0.547	(0.962)	1.280	(1.110)	2.067	(1.042)
Other caretaker	− 1.794	(1.873)	− 1.657	(2.053)	0.202	(1.854)
Caretaker respondent, round 3 (ref = Father)						
Mother	2.029	(1.493)	1.541	(1.472)	0.553	(0.898)
Other caretaker	1.951	(2.311)	0.999	(2.171)	1.955	(1.471)
Constant	19.855***	(4.226)	41.535***	(3.360)	57.981***	(3.052)
Observations	1713		1713		1713	
R-squared	0.165		0.176		0.311	

Standard errors in parentheses

Significance † $p < 0.10$* $p < 0.05$** $p < 0.01$*** $p < 0.001$

Table 4 OLS regression examining the links between intra-round shock exposure and testing outcomes

	Math		Reading		Vocabulary	
	Model 4		Model 5		Model 6	
	B	SE	B	SE	B	SE
Number of shocks per round						
Round 2	0.042	(0.483)	− 0.323	(0.677)	− 0.261	(0.333)
Round 3	0.258	(0.378)	0.420	(0.332)	0.108	(0.309)
Round 4	0.117	(0.311)	− 0.457	(0.285)	− 0.413	(0.254)
Round 5	− 0.833*	(0.335)	− 0.907	(0.516)	− 0.943**	(0.283)
Child characteristics (measured at baseline)						
Gender (female)	− 3.313***	(0.665)	0.282	(0.787)	− 2.265***	(0.439)
Age in months	0.049	(0.088)	0.281*	(0.098)	0.256**	(0.066)
Child's language (ref = other)	− 0.398	(1.120)	− 0.140	(0.977)	0.707	(0.643)
Spanish						
Child has ever migrated between rounds 1–5	4.471	(2.542)	5.216*	(2.378)	7.063***	(1.676)
Relationship to household head (ref = other)						
Biological child	0.920	(1.089)	0.565	(1.007)	0.325	(0.810)
Household characteristics (measured at baseline)						
Mother's age	0.117*	(0.051)	0.020	(0.037)	-0.005	(0.042)
Mother's education (ref = primary or less)						
Secondary or more	5.227***	(1.000)	4.376***	(0.593)	4.403***	(0.716)
Female-headed household	1.276	(0.811)	2.303**	(0.794)	1.712**	(0.567)
Wealth index	12.484***	(2.353)	12.723***	(2.695)	14.302***	(2.099)
Household member engaged in agriculture	1.080	(0.810)	2.639**	(0.830)	− 0.132	(0.685)
Community characteristics (measured at baseline)						
Rural	− 1.082	(1.532)	-1.801	(1.310)	-0.671	(1.243)
Region (ref = coast)						
Andes	2.776	(1.573)	2.008*	(0.821)	2.044	(1.404)
Jungle	0.001	(1.557)	0.625	(0.944)	0.201	(1.397)
Paved road access to community	2.013	(1.342)	1.623	(0.834)	1.759	(1.018)
Predominant language in community (ref = other)						
Spanish	− 1.783	(1.321)	0.050	(1.289)	-0.888	(1.370)
Caretaker respondent, round 2 (ref = Father)						
Mother	− 0.556	(0.942)	1.215	(1.098)	2.027	(1.040)
Other caretaker	− 1.689	(1.932)	− 1.528	(2.140)	0.276	(1.900)
Caretaker respondent, round 3 (ref = Father)						
Mother	2.012	(1.468)	1.600	(1.341)	0.556	(0.864)
Other caretaker	1.820	(2.301)	0.853	(2.135)	1.803	(1.462)
Constant	20.028***	(4.370)	41.541***	(3.543)	58.073***	(2.982)
Observations	1713		1713		1713	
R-squared	0.168		0.180		0.313	

Standard errors in parentheses

Significance † $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 5 Logistic regression and Poisson models examining the links between shock exposure and measures of well-being

	Logistic regression				Poisson regression			
	Food Security		Self-rated health		Time on chores		Time studying	
	Model 7		Model 8		Model 9		Model 10	
	B	SE	B	SE	B	SE	B	SE
All Shocks	− 0.081***	(0.020)	− 0.038	(0.026)	− 0.001	(0.008)	0.003	(0.005)
	Model 11		Model 12		Model 13		Model 14	
All shocks by round								
Round 2	− 0.005	(0.047)	-0.076	(0.054)	− 0.025	(0.017)	0.011	(0.013)
Round 3	− 0.074	(0.052)	0.101	(0.052)	− 0.007	(0.019)	0.015	(0.012)
Round 4	− 0.061	(0.063)	0.008	(0.049)	− 0.029	(0.021)	− 0.008	(0.011)
Round 5	− 0.156**	(0.058)	− 0.177**	(0.056)	0.046**	(0.014)	− 0.006	(0.011)

Control variables included in the models but not shown

Standard errors in parentheses

Significance † $p < 0.10$* $p < 0.05$** $p < 0.01$*** $p < 0.001$

significantly negatively associated with the likelihood that a child reports always having enough to eat. However, cumulative shocks are not significantly associated with self-rated health or time use. Consistent with our models of intra-round shocks and testing outcomes, shocks experienced between rounds 4 and 5 have the strongest negative effect on youth well-being. Children who experienced shocks between rounds 4 and 5 were significantly less likely to report being food secure, less likely to report being in good or very good health, and spent significantly more hours per day on household chores. Finally, in Table 8 (see Appendix), we examine well-being outcomes using a categorical shock predictor variable and differentiate between types of shocks. Income/agricultural shocks are associated with a lower odds of food security, while environmental shocks are associated with lower odds of self-reported health. Exposure to 1–2 shocks, compared to zero shocks, is associated with a significantly lower odds of food security, increased time spent on chores, and reduced time spent studying, and exposure to 3 + shocks is associated with a significantly lower odds of food security.

Discussion and Conclusions

In this study, we used longitudinal data collected over a 15-year timespan to examine the extent to which lifetime exposure to household shocks is associated with testing and well-being outcomes among adolescents in Peru. The results suggest that shock exposure across childhood is linked with poorer schooling and well-being outcomes, particularly if shocks are experienced in later childhood.

Firstly, we found that experiencing more shocks across a child's lifetime is associated with significantly lower reading and vocabulary scores, as well as with

a lower likelihood of always having enough to eat. Our findings are consistent with previous studies which found that shocks negatively impact schooling outcomes and food security (Gitter & Barham, 2007; Lazzaroni & Wagner, 2016; Marchetta et al., 2019; Nguyen & Nguyen, 2020; Randell & Gray, 2016; Shah & Steinberg, 2017; Zamand & Hyder, 2016). Economic and environmental shocks may result in older children staying home from school or diverting their time to household domestic or income generation tasks rather than school work, while younger children may be impacted if caretaker time for supporting academic progress is undermined or if shocks affect their health or nutrition (Marchetta et al., 2019; Shah & Steinberg, 2017; Zamand & Hyder, 2016). Similarly, family shocks may impact children's psychological well-being, concentration, or divert caretaker attention and resources away from a child's school progress (Chae, 2016; Dhanaraj, 2016; Woldehanna & Hagos, 2015). Further research is needed to elucidate the mechanisms through which childhood shock exposure impacts testing outcomes in adolescence.

Secondly, we examined shock exposure during each intra-round interval in order to understand whether critical time periods of exposure exist in this context. We found that shocks experienced in later childhood, between rounds 4 and 5 when the children were approximately 12–15 years old, were negatively associated with multiple testing and well-being outcomes. Exposure to shocks during this time period was associated with lower math and vocabulary scores, more time spent on chores, lower self-rated health, and lower food security. This finding echoes prior research that has found older children to be more likely to be aware of household shocks, and more likely to provide support or leave school for work (Berhane et al., 2016; Gitter & Barham, 2007; Woldehanna & Hagos, 2015). In addition, the 12–15 age group corresponds with the transition from primary to secondary schooling, a time when children are particularly vulnerable to dropping out or falling behind in their studies (Cuervo et al., 2011; Zimmermann, 2020). Indeed, our results suggest that the recent experience of shocks may exacerbate negative schooling outcomes, as well as children's health and time available for learning and leisure. In other words, during a time period in which children are already vulnerable to negative schooling outcomes, shock exposure may further exacerbate risks to school performance and well-being.

This study is subject to several limitations. First, self-reported shocks offer a less precise measure of environmental shock exposure than meteorological data (Guiteras et al., 2015; Nguyen & Nguyen, 2020). However, some have called for both self-report and measured environmental shock data in conjunction to better understand the impact of environmental shocks (Karim, 2018; Nguyen & Nguyen, 2020). Other research suggests that self-reported shocks are more appropriate for gauging household responses to environmental shocks, as households are primed to recall events that trigger household coping mechanisms (Anglewicz & Myroniuk, 2018; Zamand & Hyder, 2016). Given our interest in the impact of different types of shocks on children's schooling and well-being, self-reported shocks offer an opportunity to better understand the household coping mechanisms that may influence children's learning and well-being.

Second, a small sample size limits our statistical power. However, panel data that include detailed information on shock exposure over time as well as in-depth

cognitive testing and well-being measures provide invaluable contributions to our understanding of the effects of repeated shock exposure across childhood. Lastly, questions on exposure to many of the shocks were asked beginning in the second round of the survey, such that the recall period for assessing shock exposure begins when sample children were 1 year old on average (ranging from 6 to 18 months at the time of the first survey). As a result, we do not have data on household shock exposure during the first six to 18 months of a child's life or during the child's prenatal period. Prior studies have found that exposure to shocks in utero and during the 1st year of life can have long-term negative impacts on health and well-being (Maccini & Yang, 2009; Randell, Gray, & Grace, 2020; Rosales-Rueda, 2018). Thus, due to data limitations, we are unable to assess whether shock exposure in utero and during infancy is associated with test scores in adolescence. Finally, shocks experienced by children and families may vary in severity, with important implications for children's schooling and well-being. However, data limitations do not allow for a measure of shock intensity.

Despite these limitations, this study offers unique insight into the relationships between shock exposure and cognitive and well-being outcomes in adolescence. Evaluating the links between lifetime shock exposure and testing and well-being outcomes for secondary school children in Peru sheds light on the ways that shocks may influence learning, health, and time use in low- and middle-income countries. In light of increasingly frequent and severe extreme weather events associated with climate change, as well as recent large-scale economic and health crises, it is critical for policies to minimize the negative impacts of shocks on learning and well-being outcomes. Potential policy solutions to mitigate the negative effect of economic, family, and environmental shocks on the well-being of children and adolescents include expanding social protection programs such as conditional or unconditional cash transfers and developing higher quality and more widely available crop or livestock insurance products (Agrawal et al., 2019; de Janvry et al., 2006; Jensen & Barrett, 2017). Future research should explore the mechanisms through which economic, family, and environmental shocks affect schooling and well-being outcomes in order to design and implement more targeted and effective interventions.

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Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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