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. I assess how exposure to 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 negatively affects scores. Additionally, high prenatal rainfall has a heterogeneous positive impact on scores, only affecting 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. I also provide evidence that this mechanism operates heterogeneously for prenatal exposure, allowing parents to substitute for more work prior to birth, becoming more available in the household immediately after their child is born.

JEL codes: I31, J13, J24, O15, Q54
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1 Introduction

A causal link between early life experiences and later life outcomes is well established, covering a range of outcomes, from anthropometric and health indicators to employment, educational attainment, and human capital formation (see reviews Almond and Currie (2011); Almond et al. (2018); Currie and Vogl (2013)). A growing strand of this literature considers exposure to abnormal rainfall during the perinatal phase as a plausibly exogenous shock in order to study the causal effects on human capital formation, with early contributions from Pathania (2007) and Maccini and Yang (2009). However, while the relationship between early life rainfall and the cognitive dimension of human capital is well explored (Carrillo, 2020; Nübler et al., 2020; Rosales-Rueda, 2018; Shah and Steinberg, 2017; Thai and Falaris, 2014; Zimmermann, 2020), much less studied is the relationship between early life conditions and the evolution of later-life personality traits (often referred to as non-cognitive or 'soft' skills) which are closely tied with cognitive ability in determining future socioeconomic outcomes (Heckman, 2007; Almlund et al., 2011). As such, providing evidence of a causal relationship between early life and these soft skills could be beneficial for future policy, reinforcing the importance of this period as a critical stage in development.

This paper contributes to this strand of literature by estimating the effect of perinatal exposure to rainfall shocks on personality trait formation, as measured in adolescence and early adulthood, using the Peruvian sample of Young Lives, a cohort study of childhood poverty and transitions to adulthood conducted in four low- and middle-income countries. I assess the impact of exposure to precipitation shocks, identified as short run fluctuations from the mean of the long term community and month-of-year specific distribution, in-utero and during the first 3 years of life, on measures of the respondents' core self-evaluations (CSE) – a higher construct which concerns an individual's appraisal of their own self-worth, competence, and capabilities (Chang et al., 2012; Judge et al., 1998). The outcome is constructed indirectly using a latent factor model, consisting of Likert scale responses to items from three pre-existing scales: Self-esteem (Marsh, 1990), Self-efficacy (Schwarzer and Jerusalem, 1995) and the Young Lives agency scale, closely related to locus of control (Rotter, 1966). Peru represents an important context in which to understand this relationship, given its diverse climate and vulnerability to repeated extreme precipitation anomalies as a result of the El Niño Southern Oscillation (Ramírez and Briones, 2017).

I find a 1-month exposure to a positive shock (monthly precipitation greater than +1.5 S.D. from the long-term mean) in the prenatal period is associated with a 0.068 S.D. higher CSE score-for-age, while exposure to the same 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. I also find no effect of exposure to negative, drought-like conditions (less than -1.5 S.D. from the monthly mean) in any period. As is common in the wider literature, I find a heterogeneous effect of prenatal shocks on girls, compared with a null effect for boys (Almond et al., 2018; Currie and Vogl, 2013), as well as for those in the poorest households. Results are robust to an alternative measure of shock exposure, suggesting that findings are not an artefact of the method of construction — in fact, evidence suggests the original specification provides a better fit for the historical distribution of rainfall in the region.

These results contribute to the literature which identifies the importance of early life circumstances in determining future human capital stock, expanding the very limited literature on the effects on soft skill development (Brando and Santos, 2015; Leight et al., 2015; Moorthy, 2021; Shoji, 2022; Webb, 2022). Of the few papers which assess this relationship, the methodology varies significantly: by measurement and definition of rainfall shocks; exposure period considered; age at follow up; and socio-emotional outcome used. Most closely related to this study are two recent contributions by Chang et al. (2022) and Krutikova and Lilleør (2015), although their treatment of the CSE outcome differs. Using a sample drawn from rural Tanzania, Krutikova and Lilleør (2015) find that exposure in-utero to a 10% increase in rain season precipitation from the 10-year average is associated with a 0.08 S.D. increase in CSE scores at age 17-28, significant at the 5% level. In contrast, Chang et al. (2022), looking at cognitive and non-cognitive outcomes in Andhra Pradesh, find a -0.161 S.D. (significant at 5%) decrease in CSE at age 15 associated with prenatal exposure to a 1-month rainfall shock exposure $> (\pm)1.5$ S.D. from the 1900-2014 mean. However, they model positive and negative shocks as the same treatment, with the majority of their sample experiencing at least one shock during gestation and 30.9% experiencing extreme shocks ($> (\pm)2$ S.D.), which may influence the result they derive. I examine these shocks separately, finding effects for in-utero exposure that are consistent in magnitude and sign to those found by Krutikova and Lilleør (2015).

I expand on these studies in three ways. First, I provide an extensive assessment of potential mechanisms, whereas previous studies provide only limited discussion. I find that in response to higher rainfall parents work longer hours in the short run across all economic activity. This likely impacts the time parents can spend interacting with their child in the early years, affecting the long-term parent-child relationship. Other household adults also work more in response to shocks, and siblings do not alter their time use, therefore it is unlikely others make up for this reduction in interaction. Results suggest this affects the socio-emotional bond developed through parent-child interaction, and this is consistent with evidence from experimental literature, which find supervised psycho-social stimulation of toddlers and preschool-aged children by mothers in the home had lasting benefits on personality trait formation (Attanasio et al., 2020; Heckman et al., 2013; Sevim et al., 2023; Walker et al., 2022). Postnatal exposure to positive rainfall shocks is negatively associated with measures of both the caregiver and child's perceptions of their relationship, while there is no evidence of any effects on material investments, children's physical health and nutrition, or parent's mental wellbeing. Additionally, I provide suggestive evidence that this mechanism operates differently prior to birth, with parents responding to shocks before birth by substituting working more hours before the child is born, allowing them to work less and spend more time at home in the following period immediately after birth, facilitating a positive effect of prenatal shock exposure on socio-emotional bonding and personality trait formation.

Second, I considering not just the prenatal period but also the potential for a sensitive period after-birth, through which I can address the experimental literature discussed above. Third, I offer a more robust approach to my estimation strategy than previous studies. I provide a detailed exploration of how both outcome and treatment variable construction 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 paper is as follows: the study setting and data are described in **section 2**. The empirical strategy is outlined in **section 3**. The main results, analysis of heterogeneous effects and robustness checks are presented in **section 4**, with the potential mechanisms underlying these results explored in **section 5**. Finally, concluding remarks are provided in **section 6**.

2 Context and Data

2.1 Context

Peru has 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, precipitation 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 region of Andean South America, prone to quasi-periodic extreme precipitation and temperature anomalies associated with the El Niño-Southern Oscillation (ENSO)(Ramírez and Briones, 2017). Additionally, as

[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.

a middle-income country, often individuals are 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 identify significant impacts of early life exposure to ENSO related rainfall shocks [2]. Within Peru, Danysh et al. (2014) report an increasing trend over time in height-for-age (HFA) of 0.09 S.D./year for cohorts born in Tumbes, a region on the far north coast, that is particularly prone to the effects of El Niños between 1991-1997. They find this rate is more than halved 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. Looking at more frequent shock exposure in a multi-country study, Zamand and Hyder (2016) find that receptive vocabulary scores and BMI-for-age are lower amongst children in Peruvian households reporting drought exposure in the 4 years prior to interview. They find no effect on HFA, school enrolment or mathematical ability. A limitation of this study however, is that it relies on self-reporting of shocks, which is likely endogenous and subject to significant measurement error (Bound et al., 2001), due to systematic over- or under-reporting based on the frequency and intensity of exposure, and the vulnerability of households to these shocks (Nguyen and Nguyen, 2020). Furthermore, these effects represent a short run impact of recent exposure during late childhood and adolescence, whereas this study focuses on the potential for longer run effects of early life exposure. Finally, Sanchez (2018) evaluates the impact of abnormally low temperatures in the Peruvian highlands in the first 36

[2] Including on educational attainment (Duque et al., 2019), health, cognitive ability, and mental wellbeing (Brando and Santos, 2015; Carrillo, 2020; Rosales-Rueda, 2018).

months of life on HFA, cognitive ability, and self-esteem for a sample of children born in poor households, finding a negative effect of increased cold exposure on HFA at age 5. This study will contribute to this literature of the effects in the region by providing the first estimates of the effects of early life shock exposure on personality trait formation.

2.2 Data

2.2.1 Young Lives

Young Lives (YL) is a longitudinal study of just under 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 were born in 2000-2002 and were tracked from age 6-18 months in 2002 and revisited in 2006, 2009, 2013, and 2016 at ages 5, 8, 12, and 15 respectively. An older cohort, born in 1994-1996, were interviewed concurrently at ages 8, 11, 15, 19 and 22. This analysis focuses on the Peruvian sample.

In Peru, the YL study employs a multi-stage, cluster-stratified, random sampling technique. Using a nationwide poverty index compiled in 2000, Peruvian districts were listed in rank order by population size and divided into equal population groups. To achieve the aim of oversampling poor households, the top 5% wealthiest districts were excluded. A random starting point was then selected, and a systematic sample of districts was chosen. The sample of 20 clusters drawn were examined to ensure they were logistically feasible, with a Census tract within each district, and then one block of housing (manzanas or centros poblados) within the tract, randomly chosen. All houses were visited in the block, or if necessary neighbouring blocks, until 100 eligible households were found. In comparison with nationally representative surveys, households were found to be similar to the average household, although with slightly better access to health, education and other services. Therefore the sample is considered suitable for analysing causal relations on child welfare and its longitudinal dynamics (Escobal and Flores, 2008).

At round 1 the total sample consists of 2766 children, with 2052 in the younger cohort and 714 in the older cohort. Attrition is low given extensive tracking: by round 5 (2016) attrition due to respondent refusal, moving abroad, death, or being untraceable was 8.2% and 14.1% respectively, with 2468 respondents present in all rounds. For each round, two main questionnaires are administered: an individual child-level and a household questionnaire. Additionally, GPS coordinates are collected for the centre of a community with 3 or more respondents from round 2 onward[3]. This GPS dataset was cleaned, validated, and matched to climate data (McQuade, Forthcoming), allowing identification of potential exposure to rainfall shocks using respondent's date of birth for 2386 of the respondents in 118 communities. Accounting for missing responses for outcomes and control variables, a sample of 2089 respondents is derived.

As children were not tracked prior to birth, a problem encountered is pinpointing if the mother resided in the relevant community from the date of conception throughout the period considered. To assess this, I specify the likely date of conception, using a gestational period for a full-term pregnancy of 40 weeks prior to birth[4]. From round 2, mothers were asked how long they have lived in the cur-

[3]For round 2, some large/disparate round 1 communities are split into smaller communities with separate identifiers. In this case, the new round 2 community is used as the location of the individual in round 1, assuming no movement between these disaggregated communities between rounds 1 and 2.

[4]While full term pregnancies commonly occur across a range of 37-42 weeks, given limited

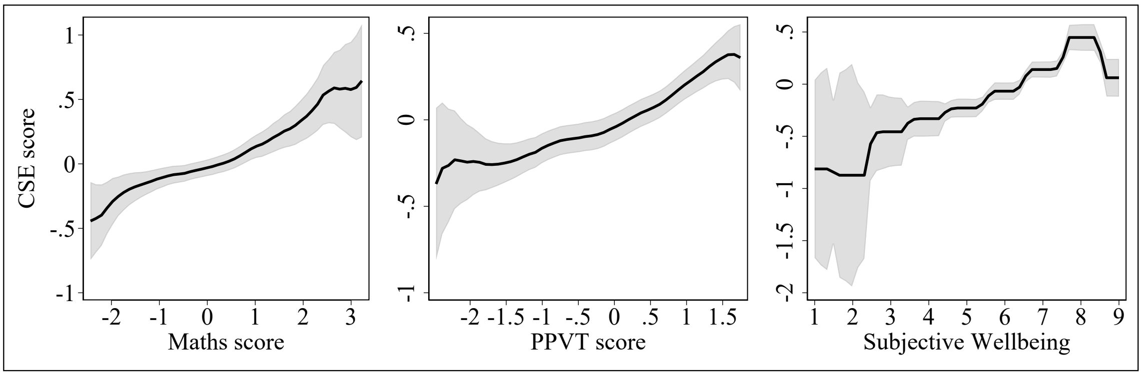
rent community in full years. Using the date of interview, I calculate the date of community move-in for the mother. Respondents whose likely date of conception occurs after this date are considered to have been conceived in the community. Using this definition I specify an 'in-community' sub-sample (N=1675, 80.2% of the final sample), of those definitely conceived and raised in the community throughout the perinatal period considered. 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 the analysis is conducted on both samples, allowing for the potential for migration effects to be assessed.

2.2.2 Core Self-Evaluation

The outcome of interest is a measure of an individual's Core self-evaluation (CSE) (Judge et al., 1998), and is measured in round 5 when respondents are in adolescence and young adulthood, aged between 14-23 years old. CSE is closely related to life satisfaction (Chang et al., 2012) and economic outcomes such as earnings and educational attainment (Judge and Hurst, 2007). It reflects an individual's confidence in their own abilities and self-control. A high score indicates 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, an indirect approach (Chang et al., 2012) is used, drawing responses from the self-

information about length of pregnancy in the YL survey (self-reported prematurity is only available for the younger cohort), a specific cut-off is defined for simplicity. The assumption required to establish mother's location prior to conception also informed the use of a longer period.

Figure 1: Within sample association between CSE and 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.

esteem, self-efficacy, and agency scales[5]. Self-esteem is derived from the Marsh (1990) self-description questionnaire II, and is a widely used measure in longitudinal studies (Laajaj and 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 validated in a range of low- and middle-income countries. The agency scale was developed specifically for the YL survey to be administered to children in developing countries (Yorke and Ogando, 2018), and is closely related to Rotter's 'locus of control' concept (Rotter, 1966). These measures are well validated and display high internal consistency and reliability in YL samples (see Porter et al., Forthcoming). Within sample associations between CSE and age-standardised cognitive test scores and subjective wellbeing (Cantril, 1965) at outcome (round 5) are shown in **figure 1**.

[5]The big five inventory (BFI) neuroticism/emotional stability scale (John, 1990; Costa and McCrae, 1992) is often included in construction of CSE measures. However, this scale is administered in round 5 only for the small older cohort (596 respondents). Therefore, to allow a sufficient sample size and spatial/temporal variation in shock exposure, I only use scales available for the full sample.

I specify a latent factor model, similar to Cunha et al. (2010), consisting of items from the three scales, using exploratory factor analysis, a method commonly used to assess the psychometric properties of scale items, as well as for dimension reduction Osborne (2015). This has the advantage over other methods, such as an aggregated composite score, that it allows 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. All item scores are first standardised by age in years and negatively phrased items were reverese-coded to ensure unidirectionality[6]. 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, therefore was excluded for non-relevancy and to preserve sample size. In total 22 items are included in the initial analysis (**appendix table A2**), which estimates the latent factor model by principal factors. Overall results strongly support the *a priori* assumption of a one factor model, with the first factor explaining 95.3% of shared variance. This result is further strengthened by a range of criteria that indicate that a single factor should be extracted. These criteria and results are discussed in detail in **appendix A**. Additionally, to assess the robustness of results to an alternative outcome specification, I follow Laajaj and Macours (2021) and construct a 'naïve' factor score – the average score of all age-standardised items in the 3 constituent scales.

[6]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"*).

2.2.3 Controls

Controls are included for child, maternal, and household characteristics. Child controls are indicators for gender and if their native tongue is Spanish. Mother's age and an indicator of if she has completed primary education are included as covariates for maternal/family characteristics. Household background characteristics are controlled for using indicators for the dwelling's urban/rural location and by a household wealth index taken from round 1, constructed specifically for the Young Lives survey, as a measure of household socioeconomic status using country-specific cut-offs — for details, see Briones (2017)[7]. 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, 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.

2.2.4 Climate data

To assess the effects of early life rainfall shocks on a child's personality trait formation, I exploit spatial and temporal variation in precipitation to identify potential exposure to abnormal amounts of rainfall. Identification relies on short-run fluc-

[7]While it would be preferred to control for pre-treatment values for household socioeconomic status, as measures such as income or expenditure may be impacted by shock exposure, the first round of data collection does not occur until after children are born. The wealth index is chosen as it captures longer-term indicators of household wealth, such as housing quality (building materials) and access to services (sanitation, electricity) and therefore is less likely to be sensitive to short run deviations in climate conditions.

Table 1: Sample 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

tuations from the long-run month-specific mean rainfall for a location being unpredictable and plausibly exogenous. YL households provide self-reports of their experience of recent climate shocks. However, this data is likely endogenous and subject to significant measurement error (Bound et al., 2001), depending on the respondent recall and perceived impact of the shock, for which they may systematically over- or under-report exposure (Nguyen and Nguyen, 2020). Additionally, it is difficult to verify the timing and intensity of self-reported shocks in this data set. I therefore match the location of respondents at the community level to climate data from the Terrestrial Precipitation Gridded Monthly Time Series (v5.01, 1901-2017)(Matsuura and Willmott, 2018) from the University of Delaware (UDel). This dataset provides estimates of monthly total precipitation at 0.5x0.5° intervals (roughly 50x50km at the equator) across a global grid for the period 1901-

2017[8]. The advantage of using a gridded dataset is that it provides full spatial and temporal coverage, which can allow estimates of weather in regions with poor coverage/low quality of station data (Dell et al., 2014). However, if station density in a region is low, this can lead to data points being interpolated over a large area, potentially smoothing trends in climate variables and reducing the extremes of precipitation event estimates compared to the actual on-the-ground conditions observed (Auffhammer et al., 2013; Harris et al., 2020). For this application, I find that in comparison to precipitation records for a subset of YL communities with nearby stations included in the Global Historical Climatology Network-Monthly (GHCN-M) and Global Summary of the Month (GSOM), estimates derived from the UDel dataset track raw records relatively well across all four YL study countries, with exception of underestimating a few rare, extremely high precipitation events (McQuade, Forthcoming).

To approximate rainfall experienced by respondents in early life, an inverse distance weighted (IDW) interpolation algorithm is used. The distance between the community centre point and the four nearest grid points is measured. For each point, p, a weighting, w_p, is calculated:

$$w_p = \frac{distance_p^{-1}}{\sum_{p=1}^{4} distance_p^{-1}} \tag{1}$$

Where $w_p \in (0, 1]$, such that the closest grid points have a greater influence on the community estimate – the weighted mean value of those four points. This

[8]This uses underlying terrestrial station data from a number of sources, employing climatologically-aided interpolation (Willmott and Robeson, 1995), based on a spherical version of Shepard's inverse distance-weighting algorithm (Shepard, 1968; Willmott et al., 1985), to produce a balanced grid of point estimates. The number of stations influencing a single node estimate is 20. See (Matsuura and Willmott, 2018) for more details.

provides an estimate of rainfall at each community, g, for each month, m, of each year, y. 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. 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[9] 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[10]. To account for zero precipitation, a mixed distribution is defined, with the cumulative probability function:

$$H(x) = q + (1 - q)G(x) \tag{2}$$

where $q = P(x = 0) > 0$ is the probability of zero reainfall and where $G(x)$ is the incomplete gamma function:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}} e^{-\frac{x}{\hat{\beta}}} dx \tag{3}$$

With estimates of parameters $\hat{\alpha}$, $\hat{\beta}$. $H(x)$ is transformed to the standard normal distribution to derive an SPI, using the approximate conversion listed in

[9]UDel dataset does not specify the density of stations or reliability of records in a region, however discussion with the YL Peru country team revealed a distinct drop off in the number of stations with records available prior to 1980 (based on data from the Peruvian meteorological service, SEMANHI), prompting the use of a 30-year period over longer records.

[10]Data was fitted using maximum likelihood over 2000 iterations, however for cases where convergence was not achieved, parameters α and β were estimated by approximation following Thom (1958).

Abramowitz, M. and Stegun (1964)[11]. This is conducted separately for each month of year at each community to provide 12 month-specific approximately normal distributions with mean 0 and standard deviation 1; therefore it is expected that SPI values typically fall within $(\pm)1$ S.D. and $(\pm)2$ S.D. approximately 68% and 95% of the time across the entire distribution, respectively (Hayes et al., 1999). Following McKee et al. (1993), I consider a monthly SPI value of less than -1.5 S.D. from the mean as an indicator of severe drought like conditions, herein referred to as a negative rainfall shock (unrelated to the potential beneficial or detrimental effect of the shock, simply the direction of the value relative to the long-term mean), and similarly rainfall greater than +1.5 S.D. from the mean as a positive shock.

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. – therefore these cut off points are unsuitable for use, with results estimated being potentially spurious for cases of almost universal exposure or impacted by outliers, inaccurately estimated, and subject to low statistical power in the case of few exposures. The distribution of shock exposure (of at least one month) within different periods of the perinatal period — 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 3rd birthday) for the postnatal phase – across the full and restricted in-community sample is provided in 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.

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 fitted to a gamma distribution, however it can also be fitted as a lognormal,

[11] See LLoyd-Hughes and Saunders (2002) for an in-depth discussion of SPI construction.

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

% 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.

Weibull, or exponential, given similar characteristics. The optimal distribution can be different for differing climates and locations (Mishra and Singh, 2010). Therefore, I specify an alternative SPI measure of shock exposure defined by fitting data to a lognormal distribution to test if results are impacted by choice of fitting distribution – see **section 4.3**.

3 Empirical strategy

Following Dell et al. (2014), to assess the effect of climate on skill formation, I wish to determine the relationship:

$$CSE = f(\mathbf{C}, \mathbf{X}) \tag{4}$$

in which the unknown function $f(\cdot)$ links the vectors of climate variables, $\mathbf{C}$, and controls, $\mathbf{X}$, to the outcome, CSE. Assessing climate conditions in terms of precipitation, I estimate the linearised reduced form,

$$CSE_{ijgr} = \beta_0 + \delta_{\mathbf{n}}^{'}\mathbf{S_{kgt}} + \beta_{\mathbf{1}}^{'}\mathbf{H_{ij}} + \beta_2 V_g + \beta_3 B_{t_0} + \varepsilon_r \tag{5}$$

Where CSE_{ijgr} is the measure of CSE at outcome in round 5 (age 14-23), for child i, born in household j, in community g, located in district r, measured in S.D. from the age-specific sample mean. S_{kgt} is a vector of rainfall shock variables for each community, of type $k = \{positive, negative\}$, for each of the 4 periods, t: 9 months of gestation (prenatal phase) and first, second, and third year of life (postnatal phase). I define shock variables as the total number of each of these shocks within a specific period,

$$S_{kgt} = \sum_{m=1}^{x} SPI_{kgm} \tag{6}$$

Where S_{kgt} is the magnitude of the shock of type k, experienced in community g in period t. This allows for shock severity to be captured by the cumulative number of months m in each period the child is exposed to that shock type. $\mathbf{H_{ij}}$ is a vector of child- and household-specific controls, as described in the previous section. Finally, I include community fixed effect, V_g, which controls for time-invariant characteristics of the community, and a fixed effect, B_{t_0}, for each year-month birth cohort t_0.

Given the potential for high spatial correlation of climate variables, estimates of standard errors can be biased unless corrected to allow for spatial correlation (Auffhammer et al., 2013). Therefore, I cluster standard errors in the base specification by district, a higher administrative level than the community, to allow for local spatial correlation in the covariance matrix, 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, inference based on standard asymptotic tests will lead to an over-rejection of the null hypothesis as standard errors are biased towards zero. As such I implement the cluster wild bootstrap procedure to derive adjusted p-values, as described by Cameron et al. (2008), based on 10,000 iterations. additionally, to assess the potential for arbitrary spatial correlation over space regardless of administrative boundaries, I compute standard errors adjusting for arbitrary 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 **appendix table B8**.

4 Results

4.1 Main results

Results for the impact of rainfall shocks for each period of the perinatal phase on the full and in-community sample standardised CSE scores at outcome (measured in standard deviations form the age-specific sample mean) 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 parenthesis; 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 larger than the cluster robust p-value, representing a more conservative indicator of the statistical significance of results in a case where simple clustering may lead to a greater rate of null-rejection. Interestingly, the p-value derived from Conley spatially robust standard errors are generally smaller than the cluster robust values. While this may reflect that the wild bootstrap values are too conservative, it is likely due to many communities in the sample being located within 50km of others[12], given the clustered nature of sampling in YL. This leads to there being relatively few independent clusters, fewer than by clustering at district level in cases where the distance from a community to the district borders are smaller than a 50km radius. As this methodology is also asymptotically justified, standard errors will be downwards biased[13]. Therefore, this method likely does not represent a refinement over cluster robust standard errors. A further option which could be considered is to follow a randomisation inference procedure, however under a natural experiment setting this requires strong assumptions about what determines variation in left-hand side variables, and as such is not implemented here. For the rest of the analysis the more conservative wild bootstrap approach is the preferred specification and are reported in all subsequent tables, with alternative p-values reported in **Appendices B** and **C**.

A pattern is clear across all specifications, that a positive 1.5 S.D. rainfall shock experienced in the 2nd and 3rd year of life are associated with a statistically significant decrease in age-standardised CSE scores in young adulthood, while a similar positive shock experienced in the prenatal phase is associated with a statistically significant increase in standardised CSE scores — with exception of a marginally insignificant effect under the wild bootstrap procedure for the full sample naïve score model. This is likely the noisiest measure of CSE due to: a) the inclusion of items which loaded poorly on the CSE factor in the EFA model, with no weighting to account for the underlying structure; and b) the full sample being the most likely to include individuals who did not fully comply with treatment. Therefore, it is likely to suffer from the greatest measurement error. An insignificant increase

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

[13]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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on clustered robust SEs at district level are in Parenthesis "(.)"; 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.

is estimated for exposure to 1st year positive shocks, across all specifications. Similarly, for negative values there is no clear pattern of results, with estimates not significant at any conventional level.

That results are similar to the in-community sample suggests exposure to shocks does not seem to influence migration choices. Additionally, exposure to short 1-month SPI (±)1.5 S.D. shocks may not be severe or long-lasting enough to elicit a migratory response.

Estimates are more precise for the main measure of interest, the EFA 1st factor score, than for the naïve score. As noted above, it is intuitive that EFA provides a more accurately estimated coefficient than the noisier naïve score, as the technique extracts as the 1st factor the dimension which explains the greatest amount of variation the data. 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)(See **appendix table B1**)[14]. As such, estimates using the EFA 1st factor measure obtained with the full sample represent the headline results of this analysis.

Exposure to a 1-month positive rainfall shock of greater than 1.5 S.D. from the long-run month-specific mean during the prenatal phase is associated with a 0.068 S.D. increase in CSE scores, statistically significant at the 10% level. This result is similar in magnitude and direction to that found by Krutikova and Lilleør (2015) in rural Tanzania, who find an 0.083S.D. increase in scores associated with a 10%

[14]**Table B1** provides evidence that while the pattern of effects is similar when naïve scores of individual scales are regressed on shock exposure, the magnitude of effect is different across scales, with the largest effect sizes estimated for the Marsh self-esteem measure, particularly during the prenatal period.

increase in the natural log deviation of rainfall in the year preceding birth from the 10 year average, significant to 5%. Interestingly, exposure to such a shock in the 2nd and 3rd year of life however is significantly associated with a -0.090S.D. and 0.105S.D. decrease in scores respectively 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 estimate a small negative effect on CSE scores of exposure to increased annual 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 an 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. These are considered in-depth in the mechanisms section. Next, I assess the potentially heterogeneous nature of these effects across different sub-groups.

4.2 Heterogeneous effects

It is common in early-life shock literature to find that shocks impact outcomes heterogeneously across different sub-groups, particularly across gender and socio-economic standing (Almond et al., 2018; Currie and Vogl, 2013), with results often being driven predominantly by the impact on boys or girls, and the strongest effects generally found amongst the poorest and least-educated households. To assess the potential for heterogeneous effects, shock variables are interacted with indicators for: if a respondent child is female; if the mother has completed primary education (achieved grade 6 or higher); and if the household is in the poorest category of wealth, as defined by the country specific wealth index. Following Briones (2017), the wealth index can be split in to four categories: 'poorest', 'very poor', 'less poor', and 'better-off'. Using the country specific cut-off points for Peru, I define a household as being in the 'poorest' group if, as measured in round 1, it has a wealth index score of <0.25. This applies to 26% of respondent households in the sample. Lastly, it is hypothesised that rainfall shock exposure disproportionately impacts those communities in which agriculture is the predominant economic activity, given they may be heavily reliant on rainfall for crop production. A community is considered agricultural if, for all households in the YL sample in round 1 for that community, 40% or more report household members being actively engaged in agricultural work. Estimated effects on 1st factor EFA CSE scores are shown in **table 4**.

Notably, there is a large 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, with the main term remaining insignificant at all levels. This suggests the positive effect estimated for prenatal shock exposure is driven predominantly by the effect higher rainfall has on a) girls — a common finding within the wider literature — and b) those from the lowest wealth households. In contrast for post-birth shock exposure there is no evident heterogeneous effect by gender. Interestingly, the significant main effect and almost equally large and opposite signed additional effect estimated for the poorest households suggests that overall there is little to no negative effect of exposure to a shock in the 3rd year for the poorest households. This may reflect that, at least amongst these households,

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

* 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**.

any negative impact that high rainfall has on CSE is offset by other the benefits of high rainfall that the household may experience. In contrast, whilst mother's level of education is an important factor in determining CSE scores, there is no strong evidence of any interaction. 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[15].

4.3 Robustness checks

A concern with using a probabilistic measure as a shock variable is that results may be a statistical artefact of the construction of the index, in particular the choice of theoretical distribution to fit the long term distribution of rainfall (Mishra and Singh, 2010). To assess this, an alternative definition of shock exposure, based on fitting rainfall values to a lognormal function rather than a gamma function are provided in **appendix table B3**. Results show a similar pattern, however the magnitude and significance of some results differ, likely impacted by outliers (column 2 of **table B3** shows much lower exposure to positive shocks under this specification) and poor fit of data to the lognormal. **Figures B1** and **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) over the same range of values, overlayed in red, for the gamma-fitted and lognormal-fitted SPIs respectively. Derived SPI values should be approximately

[15] This does not seem to 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. Results available on request from the author.

normally distributed if the underlying rainfall data is well fitted to the theoretical distribution chosen. **Figure B1** shows that with exception of a few outliers, 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). However, under the lognormal specification in **figure B2**, SPI values for every month display a significant negative skew, and a large peak above zero, but with very few extreme positive values. This suggests that fitting to lognormal provides a poor fit for the relative distribution of rainfall experienced in YL communities in Peru, as the log transformation of the data does not appear to be normally distributed[16].

A further concern may be that there is not just spatial but an auto-correlative structure affecting the results obtained when estimating the effects of shock exposure in different periods jointly. **Table B4** shows the results obtained when age-standardised CSE scores at follow up are regressed on shock exposure in each period individually. The overall pattern remains for the sign and magnitude of effects, with exposure to postnatal positive rainfall shocks in the 2$^{\text{nd}}$ and 3$^{\text{rd}}$ year of life (columns 3 and 4) associated with a negative effect on CSE scores, both significant at the 5% level. Additionally, there is no significant effect estimated for exposure to negative shocks in any period. However, the magnitude of the prenatal effect is somewhat reduced (0.049 S.D.) and is no longer significant at conventional levels (wild bootstrap p-value = 0.185). This suggests that the effect estimated for the prenatal period may be correlated with subsequent exposure in the post-

[16]This would likely also impact results obtained using the log deviation of rainfall from the mean, as used by Maccini and Yang (2009) and Krutikova and Lilleør (2015), given the non-normality of the log-transformed variable. Additionally, Couttenier and Soubeyran (2014) provide evidence that the SPI and other related indices, when well-defined, are more efficient than these commonly used linear measures.

natal period. In spite of this, column 1 of **Table B5** shows that when controlling for the cumulative number of positive or negative shocks, the estimates obtained for cumulative shock exposure are not significant, suggesting any such link with subsequent exposure is weak. Under this specification, the prenatal effect remains significant at the 10% level, and the pattern of results remains similar, although the previously significant 2nd year effect is now marginally insignificant just above the 10% level (p-value=0.118) under the wild bootstrap procedure specification. Columns 3 and 4 of **Table B5** reports the effect of shock exposure separately by shock type (positive or negative), with results similar in sign, magnitude, and significance to the main results.

Furthermore, to test if estimates obtained for other periods outside the window of gestation and the first 3 years of life are significant, either truly because they are important for personality formation, or falsely because there is a spurious effect being estimated due to auto-correlation between periods, 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 4th year of life. To minimise measurement error, this is estimated for the in-community sample only, for which it is certain all respondent's 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 is the same as under the main specification, with a positive effect of exposure to positive rainfall shocks in-utero compared with a negative effect in the 2nd and 3rd year of life, no significant effect estimated in the 1st year, and with no significant effect estimated for negative exposure in any period. No significant effect is found for exposure of the mother to shocks in the year prior to conception, or for exposure of the child in the 4th year of life.

However, notably the size of effect estimated for the prenatal period is slightly inflated compared with the main specification, or when exposure is measured in each period separately. This indicates, while results do not seem to be spurious and are relatively robust across all specifications, there may be some level of positive correlation between exposure in different periods, which may inflate the value of estimates obtained 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. They suggest that not controlling for temperature may lead to omitted variable bias in estimating the effects of precipitation. Column 1 of **table B6** estimates the main specification controlling for community-specific average temperature across each period, with results remaining unchanged.

One hypothesised mechanism for the effect of precipitation shocks on trait formation is that rainfall deviations impact households directly through their relationship with agricultural output, which can affect children in early life by influencing the availability of food or agricultural income of the household, or by increasing/decreasing the amount of time household adults spend working in agriculture or related jobs. The YL sample includes several communities which are located within or on the outskirts of Lima. Lima represents a large highly-urbanised and globally connected metropolitan area, and it would be reasonable to posit that individuals in these communities may be the least affected by short-term deviations in rainfall, particularly if effects are transmitted predominantly through impacting local agriculture. I test if results are robust to the exclusion of these urban communities, a practice common in studies of the effects of climate on human capital formation (e.g. Maccini and Yang (2009)). Results are reported in column 3 of

table B6 and remain consistent with the full sample.

Additionally, if results are predominantly driven by the effect on local agriculture, then it would be expected that rainfall shocks which occur during the growing season of primary crops would be the most salient for personality trait formation. As a climatically and geographically diverse country, the primary crop grown, and the exact timing of planting and harvesting for that crop, likely varies across the YL communities. To test this, I follow a similar procedure to Webb (2022) and Auffhammer et al. (2013) to define the primary crop growing season. I first identify the main crop grown in each community, as defined by total area sown, using data from the Peruvian Ministry of Agriculture (MINAGRI)[17] on department-level yields for 6 different crops[18] in 2010. The primary crop by department is shown in **figure B3**. I then estimate the department-level mean planting and harvesting dates using gridded crop calendar data (Sacks et al., 2010)[19] which provides estimates of planting and harvesting days for 19 crops on a 0.5x0.5° global grid, based on the nearest agricultural census data from 2000. 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-of-year level.

A growing season shock is therefore defined if, for a given month, that month-of-year falls between the estimated planting and harvesting month for the primary crop of the department in which the YL community is located, and the community-specific monthly rainfall deviation as defined by the SPI is $(\pm)1.5$ S.D. from the

[17]The data used was obtained as part of the "cropdatape" R package, available at: `https://github.com/omarbenites/cropdatape`.

[18]rice, quinoa, potato, sweet potato, tomato and wheat. Tomato was excluded as a perennial crop.

[19]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/`

long term mean. The intensity of shock exposure is defined as the total number of growing season months of shock exposure, as defined in the main analysis. The effect of early life growing season shock exposure on CSE scores at outcome is estimated in column 2 of **table B6**. the pattern of results remains consistent, however only the negative effect of exposure to a positive shock in the 3$^{\text{rd}}$ year remains significant, with the magnitude of estimates for prenatal and 2$^{\text{nd}}$ year exposure diminished and no longer significant at conventional levels. While this may suggest the effects found in these periods are not robust, it may also be possible that local farmers adapt to shocks by switching or diversifying the crops they grow. 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. What remains clear is that there is a particularly robust and strong significant effect of exposure to positive rainfall shocks in the 3rd year of life.

The Young Lives study is structured as a cohort study, with 2 primary cohorts defined – the main, younger cohort, born between 2000-2002 and a smaller, older cohort born between 1994-1996[20]. 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.

As noted by Almond et al. (2018), several studies of early life circumstance

[20] A further cohort, consisting of the nearest younger sibling in age to the younger cohort child is also defined, however, as not all required outcomes were administered to these children they are not included in this analysis.

provide evidence of effects of in-utero shocks on sex ratios, reducing the number of boys born, who seem to be more prone to being miscarried (in particular studies of Ramadan fasting during pregnancy, e.g. Almond and Mazumder (2013)). To assess if there is sex selection within the sample conditional on shock exposure, I regress the sex of the child as reported in round 1 on prenatal shock exposure (as well as postnatal exposure, which while expected to have a null effect, would indicate a potential spurious relationship between climate shocks and sex). Results are reported in column 1 of **table B7**, and indicate that there does not seem to be any effect of shock exposure on sex ratio within sample. This was expected, as short run deviations in rainfall are expected to be mild compared with shocks that could cause extreme maternal nutritional deficiencies.

A further potential threat which could bias the results of the main analysis is if shock exposure is predictive of selection in to the sample. In particular for this studies setting, where data collection occurs post-birth, if shock exposure influences migration decisions, then it may be that those exposed pre-birth may migrate migrate out of shock-prone communities. While this is not directly testable within this analysis, I can test if exposure to shocks is predictive of the household's choice to migrate after the birth of the child. Column 2 of **table B7** shows that shock exposure in the prenatal period and years 1-3 of life does not predict the decision to migrate by round 2 (when respondents are aged 4-13).

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 seemingly isolated to the 3rd trimester of pregnancy. As shown in **table B9**, exposure to a positive shock in the final trimester (defined roughly as months 7-9 since conception) is associated with a large positive effect on later life CSE, equal to a 0.115 S.D. increase for each month of shock exposure. Interestingly, while there is no significant effect of negative shock exposure in-utero found within the main analysis, there is a large negative effect estimated for exposure in the 3rd trimester (-0.133 S.D. per month of -1.5 S.D. shock exposure). Overall this is suggestive that experience of rainfall in the final trimester, just before birth may be the most important for future personality trait formation, whether it be due to a direct effect on the mother and child of shock exposure, or indirectly by impacting the home environment and resources available within the household immediately after-birth.

Lastly, for the main specification, test statistics are reported for eight treatments across two samples for two types of outcome construction. A concern is the increased likelihood of committing type 1 errors, that is over rejecting the null hypothesis, due to multiple inference (Romano and Wolf, 2005). A common solution is to control for the familywise error rate (FWER), for example using the Bonferroni correction, which limits the probability of making any type I error. However, due to a large number of tests being conducted this correction would likely produce very inflated adjusted p-values, providing very low statistical power (e.g. Bonferroni p-values can potentially exceed 1). Instead, 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 to preserving statistical power and reducing false positives by vastly reducing the penalty of additional hypotheses. These are reported in **table B8**. The outcomes of interest remain significant when controlling FDR at q=0.10, with exception of the effect of prenatal positive shock exposure for the full sample model using a naïve z-score measure of CSE (q-value = 0.203), the noisiest measure of CSE, and model most subject to measurement error.

5 Mechanisms

The evidence above suggests there is an impact of exposure to early life rainfall shocks on personality trait formation, however the exact causal channel through which this effect is realised remains unclear. Furthermore, that exposure to the same type of shock pre- and post-birth has a differential effect on later life CSE scores suggests that the causal transmission channel operates differently across these two phases of life. This section explores several potential mechanisms and presents a body of evidence across a range of additional analyses.

5.1 Nutrition

Rainfall shocks may impact personality trait formation in low- or middle- income settings by affecting nutrition. This may occur directly, with changes to rainfall influencing local food availability, impacting children in-utero through intrauterine exposure to maternal undernutrition or immediately post-birth by affecting breast-feeding and/or early nutrition when weaning (Krutikova and Lilleør, 2015; Rosales-Rueda, 2018). The relationship between exposure to positive rainfall shocks and an indicator of if a child was found to be stunted at age 8[21] is assessed using a linear probability model and reported in column 1 of **table C1** in **appendix C**. Stunting

[21]age 8 is the first observation available for children in the older cohort.

is a common indicator of chronic or long-term undernutrition and repeated infection[22]. No significant effect on the probability of stunting is found for exposure to positive rainfall shocks, suggesting that nutrition is not a key mechanism for the relationship in personality trait formation.

5.2 Child health

Alternatively, rainfall variation can impact child health beyond nutrition. High rainfall may disrupt sewage or drainage, contaminating water supplies (Rocha and Soares, 2015) or may damage crops and lead to an increase in bodies of standing water, which can contribute to the incidence of water-borne diseases, such as malaria (Venkataramani, 2012). To assess the potential mechanism of poor child health, I estimate the relationship between rainfall shock exposure and 3 binary indicators of child health and disease burden: a) if an individual self-reports having good or very good health in round 5, a measure of overall adult health; b) if a child has suffered a serious illness since birth until the end of the postnatal period, from which their caregiver thought they could possibly die; and c) if a child reports having a long-term disability in round 5. Results are reported in columns 2-4 of **table C1**. Overall, there is no evidence of a link between child health or nutrition and positive rainfall shock exposure in early life in this setting.

[22] A child is defined as stunted if their height is more than 2S.D. below the median height of reference children of the same age and gender, based on the World Health Organisation (WHO) child growth standards reference: `http://www.who.int/childgrowth/standards/height_for_age/en/`

5.3 Caregiver stress

The effect of rainfall shocks may be transmitted through impacts on parental mental wellbeing and subsequently their investment responses. Pressures caused by shocks on finances, food availability and employment may increase parental stress and negatively impact mental health – affecting their parenting practices, availability, or temperament (Duque, 2017; Shoji, 2022). Mental wellbeing is assessed for the caregiver of younger cohort children in Peru in each round using the WHO self-reported questionnaire (SRQ-20), a screening tool measuring the number of symptoms of non-clinical anxiety and depression caregivers experienced in the 30 days prior to interview (Tuan et al., 2004). Using data from rounds 1-5, I construct a total score (0-20), a unit increase in which indicates an increase in the number of reported symptoms, as well as a 'caseness' score for respondents reporting 7 or more symptoms[23]. In columns 1-3 of **table C3**, insignificant null effects are estimated for positive shock in the 12 months prior to date of interview.

Assessing the potential for changes in parenting practices resulting from additional stress, I regress z-score of an index of parenting practices on prenatal shock exposure in column 4 of **table C3**. Following Favara (2018), I construct this measure using questions administered to the younger cohort in round 1 (only in Peru) when the child is in infancy, regarding what actions a mother takes 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 a greater likelihood of reporting bad or detrimental practices (such as ignoring, shaking, or spanking the child, coded as -1). A list of

[23]Additionally, as a robustness check I construct an alternative caseness score for 8 or more symptoms (Beusenberg and Orley, 1994), reported in the column 3 of **table C3**.

reported practices is available in **table C2**. Results do not provide evidence of an association between positive prenatal rainfall shocks and a change in early life parenting practices.

5.4 Parent-child relationship

An important mechanism through which personality traits may be affected by early life conditions is by influencing the time available for parents to invest in nurturing and interacting with children. A transitory positive rainfall shock could have either an income or substitution effect on households. Parents may increase their labour supply due to an increase in agricultural or related industry wages, or demand for labour in these sectors. This income effect may have a positive effect on children's outcomes if it increases the resources that can be allocated to children in early life[24]. However, there is also the potential substitution effect that higher returns to working in agriculture-related roles, or on a family farm, increases the opportunity cost of spending time in the home. In response to short term increases in agriculture-related wages and opportunities, a parent may allocate more time to work, or take on additional jobs, reducing the time they are able to spend interacting with and providing social stimulation young children. Evidence from neurobiology shows that a strong positive attachment with parents in early life promotes healthy brain development Schore (2001). Additionally, While few studies have directly assessed the impact of reduced time investment, there have been several controlled trail studies which increase time spent on positive enrichment through providing supervised social stimulation investments in early

[24]This may be particularly true if positive rainfall in the year prior to birth allows parents to increase their labour supply in the period before birth, allowing them to work less and spend more time with their child immediately post-birth.

years, particularly between mothers and children (Attanasio et al., 2020; Heckman et al., 2013; Walker et al., 2022), which show long-lasting differences in personality traits, even when differences in other dimensions such as cognitive ability diminish as children age. 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 reduction in parents' involvement with, and investment in, their children.

In rounds 2 and 4, adult household members were asked about hours spent working in up to three economic activities, and which of those activities is the most important in terms of income. In **table 5** I regress measures of adult working hours on the number of months of rainfall shock exposure in the 12 months prior to the month of interview, to capture the short run response of the household to shocks. In **panel A** I define as dependent variable the average hours spent working in a day on the activity identified as the most important for income. However, main activity working hours may be inflexible if that activity is contracted/salaried. It is also common for respondents to 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 working hours may be masked if adults respond by working more in another activity. Therefore, in **panel B** I also consider the effect of shock exposure on average hours worked across the sum of all reported paid activity. Column 1 reports the impact of shock exposure on hours worked by parents. 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).

Additionally, other household members, such as adult older siblings, aunts and uncles, or grandparents, who may be involved with caring for or playing with the child, may also change their working hours in response to rainfall shocks, substituting for more work or more childcare to accommodate the parent's responsibilities. Therefore, I additionally report the same specifications, estimated for the sample of all working age (15-64) household members in columns 3 and 4. For columns 2 and 4, the p-value of the linear hypothesis test that the sum of coefficients of the positive shock exposure level term (reference group male) and interaction term (the additional effect for being female) is significantly different from zero, reported separately for each panel.

Controls are included for if a household is in a rural location; the round 1 wealth index of household; respondent gender, age, and age-squared, and fixed effects for survey round, month of interview and community are included and suppressed. Across all specifications, exposure to a month of rainfall 1.5 S.D. above the long-term month mean is associated with increased working hours in paid work. The effect for all paid activity is slightly larger for parents compared to the full sample of working age adult members, but overall the finding is that all household adults work more hours in response to recent positive rainfall shocks across both the main activity and all paid economic activity. Based on results in column 1, it is estimated that for each month of positive rainfall shock exposure a parent works an additional 11 minutes and 26 minutes on average per day, on the main activity and all paid work respectively. Young Lives provides a variable for sector of work (based on ISIC Rev.3), however a large proportion of the sample either do not report a sector code or record as non-applicable, likely due to a large

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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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 C4**.

number of informal workers who do not work in one single industry. Therefore it is not possible to accurately assess if effects disproportionately impact a specific sector[25].

Looking at the differences across respondent sex, results differ between the main activity and all paid work. For the primary economic task, while women report working less hours generally, there is no significant difference by sex in the response to positive shocks, with both men and women seeming to work more in their main job, and the interaction term for being female insignificant for both parents and all household adults. the reported p-value for the linear hypothesis suggests that the combined estimated effect for women is significantly different from zero, rejecting the null hypothesis at the 10% and 5% level in each sample.

Alternatively, for all paid economic activity there is a large increase in the time spent working for men, of approximately 55 minutes for fathers and 44 minutes for all household working age males per month of shock exposure, significant at the 1% and 5% level respectively. In contrast a large decrease is estimated for the additional effect for women, both significant at 5%. We cannot reject the null that the combined effect for women across all paid work is different from zero at a conventional level. This suggests that while women may have a small increase the main activity, the largest effect of a recent positive shock on household labour supply is through the impact on mens' total labour, in particular the father of the YL child, who work significantly more over all activities.

[25] However additional analysis using multiple waves of a large representative cross-sectional household survey, the Encuesta Nacional de Hogares (ENAHO), conducted by the Peruvian National Institute of Statistics (INEI) to monitor household living conditions, which suggests a 1-month exposure to an equivalent +1.5 S.D. rainfall shock at district level is associated with a moderate increase in hours worked per week by respondents working in an agriculture related occupation (based on ISIC Rev.4 4-number occupation code). Results from ENAHO are reported in **table C9**.

Furthermore, if household adult members respond to positive rainfall shocks by working more hours, the burden of childcare, domestic work and other unpaid work within the family home, farm or business may be shifted to other non-adult members of the household, in particular, 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. For older siblings of the YL child, I regress the number of hours spent on each time use on the number of months of exposure to rainfall shocks in the previous 12 months. Results are shown in **table C5**. No category is associated with any statistically significant or meaningful changes in response to shock exposure. Overall, this suggests that in response to shock exposure, parents (particularly fathers) increase their working hours across all economic activity, and that this increase in time spent working likely reduces the time a parent has available to interact with and care for children during the early life period. This reduction in availability for care is not substituted for by other adult household members, who also work more, or by older sibling children, who do not change their routines. As a result, a child may be experiencing less quality time with parents, which is not adequately adapted for by other household members, negatively impacting opportunities for psycho-social stimulation and play.

However, given it is unclear theoretically whether the substitution or income effect of a rainfall shock dominates, it may be that increased income leads to greater or lesser investments in children at this early stage by parents, outweighing a reduction in availability of parents. A wider literature studies parental response to rainfall shocks as a mechanism, suggesting parents may invest unequally in children in terms of material investments – subsequently either compensating for or reinforcing shocks to human capital formation. For example, Fan and Porter (2020) examine how parents respond to differences in child ability across siblings in Ethiopia using Young Lives data, exploiting rainfall variation as an exogenous shock to ability. Their results show that on average parents compensate the disadvantaged child, paying a little more in educational fees compared to the other child in a sibling pair[26]. As such if the income effect dominates, it may be expected that parents will either invest more or less in children who are exposed to early life shocks.

I measure material investment in children using two variables. First, using questions administered exclusively to caregivers in Peru for round 3 regarding their investment in their child's reading habits and household reading resources, I construct an index of reading encouragement and investment in reading materials. For each question, 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. A list of included questions is available in **table C6**. Additionally, I construct a measure of expenditure on education for the child in round 3. Total expenditure in the last year is reported for: footwear, school uniform, matriculation fees, other school fees, schoolbooks and stationery, transport to school and other miscellaneous educational expenses. Respondents are also asked how much of this expenditure is for the index child: none, less than half, half, more than half, and all. I code these as rough proportions of 0, 0.25, 0.5, 0.75, and 1 respectively to get an estimate of total log expenditure for education on the index child. Results are reported in columns 3 and 4 of **table 6**. Controls and fixed effects are the same as in the main analysis.

[26] See Almond and Mazumder (2013) for a review of this literature.

If however, the substitution effect of a positive rainfall shock dominates, then, as hypothesised above, we would expect to see some negative impact on the parent and child relationship. to test this I construct two measures for the parent child relationship. First I proxy the caregiver's perception of the relationship by constructing an index measuring the level of their involvement and knowledge of their child's life. In round 3, caregivers were asked about their knowledge of several aspects of their child's life (for example, if they know the name of the child's teacher, or if they feel close to their child -– items are listed in **table C6**). as with the reading encouragement index above, 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 as an index of a parent's involvement in, and familiarity with, their child's life.

As values used in this measure, reported in column 1 of **table 6**, are based on caregiver's self-reporting, it is likely contaminated with measurement error if a caregiver over reports their involvement or knowledge, due to social expectations or embarrassment. Therefore, I also 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 parents. As with my main outcome, I construct an EFA 1st factor score using age-standardised item responses. The scale shows high unidirectionality and internal consistency (Yorke and Ogando, 2018), with all items loading highly on the 1^{st} factor only. A list of the included scale items and 1^{st} factor loadings is given in **table C7**[27].

[27]Scale items were only administered to respondents if at least one parent is alive at the time

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
	[0.629]	[0.044]**	[0.125]	[0.166]
1st year	-0.047	0.013	-0.066	-0.070
	[0.413]	[0.836]	[0.166]	[0.117]
2nd year	0.036	-0.006	0.081	0.030
	[0.349]	[0.871]	[0.111]	[0.671]
3rd year	-0.109	-0.062	0.018	0.016
	[0.003]***	[0.027]**	[0.652]	[0.728]
Controls	Yes	Yes	Yes	Yes
N	2089	1995	2089	2089

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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 C8**.

Effects estimated for material investments, measured both by education expenditure and by the reading encouragement index, are insignificant at conventional levels for positive shock exposure in any period. However several coefficients are only marginally insignificant, suggesting it is unlikely that there is absolutely no effect of positive shocks on material investments and household resources, although any impact may be very weak.

A clearer pattern is evident for measures of the social relationship between children and parents. While an insignificant effect is estimated for shock exposure in the 2^{nd} year of life, an increase in the parental relations scale of 0.085 S.D. is associated with a unit increase prenatal exposure to positive rainfall shocks, while a 0.062 S.D. decrease per month of exposure is estimated for for the 3rd year of life, both significant at the 5% level. This pattern is similar to that found for

of the round 4 interview.

CSE and is partially mirrored by the variation in the caregiver-reported parent involvement index, with a highly significant 0.109 S.D. decrease associated with shock exposure in the 3rd year.

This provides further support to the hypothesis that the negative substitution effect of positive shocks dominates any positive income effect, at least in the post-natal period. However, given that the effect of shock exposure on an individual's relationship with their parent is influenced differently by shocks in different time periods, echoing the pattern observed for the effect on later life CSE scores, it is suggestive that the effect of shocks pre-birth may have a differential effect on parental labour supply than exposure post-birth. For example, while a parent of a child who experiences a positive rainfall shock after-birth may spend more time working in response to increased rainfall, leading to a decrease in time for enrichment with their child, exposure to positive shocks during pregnancy may not impact through this mechanism, or may have some benefit — for example, by increasing the hours worked before the child is born, increasing household income, and allowing parents to work fewer hours after the child is born. to test this, I assess how the labour supply post-birth of adults in a household with newborn children reacts to positive shocks experienced before birth, during the prenatal period.

First, I exploit a sub-sample of respondent households, using the round 1 data for the younger cohort, for which labour supply is reported within 6-18 months of birth, and for which I can accurately identify the exact date of birth and prenatal period. Unfortunately the information on labour supply available in round 1 is not directly comparable to rounds 2 and 4, as household adults are asked only for the rough number of days per week[28] they are involved in economic activity (up to 3 reported activities), not the hours worked per day, and which one is the most important activity to them. the dependent variables are defined as the log (given an evident positive skew in the raw data) number of reported days in the main activity and across all reported activity, and are regressed separately for parents and all household adults on the number of months of shock exposure experienced during the prenatal period. Result are reported in **table 7**.

Table 7: Impact of prenatal +1.5S.D. shocks on days worked after-birth

	Main activity		**All activities**	
	Parents	All HH adults	Parents	All HH adults
+1.5 S.D. shock	-0.170	-0.094	-0.039	-0.026
	[0.022]**	[0.282]	[0.077]*	[0.278]
Controls	Yes	Yes	Yes	Yes
N	2293	3311	2293	3311

* p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on wild bootstrapped procedures (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 month of interview and community are suppressed. Alternative p-values are reported in **Table C10**.

The effect on post birth labour supply of rainfall in the previous period before birth is isolated to parents, with an estimated 17% and 4% decrease in main activity and all activity days respectively, significant at the 5% and 10%, against non-significant effects estimated for all adults. This is suggestive of an inter-temporal substitution of labour supply to before birth, wherein parents respond to short term rainfall shocks within the prenatal period by increasing labour supply in the short term, allowing them to work less may in the next period, after the

[28]responses are coded as intervals: 6-7 days per week; 3-5, 1-2, and less than 1 per week. For convenience, these are recoded to their lower bounds: 5, 3, 1, and 0.

birth of the child.

A limitation of this analysis is that all respondents in this sub-sample have newborn children, therefore it cannot be distinguished that this effect of the positive shock in the previous period is unique to the prenatal period, and not just a general effect of exposure in one period on labour supply in the following period. To attempt to assess if this negative effect on labour supply is unique to the case where a child is soon to be born, I return to the sample collected from round 2 and 4. I measure the effect on average hours worked across all paid activity of the interaction between positive shock exposure in the previous period (13-24 months before the month of interview) and the birth of a child in the current period, as defined by the presence of a child of the parents aged 0 or 1 in the household roster at interview. Results are reported in **table 8**.

Table 8: Impact of prenatal +1.5S.D. shocks on hours worked, newborn present in household

	All adults	Parents	Mothers	Fathers
Newborn in HH	0.605	0.134	-0.895	0.718
	[0.026]**	[0.665]	[0.018]**	[0.063]*
Positive shock 13-24 months before	-0.172	-0.127	-0.201	0.114
	[0.562]	[0.639]	[0.461]	[0.830]
**Interaction*	-0.469	-0.392	-0.412	-0.418
	[0.206]	[0.264]	[0.470]	[0.261]
Controls	Yes	Yes	Yes	Yes
$H_0 : \beta_2 + \beta_3 = 0$ p-val.	0.036	0.061	0.150	0.373
N	7438	5394	2270	3106

* p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in Parenthesis "(.)"; 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. Alternative p-values are reported in **Table C11**.

Results are reported for all adults in column 1, parents only in column 2, and dis-aggregated by mothers and fathers in columns 3 and 4. There is a large significant positive effect of the presence of a newborn in the household on the hours worked by all household adults. Looking at parents specifically this effect is diminished and insignificant for p-values obtained under the wild bootstrap procedure, however columns 3 and 4 suggest this is because mothers respond to a newborn by decreasing hours worked significantly, while fathers significantly increase working hours. Exposure to a positive shock 13-24 months before interview is estimated to have a small negative effect on hours worked, insignificant across all 4 samples. In contrast, the interaction between the presence of a newborn and shock exposure in the previous period is associated with a large negative effect 3-4 times the size of the level term effect of shock exposure, but this is not separately significant at conventional levels in any sample. This may be influenced by the fact that only 4.5% of the sample experience both a newborn child and at least one positive shock exposure 13-24 months before interview. Additionally, this sample consists only of households who already have children and for which the age of parents skews older, with subsequent children in round 2 and 4 born at least 5 and 12 years after the YL index child. Interestingly however, p-values reported for the linear hypothesis test of the combined effect indicate that, at least for the all household adults and combined parents samples (columns 1 and 2), we can reject the null hypothesis of a null net effect at the 5% and 10% level respectively. This is suggestive that there is a non-zero negative effect of exposure to positive shocks in the period prior to the birth of a child on the labour supply of the household after birth.

In total, the evidence above suggests that the effect of exposure to early life positive rainfall shocks on later life personality operates through influencing household adult labour supply. In response to short term increases in rainfall, household adults, in particular the fathers of children, work significantly more hours. This likely reduces the availability of parents to interact with children during a key stage in socio-emotional development, an absence which is not adequately adjusted for by other household adults or older siblings, suggesting children experience a reduction in quality social stimulation and play. This has a negative effect on the relationship between children and parents and likely causally impacts personality trait formation long term. While the effect of a transitory positive rainfall shock after birth is associated with a negative effect on personality development, driven by a decrease in availability of parents, there is also suggestive evidence that exposure to a positive shock in the prenatal period allows parents to substitute for future labour supply in the next period after-birth by working more hours before the birth of the child. This likely allows for parents to be more available to care for the child immediately post-birth, which explains the beneficial effect of prenatal shock exposure on future CSE scores.

6 Conclusion

I contribute to the literature which identifies the importance of early life circumstances in determining future human capital stock, expanding the very limited literature on the experience of early life rainfall on personality trait formation, and offering the first in-depth discussion of the underlying channels through which these effects are transmitted. I find prenatal exposure to increased rainfall is associated with an increase in CSE score-for-age. In contrast, a similar exposure in the 2$^{\text{nd}}$ and 3$^{\text{rd}}$ year of life is associated with a decrease in scores. Importantly, I provide evidence of the underlying mechanisms for my findings. While there is no evidence the effects are facilitated through child nutrition or health, or as a result of an impact on parental well-being, there is strong evidence that increased postnatal rainfall leads to household adults – particularly the father of the child – working longer hours, and that this reduces the time they can spend interacting with the child during an important stage of development. Evidence suggests this affects the emotional and social bond developed through parent-child interaction, with the long-term parent-child relationship negatively impacted, rather than by affecting material investments in children. I provide suggestive evidence that the beneficial effect of prenatal exposure results from an inter-temporal substitution of parents labour supply, wherein they shift labour supply to before the child is born in response to positive prenatal rainfall shocks, allowing them to work less after the child is born in the next period.

Assessing potential heterogeneous effects, I find that this positive prenatal influence is experienced is driven predominantly by the effect of shock exposure on girls and those born in the poorest households, findings common in 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, with my findings suggesting that the policy interventions that allow parents adequate time for interaction with their child post-birth would be the most effective at improving core-self evaluations – for example, child benefit payments targeted at reducing the parent's need to work longer hours during the early life period. Furthermore, results suggest future evaluations of the effects of climate shocks, or interventions designed to mitigate the effects of extreme climate events, should not only quantify the impacts on physical or cognitive outcomes, but also the effects 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 Criteria for factor selection from EFA

The number of latent factors to extract is assessed using several crtieria, 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 and Osborne, 2005). Similar to Webb (2022), 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^{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, and unique variance is all that remains. The number of components for which a minimum is reached represents the number to extract.

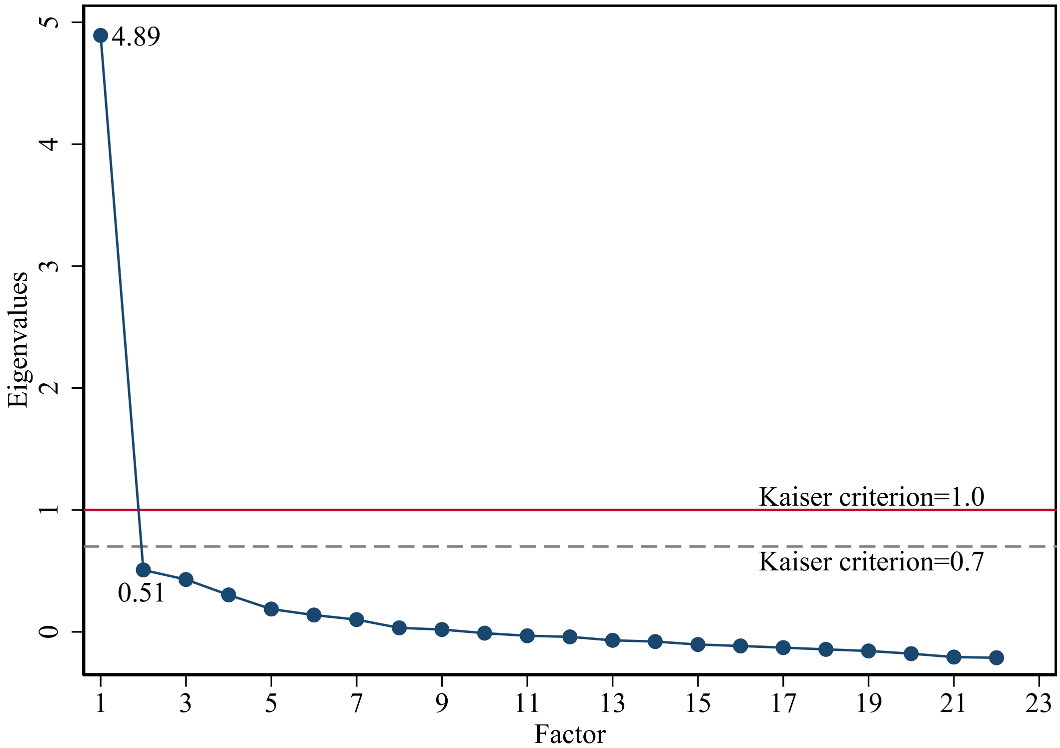
A summary of the number of factors to extract is given by **table A1**. The criteria described in 2 and 3 are shown by the scree plot of eigenvalues, **figure A1**.

Table A1: 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

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^{nd} factor eigenvalue of 0.51. There is an evident change of slope at the second factor, suggesting an 'elbow' above 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.

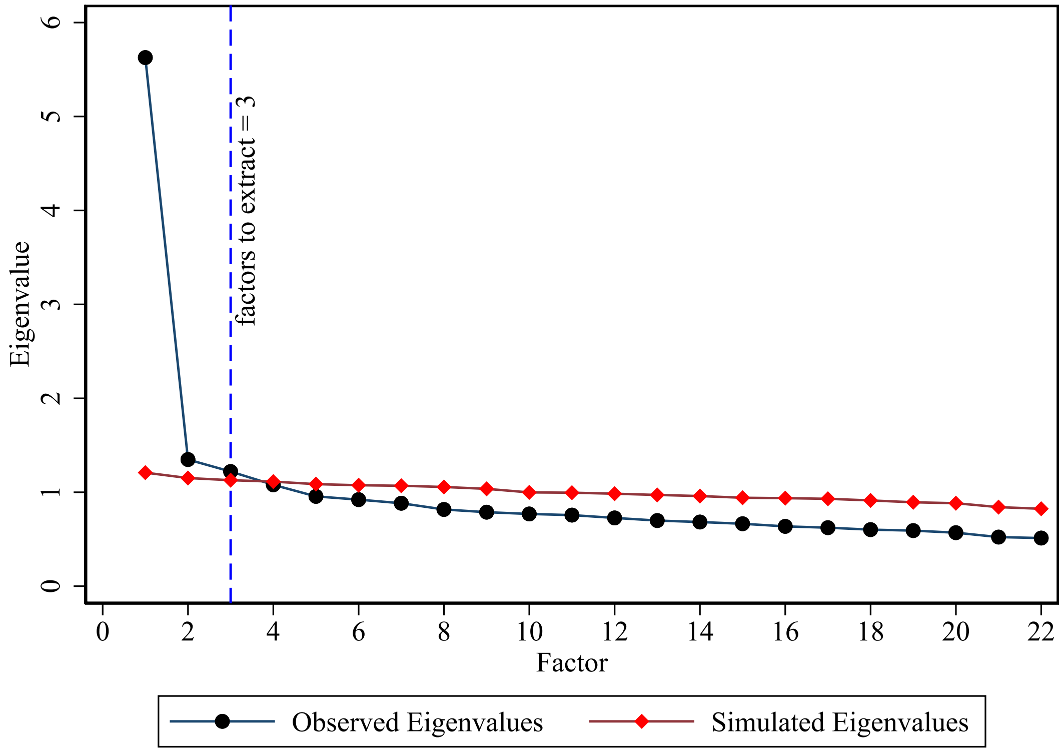
Figure A1: Screeplot of eigenvalues from EFA latent factor model



Observed eigenvalues from principle components analysis (unadjusted) of the latent factor model are plotted in **figure A2**, 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.

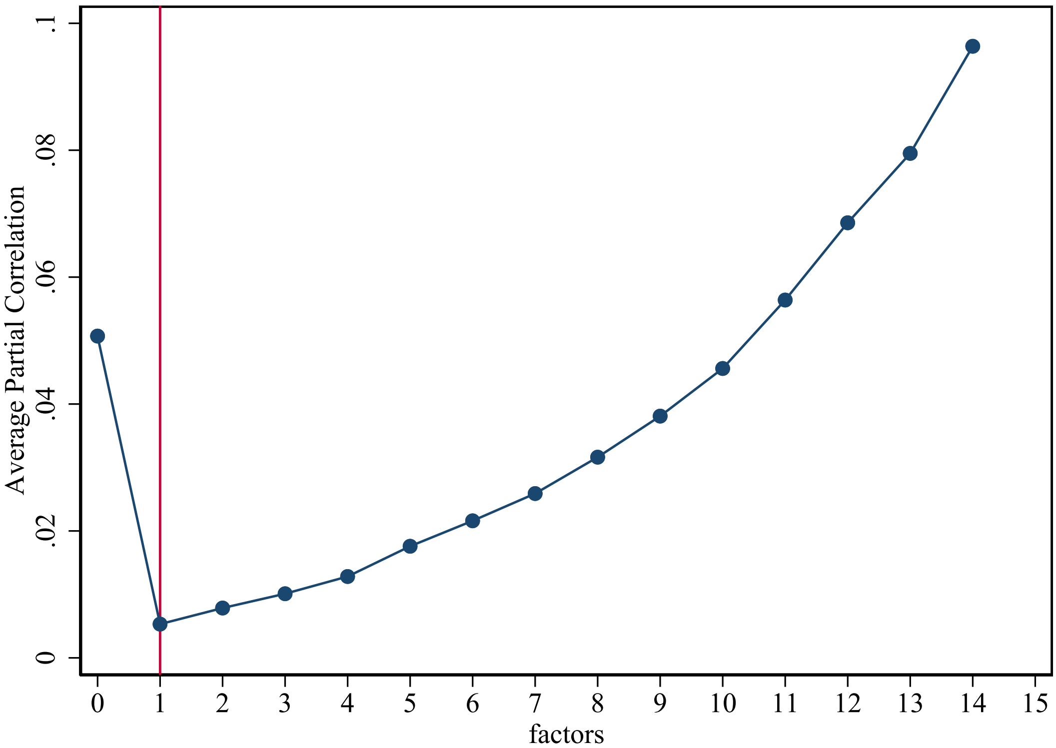
Finally, **Figure A3**, provides a graphical plot of the average partial correlations for the factor partialled out. Evidence suggests that the average partial is minimised when the 1st factor is partialled out.

Figure A2: Horn's parallel analysis



Overall the majority of criteria are aligned with the a priori assumption of a one factor model, therefore no other factors were retained. The factor loadings of each item on the 1st factor are shown in **Table A2**, alongside the share of item unique variance, Ψ. Following Attanasio et al. (2020) and Webb (2022), I discount low factor loadings below a threshold of 0.3 in constructing the 1st 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

Figure A3: Horn's parallel analysis



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 A2: 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

B Additional results and specifications

Table B1: Impact of (±)1.5 S.D shocks on constituent scale naive 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

p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in Parenthesis "(.)"; 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

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 Parenthesis "(.)"; 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	

p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in Parenthesis "(.)"; 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 $(\pm)$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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on cluster robust SEs at district level are in Parenthesis "(.)"; 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 Parenthesis "(.)"; 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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on cluster robust SEs at district level are in Parenthesis "(.)"; 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 ($\pm$)1.5 S.D. shocks on migration and child sex

	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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on cluster robust SEs at district level are in Parenthesis "(.)"; 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 (±)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

* 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 B9: 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		

* p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on cluster robust SEs at district level are in Parenthesis "(.)"; 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.

Figure B1: Multi-density plot of community-level gamma-fitted SPI values, by month

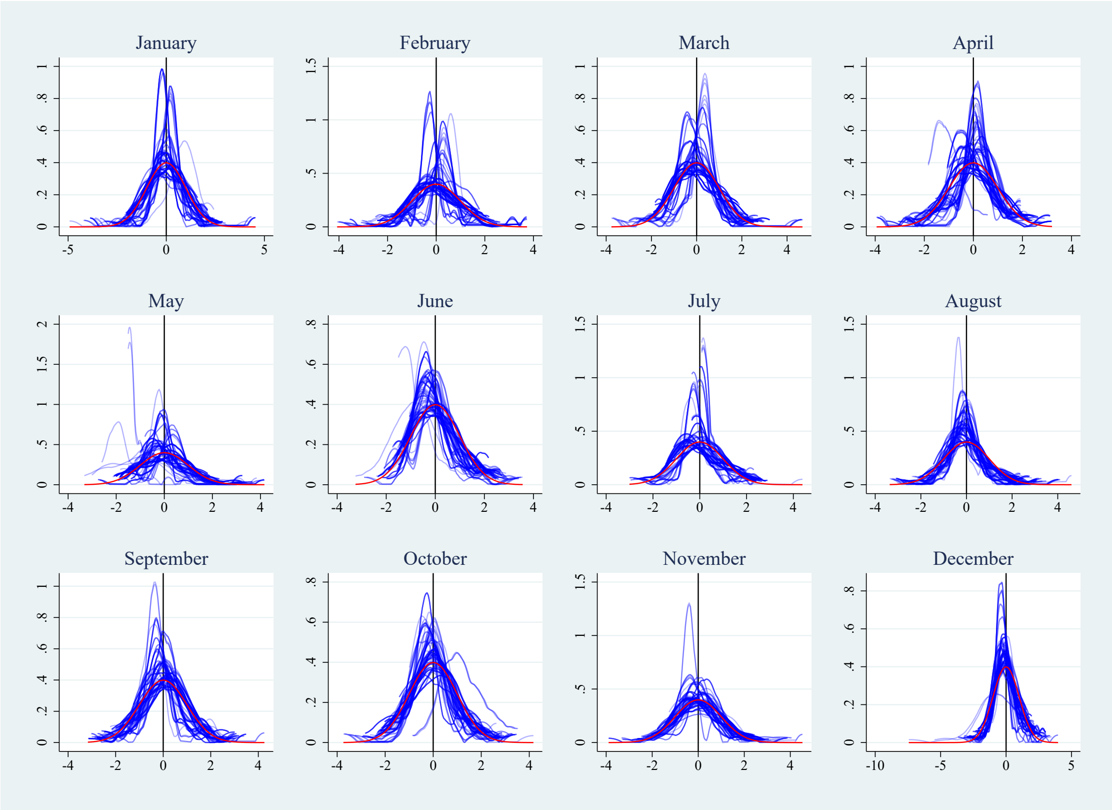


Figure B2: Multi-density plot of community-level lognormal-fitted SPI values, by month

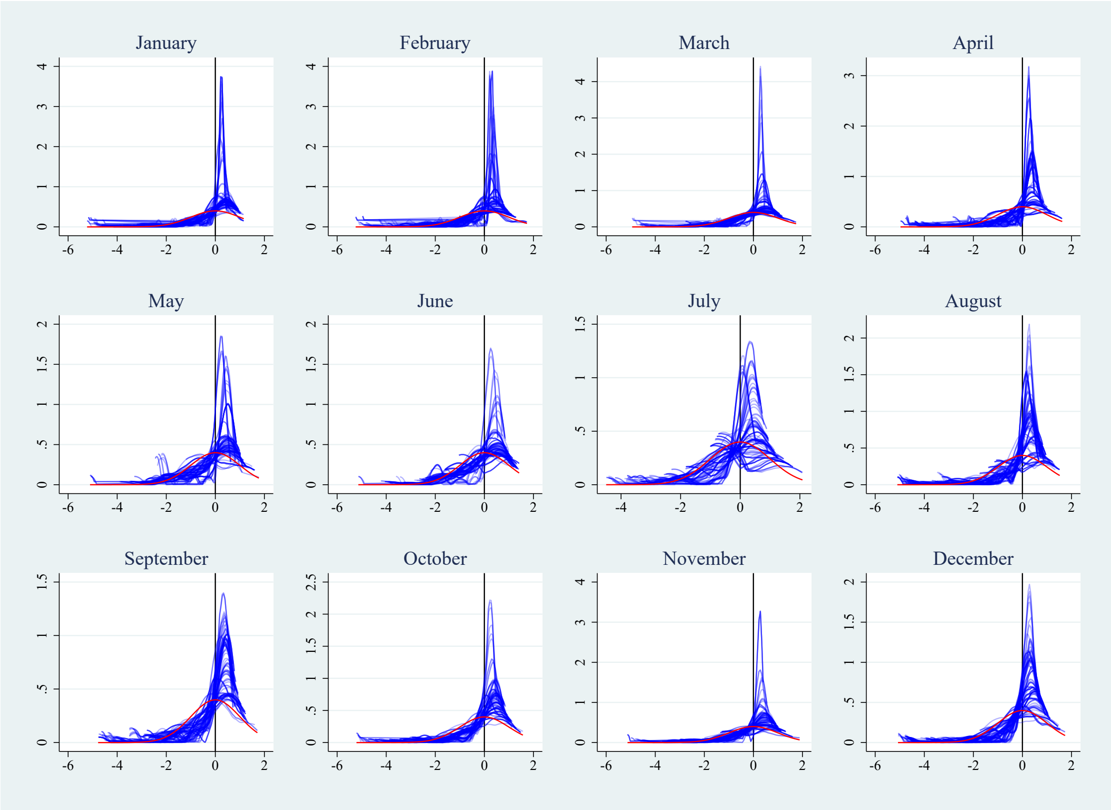


Figure B3: Primary crop (area sown in Ha) in 2010, by Department

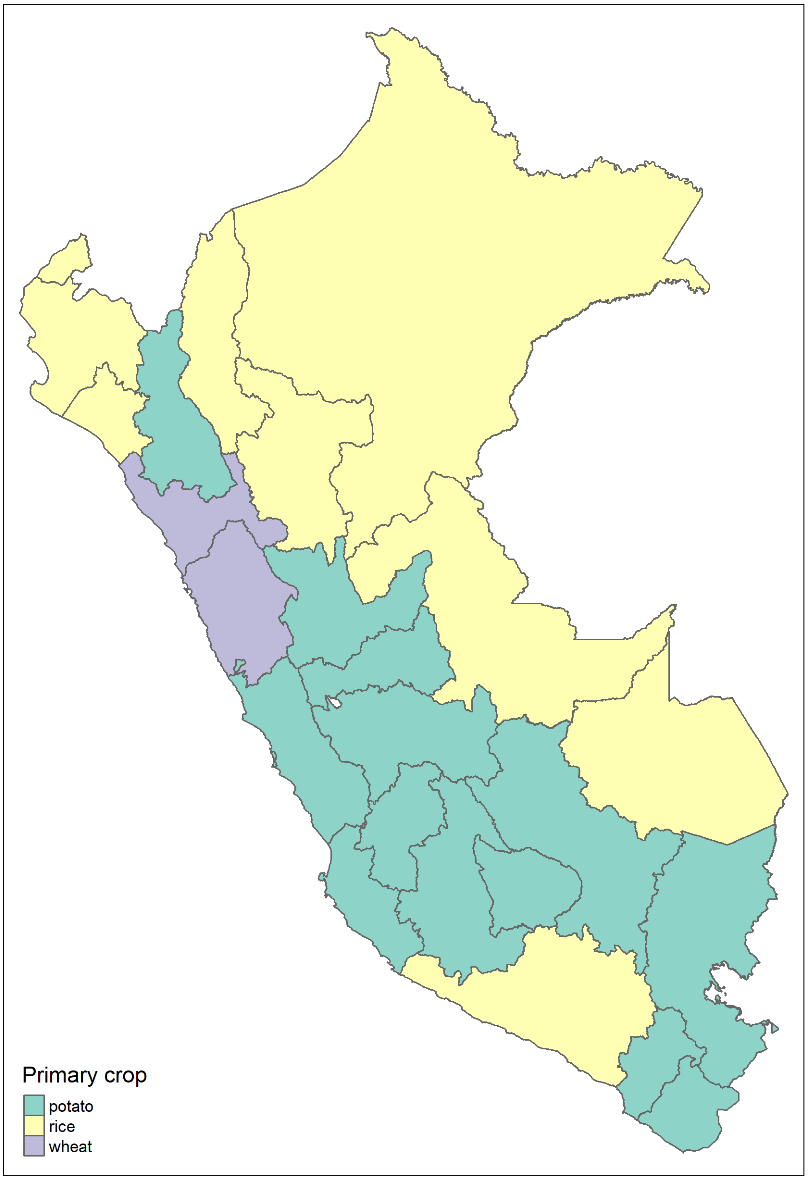
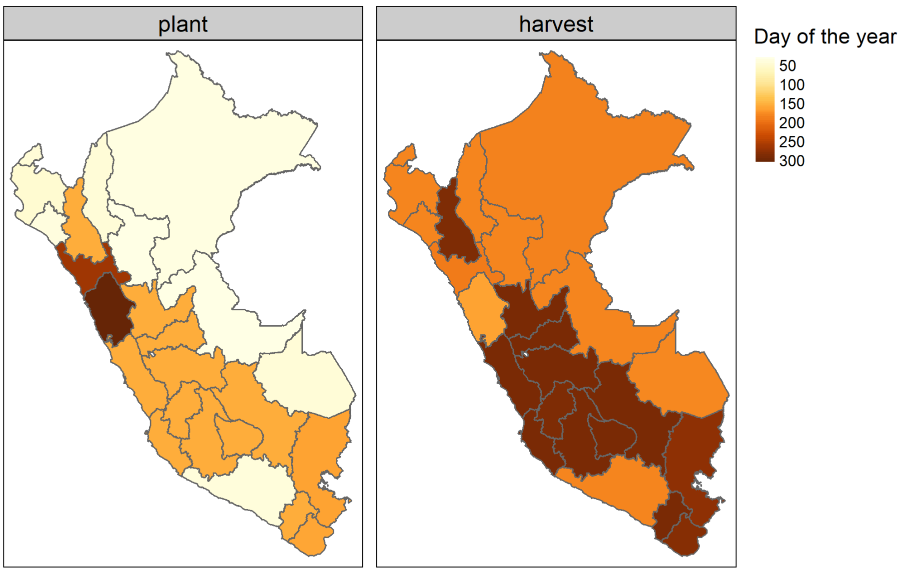


Figure B4: Mean plant and harvest day of year, primary crop, by Department



C Additional results and specifications

Table C1: Impact of +1.5 S.D shocks on health/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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on clustered robust SEs at district level are in Parenthesis "(.)"; 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 C2: 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.

Table C3: Impact of +1.5S.D. shocks on caregiver stress and 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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values based on clustered robust SEs at district level are in Parenthesis "(.)"; 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 C4: 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

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 Parenthesis "(.)"; 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 C5: 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 Parenthesis "(.)"; 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 C6: 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

Table C7: 1^{st} 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

Table C8: 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

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 Parenthesis "(.)"; 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.

Table C9: : 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

* 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 parenthesis "(.)". 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 C10: Impact of prenatal +1.5S.D. shocks on days worked after-birth

	Main activity		All activities	
	Parents	All HH adults	Parents	All HH adults
+1.5 S.D. shock	-0.170	-0.094	-0.039	-0.026
	(0.020)**	(0.271)	(0.085)*	(0.261)
	{0.010}**	{0.226}	{0.060}*	{0.226}
Controls	Yes	Yes	Yes	Yes
N	2293	3311	2293	3311

Extension of **Table 7**. * 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 month of interview, and community are suppressed.

Table C11: Impact of prenatal +1.5S.D. shocks on hours worked, newborn present in household

	All adults	Parents	Mothers	Fathers
Newborn in HH	0.605	0.134	-0.895	0.718
	(0.016)**	(0.647)	(0.019)**	(0.053)*
	{0.001}***	{0.023}**	{0.010}**	{0.033}**
Positive shock 13-24 months before	-0.172	-0.127	-0.201	0.114
	(0.461)	(0.571)	(0.407)	(0.762)
	{0.613}	{0.589}	{0.432}	{0.767}
**Interaction*	-0.469	-0.392	-0.412	-0.418
	(0.125)	(0.208)	(0.373)	(0.220)
	{0.098}*	{0.170}	{0.261}	{0.190}
Controls	Yes	Yes	Yes	Yes
$H_0 : \beta_2 + \beta_3 = 0$ p-val.	0.036	0.061	0.150	0.373
N	7438	5394	2270	3106

Extension of **table 8**. * p < 0.10, ** p < 0.05, *** p < 0.01. P-values based on clustered robust SEs at district level are in Parenthesis "(.)"; 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.