Some people feel the rain; others just get wet: Early-life shocks and personality trait formation in Peru

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Abstract

Little is known about how early-life circumstances may influence personality trait formation, particularly in low-income contexts. I assess how exposure to early life rainfall shocks impacts core self-evaluations, a construct highly associated with socioeconomic success, amongst young adults in Peru. I find high rainfall exposure in years 2-3 of life negatively affects scores. Additionally, high prenatal rainfall, specifically in the 3rd trimester, has a positive impact on scores, driven by girls and those in the poorest households. Upon examining underlying mechanisms, I find that parents increase labour supply in response to higher rainfall, which has a negative impact on early-life social interaction and parent-child bonding, with no effects on material investments or children's physical development.

JEL codes: I31, J13, J24, O15, Q54
Keywords: Human capital, Rainfall shocks, Noncognitive skills, Child development, Foetal origins hypothesis

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1 Introduction

The importance of early life experiences in determining a range of later life outcomes is well established, from anthropometric and health indicators to employment, cognitive ability and educational attainment (see Almond & Currie, 2011; Almond et al., 2018; Currie & Vogl, 2013, for reviews). A developed literature demonstrates that not only genetics, but also early life environment and shocks play an important role in determining human capital formation (Almond & Currie, 2011). A growing strand of this evidence addresses how exposure to weather shocks during the perinatal phase can have effects that may be felt for many years, with early contributions from Pathania (2007) and Maccini and Yang (2009). However, while the relationships between early life rainfall and the health and cognitive dimensions of human capital are well explored (Carrillo, 2020; Nübler et al., 2021; Rosales-Rueda, 2018; Shah & Steinberg, 2017; Thai & Falaris, 2014; Zimmermann, 2020), less studied is the relationship between early life shocks and the evolution of later-life personality traits (often referred to as non-cognitive, socio-emotional, or 'soft' skills). Understanding this relationship is important given the evidence of the potential key role they play an in determining future labour market outcomes and socioeconomic success (Almlund et al., 2011; Caliendo et al., 2015; Fletcher, 2013; Heckman & Kautz, 2012; Hilger et al., 2022; Mueller & Plug, 2006; Nordman et al., 2019), and the theoretical dynamic complementarity of early shocks and investments on later period outcomes (Cunha & Heckman, 2008; Cunha et al., 2010; Heckman, 2007).

This chapter contributes to this literature by assessing the impact of exposure to rainfall shocks around the time of birth on personality trait formation in adolescence and adulthood. Using the Peruvian sample of Young Lives, a cohort study of childhood poverty following respondents from infancy to adulthood, I estimate the impact of early life exposure to rainfall shocks on measures of respondents' appraisal of their own self-worth, competence, and capabilities, as measured by their core self-evaluation (CSE) (Chang et al., 2012; Judge et al., 1998). I construct a measure of rainfall shocks as unexpected deviations from the long-term community-specific mean, using monthly rainfall data from The University of Delaware's Terrestrial Precipitation Gridded Time Series (UDEL-TS)(Matsuura & Willmott, 2018), matching this with detailed data on the respondents' location and date of birth to identify exposure to rainfall shocks in early life.

I find a 1-month exposure to a positive rainfall shock (total monthly rainfall $\geq$ +1.5 S.D. from the long-term mean) in the prenatal period is associated with a 0.068 S.D. higher standardised CSE score in adolescence and adulthood, while exposure to the same type of shock in the 2^{nd} and 3^{rd} year of life is associated with a 0.090 S.D. and 0.105 S.D. lower score, respectively. There is no significant effect for 1st year exposure, and I find no effect of exposure to a negative shock ($\leq$ -1.5 S.D.) in any period. Considering heterogeneities, I find that prenatal exposure to a positive rainfall shock has a positive impact on female adolescent and adulthood CSE, compared with a null effect for males, with the largest effects for those in the poorest households.

These results contribute to the literature which identifies the importance of early life circumstances in determining future human capital, expanding the limited evidence base for the effects on personality trait and socio-emotional skill formation (Brando & Santos, 2015; Leight et al., 2015; Moorthy, 2021; Shoji, 2023; Webb, 2024). In this literature, the methodology varies significantly in terms of shock type and exposure period considered; age at follow up; and outcome measures used. Most closely related to this study are two recent contributions by Chang et al. (2022) and Krutikova and Lilleør (2015). Krutikova and Lilleør (2015) find that exposure in-utero to a 10% increase in total rain season rainfall compared to the 10-year average is associated with a 0.08 S.D. increase in CSE scores at age 17-28 in a sample of rural Tanzanian households. In contrast Chang et al. (2022), find a -0.161 S.D. decrease in CSE at age 15 associated with prenatal exposure to a 1-month rainfall shock in India.

I expand on these studies in three ways. First, I provide an extensive assessment of potential mechanisms. I find that a positive rainfall shock exposure is positively associated with current period household and parental labour supply, suggesting parents are less available in the household at a key period of socio-emotional development. This impacts the time parents can spend interacting with their child in the early years, affecting the socio-emotional bond developed through parent-child interaction, consistent with the experimental literature exploring the role of early life psycho-social stimulation on later-life personality trait formation (Attanasio et al., 2020; Heckman et al., 2013; Sevim et al., 2023; Walker et al., 2022). All household adults work more in response, while non-adult household members do not alter their time use, suggesting this reduction in interaction is not offset by others.

Second, I consider not just the prenatal period but also exposure during a sensitive period after-birth, which has seen an increasing focus in the recent literature (Almond et al., 2018), and through which I can address the experimental literature discussed above. Third, I offer a detailed exploration of the robustness of my estimation strategy, including how the construction of both outcome and treatment variables may lead to significant measurement error and attenuation of estimates, including a robust assessment of the suitability of a single latent factor model, testing alternative shock variable construction, and accounting for several potential sources of bias (Anderson, 2008; Cameron et al., 2008; Conley, 1999; Dell et al., 2014) which are often unaddressed in similar studies using climate data.

The rest of the chapter is as follows: the study setting and data are described in section 2 and section 3. The empirical strategy is outlined in section 4. The main results, analysis of heterogeneous effects and robustness checks are presented in section 5, with the potential mechanisms underlying these results explored in section 6. Finally, concluding remarks are provided in section 7.

2 Context

Peru experiences a complex climate with significant variation in rainfall across its geographically diverse regions, from the warm and wet tropical Amazonian jungle and lowlands in the east to the semi-arid Pacific coast in the west, both separated by the drought- and frost-prone Andean highlands which run from north to south. Since the 1960s, rainfall patterns in the region have changed drastically (Haylock et al., 2006), with an increase in the frequency and intensity of precipitation-related extreme weather events, such as rainstorms, floods, mudslides and forest fires (Gloor et al., 2013; USAID, 2011).[1] Within a wider regional context, Peru is located in a climate-sensitive Andean South American region, prone to quasi-periodic extreme precipitation and temperature anomalies associated with the El Niño-Southern Oscillation (ENSO)(Ramírez & Briones, 2017). As a middle-income country with a high degree of inequality, individuals are often less able to shield from the effects of such anomalies than in high-income contexts, particularly those in the poorest households.

There have been several studies within the wider northern South America region which assess the impacts of early life exposure to rainfall shocks on educational attainment, health, and cognitive ability (Brando & Santos, 2015; Carrillo, 2020; Duque et al., 2019; Rosales-Rueda, 2018). Within Peru specifically, Danysh et al. (2014) report an increasing trend over time in height-for-age of 0.09 S.D./year for cohorts born between 1991-1997 in Tumbes, a region on the far north coast that is particularly prone to the effects of the El Niño. They find this rate is reduced to 0.04 S.D./year for cohorts born during or after the 1997-1998 El Niño event, with the subset of children in the most flood prone households subject to negative growth rates. Considering specifically the impact of rainfall shocks on socio-emotional development, Brando and Santos (2015) assess the effect of exposure to the 2010-2011 La Niña in Colombia, finding exposure to high rainfall is associated with an increased incidence of socio-emotional problems by age 5 (0.19 S.D.). However to the best of my knowledge, this study is the first in the region to assess the longer term impacts of early life shocks on socio-emotional skill formation in adolescence and adulthood.

[1] https://climateknowledgeportal.worldbank.org/country/peru/climate-data-historical: The number of intense rainstorms, mudflows and forest fires has more than doubled in the past 10 years and floods have increased by 60% since the 1970s.

3 Data

3.1 Young Lives

Young Lives (YL) is a longitudinal study of 12,000 children and their families across four developing countries (Ethiopia, India, Peru, and Vietnam) examining the causes and consequences of poverty (Boyden et al., 2018). The younger cohort of 2052 respondents were born in 2000-2002 and were tracked at age 6-18 months beginning in 2002, being revisited in 2006, 2009, 2013, and 2016 at ages 5, 8, 12, and 15 respectively. An older cohort (714 respondents), born in 1994-1996, were interviewed concurrently at ages 8, 12, 15, 19 and 22. This analysis focuses on the Peruvian sample, including both cohorts in the sample.

In Peru, the study employs a multi-stage, cluster-stratified, random sampling technique. Although a deliberate choice is made to oversample poor households by excluding the top 5% wealthiest districts prior to randomisation, a comparison with nationally representative surveys shows that households were broadly similar to the average household, although with slightly better access to health and education services, indicating the sample is generally suitable for analysing causal relations and modelling child welfare (Escobal & Flores, 2008).

At round 1 (2002) the total sample consists of 2766 children. Attrition is low given extensive tracking: by round 5 (2016) attrition due to respondent refusal, death, or being untraceable was 8.2% and 14.1% respectively, with 2468 respondents present in all rounds. Beginning in round 2, GPS coordinates are collected for the centre of a community with 3 or more respondents.[2] This GPS dataset was cleaned, validated, and matched to climate data, allowing for the identification of potential exposure to rainfall shocks using respondent's date of birth for 2386 of the respondents in 118 communities (McQuade & Favara, 2024). Accounting for missing responses for outcomes and control variables, a final sample of 2089 respondents is derived.

Children were first tracked just after birth, therefore an issue in attributing exposure to rainfall shocks is pinpointing if the mother resided in the relevant community from the date of conception throughout the period considered. To address this, in addition to the full sample, I specify an 'in-community' sub-sample of those that can be identified as definitely conceived in the community (N=1675, 80.2% of the final sample). From round 2, mothers were asked how many years they have lived in the community. Subtracting this from the date of interview, I calculate the approximated date of community move-in for the mother. Specifying a gestational period of 40 weeks prior to their child's date of birth to determine the likely date of conception, mothers for whom this date occurs after the

[2] For round 2, some larger round 1 communities are split into smaller communities with separate identifiers. For these cases the round 2 community is used as the location of birth, assuming no movement between disaggregated communities between rounds 1 and 2.

move-in date are considered to have conceived their child in the community.[3] However, this indicator is restrictive and problematic if by round 2, when the oldest respondents in sample are aged 12-13 years old, shock exposure had systematically impacted post-exposure migration choices – representing a confounding factor, with affected families self-selecting out of the sample. Therefore I continue to conduct the analysis using both samples.

3.2 Core Self-Evaluation

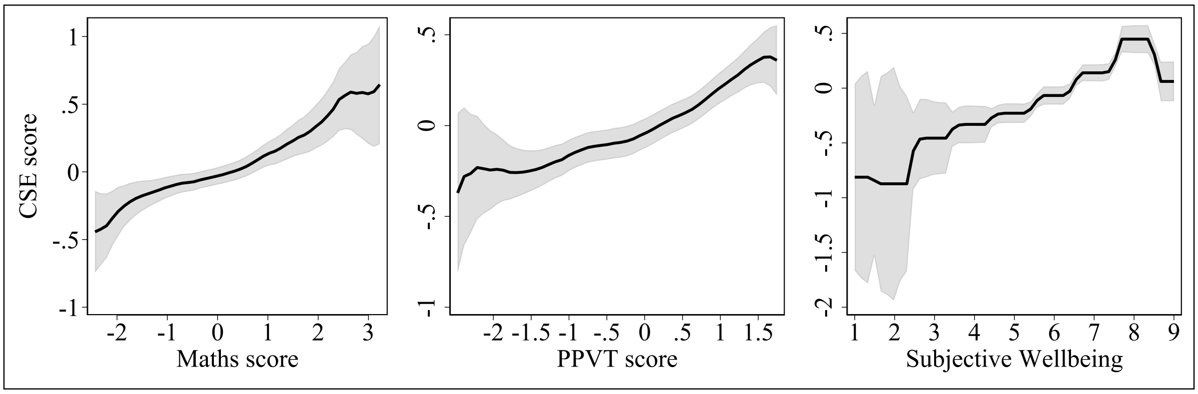
The outcome of interest is an individual's core self-evaluation (CSE) (Judge et al., 1998), measured in round 5 when respondents are aged between 14-23 years old. CSE has been shown to be strongly associated with life and job satisfaction, earnings, and educational attainment (Chang et al., 2012; Judge & Hurst, 2007). It reflects an individual's confidence in their own abilities and self-control, with a high score indicating a person has a positive and proactive view of themselves and their relationship to the world (Almlund et al., 2011). In the absence of a dedicated CSE questionnaire in the Young Lives study, an indirect approach (Chang et al., 2012) is used, drawing responses from the self-esteem, self-efficacy, and agency scales.[4] Self-esteem is derived from the Marsh (1990) self-description questionnaire II, and is a widely used measure in longitudinal studies (Laajaj & Macours, 2021). Self-efficacy (an individual's belief in their ability to cope with adversity and succeed) is measured using a scale developed by Schwarzer and Jerusalem (1995), and is well validated in a range of low- and middle-income countries. The agency scale was developed specifically for Young Lives to be administered to children in developing countries, and is closely related to Rotter's 'locus of control' concept (Rotter, 1966). These measures have been validated and display high internal consistency and reliability in YL samples (Yorke & Ogando Portela, 2018). Within sample associations between CSE, age-standardised cognitive test scores and subjective wellbeing (Cantril, 1965) at outcome are shown in Figure 1.

I specify a latent factor model, similar to Cunha et al. (2010), using exploratory factor analysis, a method commonly used to assess the psychometric properties of scale items, as well as for dimension reduction (Osborne, 2015). An advantage of this method over a simple average composite score is that it accounts for the disproportionate contribution of each item to the CSE construct to be recognised, allowing the shared variance between items and each item's unique variance to be distinguished. Negatively phrased items were

[3] While full term pregnancies commonly occur across a range of 37-42 weeks, given limited information about length of pregnancy in the YL survey (self-reported prematurity is only available for the younger cohort), a specific, relatively conservative cut-off is defined for simplicity.

[4] The big five inventory (BFI) neuroticism/emotional stability scale (Costa & McCrae, 2008; John, 1990) can also be included in the construction of CSE measures, however this scale is not administered amongst the younger cohort.

Figure 1: Within-Sample Association Between CSE and Cognitive and Wellbeing Outcomes



Polynomial line fit using Epanechnikov kernel, plotted with 95% CIs. CSE, PPVT and Maths scores are age-standardised based on age at R5. Subjective wellbeing is measured using a 9-point Cantril's ladder scale.

first reverse-coded to ensure unidirectionality.[5] All item scores were then standardised by age in years. In total 22 items are included in the initial model (see Table C20), with latent factors estimated using principal factors. Results strongly support the *a priori* assumption of a one factor model, with the first factor explaining 95.3% of shared variance, and a range of criteria, presented in Appendix C, indicating that a single factor should be extracted. To assess the robustness of results to an alternative method of outcome construction, I follow Laajaj and Macours (2021), defining a 'naïve' factor score – the standardised average score of all items in the 3 constituent scales.

3.3 Controls

Child level controls include indicators for gender and if their mother tongue is Spanish. Maternal controls for age and an indicator of if she has completed primary education are also included. Household characteristics are captured by an indicator of if the household is in a rural area and the round 1 household wealth index, a country-specific measure of household socioeconomic status (Briones, 2017).[6] Fixed effects are included for the child's year-month birth cohort and district of birth. Summary statistics for the main sample are provided in Table 1. The wealth index is a continuous measure with values ranging between 0 and 1 for the poorest and wealthiest household respectively, as such the sample is slightly pro-poor. Additionally, while only 29% report the household being rural,

[5]Two items from the agency scale were negatively worded such that a higher score reflected lower self-agency (e.g. *"I have no choice about the work I do - I must do this sort of work"*). Additionally, one item from the agency scale, *"If I study hard at school, I will be rewarded by a better job in the future"* was missing for a third of respondents, the majority of whom are no longer in school, and therefore was excluded for non-relevancy and to preserve sample size.

[6]While the wealth index is potentially measured contemporaneously or post-shock exposure, it captures longer-term indicators of household wealth, such as housing quality, access to services, and durable goods, therefore is less likely to be sensitive to short run deviations in climate conditions.

61% of the sample live in communities where the most important economic activity is agriculture, as reported in the community questionnaire, and 56% of households reported being actively engaged in agricultural work in round 1.

Table 1: Summary Statistics

	Mean	S.D.	Min	Max
Child characteristics				
EFA 1st factor CSE score	-0.00	(1.00)	-4.70	3.14
Naïve CSE score	0.00	(1.00)	-3.90	3.48
Age in years at outcome	16.67	(3.03)	14.08	22.83
Female	0.49	(0.50)	0.00	1.00
Spanish first language	0.86	(0.35)	0.00	1.00
Mother characteristics				
Completed primary	0.63	(0.48)	0.00	1.00
Age at child birth	26.56	(6.80)	13.00	48.00
Household characteristics				
Wealth index	0.44	(0.24)	0.00	0.92
House location is rural	0.29	(0.46)	0.00	1.00
Agricultural community	0.61	(0.49)	0.00	1.00
Engaged in Agricultural work	0.56	(0.50)	0.00	1.00
N	2089			

Notes: Sample means are reported with standard deviations in parentheses.

3.4 Climate Data

I exploit spatial and temporal variation in precipitation to identify exposure to abnormal amounts of rainfall. Identification relies on short-run fluctuations from the long-run month-specific mean rainfall for a location being unpredictable and plausibly exogenous. While YL households provide self-reports of their experience of recent climate shocks, this data is likely endogenous and subject to significant measurement error (Bound et al., 2001), depending on respondent recall and their perceived impact of the shock, for which they may systematically over- or under-report exposure (Nguyen & Nguyen, 2020). Additionally, it is difficult to verify the timing and intensity of self-reported shocks.

Data on rainfall comes from the Terrestrial Precipitation Gridded Time Series (v5.01, 1901-2017) (Matsuura & Willmott, 2018) from the University of Delaware (UDEL-TS). This data provides estimates of monthly total precipitation on a 0.5x0.5° grid, derived from a range of publicly available station records. I match this data to the location of Young Lives communities to create community-level estimates of monthly total rainfall (McQuade & Favara, 2024).[7]

[7] Community estimates are calculated as the inverse distance-weighted average of the four nearest grid points to the community centre point, which is defined as the main square, or in their absence, an

To identify exposure to an abnormal rainfall shock, I derive a standardised precipitation index (SPI) (McKee et al., 1993). The SPI is a widely used drought index which benefits from its simplicity in calculation, requiring only precipitation data. It is used to identify the duration and/or severity of a drought or high level of rainfall on a relative scale (Hayes et al., 1999). Rainfall is non-negative and typically positively skewed in the short run, therefore non-zero estimates of community rainfall across 1988-2017 were fitted to a two-parameter gamma distribution, to approximate the long-term distribution of rainfall for each month of the year at each community location. Resulting distributions are transformed to standard normal with mean 0 and standard deviation 1 (S.D.), following Abramowitz and Stegun (1968). Following the drought classifications defined by McKee et al. (1993), I consider a monthly SPI value of ≤ -1.5 S.D. from the long-term mean as an indicator of severe drought-like conditions, (herein, a "negative" rainfall shock) and similarly rainfall $\geq +1.5$ S.D. as a "positive" shock (corresponding to the "severely wet" category). For greater detail, see McQuade and Favara (2024) and Lloyd-Hughes and Saunders (2002).

Table 2: Exposure to (±)1.5 S.D. Shocks, by Period and Sample

	% Exposed		**Mean exposure**	
	Full	In-comm.	Full	In-comm.
Positive shocks				
Prenatal	53.9	53.5	0.66	0.64
1st year	66.7	67.5	0.80	0.81
2nd year	61.9	61.1	0.95	0.94
3rd year	38.4	36.4	0.63	0.60
Negative shocks				
Prenatal	19.3	19.2	0.25	0.25
1st year	35.1	32.7	0.47	0.43
2nd year	28.4	28.5	0.31	0.31
3rd year	22.5	21.6	0.26	0.25
N	2089	1680	2089	1680

Notes: % Exposure is the share of sample exposed to at least 1 monthly shock in each period between conception and 3rd Birthday. Mean exposure captures the mean number of months of exposure experienced. "In-comm." refers to the the restricted in-community sample, consisting only respondents who are definitely resident in the community from conception until round 2.

Almost all children were exposed to at least one mild shock of 1 S.D. in some periods, while very few were exposed to any extreme shock >2 S.D., as such these cut off points are unsuitable for use. The distribution of shock exposure (of at least one month) within the perinatal period, estimated separately for the prenatal phase (9 months prior to birth) and each of the first three years of life (up to the month of the child's 3$^{\text{rd}}$ birthday) for the postnatal phase, across the full and restricted in-community sample are provided in

important landmark such as a church, school, or post office.

columns 1 and 2 of Table 2, respectively. The mean number of months of exposure in each period is provided in columns 3 and 4.

4 Empirical Strategy

To assess the effects of early life rainfall shock exposure on personality trait formation in adolescence and adulthood, I estimate the following equation using ordinary least squares (OLS):

$$CSE_{ijgr} = \beta_0 + \beta_1^{'} P_{gt} + \beta_2^{'} N_{gt} + \beta_3^{'} H_{ij} + V_g + B_{t_0} + \varepsilon_r \tag{1}$$

Where CSE_{ijgr} is age-standardised CSE measured at outcome in round 5 (age 14-23), for child i, born in household j, in community g, located in district r. P_{gt} and N_{gt} are vectors of community-level rainfall shock indicators for each of the 4 periods, t: 9 months of gestation (prenatal phase) and the first, second, and third year of life (postnatal phase). These are defined:

$$P_{gt} = \sum_{n=1}^{m} \mathbb{1}(SPI_{gn} \geq 1.5), \qquad N_{gt} = \sum_{n=1}^{m} \mathbb{1}(SPI_{gn} \leq -1.5) \tag{2}$$

where P_{gt} and N_{gt} capture the magnitude of positive and negative shocks experienced in community g in period t, respectively. These are measured in units of months m, where the function $\mathbb{1}(\cdot)$ takes a value of one if the SPI value for community g in month $n = 1, 2, ..., m$ is equal to or more extreme than the cutoff values defined in subsection 3.4. $\mathbf{H_{ij}}$ is a vector of child- and household-specific controls, as described in subsection 3.3. V_g is a time-invariant community fixed effect, and B_{t_0} is a year-month birth cohort fixed effect.

Given potential similarities in weather patterns across nearby communities, estimates of standard errors at the treatment level are likely biased (Auffhammer et al., 2013). Therefore, I cluster standard errors in the base specification by district, r, a higher administrative level than the community, to allow for local spatial correlation across communities within the same district area, as recommended by Dell et al. (2014). However, this yields a relatively small number of clusters (38) of unequal size. Asymptotic justification for cluster robust standard errors assumes many clusters, generally exceeding 40-50 groups, of equal size. In the presence of too few clusters, standard errors are biased towards zero and inference based on standard asymptotic tests will lead to an over-rejection of the null hypothesis. As such, I implement a cluster wild bootstrap procedure, as recommended by Cameron et al. (2008), to derive adjusted p-values, based on 10,000 iterations.

Additionally, to allow for arbitrary spatial correlation over space regardless of administrative boundaries, I compute standard errors adjusting for spatial correlation between nearby units, as proposed by Conley (1999), using a Bartlett kernel decay which allows for a spatial-weighted covariance matrix with weights declining linearly from one to zero over a distance of 50km from the community. Finally, I assess the robustness of results to adjustments for multiple hypothesis testing, deriving adjusted q-values following Anderson (2008), reported separately in Table B9.

5 Results

5.1 Main Results

Results for the impact of rainfall shocks for each period of the perinatal phase on full and in-community sample age-standardised CSE scores are listed in Table 3. For the main results, three p-values are reported: those derived from a) the potentially downwards biased cluster robust standard errors, reported in parentheses; b) cluster wild bootstrap procedure using 10,000 replications, reported in square brackets, and c) the spatial correlation robust standard errors (Conley, 1999), reported in curled brackets. As expected, the p-values for wild bootstrap specifications are generally more conservative than standard cluster robust p-values. Interestingly, the p-value derived from Conley spatially-robust standard errors are generally smaller than the cluster robust values. this is likely due to many communities in the sample being located within 50km of others, given the clustered nature of sampling in YL.[8] This leads to there being relatively few independent clusters, and potentially fewer than by clustering at district level in cases where the distance from a community to the district border is smaller than a 50km radius. As this methodology is also asymptotically justified, standard errors will be downwards biased.[9] Therefore, this method likely does not represent a refinement over cluster robust standard errors. For the rest of the analysis the more conservative wild bootstrap approach is the preferred specification with p-values reported in all subsequent tables, and alternative p-values reported in the relevant appendix tables.

A pattern is clear across all specifications, that a positive rainfall shock (+1.5 S.D.) experienced in the 2$^{\text{nd}}$ and 3$^{\text{rd}}$ year of life is associated with a lower age-standardised CSE score in adolescence and young adulthood. Exposure to a similar positive shock in the prenatal phase is associated with a higher later-life standardised CSE score, with exception of the full sample naïve score estimated effect, which is marginally insignificant under the wild bootstrap procedure. There is no significant effect estimated for exposure to a positive shock in the 1$^{\text{st}}$ year of life. Similarly, there are no statistically significant effects estimated for exposure to negative shocks in any period. Results are consistent

[8]The mean number of communities within 50km is 8.

[9]For an example of this, see: https://blogs.worldbank.org/impactevaluations/randomly-drawn-equators

Table 3: Impact of (±)1.5 S.D Shocks on CSE Scores, by Measure and Sample

	EFA 1st Factor		**Naive z-score**	
	Full	In-comm.	Full	In-comm.
Positive shock				
Prenatal	0.068	0.096	0.052	0.081
	(0.036)**	(0.013)**	(0.096)*	(0.037)**
	[0.055]*	[0.041]**	[0.123]	[0.074]*
	{0.019}**	{0.002}***	{0.084}*	{0.017}**
1st year	0.043	0.051	0.027	0.043
	(0.175)	(0.262)	(0.430)	(0.338)
	[0.162]	[0.280]	[0.424]	[0.368]
	{0.124}	{0.216}	{0.339}	{0.260}
2nd year	-0.090	-0.093	-0.091	-0.095
	(0.007)***	(0.016)**	(0.007)***	(0.012)**
	[0.006]***	[0.016]**	[0.007]***	[0.014]**
	{0.005}***	{0.008}***	{0.004}***	{0.005}***
3rd year	-0.105	-0.129	-0.097	-0.115
	(0.001)***	(0.004)***	(0.003)***	(0.009)***
	[0.003]***	[0.009]***	[0.006]***	[0.020]**
	{0.000}***	{0.001}***	{0.001}***	{0.004}***
Negative shock				
Prenatal	-0.030	-0.062	-0.036	-0.073
	(0.434)	(0.190)	(0.346)	(0.147)
	[0.434]	[0.257]	[0.364]	[0.246]
	{0.424}	{0.169}	{0.351}	{0.139}
1st year	0.066	0.075	0.036	0.043
	(0.170)	(0.232)	(0.423)	(0.510)
	[0.180]	[0.255]	[0.420]	[0.543]
	{0.149}	{0.199}	{0.405}	{0.492}
2nd year	-0.056	-0.048	-0.056	-0.033
	(0.478)	(0.517)	(0.457)	(0.637)
	[0.571]	[0.550]	[0.556]	[0.662]
	{0.470}	{0.520}	{0.451}	{0.642}
3rd year	-0.084	-0.069	-0.071	-0.045
	(0.120)	(0.258)	(0.170)	(0.399)
	[0.168]	[0.287]	[0.235]	[0.414]
	{0.119}	{0.209}	{0.170}	{0.355}
Controls	Yes	Yes	Yes	Yes
N	2089	1675	2089	1675

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Full sample refers to children geolocated in round 1. In-community restricts sample to those whose mother lived in the same community from conception until round 2. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

between the full and in-community samples, suggesting shock exposure does not seem to influence migration choices.[10]

Estimates are more precise for the preferred EFA-derived score compared to the naïve score. As noted above, it is intuitive that EFA provides a more precise estimate, as the technique extracts as the 1st factor the dimension which explains the greatest amount of variation, reducing dimensionality and noise. Additionally, the naïve score treats all three scales as contributing with equal weighting towards the higher order construct of CSE, even though there is strong evidence that the different constituent scales contribute asymmetrically (Chang et al., 2012).[11]

In the primary specification, exposure to a positive rainfall shock during the prenatal phase is associated with a 0.068 S.D. higher CSE score (cluster wild bootstrap p-value p = 0.055). This result is consistent with Krutikova and Lilleør (2015), who find an 0.083S.D. higher CSE score associated with a 10% increase in the natural log deviation of rainfall in the year preceding birth in Tanzania. Considering the postnatal period, exposure to a similar shock in the 2nd and 3rd year of life is instead associated with a -0.090S.D. and -0.105S.D. lower score respectively, significant at the 1% level. This reverse of direction compared to the in-utero period is again consistent with the findings of Krutikova and Lilleør (2015) who, in an additional analysis, estimate a small negative effect on CSE scores of exposure to increased rainfall in the 2nd year of life (they do not assess the impacts for a 3rd year of life), however their result is not significant. That a significant effect is estimated for the 2nd to 3rd year of life, may reflect the pattern of brain development and plasticity, with the number of synapses per neuron in the brain growing from approximately 2500 at birth to a peak of around 15,000 between age 2 and 3 (Gopnik et al., 1999). However, the potential channels through which rainfall impacts CSE and how they may have a heterogeneous effect in different periods of exposure are not clear *a priori*, and are discussed in more detail in section 6. Next, I assess the potential for heterogeneity across different sub-groups.

5.2 Heterogeneous Effects

A common finding in the literature is that early-life shocks impact outcomes heterogeneously across different sub-groups, particularly across gender and socio-economic standing (Almond et al., 2018; Currie & Vogl, 2013), with results often being driven predominantly by the impact on boys or girls, and the strongest effects generally found amongst the poorest or least-educated households. To assess this, shock variables are interacted with indicators for: a) if a respondent child is female; b) if the mother has completed

[10] Exposure to these short-run, relatively mild shocks is likely not severe or long-lasting enough to elicit a migratory response.

[11] Table B1 estimates the impact of shock exposure on the three component scales separately. While the pattern of effects are similar, the magnitude of effect is different across scales, with the largest effect sizes estimated for the Marsh self-esteem measure.

primary education (achieved grade 6 or higher); and c) if the household is in the bottom quartile of the wealth index (Or "poorest" category, see Briones, 2017). Lastly, it is hypothesised that rainfall shocks may disproportionately impact agricultural communities which are reliant on rainfall for crop production. A community is considered agricultural if, for all households in that community, 40% or more report household members being actively engaged in agricultural work. Estimated effects for EFA 1st factor CSE scores are shown in Table 4.

Notably, there is a positive effect estimated for the interaction between a prenatal shock and if the respondent is female or from the poorest households, both significant at the 5% level, accompanied with an insignificant baseline effect. The linear combinations of the shock exposure and the interaction terms are both statistically significant, with cluster wild bootstrap p-values of $p < 0.001$. This suggests that the mainline positive effect estimated for prenatal shock exposure is driven predominantly by the effect higher rainfall has on girls and those from the lowest wealth households. In contrast, for post-birth shock exposure there are no evident heterogeneous effects by gender. Interestingly, a large and significant baseline effect is estimated along with an almost equally large and oppositely signed interaction term for the poorest households, suggesting the negative effect of exposure in the 3rd year is nullified for the poorest households (I fail to reject the null hypothesis that the linear combination is statistically different from zero; cluster wild bootstrap p-value $p = 0.887$). This suggests that any potential benefit from increased rainfall for the poorest households may offset the negative effect seen in more affluent households.

In contrast, whilst mother's level of education, as measured by an indicator of if she completed primary education, is an important factor in determining CSE scores, there is no strong evidence of any interaction with shock exposure. Lastly, it was hypothesised that agricultural communities may be more vulnerable to the impacts of rainfall shocks, but there is no clear evidence of a differentiated experience of shocks.[12] The next section reports the results of a range of robustness and validation checks.

5.3 Robustness Checks

The results of calculating an SPI measure can be influenced by the choice of distribution used. Most commonly short interval data (1- or 3-month SPIs) are best fitted to a gamma distribution, however it can also be fitted as a lognormal, Weibull, or exponential distribution, and the optimal distribution differs based on local climate characteristics

[12]This does not result from the indicator being a poor measure of if a community is agricultural, as alternative specifications (at household level, if an the individual HH reports a member of the household being engaged in agriculture as a primary activity or the location type of a household is rural; or at community level if a community leader reports arable crop or livestock farming as the primary activity for the community) do not yield qualitatively different results.

Table 4: Heterogeneous Effects of +1.5 S.D Shocks on CSE Scores

	Female	Poorest	Mother's education	Agricultural
Level term	0.087	-0.193	0.226	-
	[0.519]	[0.350]	[0.004]***	
Positive shock				
Prenatal	0.024	0.046	0.073	0.038
	[0.650]	[0.222]	[0.189]	[0.405]
**Interaction*	0.100	0.173	-0.004	0.086
	[0.080]*	[0.024]**	[0.949]	[0.183]
1st year	0.057	0.062	0.081	0.078
	[0.354]	[0.136]	[0.246]	[0.328]
**Interaction*	-0.029	-0.040	-0.059	-0.041
	[0.760]	[0.782]	[0.446]	[0.666]
2nd year	-0.106	-0.081	-0.055	-0.125
	[0.010]**	[0.021]**	[0.224]	[0.154]
**Interaction*	0.032	-0.046	-0.055	0.034
	[0.601]	[0.426]	[0.493]	[0.735]
3rd year	-0.100	-0.142	-0.116	-0.114
	[0.073]*	[0.000]***	[0.001]***	[0.049]**
**Interaction*	-0.013	0.133	0.010	0.038
	[0.825]	[0.024]**	[0.890]	[0.586]
Negative shock				
Prenatal	0.029	-0.051	0.019	-0.022
	[0.576]	[0.177]	[0.850]	[0.597]
**Interaction*	-0.122	0.153	-0.071	0.006
	[0.118]	[0.267]	[0.551]	[0.960]
1st year	0.082	0.071	0.066	-0.062
	[0.256]	[0.255]	[0.307]	[0.670]
**Interaction*	-0.039	0.015	-0.004	0.143
	[0.656]	[0.848]	[0.952]	[0.360]
2nd year	0.009	-0.046	0.020	0.085
	[0.955]	[0.473]	[0.759]	[0.445]
**Interaction*	-0.122	-0.041	-0.123	-0.190
	[0.345]	[0.743]	[0.096]*	[0.181]
3rd year	-0.071	-0.080	-0.062	-0.147
	[0.388]	[0.297]	[0.347]	[0.283]
**Interaction*	-0.035	-0.037	-0.042	0.120
	[0.726]	[0.796]	[0.681]	[0.316]
Controls	Yes	Yes	Yes	Yes
N	2089	2089	2089	2089

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed. Alternative p-values are reported in Table B2.

(Mishra & Singh, 2010). I define an alternative shock measure, fitting values to a lognormal distribution, as shown in Table B3. Results indicate a similar pattern, however the magnitude and significance of some results differ, likely impacted by outliers and poor fit of data. Figure B1 and Figure B2 show the multi-density plot of monthly SPI values for each community in blue, in comparison with a standard normal density plot (of mean zero and standard deviation one) overlayed in red, for the transformed gamma-fitted and lognormal-fitted SPI measures respectively. SPI values should be approximately normally distributed if the underlying rainfall data is well-fitted to the theoretical distribution chosen. With exception of a few outliers, gamma-fitted distributions for each month generally follow an approximately normal distribution around mean zero (although often with a greater peakedness, suggesting extreme values may be less common than under the theoretical normal distribution). In contrast the lognormal-fitted SPI distributions for every month display a significant negative skew, and a large peak above zero, but with very few extreme positive values, indicating that lognormal provides a poor fit for the relative distribution of rainfall in YL communities in Peru.[13]

Although I address arbitrary spatial correlation in estimates, it is possible that there is a temporal auto-correlative component impacting results when the effects of shock exposure in different periods are estimated jointly. Table B4 shows the results obtained when age-standardised CSE scores are regressed on shock exposure in each period individually. The overall pattern of results remains, with exception that the prenatal effect is diminished in magnitude and not significant at conventional levels (wild bootstrap $p = 0.185$), which could suggest that the effect estimated for the prenatal period may be correlated with subsequent exposure in the postnatal period. However, column 1 of Table B5 shows that when controlling for the cumulative number of positive or negative shocks, the estimated effect of cumulative shock exposure is non-significant, suggesting the link with subsequent exposure is likely weak. Under this specification, the prenatal effect remains significant at the 10% level, and the pattern of results remains similar. Columns 3 and 4 of Table B5 report the effects of shock exposure when estimated separately by shock type (positive or negative), with results similar in sign, magnitude, and significance to the mainline results.

Furthermore, I test if other periods outside the window of gestation and the first 3 years of life have an impact on later-life CSE. Column 2 Table B5 estimates the effect of exposure to shocks across all base periods as well as for the year prior to conception and 4^{th} year of life. To minimise measurement error, this is estimated for the in-community sample only, for which it is certain all respondent mothers are resident in the community across the whole period from before conception up until age 4 (the age of the youngest individuals interviewed in round 2). The pattern of results remains, with no significant

[13] Additionally, Couttenier and Soubeyran (2014) show that the SPI and other related indices, when well-defined, are more efficient than other commonly used linear measures.

effect found for exposure to shocks in the year prior to conception, or in the 4$^{\text{th}}$ year of life. Overall these robustness checks suggest that results are unlikely to be spurious and are robust across specifications, although there may be some correlation between exposure in different periods, which may inflate the effect size when estimated jointly.

Auffhammer et al. (2013) show that precipitation and temperature can be correlated, with the sign of this correlation dependent on the region, and suggest that not controlling for temperature may lead to omitted variable bias. Column 1 of Table B6 estimates the main specification controlling for community-specific average temperature across each period, with results remaining unchanged.

A potential transmission mechanism for early life rainfall shocks is that the shock impacts households directly through an agricultural channel. This can operate by affecting household agricultural yields and local food prices, or by increasing/decreasing the amount of time household adults spend working in agriculture-related employment. The YL sample includes several communities which are located within or on the outskirts of Lima, a large highly-urbanised and globally connected metropolitan area. It is likely that these communities would be the least affected by shocks if effects operate through this channel. I therefore re-estimate the main results on a sub-sample excluding these urban communities, as is common in studies of the effects of climate on human capital (e.g. Krutikova and Lilleør (2015) and Maccini and Yang (2009)). Results are reported in column 3 of Table B6 with estimates of the coefficients of interest being 8-21% larger in magnitude.

Additionally, if results are predominantly driven by the effect on local agriculture, then it is possible that rainfall shocks which occur during the growing season of primary crops are most salient (similar to Krutikova & Lilleør, 2015). As a climatically and geographically diverse country, the primary crop grown and timing of planting and harvesting varies across the YL communities. Using data from the Peruvian Ministry of Agriculture (MINAGRI) on department-level yields for 6 different crops in 2010, I identify the primary crop by area sown in each department, as shown in Figure B3.[14]

Following a similar procedure to Webb (2024) and Auffhammer et al. (2013) I estimate the department-level mean planting and harvesting dates using gridded crop calendar data (Sacks et al., 2010). Estimates of the average planting and harvesting days for 19 crops are provided on a 0.5x0.5° global grid, based on the nearest agricultural census data from 2000.[15] I aggregate this grid-level data to the department level to obtain the mean planting and harvesting date for the primary crop, rounding to the month level.

A growing season shock is defined if, for a given month, that month-of-year falls between the estimated planting and harvesting month (inclusive) for the primary crop of

[14] The data used was obtained as part of the "cropdatape" R package, available at: https://github.com/omarbenites/cropdatape. Crops included are rice, quinoa, potato, sweet potato, tomato and wheat. Tomato was excluded as a perennial crop.

[15] available from the Center for Sustainability and the Global Environment at the University of Wisconsin-Madison: https://sage.nelson.wisc.edu/data-and-models/datasets/crop-calendar-dataset/

the department in which the YL community is located, using the same measure of shock as in the main results. The effects of early life growing season shock exposure on CSE scores at outcome are estimated in column 2 of Table B6. The pattern of results remain consistent, however the magnitude of estimates for prenatal and 2nd year exposure are diminished and not significant at conventional levels. Due to data limitations, the exact crops which are the most important for YL households cannot be accurately identified, and the crops sown and activities carried out by households may differ significantly from the department level trend on a year-to-year basis.

The Young Lives study is structured as a cohort study, with the primary, younger cohort, born between 2000-2002, and a smaller, older cohort, born between 1994-1996.[16] While the main specification controls for time-invariant characteristics specific to every month-year birth group, there may be wider time-invariant differences in characteristics and response patterns between the older and younger cohorts. Column 4 of Table B6 reports estimates after including a cohort fixed effect, with results remaining consistent and unchanged.

Another threat to my design is that early life shocks may lead to selective mortality, potentially altering sex ratios (E.g. Hoffmann, 2014). To assess potential sex selection within the sample conditional on shock exposure, I regress the sex of the child on prenatal shock exposure (as well as postnatal exposure, to test for any potential spurious relationship between climate shocks and sex). Results are reported in column 1 of Table B7, with no evidence of impacts of shock exposure on sex ratio within sample. This is expected, as short run deviations in rainfall are mild compared to extreme shocks that could influence mortality (Almond et al., 2018).

Furthermore, results could be biased if shock exposure is predictive of selection into the sample. In particular if shock exposure influences migration decisions, those exposed prebirth may migrate out of shock-prone communities. While this is not directly testable within this analysis, I test if shock exposure is predictive of the household's choice to migrate between birth and round 2 (when respondents are aged 4-13). Column 2 of Table B7 shows that shock exposure in the prenatal period and years 1-3 of life does not predict migration.

Given the finding of a positive effect on later life CSE of prenatal exposure to positive shocks, it is of interest to understand if the effect of exposure is isolated to a specific trimester of gestation. Both Krutikova and Lilleør (2015) and Chang et al. (2022) assess the effect of exposure to precipitation shocks by trimester in-utero on later life CSE, with both finding no differential effect of shocks by trimester. In contrast, I find that the effects of prenatal shock exposure are isolated to the 3rd trimester of pregnancy, with exposure to a positive shock in this period associated with 0.115 S.D. higher adolescent and

[16] An additional panel of the nearest younger sibling in age to the younger cohort child is also defined, however not all required outcomes were administered in this sample.

adulthood CSE, as shown in Table B8. Additionally, a negative shock in the 3$^{\text{rd}}$ trimester is associated with a -0.133 S.D. lower score. Overall, this is suggestive that exposure in the final trimester is particularly important for future personality trait formation, whether due to a direct effect on the mother and child, or indirectly by impacting the home environment and resources available within the household immediately after-birth.

Lastly, given a large number of hypotheses being tested in the main results, a concern is the potential for over-rejecting the null hypothesis (type I error) due to multiple inference. In Table B9 I control for the false discovery rate (FDR), the expected proportion of rejections that are type I errors, computing sharpened q-values as described by Anderson (2008). This procedure presents a trade-off between preserving statistical power and reducing false positives by vastly reducing the penalty of additional hypotheses.[17] The outcomes of interest remain significant when controlling FDR at q=0.10, with exception of the prenatal effect in the full sample naïve z-score measure (q-value = 0.203).

6 Mechanisms

The exact causal channel through which early life rainfall shocks impact adolescent and adulthood personality trait formation is unclear *a priori*. This section explores several potential mechanisms and presents a body of evidence across a range of additional analyses.

6.1 Nutrition

Rainfall shocks may impact personality trait formation in low- or middle-income settings by affecting nutrition. This could occur directly, influencing local food availability, impacting the child in-utero through intrauterine exposure to maternal under-nutrition, or immediately post-birth by affecting breastfeeding and/or early nutrition when weaning (Krutikova & Lilleør, 2015; Rosales-Rueda, 2018). I assess the role of nutrition by regressing early life shock exposure on an indicator of being stunted at age 8. Stunting, a commonly used indicator of chronic under-nutrition or poor health, is defined as height $\leq$ -2 S.D. from the age and gender specific mean (height-for-age), following World Health Organisation (WHO) child growth standards (WHO, 1995). Using Young Lives data, Dercon and Sanchez (2013) show a positive association between age 8 height-for-age and self-esteem, a component of my CSE measure, in Peru. Results are reported in column 1 of Table B10. No significant effect is found on the probability of being stunted, suggesting that nutrition is not a primary transmission mechanism between early life shock exposure and personality trait.

[17] For comparison, the Bonferroni method is generally overly conservative (Romano & Wolf, 2005), providing low statistical power.

6.2 Child Health

Additionally, rainfall variation can impact child health beyond nutrition. Increased rainfall may disrupt sewage or drainage, contaminating water supplies, damaging crops, and leading to bodies of standing water, which can contribute to the incidence of water-borne diseases (Rocha & Soares, 2015). To assess the role of poor health, I assess the impact of shock exposure on 3 binary indicators of child health and disease burden: a) self-reported good/very good health at outcome, a measure of overall health; b) if a child has suffered a serious illness between birth and age 8; and c) if a child reports a long-term disability at outcome. Results are reported in columns 2-4 of Table B10. I find no evidence of a link between child health and positive rainfall shock exposure.

6.3 Caregiver Stress

Alternatively the effects of early life shock exposure may be transmitted indirectly by impacting parental mental wellbeing. Pressures caused by shocks on finances, food availability, and employment may increase parental stress – affecting their parenting practices, availability, or temperament (Duque, 2017; Shoji, 2023; Trinh et al., 2021). Primary caregiver mental wellbeing is assessed for the younger cohort in each round using the WHO self-reported questionnaire (SRQ-20), a screening tool measuring symptoms of non-clinical anxiety and depression that caregivers experienced in the 30 days prior to interview (Tuan et al., 2004). Using data from rounds 1-5, I construct a measure of the total number of symptoms reported (0-20), as well as a 'caseness' score for respondents reporting 7 or more symptoms. Results are reported in Table B11.[18] I find no evidence of an effect of positive shocks in the 12 months prior interview on caregiver mental wellbeing.

Following Favara (2018), I construct an index of early parenting practices using questions administered to caregivers of the younger cohort in the 1st round regarding what actions they take in response to their child crying. A positive score indicates the respondent reports more good practices (such as cradling the child or singing to them, coded as +1), and a negative score indicates they report more detrimental practices (such as ignoring, shaking, or spanking the child, coded as -1). A list of reported practices is available in Table B12. Results are reported in column 4 of Table B11 and do not provide evidence of an association between positive prenatal rainfall shocks and a change in early life parenting practices.

6.4 Parent-Child Relationship

An important mechanism through which personality traits may be affected by early life shocks is by the influence they have on both the time and resources available for parents

[18] As a robustness check I construct an alternative caseness score for 8 or more symptoms (Beusenberg et al., 1994), reported in column 3 of Table B11.

to invest in nurturing and interacting with children in the early years of development. A positive rainfall shock could have either an income effect, where higher rainfall may impact household income from agricultural work, leading to greater material investments, or a substitution effect, with parents increasing their labour supply in response to increased labour demand, reducing the time they are available in the household to care for the child. Evidence from neurobiology shows that a strong positive attachment with parents in early life promotes healthy brain development (Schore, 2001). Additionally, experimental literature on early life investments show that increased social stimulation and interaction between parents and children in early years has a lasting benefit on socio-emotional skills and personality traits, even when effects on other outcomes, such as cognitive ability, diminish as children age (Attanasio et al., 2020; Heckman et al., 2013; Walker et al., 2022). However, it is unclear *a priori* which effect dominates in the case of positive rainfall exposure (Kochar, 1999; Nordman et al., 2022). Therefore, I assess how rainfall shocks in the year prior to interview may impact the reported working hours of parents, and subsequently how this may drive a change in parents' investments, both materially and psycho-socially, in their children.

In rounds 2 and 4, adult household members were asked about their average daily hours spent working in up to three economic activities, and the relative importance of each activity in terms of income. In column 1 of panel A of Table 5 I assess the effect of a positive rainfall shock in the 12 months preceding interview on the daily working hours for the most important (main) activity. Controls for household rural location; household wealth index; respondent gender, age and age-squared; and fixed effects for survey round, month of interview and community are also included. I estimate that for each month of positive rainfall shock experienced in the previous 12 months, a parent works an additional 11 minutes per day in their main activity. This suggests parents are working more and spending less time in the household, although this effect may not be substantial in practical terms.

However, it is possible that main activity labour supply is inelastic to shock exposure if that activity is contracted/salaried with fixed hours. 46% of respondents report more than one activity, with the most important task economically not always the task for which respondents spend the most time working on. Therefore, changes in labour may be masked if adults respond by working more in other activities. In panel B I assess the effect of shock exposure on the average sum of hours worked across all reported paid activity. I find that each month of exposure to a positive rainfall shock is associated with an additional 26 minutes per day of work, indicating that parents respond by working more in all reported activities, for which labour supply may be more elastic.

It is expected that mothers and fathers may respond differently to shock exposure, particularly if there is an uneven distribution of childcare and domestic work. As such, column 2 reports the impact of a positive shock including an interaction term for if the respondent is female (e.g. the mother) for the main activity (panel A) and all paid activity (panel B). Looking at the differences between fathers and mothers, results differ between the main activity and all paid work. For the primary economic task, while mothers report working fewer hours generally, there is little difference by sex in the response to positive shocks, with both men and women increasing work in their main job. the p-value for the linear hypothesis suggests that the total estimated effect for women of 10 minutes per day is significant at the 10% level. In contrast in Panel B, while the effect for the base group (fathers) is large (+55 minutes per day for each month of exposure), a large negative additional effect is estimated for mothers, and I cannot reject the null hypothesis for the combined effect at conventional levels.

Additionally, other household members, such as adult older siblings, aunts and uncles, or grandparents, who may assist with caring for the child, may also alter working hours in response to rainfall shocks, substituting for more work or more childcare to accommodate the parent's responsibilities. Therefore, I report the same specifications for all working age (15-64) household members present in the household roster and reporting economic activity in columns 3 and 4. Results for the main effect indicate a very similar impact of shock exposure on the main activity working hours of all household members, with the total effect in column 3 estimated at 11 minutes, and the combined effect for women of 10 minutes, both significant at the 5% level. Similar to parents, for all paid activity, a base group effect for men of 45 minutes is estimated, but I cannot reject the null of a zero effect on total working hours for women.

These results could indicate that while men, in particular fathers, experience a large increase in all activity, women may shift labour supply between economic activities such that although they increase hours slightly in their primary activity, there is no overall effect in total working hours. It may also indicate that women carry out set of additional economic tasks compared to men, which are not impacted by changes in rainfall. However, a limitation of the Young Lives dataset is that data on specific activity or industry code is missing for a large proportion of the sample, likely reflecting a high level of informal work.[19]

In summary, across all specifications, exposure to a positive rainfall shock is associated with an increase in working hours in paid work. The effect for all paid activity is slightly larger for parents, but the pattern of results shows that all household adults work more hours in response to recent positive rainfall shocks across both the main activity and all paid economic activity.

If household adult members respond to positive rainfall shocks by increasing labour

[19]Additional analysis using the 2015-2017 waves the Encuesta Nacional de Hogares (ENAHO), a nationally representative cross-sectional household survey, suggests a 1-month exposure to a positive rainfall shock at district level is associated with a moderate increase in hours worked per week by respondents working specifically in an agriculture related occupation (based on ISIC Rev.4 4-number occupation code). Results from ENAHO are reported in Table B14.

Table 5: Impact of +1.5 S.D Shocks in Previous Year on Adult Hours Worked

	Parents		All HH adults	
	(1)	(2)	(3)	(4)
Panel A: Main activity				
Female	-1.808	-1.837	-1.541	-1.548
	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Positive Shock	0.190	0.208	0.189	0.202
	[0.073]*	[0.096]*	[0.047]**	[0.045]**
**interaction*		-0.037		-0.031
		[0.786]		[0.754]
$H_0 : \beta_2 + \beta_3 = 0$ p-val.		0.057		0.027
N	5324	5324	7341	7341
Panel B: All paid activity				
Female	-4.384	-3.534	-3.479	-2.793
	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Positive Shock	0.432	0.917	0.356	0.743
	[0.038]**	[0.000]***	[0.005]***	[0.000]***
**interaction*		-1.160		-0.983
		[0.020]**		[0.012]**
$H_0 : \beta_2 + \beta_3 = 0$ p-val.		0.372		0.233
N	5394	5394	7438	7438

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on wild bootstrap procedure (10,000 replications) provided in "[.]" brackets; Controls include: if HH is rural and wealth index (R1); respondent is female; age and age-squared. Fixed effects for survey year, month of interview, and community are suppressed. Alternative p-values are reported in Table B13.

supply, it is possible the burden of childcare and domestic work within the family home, farm, or business may shift to non-adult household members, such as older siblings. Young Lives collects time use data for all household members between the ages of 5 and 17 between rounds 2 and 5, asking how many hours are allocated across several categories on a normal weekday. In Table B15, for older siblings of the YL child, I regress the average daily number of hours spent in each time use category on exposure to rainfall shocks in the previous 12 months. No category is associated with any statistically significant or meaningful changes in response to shock exposure, suggesting that the increased hours in work is not substituted for by other adult household members, who also work more, or by older sibling children, who do not alter their routines. As a result, a child may be experiencing less quality time with parents, negatively impacting opportunities for psycho-social stimulation and play.

However, it remains unclear theoretically whether the substitution or income effect of a rainfall shock dominates. For example, it may be that increased income leads to greater material investments in children, outweighing a reduction in availability of parents. I measure material investment in children in two ways. First, using questions administered to caregivers in round 3 regarding their investment in household reading resources (number of books, dictionary ownership, and child reading habits), I construct an index of "reading encouragement". For each question in Table B16, if the caregiver responds affirmatively to these questions, they score a 1, otherwise scoring 0. A z-score is derived of the mean item score. Additionally, I construct a measure of educational expenditure on the YL child in round 3, including on clothing, fees, materials and transport. Results are reported in columns 3 and 4 of Table 6.

If however, the substitution effect of a positive rainfall shock dominates, then, as hypothesised above, we would expect to see some negative impact on measures of the social relationship between parents and children. to test this I construct two measures for the parent child relationship, from the perspective of both parties. First I proxy the caregiver's perception of the relationship by constructing an index measuring the level of involvement and knowledge of their child's life, based on questions administered in round 3, listed in Table B16. Construction follows the same procedure as the reading encouragement scale. Results for the impact of early life rainfall shock exposure on this index are reported in column 1 of Table 6. I measure the child-parent relationship from the perspective of the child (column 2), using the parent relations scale of the Marsh Self description questionnaire-II (Marsh, 1990), administered as a self-reported measure for both cohorts in round 4. A higher score indicates a child has a positive relationship with their parents. Similar to the main CSE outcome, I construct an EFA 1st factor score using age-standardised item responses. The scale shows high unidirectionality and internal consistency (Yorke & Ogando Portela, 2018), with all items loading highly on the 1st factor only. A list of the included scale items and 1st factor loadings is given in

Table B17.[20]

Table 6: Impact of +1.5 S.D Shocks on Parent-Child Relationship Measures

	Parent involvement	Parent Relations	Reading encouragement	Education expenditure
Prenatal	-0.017	0.085	-0.053	-0.044
	[0.641]	[0.042]**	[0.137]	[0.172]
1st year	-0.047	0.013	-0.066	-0.070
	[0.408]	[0.840]	[0.170]	[0.122]
2nd year	0.036	-0.006	0.081	0.030
	[0.339]	[0.875]	[0.112]	[0.682]
3rd year	-0.109	-0.062	0.018	0.016
	[0.003]***	[0.028]**	[0.647]	[0.727]
Controls	Yes	Yes	Yes	Yes
N	2089	1995	2089	2089

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on wild bootstrapped procedures (10,000 replications) provided in "[.]" brackets. Controls: HH is rural and HH wealth index; mother age and education; child gender, mother tongue, age, and if they were enrolled in pre-school. Fixed effects for birth month cohort and community are suppressed. Alternative p-values reported in appendix Table B18.

Effects estimated for material investments are insignificant at conventional levels for positive shock exposure in any period. In comparison, prenatal exposure to a positive shock is associated with a 0.085 S.D. increase in the child's perception of the parent-child social relationship, while exposure in the 3^{rd} year of life is associated with a -0.062 S.D. decrease, both significant at the 5% level. This pattern is similar to that found for CSE and is partially mirrored by the variation in the caregiver-reported parent involvement index, with a significant -0.109 S.D. decrease associated with shock exposure in the 3^{rd} year, although no significant relationship for this measure is estimated for prenatal exposure.

This supports the hypothesis that the negative substitution effect of the shock dominates a positive income effect, at least in the postnatal period. However, it remains unclear how positive shock exposure in the prenatal period translates to a positive impact on adolescent and adulthood personality trait formation. That shock exposure affects an individual's relationship with their parent in the same pattern observed for later life CSE scores may suggest that the effect of shocks pre-birth have a differential effect on parental labour supply than exposure post-birth. For example, exposure to positive shocks during pregnancy could have a positive effect, by increasing the hours worked before the child is born, allowing for consumption smoothing and for parents to be able to reduce labour supply in the following period after the child is born.

However as a limitation of this study, I am unable to assess how parental labour

[20] The sample size is smaller than the full sample as i) scale items were only administered to respondents if at least one parent is alive at the time of the round 4 interview, and ii) the scale was not constructed if respondents were missing at least one item.

supply responds to shocks before and just after the birth of a child. As households are first tracked shortly after birth, no data was collected on parental labour supply prior to the birth of the young lives child. Additionally, as Young Lives is a cohort study, it would be difficult to disentangle the effects of shock exposure for households from the general effect on labour supply of having a newborn in the household. I am therefore unable to provide further insight into the underlying mechanisms for effects of shock exposure prior to birth.

7 Conclusion

I contribute to the literature identifying the importance of early life circumstances in determining later-life human capital stock, expanding the limited evidence on the effects of early life rainfall shocks on personality trait formation, and offer extensive analysis of the transmission mechanisms. I find prenatal exposure to a positive rainfall shock is associated with a higher core self-evaluation in adolescence and adulthood. In contrast, a similar exposure to a positive shock in the 2^{nd} and 3^{rd} year of life is associated with a lower later-life CSE score.

Considering mechanisms, there is no evidence that this effect operates through child nutrition or health, parental mental health, or through influencing material investments in children. In contrast, I find that households respond to a positive rainfall shock by increasing labour supply, particularly for the father of the child. Evidence suggests that this affects the emotional and social bond developed through parent-child interaction, with both parent and child perceptions of their long-term relationship being impacted by postnatal exposure to rainfall shocks. However it remains unclear how the positive effects of a prenatal shock exposure are transmitted.

Assessing heterogeneity, I find that the positive effect on CSE of a prenatal shock is isolated to girls and those born in the poorest households, findings common in the early life circumstances literature (Almond et al., 2018). Results are robust to asymptotic refinements which adjust for too few clusters, providing more conservative test statistics, and remain robust after adjusting for multiple hypothesis testing.

That there are differential impacts of rainfall shocks pre- and post-birth indicates that the timing of exposure is important, suggesting that policy interventions that allow households to smooth consumption over periods, and facilitate greater early childhood social stimulation between children and parents, could be the most effective at improving later-life socio-emotional skills – for example, child benefit payments targeted at the early years of childhood. Furthermore, results suggest future evaluations of the effects of climate shocks should incorporate the potential long-term impacts on non-cognitive outcomes, with a growing literature showing that, even when cognitive differences diminish over time, socio-emotional effects often persist (Attanasio et al., 2020; Heckman et al., 2013;

Sevim et al., 2023; Walker et al., 2022). This will likely become increasingly important as abnormal climate shocks become more frequent due to climate change.

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Appendices

A Additional tables and figures

B Additional Tables and Figures

Figure B1: Multi-Density Plot of Community-Level Gamma-Fitted SPI Values, by Month

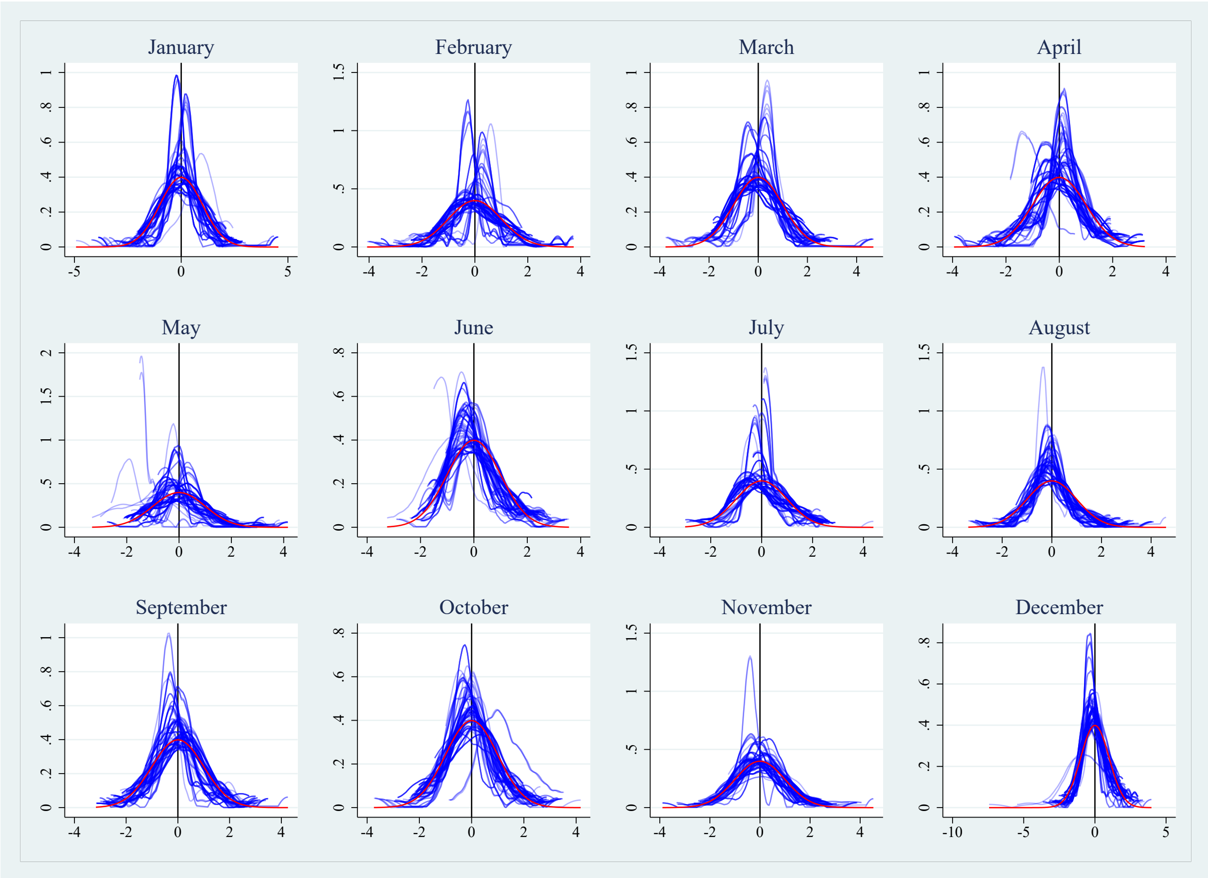


Figure B2: Multi-Density Plot of Community-Level Lognormal-Fitted SPI Values, by Month

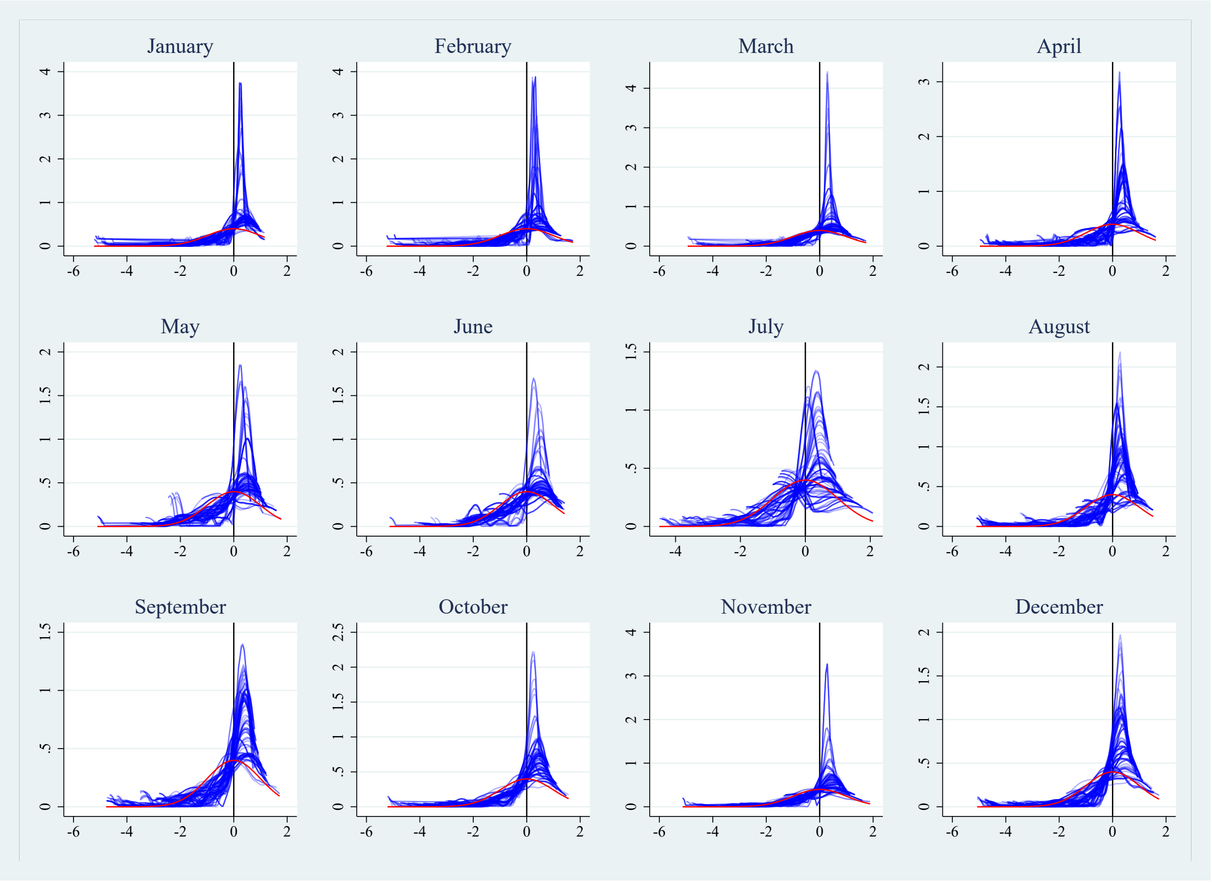


Figure B3: Primary Crop (Hectares Sown) in 2010, by Department

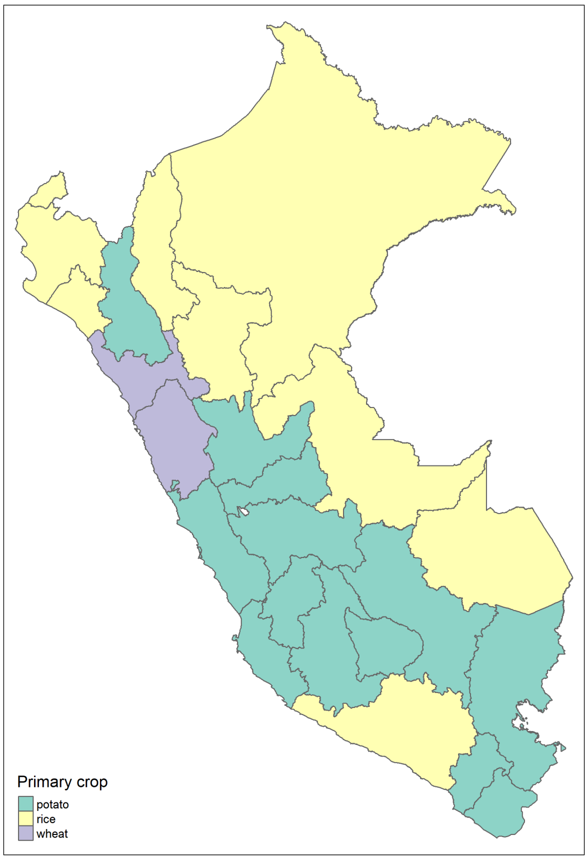


Table B1: Impact of (±)1.5 S.D Shocks on Constituent Scale Naïve Scores

	Agency	Self-esteem	Self-efficacy
Positive shock			
Prenatal	0.027	0.073	0.024
	(0.365)	(0.047)**	(0.511)
	[0.399]	[0.103]	[0.538]
	{0.339}	{0.010}***	{0.501}
1st year	0.018	0.004	0.033
	(0.680)	(0.919)	(0.352)
	[0.710]	[0.923]	[0.364]
	{0.622}	{0.850}	{0.288}
2nd year	-0.049	-0.094	-0.065
	(0.141)	(0.014)**	(0.065)*
	[0.146]	[0.020]**	[0.080]*
	{0.077}*	{0.009}***	{0.047}**
3rd year	-0.046	-0.087	-0.084
	(0.224)	(0.008)***	(0.006)***
	[0.272]	[0.015]**	[0.018]**
	{0.209}	{0.008}***	{0.002}***
Negative shock			
Prenatal	-0.051	-0.047	0.002
	(0.238)	(0.249)	(0.972)
	[0.350]	[0.408]	[0.975]
	{0.213}	{0.220}	{0.971}
1st year	-0.063	0.013	0.094
	(0.238)	(0.771)	(0.102)
	[0.267]	[0.787]	[0.131]
	{0.227}	{0.786}	{0.078}*
2nd year	0.086	-0.097	-0.074
	(0.126)	(0.186)	(0.298)
	[0.200]	[0.268]	[0.389]
	{0.114}	{0.293}	{0.273}
3rd year	0.058	-0.108	-0.083
	(0.379)	(0.044)**	(0.200)
	[0.468]	[0.098]*	[0.271]
	{0.348}	{0.018}**	{0.172}
Controls	Yes	Yes	Yes
N	2089	2089	2089

Notes: p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B2: Heterogeneous effects of (±)1.5 S.D shocks on CSE scores

	Female	Poorest	Mother's education	Agricultural
Level term	0.087	-0.193	0.226	-
	(0.469)	(0.299)	(0.004)***	(-)
	{0.366}	{0.320}	{0.001}***	
Positive shock				
Prenatal	0.024	0.046	0.073	0.038
	(0.615)	(0.185)	(0.172)	(0.396)
	{0.581}	{0.156}	{0.151}	{0.331}
**Interaction*	0.100	0.173	-0.004	0.086
	(0.070)*	(0.017)**	(0.948)	(0.127)
	{0.043}**	{0.012}**	{0.948}	{0.081}*
1st year	0.057	0.062	0.081	0.078
	(0.315)	(0.133)	(0.237)	(0.243)
	{0.222}	{0.074}*	{0.190}	{0.104}
**Interaction*	-0.029	-0.040	-0.059	-0.041
	(0.734)	(0.764)	(0.416)	(0.624)
	{0.707}	{0.764}	{0.395}	{0.551}
2nd year	-0.106	-0.081	-0.055	-0.125
	(0.004)***	(0.013)**	(0.219)	(0.101)
	{0.002}***	{0.010}**	{0.203}	{0.061}*
**Interaction*	0.032	-0.046	-0.055	0.034
	(0.557)	(0.415)	(0.456)	(0.706)
	{0.555}	{0.412}	{0.458}	{0.667}
3rd year	-0.100	-0.142	-0.116	-0.114
	(0.030)**	(0.000)***	(0.004)***	(0.005)***
	{0.032}**	{0.000}***	{0.001}***	{0.000}***
**Interaction*	-0.013	0.133	0.010	0.038
	(0.796)	(0.017)**	(0.866)	(0.550)
	{0.809}	{0.005}***	{0.867}	{0.505}
Negative shock				
Prenatal	0.029	-0.051	0.019	-0.022
	(0.574)	(0.169)	(0.828)	(0.578)
	{0.566}	{0.173}	{0.804}	{0.567}
**Interaction*	-0.122	0.153	-0.071	0.006
	(0.081)*	(0.171)	(0.510)	(0.952)
	{0.093}*	{0.123}	{0.473}	{0.945}
1st year	0.082	0.071	0.066	-0.062
	(0.209)	(0.239)	(0.280)	(0.592)
	{0.157}	{0.221}	{0.263}	{0.549}
**Interaction*	-0.039	0.015	-0.004	0.143
	(0.605)	(0.848)	(0.950)	(0.294)
	{0.573}	{0.849}	{0.951}	{0.230}
2nd year	0.009	-0.046	0.020	0.085
	(0.938)	(0.470)	(0.746)	(0.376)

	{0.934}	{0.468}	{0.730}	{0.295}
**Interaction*	-0.122	-0.041	-0.123	-0.190
	(0.234)	(0.690)	(0.084)*	(0.102)
	{0.189}	{0.670}	{0.065}*	{0.091}*
3rd year	-0.071	-0.080	-0.062	-0.147
	(0.351)	(0.246)	(0.323)	(0.061)*
	{0.355}	{0.232}	{0.322}	{0.049}**
**Interaction*	-0.035	-0.037	-0.042	0.120
	(0.715)	(0.769)	(0.665)	(0.183)
	{0.660}	{0.765}	{0.658}	{0.175}
Controls	Yes	Yes	Yes	Yes
N	2089	2089	2089	2089

Notes: Extension of Table 4. * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B3: Impact of Lognormal SPI (±)1.5 S.D Shocks on CSE Scores

	EFA 1st factor	% Exposed
Positive shock		
Prenatal	0.220	7.6
	(0.004)***	
	[0.034]**	
	{0.001}***	
1st year	0.123	7.7
	(0.406)	
	[0.457]	
	{0.284}	
2nd year	-0.077	3.4
	(0.488)	
	[0.489]	
	{0.434}	
3rd year	-0.356	0.8
	(0.015)**	
	[0.354]	
	{0.008}***	
Negative shock		
Prenatal	-0.070	32.3
	(0.083)*	
	[0.236]	
	{0.061}*	
1st year	-0.027	43.6
	(0.577)	
	[0.603]	
	{0.553}	
2nd year	-0.059	49.0
	(0.178)	
	[0.243]	
	{0.167}	
3rd year	0.053	47.7
	(0.213)	
	[0.233]	
	{0.148}	
Controls	Yes	
N	2089	

Notes: p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed. % Exposed refers to the share of sample exposed to at least 1 monthly shock in each period between conception and 3rd Birthday.

Table B4: Impact of (±)1.5 S.D. Shocks on CSE Scores, by Period of Exposure

	Prenatal	1st year	2nd year	3rd year
Positive shock	0.049	-0.000	-0.066	-0.067
	(0.141)	(0.988)	(0.033)**	(0.033)**
	[0.185]	[0.989]	[0.044]**	[0.044]**
	{0.134}	{0.987}	{0.029}**	{0.020}**
Negative shock	-0.055	0.053	-0.069	-0.048
	(0.232)	(0.332)	(0.300)	(0.224)
	[0.272]	[0.377]	[0.335]	[0.237]
	{0.222}	{0.289}	{0.283}	{0.220}
Controls	Yes	Yes	Yes	Yes
N	2089	2089	2089	2089

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on cluster robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Cumulative shocks refers to the total number of periods a respondent experience at least one of that shock type. Controls include child gender and if Spanish is their mother tongue; mothers age and if mother completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B5: Impact of (±)1.5 S.D. shocks on EFA CSE scores, robustness checks

	Cumulative	**Other periods**	**Shock type**	
			Positive	Negative
Positive shock				
-2nd Year		0.054		
		(0.299)		
		[0.315]		
		{0.252}		
Prenatal	0.081	0.114	0.077	
	(0.072)*	(0.018)**	(0.023)**	
	[0.079]*	[0.034]**	[0.051]*	
	{0.049}**	{0.006}***	{0.011}**	
1st Year	0.059	0.060	0.054	
	(0.129)	(0.214)	(0.099)*	
	[0.127]	[0.245]	[0.101]	
	{0.059}*	{0.166}	{0.059}*	
2nd Year	-0.071	-0.095	-0.090	
	(0.076)*	(0.017)**	(0.009)***	
	[0.118]	[0.029]**	[0.010]**	
	{0.075}*	{0.007}***	{0.008}***	
3rd Year	-0.091	-0.136	-0.099	
	(0.011)**	(0.004)***	(0.003)***	
	[0.033]**	[0.009]***	[0.005]***	
	{0.007}***	{0.001}***	{0.001}***	
4th Year		0.000		
		(0.996)		
		[0.996]		
		{0.995}		
Negative shock				
-2nd Year		-0.021		
		(0.633)		
		[0.687]		
		{0.619}		
Prenatal	-0.069	-0.056		-0.055
	(0.307)	(0.266)		(0.215)
	[0.417]	[0.367]		[0.278]
	{0.215}	{0.252}		{0.210}
1st Year	0.034	0.085		0.050
	(0.596)	(0.141)		(0.344)
	[0.652]	[0.139]		[0.359]
	{0.579}	{0.114}		{0.301}
2nd Year	-0.097	-0.031		-0.037
	(0.493)	(0.683)		(0.575)
	[0.662]	[0.724]		[0.593]
	{0.467}	{0.685}		{0.559}
3rd Year	-0.132	-0.038		-0.076

	(0.243)	(0.549)		(0.098)*
	[0.367]	[0.580]		[0.122]
	{0.210}	{0.522}		{0.113}
4th Year		0.102		
		(0.181)		
		[0.215]		
		{0.077}*		
Cumulative shocks				
Positive	-0.032			
	(0.469)			
	[0.508]			
	{0.431}			
Negative	0.071			
	(0.566)			
	[0.632]			
	{0.532}			
Controls	Yes	Yes	Yes	Yes
N	2089	1675	2089	2089

* p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on cluster robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Cumulative shocks refers to the total number of periods a respondent experience at least one of that shock type. Controls include child gender and if Spanish is their mother tongue; mothers age and if mother completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B6: Impact of (±)1.5 S.D. Shocks on CSE Scores, Additional Specifications

	Avgerage temperature	Growing season	Exlcude Lima	YC fixed effect
Positive shocks				
Prenatal	0.068	0.040	0.081	0.068
	(0.037)**	(0.442)	(0.024)**	(0.036)**
	[0.053]*	[0.453]	[0.068]*	[0.058]*
	{0.022}**	{0.416}	{0.015}**	{0.019}**
1st Year	0.046	0.035	0.048	0.043
	(0.169)	(0.419)	(0.164)	(0.175)
	[0.172]	[0.428]	[0.134]	[0.159]
	{0.102}	{0.379}	{0.150}	{0.124}
2nd Year	-0.087	-0.051	-0.109	-0.090
	(0.011)**	(0.307)	(0.005)***	(0.007)***
	[0.016]**	[0.318]	[0.004]***	[0.006]***
	{0.008}***	{0.312}	{0.002}***	{0.005}***
3rd Year	-0.104	-0.094	-0.113	-0.105
	(0.003)***	(0.032)**	(0.002)***	(0.001)***
	[0.019]**	[0.044]**	[0.011]**	[0.003]***
	{0.002}***	{0.029}**	{0.001}***	{0.000}***
Negative shocks				
Prenatal	-0.027	-0.032	-0.039	-0.030
	(0.467)	(0.525)	(0.374)	(0.434)
	[0.469]	[0.564]	[0.391]	[0.433]
	{0.452}	{0.485}	{0.358}	{0.424}
1st Year	0.067	0.081	0.088	0.066
	(0.168)	(0.250)	(0.063)*	(0.170)
	[0.192]	[0.317]	[0.085]*	[0.177]
	{0.150}	{0.200}	{0.051}*	{0.149}
2nd Year	-0.051	-0.040	-0.058	-0.056
	(0.541)	(0.595)	(0.456)	(0.478)
	[0.639]	[0.612]	[0.550]	[0.559]
	{0.531}	{0.541}	{0.446}	{0.470}
3rd Year	-0.097	-0.077	-0.103	-0.084
	(0.064)*	(0.309)	(0.055)*	(0.120)
	[0.110]	[0.407]	[0.097]*	[0.171]
	{0.070}*	{0.326}	{0.049}**	{0.119}
Controls	Yes	Yes	Yes	Yes
N	2089	2089	1754	2089

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on cluster robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and if Spanish is their mother tongue; mothers age and if mother completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B7: Impact of (±)1.5 S.D. Shocks on Migration and Sex of Child

	Female	Migration
Positive shocks		
Prenatal	-0.002	0.007
	(0.929)	(0.561)
	[0.938]	[0.558]
	{0.934}	{0.546}
1st Year	-0.016	0.014
	(0.498)	(0.414)
	[0.571]	[0.462]
	{0.466}	{0.383}
2nd Year	0.008	0.013
	(0.683)	(0.294)
	[0.699]	[0.339]
	{0.709}	{0.271}
3rd Year	0.008	0.016
	(0.741)	(0.290)
	[0.771]	[0.348]
	{0.729}	{0.237}
Negative shocks		
Prenatal	0.002	-0.003
	(0.945)	(0.905)
	[0.943]	[0.934]
	{0.946}	{0.903}
1st Year	0.002	-0.026
	(0.943)	(0.174)
	[0.941]	[0.199]
	{0.940}	{0.125}
2nd Year	-0.007	0.010
	(0.863)	(0.653)
	[0.891]	[0.674]
	{0.856}	{0.624}
3rd Year	0.021	-0.015
	(0.418)	(0.300)
	[0.456]	[0.318]
	{0.431}	{0.241}
Controls	Yes	Yes
N	2089	2089

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on cluster robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and if Spanish is their mother tongue; mothers age and if mother completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B8: Impact of Prenatal (±)1.5 S.D Shocks on CSE Scores, by Trimester

	EFA 1st Factor	% Exposure	Mean exposure
Positive shock			
1^{st} trimester	-0.017	23.5	0.25
	(0.711)		
	[0.705]		
	{0.722}		
2^{nd} trimester	0.079	20.2	0.21
	(0.235)		
	[0.269]		
	{0.196}		
3^{rd} trimester	0.115	19.2	0.20
	(0.052)*		
	[0.079]*		
	{0.048}**		
Negative shock			
1^{st} trimester	0.025	9.0	0.10
	(0.772)		
	[0.801]		
	{0.767}		
2^{nd} trimester	-0.065	6.9	0.07
	(0.700)		
	[0.743]		
	{0.689}		
3^{rd} trimester	-0.133	7.4	0.08
	(0.029)**		
	[0.040]**		
	{0.025}**		
Controls	Yes		
N	2089		

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on cluster robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed. % Exposure is the share of sample exposed to at least 1 monthly shock in each trimester. Mean exposure captures the mean number of months of exposure experienced.

Table B9: Impact of (±)1.5 S.D Shocks on CSE Scores, Adjusted Q-values

	EFA 1st Factor		**Naive z-score**	
	Full	In-comm.	Full	In-comm.
Positive shock				
Prenatal	0.068	0.096	0.052	0.081
	[0.085]*	[0.049]**	[0.203]	[0.085]*
1st year	0.043	0.051	0.027	0.043
	[0.277]	[0.345]	[0.440]	[0.422]
2nd year	-0.090	-0.093	-0.091	-0.095
	[0.044]**	[0.049]**	[0.044]**	[0.049]**
3rd year	-0.105	-0.129	-0.097	-0.115
	[0.030]**	[0.038]**	[0.038]**	[0.044]**
Negative shock				
Prenatal	-0.030	-0.062	-0.036	-0.073
	[0.440]	[0.286]	[0.422]	[0.277]
1st year	0.066	0.075	0.036	0.043
	[0.277]	[0.345]	[0.440]	[0.464]
2nd year	-0.056	-0.048	-0.056	-0.033
	[0.457]	[0.464]	[0.451]	[0.494]
3rd year	-0.084	-0.069	-0.071	-0.045
	[0.242]	[0.345]	[0.277]	[0.440]
Controls	Yes	Yes	Yes	Yes
N	2089	1675	2089	1675

Notes: * q < 0.10, ** q < 0.05, *** q < 0.01. Sharpened q-values provided in "[.]" brackets. Full sample refers to children geolocated in round 1. In-community restricts sample to those whose mother lived in the same community from conception until round 2. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B10: Impact of +1.5 S.D Shocks on Health and Nutrition Mechanisms

	Stunting	Good health	Serious illness	LR health
Prenatal	0.003	-0.002	0.010	0.004
	(0.841)	(0.913)	(0.502)	(0.737)
	[0.844]	[0.919]	[0.541]	[0.737]
	{0.844}	{0.918}	{0.444}	{0.680}
1st year	0.007	0.007	-0.003	0.004
	(0.627)	(0.728)	(0.849)	(0.706)
	[0.650]	[0.741]	[0.865]	[0.713]
	{0.608}	{0.691}	{0.838}	{0.677}
2nd year	-0.001	0.036	-0.024	0.001
	(0.965)	(0.108)	(0.150)	(0.964)
	[0.966]	[0.147]	[0.190]	[0.969]
	{0.962}	{0.086}*	{0.109}	{0.958}
3rd year	-0.009	-0.001	0.014	-0.011
	(0.484)	(0.968)	(0.332)	(0.174)
	[0.483]	[0.973]	[0.377]	[0.166]
	{0.410}	{0.967}	{0.291}	{0.164}
Controls	Yes	Yes	Yes	Yes
N	2072	2089	2089	2085

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B11: Impact of +1.5S.D. Shocks on Caregiver Stress and Parenting Practices

	Stress (SRQ20)			**Practices**
	Total score	Score=>7	Score=>8	z-score
Positive shock	0.003	-0.008	-0.000	-0.033
	(0.979)	(0.419)	(0.978)	(0.461)
	[0.981]	[0.485]	[0.982]	[0.520]
	{0.729}	{0.842}	{0.713}	{0.482}
Controls	Yes	Yes	Yes	Yes
N	7044	7044	7044	1503

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include child gender and indicator for if they speak Spanish as their mother tongue; mothers age and indicator for if they completed primary; household wealth index (R1) and if in a rural location. Fixed effects for community and month of birth cohort are suppressed.

Table B12: Parenting Practices as Reported in Round 1

Good practices
Carry him/her (on front or on back).
Soothe him/her, sing to him/her.
Rock him/her, walk around with child in arms.
Give him/her water to calm him/her.
Breast or bottle feed him/her.
Swaddle him/her in blanket, tightly so he/she is quiet.
Bad practices
Smack him/her.
Shake him/her.
Threaten him/her.
Pinch him/her, squeeze him/her tightly.
Put him/her face down on bed so he/she cries into mattress.
Nothing - let him/her cry until he/she falls asleep.

Notes: Each category is coded as 1 if the caregiver reports a good practice, and -1 if they report a bad practice, as a response to their infant child crying.

Table B13: Impact of +1.5 S.D Shocks in Previous Year on Adult Hours Worked

	Parents		All HH adults	
	(1)	(2)	(3)	(4)
Panel A: Main activity				
Female	-1.808	-1.837	-1.541	-1.548
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
	{0.000}***	{0.000}***	{0.000}***	{0.000}***
Positive Shock	0.190	0.208	0.189	0.202
	(0.014)**	(0.038)**	(0.003)***	(0.010)**
	{0.005}***	{0.025}**	{0.001}***	{0.007}***
**interaction*		-0.037		-0.031
		(0.746)		(0.729)
		{0.749}		{0.723}
$H_0: \beta_2 + \beta_3 = 0$ p-val.		0.057		0.027
N	5324	5324	7341	7341
Panel B: All paid activity				
Female	-4.384	-3.534	-3.479	-2.793
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
	***	{0.000}***	{0.000}***	{0.000}***
Positive Shock	0.432	0.917	0.356	0.743
	(0.001)***	(0.000)***	(0.000)***	(0.000)***
	***	{0.000}***	{0.000}***	{0.000}***
**interaction*		-1.160		-0.983
		(0.002)***		(0.002)***
		{0.003}***		{0.002}***
$H_0: \beta_2 + \beta_3 = 0$ p-val.		0.372		0.233
N	5394	5394	7438	7438

Notes: Extension of Table 5. * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; p-values for SHAC robust SEs provided in "{.}" brackets. Controls include: if HH is rural and wealth index (R1); respondent is female; age and age-squared. Fixed effects for survey year, month of interview, and community are suppressed.

Table B14: Impact of +1.5 S.D Shocks in Previous Year, ENAHO 2015-2017

	Hours worked	
Positive shock	0.028	-0.021
	(0.601)	(0.722)
**Agricultural work*		0.212
		(0.035)**
Agricultural work	-10.638	-11.076
	(0.000)***	(0.000)***
Controls	Yes	Yes
N	144713	144713

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Data sourced from ENAHO annual waves 2015-2017. Dependent variable is total hours (usually) worked in previous week. Model (1) is the base model for all working age respondents (15-64). (2) interacts shock exposure with if the respondent reports working in an agricultural occupation (ISIC rev4. 4-number code 0100-0199). Standard errors are clustered at the district level, with p-values reported in parentheses "(.)". Controls for respondent: is female, mother tongue is Spanish, married or cohabitating, completed primary education, age and age-squared, and if works in agricultural occupation (column (1)), as well as a Rural/urban community indicator. District, month interview and year of survey fixed effects are suppressed.

Table B15: Impact of +1.5S.D. Shocks on Older Sibling Time Use

	Unpaid work	Paid work	Housework	Childcare	School	Study	Play	Sleep
Positive Shock	0.052	0.064	-0.030	-0.013	-0.045	0.008	-0.019	0.015
	(0.189)	(0.212)	(0.094)*	(0.622)	(0.532)	(0.779)	(0.627)	(0.554)
	[0.297]	[0.256]	[0.173]	[0.656]	[0.603]	[0.797]	[0.689]	[0.588]
	{0.032}**	{0.718}	{0.160}	{0.629}	{0.978}	{0.689}	{0.537}	{0.729}
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5180	5180	5180	5180	5180	5180	5180	5180

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on clustered robust SEs at district level are in parentheses "(.)"; wild bootstrapped (10,000 replications) p-values provided in "[.]" brackets; p-values for SHAC robust SEs provided in "{.}" brackets. Controls: HH is rural, respondent gender and age. Fixed effects for survey round, month of interview, and community are suppressed.

Table B16: Home Environment Measures, Summary Statistics

	Mean	S.D.	Min	Max
Parent-child relationship				
Marsh SDQ Parent relations scale	0.00	(1.00)	-5.12	2.23
Parental involvement index	0.00	(1.00)	-3.87	1.21
Parental involvement				
Know friend's names	0.84	(0.37)	0.00	1.00
Know friend's parents	0.73	(0.44)	0.00	1.00
Know teacher's name	0.96	(0.19)	0.00	1.00
Know child's after-school activity	0.95	(0.23)	0.00	1.00
Feel close with their child	0.94	(0.23)	0.00	1.00
Talk to child about politics	0.22	(0.41)	0.00	1.00
Reading index	-0.00	(1.00)	-2.38	1.65
Reading encouragement				
Encourage to read	0.52	(0.50)	0.00	1.00
Child reads for fun	0.62	(0.49)	0.00	1.00
HH has dictionary	0.88	(0.32)	0.00	1.00
Child uses dictionary	0.78	(0.41)	0.00	1.00
HH has more than 20 books	0.18	(0.39)	0.00	1.00
Education expenditure				
ln(Education expenditure on child)	5.40	(1.23)	0.00	8.56

Notes: Sample means are reported with standard deviations in parentheses.

Table B17: 1st Factor Loadings for Marsh SDQ Parent Relations Scale

	Loading	Ψ
I like my parents.	0.529	0.720
My parents like me.	0.510	0.740
My parents and I spend a lot of time together.	0.540	0.709
I get along well with my parents.	0.662	0.562
My parents understand me.	0.655	0.571
If I have children of my own, I want to bring them up like my parents raised me.	0.559	0.687
My parents are easy to talk to.	0.530	0.719
My parents and I have a lot of fun together.	0.605	0.634

Notes: Factor loadings $\geq$ 0.3 are highlighted in green. Ψ is the share of item unique variance.

Table B18: Impact of +1.5S.D. Shocks on Parent-Child Relationship Measures

	Parent involvement	Parent Relations	Reading encouragement	Education expenditure
Prenatal	-0.017	0.085	-0.053	-0.044
	(0.622)	(0.011)**	(0.132)	(0.156)
	{0.620}	{0.010}***	{0.129}	{0.152}
1st year	-0.047	0.013	-0.066	-0.070
	(0.340)	(0.816)	(0.103)	(0.107)
	{0.318}	{0.823}	{0.076}*	{0.096}*
2nd year	0.036	-0.006	0.081	0.030
	(0.335)	(0.873)	(0.068)*	(0.637)
	{0.314}	{0.871}	{0.032}**	{0.615}
3rd year	-0.109	-0.062	0.018	0.016
	(0.003)***	(0.026)**	(0.621)	(0.703)
	{0.004}***	{0.041}**	{0.594}	{0.691}
Controls	Yes	Yes	Yes	Yes
N	2089	1995	2089	2089

Notes: Extension of Table 6. * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in parentheses "(.)"; p-values for SHAC robust SEs provided in "{.}" brackets. Controls: HH is rural and HH wealth index; mother age and education; child gender, mother tongue, age, and if they were enrolled in pre-school. Fixed effects for birth month cohort and community are suppressed.

C Criteria for EFA Factor Selection

The number of latent factors to extract is assessed using several criteria, following Osborne et al. (2014):

1. **Theory:** the literature on core self-evaluations points to a single highly internally consistent construct. Therefore this provides an a priori assumption about the number of factors to extract, however this may not always be supported by EFA results.

2. **Kaiser criterion:** Kaiser (1960, 1970) suggests a rule of thumb of any eigenvalues greater than 1, as a theoretical lower bound for a true component in a principle components analysis (PCA) with an infinite sample size (Guttman, 1954). However this is often an inaccurate method, particularly as the number of items analysed increases (Costello & Osborne, 2005). Similar to Webb (2024), I also consider a less conservative 0.7 threshold.

3. **Screeplot:** Graphical assessment of the eigenvalue scree plot for evident 'elbows' in the plot, where an obvious change of slope occurs, with the number of points prior to the elbow considered a good estimate. This is not considered sufficient alone for determining the number of factors to extract.

4. **Parallel Analysis:** Observing that the eigenvalues from PCA would be greater than one in a finite sample due to sample-error and least squares bias, Horn (1965) suggests adjusting the eigenvalues of each factor by subtracting the mean sample error from many iterations of uncorrelated data sets, retaining components with adjusted eigenvalues greater than one (Dinno, 2009). Therefore using a Monte-Carlo procedure I simulate uncorrelated data of the same dimension as my sample with 5,000 replications, keeping eigenvalues greater than the 95$^{\text{th}}$ percentile value of simulated eigenvalues.

5. **Minimum Average Partial criterion:** In the context of PCA, Velicer (1976) proposes partialling out the shared variance as each component is created sequentially, to the point at which common variance is at a minimum. The number of components for which a minimum is reached represents the number to extract.

A summary of the number of factors to extract is given by Table C19. The criteria described in 2 and 3 are shown by the scree plot of eigenvalues, Figure C4.

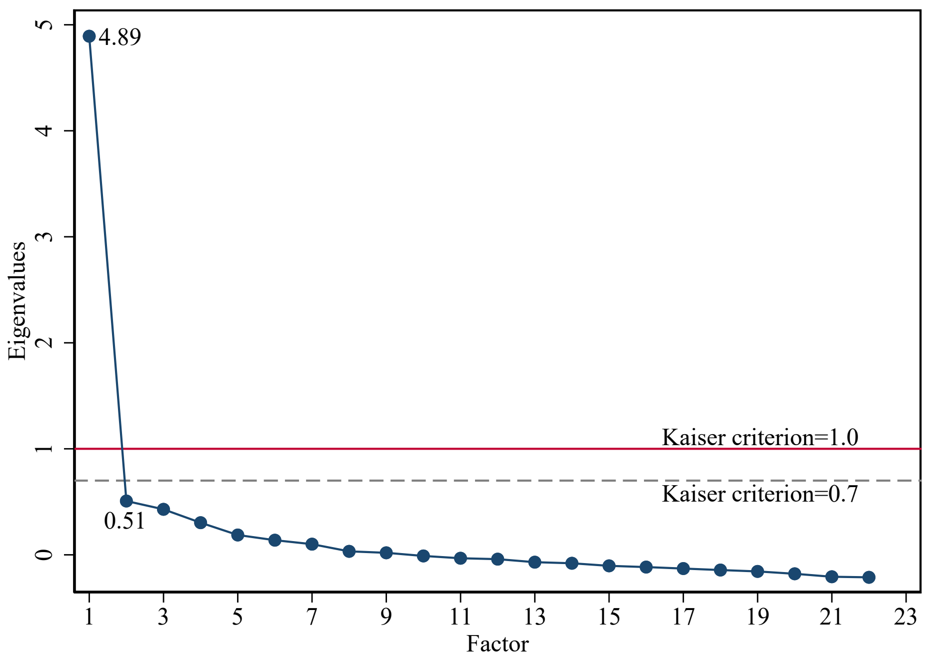
The 1st factor eigenvalue is 4.89, and explains 95.3% of the shared variance in the latent factor model. All other factors displayed an eigenvalue significantly below the threshold of 1 (and the more conservative 0.7 cut off), with the 2$^{\text{nd}}$ factor eigenvalue of 0.51. There is an evident change of slope at the second factor, suggesting an 'elbow' above

Table C19: Number of Factors to Extract, by Method

Method	# of Factors
Kaiser criterion > 1	1
Kaiser criterion > 0.7	1
Screeplot 'elbow'	1
Parallel analysis	3
Minimum average partial	1
Extracted	1

which one factor lies. Although there are other changes in slopes between further factors, this is minimal in comparison to the drastic change in slope at the identified elbow.

Figure C4: Screeplot of Eigenvalues from EFA Latent Factor Model



Observed eigenvalues from principle components analysis (unadjusted) of the latent factor model are plotted in Figure C5, with the 95th percentile of simulated eigenvalues from 5000 replications plotted in red. Three eigenvalues lie above the simulated eigenvalues, suggesting, in contrast with all other criteria, a three factor model. However there is a clear distinction of the 1st factor, while factors 2 and 3 lie marginally above their relevant threshold. As discussed by Osborne et al. (2014), with large sample sizes parallel analysis may not prove to be as useful as other criteria, with only small deviations from 1 estimated over many iterations. Finally, Figure C6, provides a graphical plot of the average partial correlations for the factor partialled out. Evidence suggests that the average partial is minimised when the 1st factor is partialled out.

Overall the majority of criteria are aligned with the a priori assumption of a one factor

Figure C5: Horn's Parallel Analysis

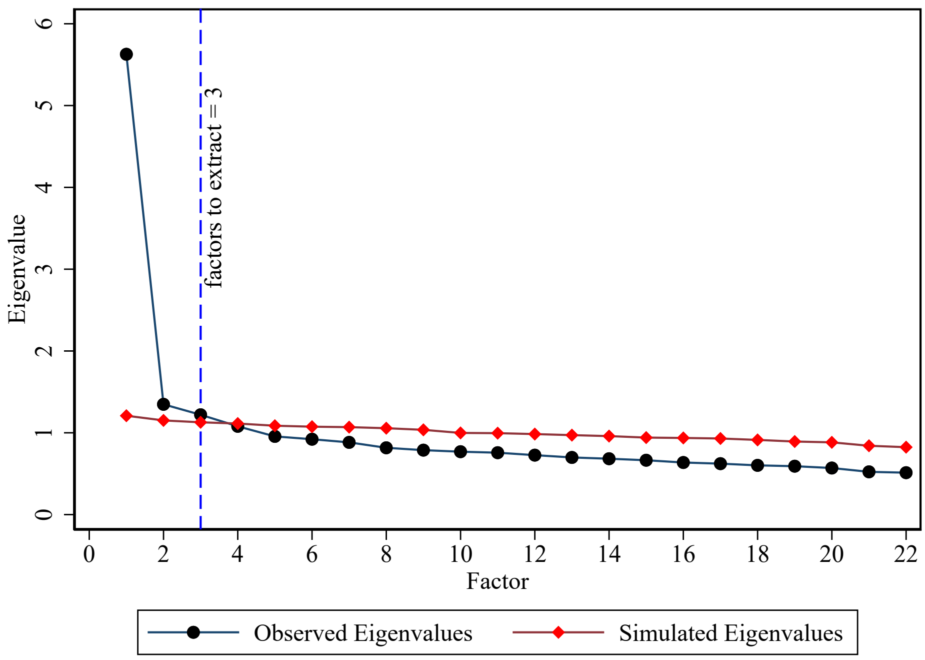
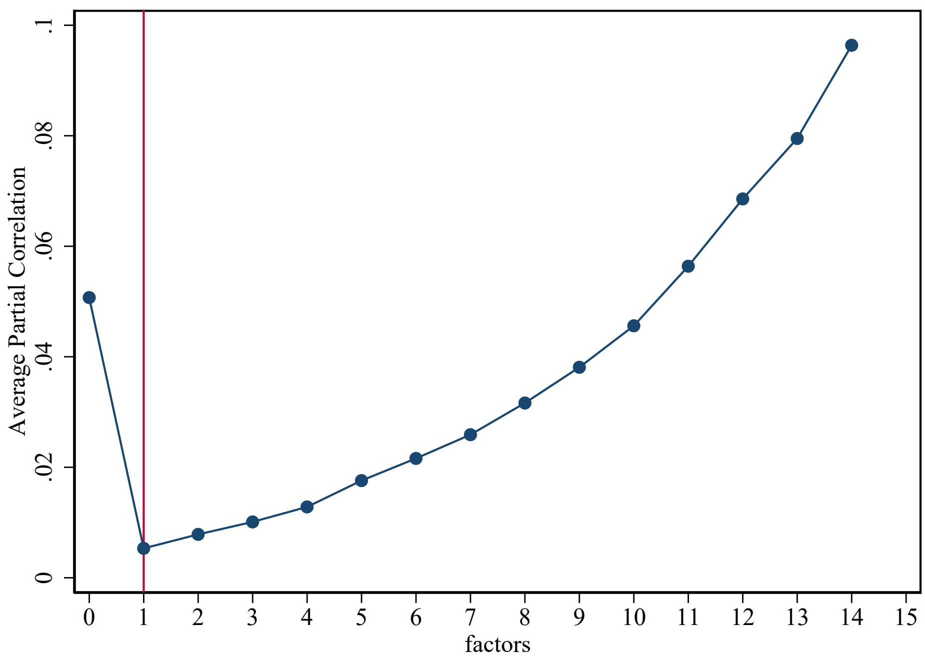


Figure C6: Mini Average Partial Correlation Analysis



model, therefore no other factors were retained. The factor loadings of each item on the 1^{st} factor are shown in Table C20, alongside the share of item unique variance, $\mathbf{\Psi}$. Following Attanasio et al. (2020) and Webb (2024), I discount low factor loadings below a threshold of 0.3 in constructing the 1^{st} factor score (A lower cut off of <0.25, as used by Krutikova and Lilleør (2015) does not alter results). In total 19 of 22 items load above the cut off within the range of 0.420 and 0.576. A factor score is constructed as a loading-weighted mean of these items. Finally, the factor score is standardised as a z-score with mean 0 and standard deviation 1.

Table C20: 1st Factor Loadings for CSE

	Loading	Ψ
YL – Agency		
If I try hard, I can improve my situation in life.	0.457	0.791
I like to make plans for my future studies and work.	0.441	0.805
I have no choice about the work I do - I must do this sort of work.	-0.033	0.999
Other people in my family make all the decisions about how I spend my time.	0.000	1.000
Self-efficacy		
I can always manage to solve difficult problems if I try hard enough.	0.573	0.671
If someone opposes me, I can find the means and ways to get what I want.	0.221	0.951
It is easy for me to stick to my aims and accomplish my goals.	0.518	0.732
I am confident that I could deal efficiently with unexpected events.	0.422	0.822
Thanks to my resourcefulness, I know how to handle unforeseen situations.	0.579	0.664
I can solve most problems if I invest the necessary effort.	0.594	0.647
I can remain calm when facing difficulties because I can rely on my coping abilities.	0.569	0.677
When I am confronted with a problem, I can usually find several solutions.	0.494	0.756
If I am in trouble, I can usually think of a solution.	0.518	0.732
I can usually handle whatever comes my way.	0.492	0.758
SDQ – Self-esteem		
I do lots of important things.	0.479	0.771
In general, I like being the way I am.	0.537	0.712
Overall, I have a lot to be proud of.	0.497	0.753
I can do things as well as most people.	0.510	0.740
Other people think I am a good person.	0.417	0.826
A lot of things about me are good.	0.529	0.720
I'm as good as most other people.	0.424	0.820
When I do something, I do it well.	0.489	0.761

Notes: Factor loadings ≥ 0.3 are highlighted in green. Ψ is the share of item unique variance.