Critical Periods in Cognitive and Socioemotional Development: Evidence from Weather Shocks in Indonesia

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Abstract

Early life circumstances are important determinants of long-run human capital and wellbeing outcomes. The first 1000 days of life are often cited as a 'critical period' for child development, but this notion has rarely been directly tested. In a setting where children are potentially subject to shocks in every year of their childhood, I estimate the impact of early life weather shocks on adult cognitive and socioemotional outcomes for individuals born in rural Indonesia between 1988 and 2000. There is a strong critical period for these shocks at age 2 for cognitive development, but no evidence for a similar critical period for socioemotional development. The effects appear to be driven by changes in agricultural income and nutritional investment. The impacts are initially latent, only appearing after age 15. I show suggestive evidence for dynamic complementarity in early life investments.

JEL Codes: *I15, I24, I31, I3, J13, J24, O1, O12, O15, Q54*

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1 Introduction

Cognitive and socioemotional skills are fundamental measures of human capital, and are predictive of adult labour market outcomes and well-being (Cunha & Heckman, 2007, 2009; Grantham-McGregor et al., 2007; Heckman et al., 2006; Attanasio, 2015). An extensive literature shows that an individual's circumstances in early life can have a major impact on their cognitive and socioemotional development, and therefore on their economic welfare (Bharadwaj et al., 2013; Almond et al., 2018; Carneiro et al., 2021; Attanasio, Cattan, et al., 2020; Walker et al., 2021). A key claim in this literature is that *timing matters*: the same shock or intervention may have different impacts at different stages of life. Which stages are particularly important for determining adult human capital? Some commentators suggest that circumstances before age 5 are most important, with younger ages being increasingly sensitive within that window (Currie & Almond, 2011; Almond et al., 2018). Others cite a narrower range, claiming that the first 1000 days of life are a "critical period" for cognitive development, thereby justifying a focus on the earliest years for policy intervention (Heckman, 2006).

There is, however, little causal evidence on how much timing matters for the effects of early life circumstance on adult human capital. Few studies directly compare the effects of policies or shocks across ages (Almond et al., 2018). The focus on the broad window (to age 5) is a convention sometimes justified by evidence that adult outcomes improve linearly with increasing exposure to beneficial policies only in this window (Hoynes et al., 2016).

In this paper, I use a setting in which individuals are subject to repeated, uncorrelated, exogenous shocks throughout their childhood and carry out a fine-grained test for the existence of critical periods in both cognitive and socioemotional development. I examine the effect of weather variation at every age from in utero to age 15 on adult cognitive and socioemotional outcomes. The data come from individuals in the Indonesia Family Life Survey (IFLS) born in rural areas between 1988 and 2000. Such individuals experience the weather variation as a shock to aggregate household welfare that translate to changes in nutritional investments for children. My approach provides causal evidence on whether the timing of such shocks matters for adult human capital.

I show evidence of a critical period at age 2 for the effect of weather variation on adult cognitive ability. A 1 standard deviation improvement in my primary weather measure at age 2 leads to a significant increase in adult cognitive ability of 0.063 standard deviations. Similar weather variation does not have a statistically significant effect at any other age (including in utero). The age 2 effect is highly robust to different empirical specifications, and I use placebo tests to demonstrate that such a strongly significant result is extremely unlikely to be the result of artefacts in the data. By contrast, there is no positive evidence of a critical period for socioemotional development: effects are either null or cannot be isolated to a single critical period.

I show suggestive evidence that weather variation has an effect on adult cognitive ability by affecting nutritional investments during childhood. Households in rural areas experience weather variation as a shock to aggregate household welfare, affecting their per capita expenditures and investment in the nutrition of young children. The effects can be isolated to 3-8 months after harvest, allowing me to pin down the timing of the shocks' impacts. Using this result, I show that adult cognitive skills are particularly sensitive to weather variation in the second half of the year after the 2nd birthday. I corroborate these results using a secondary weather measure that is constructed to be highly predictive of rice harvests in the IFLS sample. At earlier ages, parents appear to engage in compensatory behaviours that mitigate the effects of shocks. In particular, parents offset negative weather shocks by prolonging breastfeeding and avoiding a nutritional cost to children (and vice versa).

These parental reactions interact with biological factors to produce critical periods in this setting. Numerous neural mechanisms could drive an impact of nutrition on cognitive and socioemotional function. Brain and cortical growth is fast in the first 2 years of life, and is associated with sensitivity to nutritional deficiency (Gilmore et al., 2018). Malnourished children have less well-developed dendrites (the neuronal branches that receive signals from other neurons) (Cordero et al., 1993), while breastfeeding can promote myelination, in which neurons grow a fatty sheath that promotes signal transmission (Deoni et al., 2018). Other neurological processes may be sensitive to nutrition, including neuron proliferation, axonal growth, synapse formation and pruning, and the degree of cortical gyration (folding) (Prado & Dewey, 2014; Gilmore et al., 2018). All of these processes occur over different age windows, so shocks at different ages are likely to have different impacts (Nelson & Gabard-Durnam, 2020). But we currently have little direct evidence on how nutrition impacts each of the mechanisms, and how this impact can vary by age.

My empirical setting presents a number of advantages when testing for critical periods. A key advantage of my strategy is that I use serially uncorrelated shocks as an exogenous source of variation. Each child is subject to multiple weather shocks over their life, and the correlation of these shocks across periods is close to 0. Each shock therefore provides independent variation that can be used to compare effects of similar shocks at different ages of childhood, thus testing for critical periods. Previous literature, by contrast, has typically examined single shocks or interventions (e.g. Heckman et al., 2013), or shocks that are correlated over time (e.g. Adhvaryu et al., 2019). Such settings present greater challenges when trying to test for the timing of effects.

A second advantage is the richness of the IFLS data. It is a large 5-wave panel survey that includes a total of over 30,000 individuals, and is representative of 83% of the Indonesian population. All adult respondents are asked for a detailed migration history. This, along with very low attrition rates on migrants, provides an unusual opportunity to reconstruct the location of individuals for all years of their life since birth in order to examine the effects of weather shocks up until 15 years of age. The IFLS contains data to test critical periods on a range of cognitive and socioemotional measures, including Raven's matrices, depression, personality, wellbeing. The long-term panel also provides contemporaneous data on many individuals from their childhood years. I use these data to examine the mechanisms through which weather shocks may be operating, including via early-childhood investments and household consumption.

The final advantage is that Indonesia is an ideal setting for testing the timing of the effects of weather shocks. It is a geographically large country: east to west, it spans 5,100km. There are diverse patterns of weather across provinces and districts, meaning that weather varies significantly across individuals within a given year and across years (Frederick et al., 2011; Maccini & Yang, 2009). Indonesia is a lower-middle-income country with a large rural population and large agricultural sector (World Bank, 2018). This population experiences weather shocks as agricultural income shocks that affect children through changes in nutrition and other investment channels.[1] And children are vulnerable to the malnutrition that results, with 48% of children under 5 having a height-for-age that is 2 standard deviations below the norm. This high stunting rate is comparable to other lower-middle income countries, such as India, Bangladesh, and Kenya (Roser & Ritchie, 2019). The critical periods I examine are therefore highly welfare-relevant for this and other similar lower income populations, but are less likely to generalise to less vulnerable populations.

My paper contributes in a variety of ways to the literature on human capital accumulation. I test many of the claims of the Cunha-Heckman framework (Cunha & Heckman, 2007, 2008; Cunha et al., 2010) and see how they apply to the rural Indonesian context.[2]

[1]For example, Levine & Yang (2014) find that rainfall shocks are positively associated with deviations in district-level rice output from district-level mean, and rice is the main harvested crop across much of Indonesia (see Appendix Figure A3). They interpret this as justification for interpreting higher rainfall as a positive contemporaneous shock to local economic conditions in Indonesia.

[2]I thereby complement a recent literature that adapts the Cunha-Heckman framework to a developing-country setting (Attanasio, Cattan, et al., 2020; Attanasio, Meghir, & Nix, 2020).

First, the paper tests whether the timing of parental investment matters for adult outcomes. The neurodevelopmental and nutrition literatures that justify the focus on the first 1000 days are based on correlations between brain growth, stunting, and cognitive development, rather than the effects of causally identified shocks on cognitive development (Isaacs et al., 2008; Gilmore et al., 2018; Victora et al., 2010; Aiyar & Cummins, 2017; Perkins et al., 2017; Prentice et al., 2013). Another branch of studies use structural models to test when development is most malleable Cunha et al. (2010).

We therefore have little direct causal evidence on the question of timing. A notable exception is Barham et al. (2013), who show that children exposed to conditional cash transfers in Nicaragua at an earlier age (between in utero and age 2) have higher cognitive scores by age 10 than those who were exposed later (between age 2 and 5). My work contributes relative to this paper by providing a more disaggregated test of timing, by testing a wider age-range and broader set of outcomes, and by testing longer-term effects into adulthood.

Second, I contribute to the literature on dynamic complementarity that investigates whether early investments can increase the productivity of later investments (Almond & Mazumder, 2013; Adhvaryu et al., 2018; Gunnsteinsson et al., 2014; Rossin-Slater & Wüst, 2016; Malamud et al., 2016; Johnson & Jackson, 2019). The literature typically focuses on the interaction between shocks of different types, whereas my results show evidence of positive interactions for repeated shocks of the same type.

Third, I inform the debate on the differences between cognitive and socioemotional development (Cunha et al., 2010; Attanasio, Cattan, et al., 2020). My results provide some of the first causal estimates that suggest a strong critical period for weather shocks on cognitive development, but no evidence for such critical period for socioemotional development, adding to the evidence that human capital cannot be considered as a single "unidimensional object" (Attanasio, 2015).

Fourth, I provide evidence on cognitive development between the ages of 7 and 14, a poorly-understood period described as the "missing middle" (Almond et al., 2018). I show that the effects of weather shocks on adult cognitive skills are latent during middle childhood and only appear after age 15. Many studies of early-childhood interventions in the US find that treatment effects fade out by ages 8 or 9 (Currie & Almond, 2011; Garces et al., 2002; Deming, 2009). I provide evidence for an alternative explanation of apparent fade-out: longer-term effects are hard to observe during this middle childhood period and so can only be detected in adulthood. This is consistent with other papers showing very long term effects of early childhood interventions (Grantham-McGregor et al., 1991; Walker et al., 2005; Gertler et al., 2021; Walker et al., 2021).

My results also add evidence to the extensive literature on the effects of early-life weather shocks on economically relevant dimensions. Previous papers have shown that weather shocks can impact a wide range of outcomes (Dell et al., 2014), most relevantly on multiple measures of human capital, including adult height, health, socio-economic status, schooling, mortality, and birth weight (Maccini & Yang, 2009; Deschênes & Greenstone, 2011; Deschênes et al., 2009; Burgess et al., 2017; A. Barreca et al., 2016; A. I. Barreca, 2012). My results contribute by focusing specifically on how the timing of these shocks can affect the development of cognitive and socioemotional skills.

Identifying critical periods is important for policy. In this context, the impact of weather shocks on cognitive development is isolated to the year between the second and third birthdays. By contrast, there is no strong evidence for such a critical period for socioemotional development. Further research should examine whether similar critical periods exist for the effects of policies that act through similar channels, for example by affecting household income or nutritional investments. If critical periods do exist, this would imply that targeting these ages could greatly increase the cost-effectiveness of such programmes.

2 Data and measurement system

2.1 IFLS data

The main source of outcome data is the Indonesia Family Life Survey (IFLS) (Frankenberg & Karoly, 1995; Strauss et al., 1998, 2004, 2009, 2016). It is a longitudinal survey with 5 waves between 1993 and 2015, containing information on over 30,000 individuals. Individuals come from 13 of the 27 provinces in Indonesia, and are representative of 83% of the Indonesian population. Later waves include questions that assess cognitive ability and other socioemotional skills. Cognitive questions include Raven's progressive matrices (Raven, 2000) and number series tests, some of the most widely used measures in the literature. Subjective wellbeing is measured using cognitive evaluation questions such as the Cantrill Ladder. Positive and negative affect are measured using questions about the emotions the respondent felt in the last day. Personality questions are based on the "Big 5" personality traits (Rammstedt & John, 2007), and depression is measured using the CESD-10 scale (Radloff, 1977). These indexes are extensively used in psychology and economics and have been validated in developing-country contexts (e.g., Das et al., 2009; de Quidt & Haushofer, 2019; Rietveld et al., 2015; Dal Bó et al., 2018; Groh et al., 2015). More details are found in Appendix Section A.1. In order to combine skill measures into a low-dimensional set of factors, I use a latent factor model (Heckman et al., 2013) to generate factor scores (see Section 2.3). These are then used as the dependent variables in my main specification.

I use a number of additional outcome variables to test for different mechanisms, including household expenditure, childhood nutritional and parental-time investment, child height-for-age, maternal nutrition, years of schooling, and whether children are being breastfed.

I construct a year-by-year history of each individual's location using the IFLS. First, I use information from retrospective data on each person's birth location, location at age 12, and subsequent migrations. I combine this with contemporaneous data on respondents' location at each of the five IFLS waves. The sample is restricted to individuals born in rural areas, since these households are likely to be sensitive to weather shocks that change their household welfare via nutrition and agricultural income. More detail on the measures used in the IFLS data can be found in Appendix Section A.1.

2.2 *District, weather, and crop data*

The primary weather variable is the Standardised Precipitation Evapotranspiration Index (SPEI), a state-of-the-art drought index Vicente-Serrano et al. (2010). The impact of rainfall on crop cycles depends on *potential evapotranspiration* (the ability of soil to retain water), which is determined by multiple environmental features, such as temperature, latitude, wind-speed, and the number of sunlight hours. The SPEI combines information on all these features. It has been shown to be a better predictor of crop yields than other climate indexes based solely on temperature or precipitation (Beguería et al., 2014), and has recently been used in the conflict and economics literature (e.g., see Harari & Ferrara, 2018).

I use a monthly gridded dataset for SPEI from the Global SPEI database (Beguería & Vicente Serrano, 2017) and aggregate it geographically to the level of the Indonesian district. The main weather variable $SPEI_{i(t+j)}$ (or *SPEI growing season*) is constructed by averaging the district-level SPEI over the growing season of the main crop of that district in that period. The index is normalised to have a mean of 0 and a standard deviation of 1, so that a value of 1 represents weather conditions during the growing season that are 1 standard deviation *better* for crops compared to the local long-run average (1961-2015).

I match this shock to individuals using the constructed year-by-year record of each individual's location. For example, the variable $SPEI_{i(t+2)}$ for an individual i born in t denotes the normalised average SPEI during the growing season of the main crop of the district where i spent the year after her 2nd birthday. See Appendix Section A.3 for more details.

To corroborate the results with the SPEI, I construct a "predicted harvest" weather variable. This variable is a composite index of weather features that are most predictive of rice yields in the IFLS data (including, among them, the SPEI index). More details are in Appendix Section D.

2.3 *Measurement of skills*

I use the latent factor model seen in Heckman et al. (2013) to combine individual skill measures into indexes. This technique, common in the psychometric literature, helps to reduce measurement error by explicitly accounting for classical error.[3] It also reduces the dimensionality of the set of outcomes by combining correlated proxy variables that measure a single psychological trait.

The process used to generate the indices is described in Appendix Section B, and the results are summarised in Table 1. There is a single cognitive factor that uses all the available cognitive measures. I detect 3 socioemotional latent factors, which I interpret as *affect/wellbeing*, *personality*[4], and *depression*. The factor scores for each individual are used as dependent variables in the main results. Factor scores should be interpreted positively: a higher depression factor score will mean *better* mental health or *less* depression. Scores are normalised with a mean of 0 and standard deviation of 1.

2.4 *Samples and summary statistics*

Table 2 summarises the samples used in the paper. To focus on households that are most likely to be impacted by weather variation, I restrict all samples to rural areas, and contemporaneous mechanism samples to farming households.

The main sample used in Sections 4.1 and 4.2 includes all individuals born after 1988 for whom socioemotional or cognitive outcome data is available.[5] Individuals were at most 5 years old at the time of the first wave of the IFLS data in 1993. The analysis of potential mechanisms using the earliest IFLS data is therefore still relevant for the early childhood period of my main sample. The primary weather variable is based

[3] Psychological or skill measures tend to be "riddled with measurement error" (Cunha & Heckman, 2009; Heckman et al., 2013). Such error may be especially severe in low- and middle-income country contexts (Laajaj & Macours, 2019; Laajaj et al., 2019).

[4] The interpretation of the personality factor is unclear, since it combines questions that are supposed to identify distinct personality traits (e.g., extraversion and conscientiousness). This difficulty is common in studies in developing countries (Laajaj & Macours, 2019; Laajaj et al., 2019), where factor analyses do not separate the "Big 5" traits, and instead identify a single "personality" factor. I show results on the Big 5 personality traits when they are treated separately in Appendix Figure N1.

[5] The main sample does not include individuals born after 2000 because the last wave of the IFLS survey was in 2015 and individuals were only asked questions on adult cognitive and socioemotional outcomes if they were at least 15 years old.

Table 1: *Latent factors and their corresponding measures*

Cognitive	*Socioemotional*		
	"Affect / Wellbeing"	"Personality"	"Depression"
Raven's Matrices	Affect: Frustrated	Big 5: Agreeableness - Forgiving	CES-D: I was bothered by things
Maths - Written	Affect: Sad	Big 5: Agreeableness - Considerate	CES-D: I had trouble concentrating
Word Recall	Affect: Enthusiastic	Big 5: Agreeableness - Rude	CES-D: I felt depressed
Maths - Oral	Affect: Lonely	Big 5: Conscientiousness - Thorough	CES-D: I felt hopeful about the future
Number Series	Affect: Content	Big 5: Conscientiousness - Lazy	CES-D: I felt fearful
	Affect: Worried	Big 5: Extroversion - Outgoing	CES-D: My sleep was restless
	Affect: Bored	Big 5: Openness - Original	CES-D: I was happy
	Affect: Happy	Big 5: Openness - Artistic	CES-D: I felt lonely
	Affect: Angry		CES-D: I could not get going
	Affect: Tired		
	Affect: Stressed		
	Wellbeing: Life Satisfaction		
	Wellbeing: Assessment of situation		
	CES-D: I was happy		

Notes: Each column represents a single factor, containing a list of all the measures which load on that factor. The questions for each measure are in Appendix Table A1. The full process used to generate the factors is described in Appendix Section B.

Table 2: *Guide to different IFLS samples used*

Sample		*N*	*Level of observation*	*Outcomes measured in*	*Sample restrictions*
Main Sample	Cognitive & Socioemotional	5572	Individual	IFLS3-5	Born in rural area between 1988 and 2000
Mechanism Samples	Investment Indexes	4247	Individual x Wave	IFLS3-5	Living in rural farming households, ages 0-5
	Household Expenditure	11571	Household x Wave	IFLS1-4	Rural farming households
	Breastfeeding	11656	Individual x Wave	IFLS1-5	Living in rural farming households, ages 0-3

Notes: This describes the samples used in the results, including how many observations are in each sample, the unit of observation of the sample, which waves the outcomes are measured in, and any additional sample restrictions on the sample. IFLS1 was carried out in 1993, IFLS2 in 1997, IFLS3 in 2000, IFLS4 in 2007 and IFLS5 in 2015. IFLS5 is not used for the (main) household expenditure results because there was no price adjustment data available for this wave at the district $\times$ year level, as in the other waves.

on definitions of the growing season from 2000, and is also relevant for this sample.

The mechanism samples include individuals outside the main sample to increase power. Analyses of early life investments include all children aged 0-5, and analyses of breastfeeding behaviour focuses on children ages 0-3.

Appendix Table C1 presents summary statistics for individuals in the main sample. Factor scores and SPEI growing season variables are normalised with a mean of 0 and standard deviation of 1. The within-sample standard deviation is slightly lower than 1, since the target sample only covers a subset of the years (1961-2015) and districts used to standardise. 53% of the main sample are female. For the majority of the sample (52%), the highest level of education reached by a parent is elementary.

3 Empirical strategy

The main specification uses the following equation:

$$Y_{irt} = \sum_{j=-2}^{J=15} \beta_j SPEI_{i(t+j)} + \boldsymbol{X}'_{ir}\gamma \ + \delta_r + \mu_t + \varepsilon_{irt} \tag{1}$$

Here, Y_{irt} denotes the adult outcome variable of interest for an individual i born in region r (Indonesian *kabupaten*) in year t. The weather variable, $SPEI_{i(t+j)}$, describes the average SPEI over the growing season of the main crop in the district where i was located in the year after their jth birthday. $\boldsymbol{X}_{ir}$ is a vector of individual-level controls that includes dummies for the highest level of education achieved by a parent of i, religion, whether the the i was born during the growing season of their birth district, and gender. δ_r and μ_t are birth-region and birth-year fixed effects.

The coefficients of interest in this specification are the β_js. These measure the effects of weather variation on adult outcomes for every year from 2 years before birth all the way to age 15. I can disentangle effects at different ages because the serial correlation of weather variation across years is very low.[6]

The birth-year fixed effects control for any unobserved factors that are common to all individuals in the sample born in the same year, such as macroeconomic shocks. The birth-region fixed effects control for any cohort-invariant unobserved factors that are common across all individuals born in the same region. My identification strategy then relies on the claim that the variation in SPEI is exogenous, conditional on these fixed effects.

To test for the existence of critical periods in early childhood development, I carry out two types of hypothesis tests. First, I test whether there is an overall effect of weather variation (regardless of timing) on adult outcomes using an F-test on the joint null hypothesis $H_0 : \beta_{-2} = ... = \beta_{15} = 0$. Second, I test whether the effect is concentrated on specific periods by looking at individual coefficients, i.e., testing the null $H_j : \beta_j = 0$. To account for multiple hypothesis testing, I report sharpened q-values (Anderson, 2008) that control for the false discovery rate (FDR), i.e., the expected proportion of rejections that are falsely rejected (see Appendix Section J for more details).

The coefficients β_j incorporate all subsequent changes in parental investments, so should be interpreted as the *reduced-form* impact of weather variation on adult outcomes. For example, if parents react to early life shocks by investing more in a child's education, this will be incorporated into the estimates. If such parental responses are

[6] The empirical correlation in the main sample between $SPEI_{i(t+s)}$ and $SPEI_{i(t+s-1)}$ is only 0.076 (95% confidence interval: [0.071, 0.081]). Appendix Table C2 and Figure C3 show the full correlation matrix.

large, these estimates will differ from the kind of estimates used in the biomedical literature, which detect biological critical periods by testing whether the direct impact of shocks differs at different ages (and do not incorporate subsequent investment responses) (Knudsen, 2004; Knudsen et al., 2006).

Empirically, the direct impact and reduced-form impact of shocks may not differ substantially. I show that good weather only increases nutritional investment in a window between 3 and 8 months after harvest, and doesn't increase it between 1 and 2 years after harvest. This suggests that later parental responses may be empirically close to 0, although I cannot rule out investment responses along other unmeasured dimensions. In any case, the reduced-form impacts I measure are still welfare-relevant. They may even be welfare-relevant in a wider range of scenarios than direct or biological effects, since the welfare impacts of a shock depend on whether parents respond by compensating or reinforcing.[7]

Below, I outline four threats to my identification strategy and provide evidence that they do not invalidate the main results.

First, endogenous decisions to migrate in response to weather shocks could confound the causal effect of weather shocks on adult outcomes. For example, if intelligent individuals are more likely to migrate (within a given year) to areas with good weather, this selection could positively bias the causal estimate of good weather on cognitive ability. Migration threatens my estimation when people migrate into areas based on (i) current weather patterns (in the same year as the migration), or (ii) future weather patterns.[8] The migrant must be either rapid or have foresight, in addition to being selective. Although migration is relatively common in the sample, Column (2) of Appendix Table K2 shows that this type of selective migration does not occur in the main sample. The probability that an individual migrates to a specific destination district in a given year is unaffected by the weather experienced in that district, alleviating the concerns about selective migration in my context.

Second, selective mortality could bias my estimates. For example, if negative weather shocks (e.g., drought) selectively kill children with poor cognitive development, then

[7] A simple model (Appendix Section F, and particularly Appendix Section F.1) shows that the direct effect determines welfare only in cases that are unlikely to hold in practice – namely when shocks are marginal and when parents have perfect knowledge of the human capital production function. The reduced form effect has welfare implications in more general settings.

[8] By contrast, migration responses based on *past* weather patterns should be thought of as one of the potential channels through which weather impacts adult outcomes. The results in Column (1) of Appendix Table K2 suggest that migration is not a key channel through which weather variation affects adult outcomes, since the SPEI growing season in the pre-migration district does not affect the probability of migrating.

a positive relationship between weather and adult outcomes would be biased downwards. I test for such an effect in Appendix Section K. While there may be a positive impact of SPEI variation in utero on infant mortality, the magnitude is small and does not affect the probability of inclusion in my main sample.[9] This implies that selection bias is close to 0, although it cannot be ruled out entirely.

Third, two-way fixed effect specifications can yield biased estimates of the true treatment effect in the presence of heterogeneous treatment effects (Goodman-Bacon, 2018; de Chaisemartin & D'Haultfœuille, 2018; de Chaisemartin & d'Haultfoeuille, 2020). The concern arises when the fixed-effect estimator gives a higher weight to district-cohort groups with a higher average treatment effect on the treated (ATT), leading to an upward bias on the overall estimate (and vice versa). The weight assigned to each district-cohort group depends on their treatment status. In the current context, the concern is unlikely to undermine the results: the weather shocks I examine are plausibly as-good-as-random, so they are likely to be uncorrelated with the (heterogeneous) ATTs across districts and cohorts. In Appendix Section I I discuss this issue further, and show evidence that the assigned weights for each group are unlikely to be correlated with the ATT in that group.

Fourth, imperfect recall may lead to significant measurement error on retrospective reports of location in each year of childhood. A key advantage of the IFLS data is that the majority of my sample were children in IFLS households during early waves of the survey. I therefore infer individuals' locations throughout their childhood by combining retrospective questions with contemporaneous data on the individuals' locations in survey years. This is likely to mitigate much of the measurement error stemming from retrospective migration reports.

[9]Moreover, shocks during early life (after age 1) have no detectable effect on infant mortality, suggesting that the large effect on cognitive skills seen at age 2 is unlikely to be driven by selective mortality.

4 Main results

4.1 Cognitive outcomes

Table 3 and Figure 1 show the results of running the main specification with adult cognitive factor z-score as the outcome variable Y_{irt}. In column (1), there is a strong and statistically significant positive coefficient (0.063) on SPEI growing season at age 2. The q-value of 0.002 implies that the probability that the observed coefficient is a false positive is below 1%, even after adjusting for multiple hypothesis testing. The p-value on the F-test in column (1) is 0.001, implying that we can also reject the joint null across all ages. None of the other coefficients has a q-value below 0.1, suggesting that SPEI growing season has a particularly strong effect at age 2. I do not have sufficient power to rule out positive coefficients of less than 0.05 in utero, at age 1 or age 3.[10] The coefficient at age 2 is larger for males (0.071, column (2)) than for females (0.047, column (3)), but this difference is not statistically significant (p=0.667).

Given that the weather shock is mild, and outcomes are measured at least 13 years after the second birthday, the magnitude of the coefficient at age 2 is relatively large. Increasing the SPEI growing season index by one standard deviation results in an average increase of 0.063 standard deviations in adult cognitive score.[11]

The results presented are strong evidence in favour of a critical period in early childhood for cognitive development. The large estimates on age 2 suggest that this age is particularly sensitive, while there is no positive evidence of impacts on cognitive development at other ages, although I cannot rule out small positive impacts.

There are reasons to expect cognitive development to be especially sensitive to shocks in utero and in the first year of life. Brain growth, which is usually associated with vulnerability to nutritional deficiency, is very fast during this period (Gilmore et al., 2018). I find no evidence of an effect of weather variation in these early stages. There is some evidence that this is due to compensatory breastfeeding behaviours by parents (Section 5.4), and I discuss other possible explanations in the Discussion (Section 6).

To check the robustness of the critical period for cognitive development at age 2, I present a number of additional results. First, I rerun the main results with a number of different specifications (Appendix Table L1). The coefficient at age 2 remains

[10] In keeping with a possible effect at age 3, examining effects over 2-year intervals suggests that ages 2-3 have strong impacts on cognitive scores (Appendix Table L8).

[11] This effect is likely driven by an improvement in nutritional investment lasting approximately 6 months (see Section 5.1). The magnitude is therefore comparable to Maluccio et al. (2009), who estimate that a nutritional intervention targeting children for the first 36 months of their life led to 0.25SD increases in cognitive ability.

strongly positive, with a q-value below 0.05, when I: (i) expand my sample to include older individuals (column 1), (ii) use siblings fixed effects and birth order fixed effects instead of birth district fixed effects (column 2), (iii) use a different version of the SPEI weather variable (column 3), and (iv) use alternative constructions for the cognitive index based on Anderson (2008) and the equally-weighted indices of Kling et al. (2007).The coefficients are also highly stable when including age fixed effects as controls in the regression (Appendix Table L4). None of these specifications yields a q-value below 0.05 for SPEI growing season at any other age. When using a sample of people born in urban areas (columns 4 and 5), the coefficient at age 2 is close to 0, consistent with later evidence that weather variation is acting by changing nutritional investment and agricultural incomes.

Second, Appendix Table L2 shows that coefficients on early life shocks are not biased by the inclusion of later shocks in the specification. A priori, omitting interaction terms between shock variables at different ages (e.g., resulting from dynamic complementarity) could lead to omitted variable bias on earlier shocks. [12] However, any bias is empirically close to 0, since the coefficient at age 2 remains stable when removing later SPEI variables from the regression.

Third, I relax the assumption of linear effects that is built into my main specification (Equation 1). Using a non-parametric residual plot, I show that we can't reject that the effect of the shock at age 2 is linear (Appendix Figure M1). Appendix Section M shows additional results using alternative specifications, including binary shocks with different thresholds, different linear effects for positive and negative values, and squared term specification.

Fourth, Appendix Section G presents the results of two types of placebo tests. I make use of (i) shocks from before conception, and (ii) synthetic shocks that are the result of randomly reshuffling each individual's shocks within their lifetime. I show that observing a coefficient with a q-value of less than 0.05 is highly unlikely when using these placebo shocks. This verifies that my main result is picking up true variation, not just random noise.

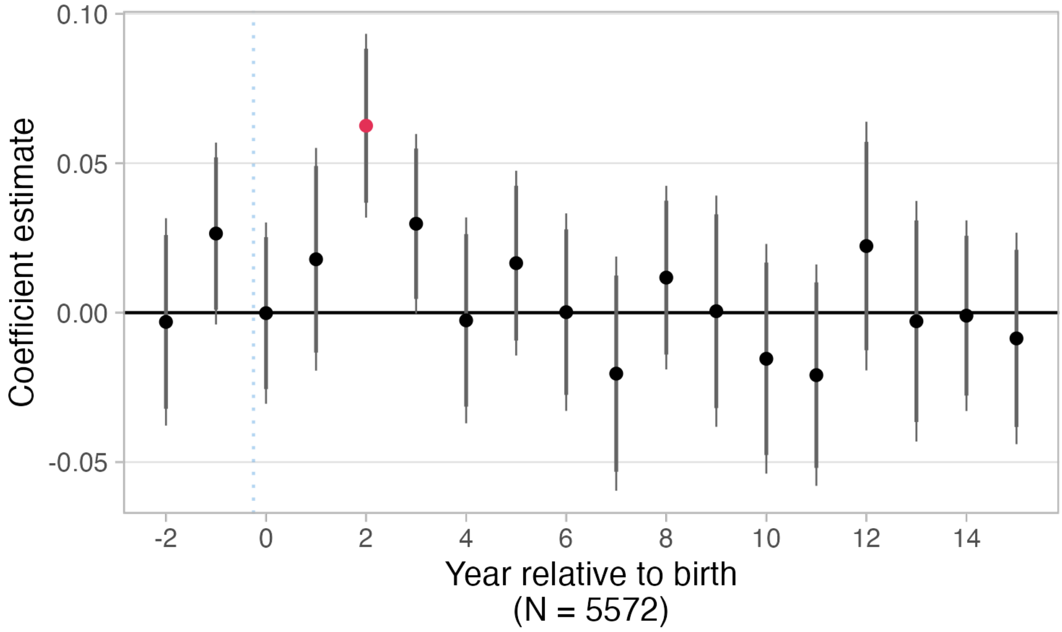
[12] The omitted variable bias would be 0 when (i) shocks across ages are independent, and (ii) the mean value of all the shocks is 0. To see this, denote D as the value of the shock and consider that $Cov(D_{i(t+j)}, D_{i(t+j)} \times D_{i(t+k)}) = E[D^2_{i(t+j)}]E[D_{i(t+k)}] - E[D_{i(t+j)}]^2 E[D_{i(t+k)}]$. A sufficient condition for this to be 0 is (i) $E[D_{i(t+j)}] = 0$ for all j, and (ii) $D_{i(t+j)} \perp D_{i(t+k)}$. The correlation between shocks at different ages is weak but not 0 (Appendix Table C2), and the mean value of all the shocks is slightly positive in most cases, so missing interaction effects may cause some bias on my coefficients.

Table 3: *Effect of SPEI growing season on adult cognitive factor score*

	Dep Var: Adult Cognitive Z-score					
	All (1)	q value (1)	Male (2)	q value (2)	Female (3)	q value (3)
SPEI growing season, age = -2	−0.003 (0.018)	[1]	−0.019 (0.021)	[1]	0.017 (0.026)	[1]
SPEI growing season, age = -1	0.026 (0.015)*	[0.884]	0.037 (0.021)*	[0.682]	0.021 (0.022)	[1]
SPEI growing season, age = 0	−0.000 (0.015)	[1]	0.010 (0.024)	[1]	−0.008 (0.021)	[1]
SPEI growing season, age = 1	0.018 (0.019)	[1]	0.014 (0.028)	[1]	0.030 (0.022)	[0.9]
SPEI growing season, age = 2	0.063 (0.016)***	[0.002]	0.071 (0.027)***	[0.182]	0.047 (0.020)**	[0.705]
SPEI growing season, age = 3	0.030 (0.015)*	[0.796]	0.048 (0.023)**	[0.512]	0.013 (0.025)	[1]
SPEI growing season, age = 4	−0.003 (0.017)	[1]	−0.009 (0.025)	[1]	0.008 (0.029)	[1]
SPEI growing season, age = 5	0.017 (0.016)	[1]	0.001 (0.024)	[1]	0.031 (0.023)	[0.9]
SPEI growing season, age = 6	0.000 (0.017)	[1]	0.006 (0.024)	[1]	0.002 (0.022)	[1]
SPEI growing season, age = 7	−0.020 (0.020)	[1]	−0.007 (0.030)	[1]	−0.032 (0.027)	[0.921]
SPEI growing season, age = 8	0.012 (0.016)	[1]	0.021 (0.027)	[1]	0.013 (0.025)	[1]
SPEI growing season, age = 9	0.000 (0.020)	[1]	−0.007 (0.027)	[1]	0.006 (0.026)	[1]
SPEI growing season, age = 10	−0.015 (0.019)	[1]	0.015 (0.027)	[1]	−0.035 (0.022)	[0.9]
SPEI growing season, age = 11	−0.021 (0.019)	[1]	0.005 (0.025)	[1]	−0.038 (0.025)	[0.9]
SPEI growing season, age = 12	0.022 (0.021)	[1]	0.002 (0.029)	[1]	0.037 (0.029)	[0.9]
SPEI growing season, age = 13	−0.003 (0.020)	[1]	−0.008 (0.026)	[1]	−0.004 (0.032)	[1]
SPEI growing season, age = 14	−0.001 (0.016)	[1]	0.019 (0.027)	[1]	−0.015 (0.025)	[1]
SPEI growing season, age = 15	−0.009 (0.018)	[1]	0.006 (0.021)	[1]	−0.033 (0.025)	[0.9]
Birth year fixed effects	Yes		Yes		Yes	
Birth district fixed effects	Yes		Yes		Yes	
F statistic	2.490		1.704		2.003	
p-value for F-test	0.001		0.044		0.012	
R^2	0.212		0.229		0.256	
N	5572		2601		2971	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are in parentheses and are clustered by birth district. The table uses Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Column (1) includes all observations, Column (2) includes only males, and Column (3) includes only females. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Figure 1: *Effect of SPEI shock at different stages of childhood on cognitive factor scores*



Notes: Each point corresponds to a coefficient from column (1) of Table 3, so represents the effect of SPEI growing season at each age on cognitive factor z-score in adulthood. The model controls for birth year fixed effects, birth district fixed effects, and individual-level controls (dummies for highest level of parental education, sex, and religion). Error bars are 90% and 95% confidence intervals based on standard errors clustered at the district level (not adjusted for multiple testing). Points are highlighted in red when the q-value is less than 0.05.

4.2 Socioemotional outcomes

Table 4 and Figure 2 show the results of estimating Equation 1 with each of the the 3 socioemotional indexes as outcome variables. In contrast to the results on adult cognitive score, there is no clear evidence of a single critical period for socioemotional development. Across all three indexes, there are no coefficients with a q-value of less than 0.05, and the majority of coefficients are not significantly different from 0 even before adjusting for multiple hypothesis testing. The p-value on the F-test for affect/wellbeing is 0.080, denoting weak evidence that the shocks together are causing variation in the adult factor score. This may be driven by a positive effect at age 10, or a negative effect at age 14, but neither coefficient is significant after adjusting for multiple hypotheses. The F-test on the personality index is insignificant; we cannot reject the null that the index is unaffected by *SPEI growing season* across all ages.[13] For depression, the F-test is highly significant. This is likely driven by a positive effect in utero (with a coefficient of 0.043) and a negative effect at age 11 (with a coefficient at -0.050). Both of these coefficients have a q-value of 0.086; they

[13]Treating the Big 5 personality traits separately yields similar results, with no coefficient with a q-value below 0.05, and no significant F-tests.

are significant after adjusting for multiple hypothesis testing, but only at the 10% level.

In Appendix Section H, I examine whether insufficient power could explain these null results. I use simulated data that uses before-conception weather to proxy the null distribution of estimated treatment effects, and show that cognitive, depression, and personality indexes all yield a power of 80% when true treatment effects are between 0.06 and 0.08SD. By contrast, the affect/wellbeing index is significantly more noisy, only yielding 80% power when the treatment effect is 0.093SD. I cannot confidently rule out smaller effect sizes, so the results should not be interpreted as strong evidence against other sensitive periods with smaller treatment magnitudes.[14]

The positive effect on depression in utero is in keeping with recent evidence on the effect of economic shocks before birth on adult mental health (Adhvaryu et al., 2019). The possible negative effect on depression at age 11 and on affect/wellbeing at age 14 is more surprising. I offer two potential explanations. First, an additional set of channels may be operating for girls and not boys, since the negative effects are more pronounced among girls (Appendix Table N1). For example, better nutrition in the early teenage years has been associated with *earlier* fertility or menarche for females (Belachew et al., 2011; Hochberg & Belsky, 2013; Barham et al., 2018), which could have a negative effect on wellbeing.[15] Second, the effects on socioemotional scores might be driven by noise on lower power tests. The coefficients are only weakly significant, and they are not robust to alternative specifications. When I include siblings fixed effects (Appendix Table N2), none of the coefficients has a q-value below 0.1, and the previously significant coefficients for depression are close to 0 and are not significant (even before multiple hypothesis testing). The coefficients in the main specification are unlikely to be picking up true critical periods in socioemotional development.

Overall, I find no strong evidence for the existence of a single critical period in the socioemotional development in rural Indonesia. Weather shocks in early life appear to have no significant effect on adult personality outcomes. Similar weather shocks

[14]To further evaluate whether the null effects are due to measurement error, Appendix Table B7 analyzes two indicators of statistical noise in the outcome variables. Serial correlation is high for cognitive skills (0.52) but much lower for depression (0.15). The 7-year gap between measurements makes this lower correlation unsurprising, but it may indicate higher measurement error. The average inter-item correlation is in the standard recommended range of 0.15-0.5 (Clark & Watson, 1995) for all indexes apart from personality, whose value is only 0.13, suggesting a more noisy dependent variable.

[15]Appendix Table N3 shows that fertility is unlikely to be a key mechanism for the negative impacts on wellbeing, because shocks in adolescence do not affect the probability of giving birth. I am unable to test whether the age of menarche is an explanatory factor.

may have some influence on adult affect/wellbeing and depression outcomes, but it is difficult to isolate the timing of this influence. There is no strong evidence for a single critical period for these outcomes, and instead there may be multiple ages in which affect/wellbeing and depression outcomes are weakly malleable, or malleable only for girls.

Table 4: *Effect of SPEI growing season on adult socioemotional factor scores*

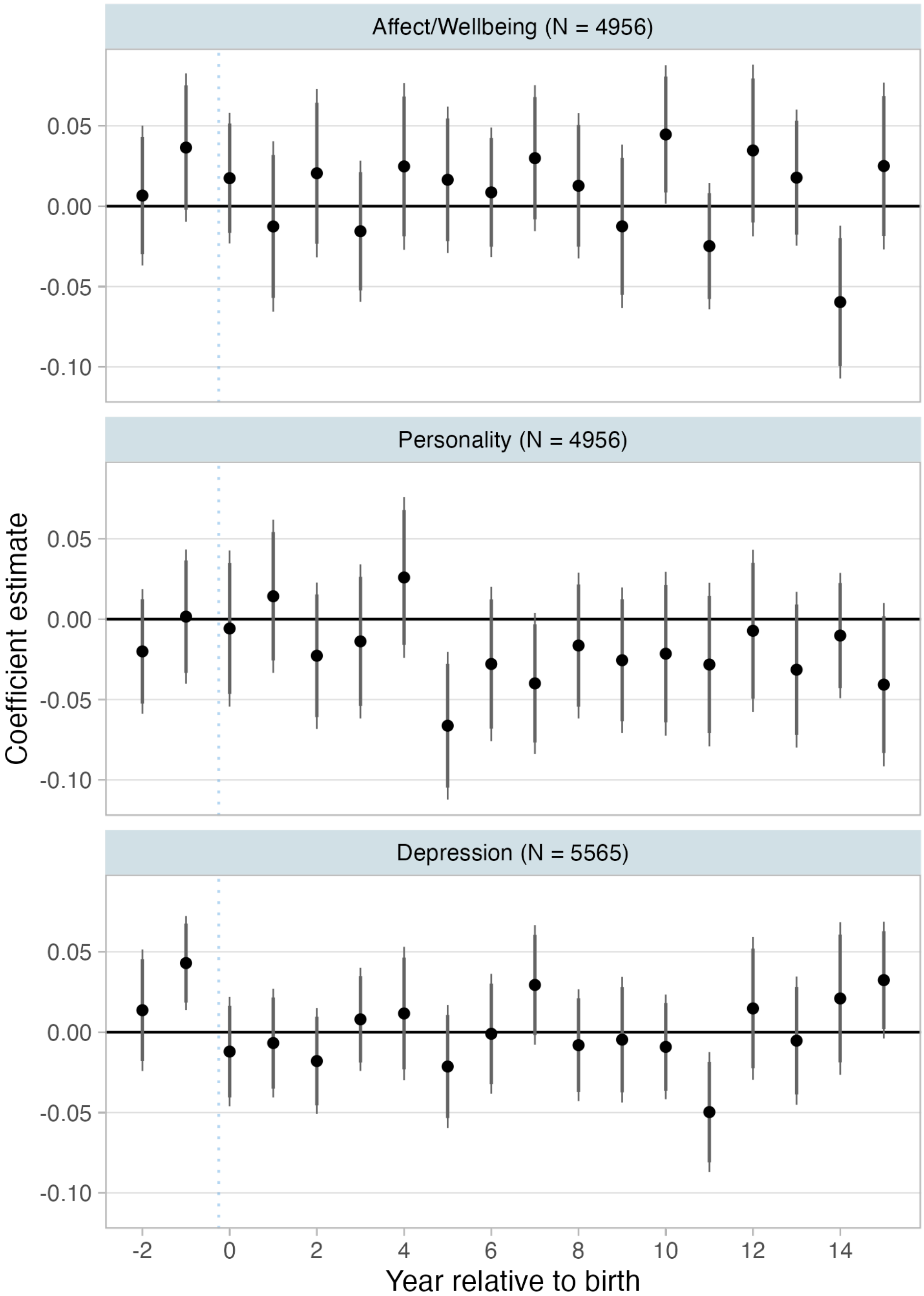
	Affect/Wellbeing (1)	q value (1)	Personality (2)	q value (2)	Depression (3)	q value (3)
SPEI growing season, age = -2	0.007 (0.022)	[1]	−0.020 (0.020)	[1]	0.014 (0.019)	[1]
SPEI growing season, age = -1	0.036 (0.023)	[1]	0.002 (0.021)	[1]	0.043 (0.015)***	[0.084]
SPEI growing season, age = 0	0.017 (0.021)	[1]	−0.006 (0.025)	[1]	−0.012 (0.017)	[1]
SPEI growing season, age = 1	−0.013 (0.027)	[1]	0.014 (0.024)	[1]	−0.007 (0.017)	[1]
SPEI growing season, age = 2	0.020 (0.027)	[1]	−0.023 (0.023)	[1]	−0.018 (0.017)	[1]
SPEI growing season, age = 3	−0.016 (0.022)	[1]	−0.014 (0.024)	[1]	0.008 (0.016)	[1]
SPEI growing season, age = 4	0.025 (0.026)	[1]	0.026 (0.025)	[1]	0.012 (0.021)	[1]
SPEI growing season, age = 5	0.016 (0.023)	[1]	−0.066 (0.023)***	[0.098]	−0.021 (0.019)	[1]
SPEI growing season, age = 6	0.009 (0.020)	[1]	−0.028 (0.024)	[1]	−0.001 (0.019)	[1]
SPEI growing season, age = 7	0.030 (0.023)	[1]	−0.040 (0.022)*	[1]	0.029 (0.019)	[0.923]
SPEI growing season, age = 8	0.013 (0.023)	[1]	−0.016 (0.023)	[1]	−0.008 (0.018)	[1]
SPEI growing season, age = 9	−0.013 (0.026)	[1]	−0.026 (0.023)	[1]	−0.005 (0.020)	[1]
SPEI growing season, age = 10	0.045 (0.022)**	[0.563]	−0.021 (0.026)	[1]	−0.009 (0.016)	[1]
SPEI growing season, age = 11	−0.025 (0.020)	[1]	−0.028 (0.026)	[1]	−0.050 (0.019)***	[0.086]
SPEI growing season, age = 12	0.035 (0.027)	[1]	−0.007 (0.026)	[1]	0.015 (0.023)	[1]
SPEI growing season, age = 13	0.018 (0.021)	[1]	−0.031 (0.025)	[1]	−0.005 (0.020)	[1]
SPEI growing season, age = 14	−0.060 (0.024)**	[0.343]	−0.010 (0.020)	[1]	0.021 (0.024)	[1]
SPEI growing season, age = 15	0.025 (0.026)	[1]	−0.041 (0.026)	[1]	0.032 (0.018)*	[0.744]
Birth year FEs	Yes		Yes		Yes	
Birth district FEs	Yes		Yes		Yes	
F statistic	1.542		0.998		2.750	
p-value for F-test	0.080		0.464		0.000	
R^2	0.069		0.071		0.089	
N	4956		4956		5565	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table uses Equation 1 with the three socioemotional factors measured in adulthood (above aged 15) as the dependent variable. All socioemotional scores are internally standardised, so the sample mean is 0 by construction. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

4.3 Cognitive: ages 7-14

Section 4.1 showed significant effects of early life weather shocks on *adult* cognitive ability. To understand whether it is possible to detect these long-term effects earlier,

Figure 2: *Effect of SPEI growing season on adult socioemotional outcomes*



Notes: Each point corresponds to a coefficient from Table 4, so represents the effect of an SPEI shock in the specific year relative to birth on the respective socioemotional Z-score in adulthood. All coefficients control for birth year fixed effects, birth district fixed effects, and individual-level controls (dummies for highest level of parental education, sex, and religion). Error bars are 90% and 95% confidence intervals based on standard errors clustered at the district level (not adjusted for multiple testing). Points are highlighted in red when the q-value is less than 0.05.

and inform the question of the "missing middle" (Almond et al., 2018), this section examines middle-childhood cognitive ability (measured between 7 and 14 years) as an outcome.

Table 5 shows that the impact of early life weather shocks on cognitive score cannot be detected in middle childhood. I use the 75% of the main sample for whom cognitive outcomes are measured at between the ages of 7 and 14.[16] Columns (1) and (2) show no evidence of any impact of SPEI growing season on cognitive scores at ages 7-14. The F-tests on both specifications are insignificant, and the strong effect at age 2 seen in adulthood is not detectable at this earlier age. Columns (3) and (4) demonstrate that the effect of weather at age 2 on adult outcomes is not *mediated* by the cognitive score at age 7-14. With adult cognitive score as the outcome, adding a control for middle-childhood cognitive score has almost no impact on the coefficients for SPEI growing season. This is true despite a very strong correlation between cognitive score in middle-childhood and adulthood (the last coefficient of column (4)). Together these results provide a warning against using the effect on cognitive scores in middle childhood as a sufficient statistic for long-term impacts on cognitive development.

4.4 Interaction effects (dynamic complementarity)

To measure whether there may be dynamic complementarity in investments over the course of childhood, I examine interaction effects of SPEI growing season at different ages. First, I focus on the earliest periods, and test for the interaction effect between the shocks at age 2 and other years below 4. Table 6, columns (1)-(3), show the results of these estimations. For females, there is no evidence of dynamic complementarity. For males, there is weak evidence of dynamic complementarity: a positive interaction between weather variation at ages 1 and 2, significant at the 5% level. The coefficient implies that experiencing weather that is 1 SD better at age 2 increases average adult cognitive score by 0.08 SD, while having 1 SD better weather at *both* ages 1 and 2 increases average adult cognitive score by 0.14 SD. In line with this, Appendix Table L5 shows that shocks in early life have weakly cumulative effects.

Next, I analyse interaction effects between early childhood and adolescence (columns (4) to (6)). These may be of particular interest if early shocks to human capital change the returns to educational investment later in life. To increase power, I average the SPEI growing season across multiple ages. While there is no interaction effect be-

[16] Individuals who enter the sample after age 14 are not included. This pattern will occur if a new individual enters a household that includes an original IFLS member. It is possible that such individuals are systematically different to the main sample, but selection into IFLS households is unlikely to be driven by early life circumstance. The strong positive effect at age 2 in column (3) is similar to the main results, mitigating concerns of a selective sample.

Table 5: *Cognitive "missing middle"*

	Dep var: Cog at 7-14		Dep var: Cog at 15+	
	(1)	(2)	(3)	(4)
SPEI growing season, age = -1	0.020	0.010	0.037**	0.032*
	(0.019)	(0.026)	(0.018)	(0.018)
SPEI growing season, age = 0	0.003	0.040	0.004	0.003
	(0.021)	(0.028)	(0.016)	(0.015)
SPEI growing season, age = 1	0.005	0.023	0.020	0.019
	(0.021)	(0.028)	(0.019)	(0.018)
SPEI growing season, age = 2	0.028	0.035	0.074***	0.067***
	(0.022)	(0.031)	(0.019)	(0.018)
SPEI growing season, age = 3	0.027	0.044*	0.030*	0.023
	(0.021)	(0.027)	(0.015)	(0.014)
SPEI growing season, age = 4	−0.022	−0.004	−0.015	−0.009
	(0.018)	(0.028)	(0.019)	(0.018)
SPEI growing season, age = 5	−0.002	−0.012	0.008	0.008
	(0.017)	(0.026)	(0.016)	(0.015)
SPEI growing season, age = 6	0.013	0.043*	0.002	−0.001
	(0.018)	(0.025)	(0.017)	(0.016)
Cog score (aged 7-14)				0.258***
				(0.017)
Birth year FEs	Yes	Yes	Yes	Yes
Birth district FEs	Yes	No	Yes	Yes
Siblings FEs	No	Yes	No	No
Birth order FEs	No	Yes	No	No
F statistic	0.773	1.010	3.709	3.342
p-value for F-test	0.627	0.426	0.001	0.001
R^2	0.170	0.851	0.225	0.270
N	4370	4370	4370	4370

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with only SPEI growing seasons from age -1 to age 6 as explanatory variables. The first two columns use the cognitive score measured between ages 7 and 14 as the dependent variable. Columns (3) and (4) use cognitive score measured in adulthood (above aged 15) as the dependent variable. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0. Appendix Table L3 shows the same results broken down by gender.

tween early-life SPEI (averaged from ages 0 to 3) and late-childhood SPEI (averaged from ages 10 to 12), there is a positive interaction between early-life SPEI and adolescent SPEI (averaged from 13-15). The complementarity is unlikely to be driven by biological changes during puberty, since the pattern is similar across genders (Appendix Table L6), and puberty occurs earlier in girls. Alternatively, changes in educational investment during middle school could explain the interaction effect. Although there are no detectable effects on the number of years children stay at school (Appendix Table L7), I cannot rule out changes along other margins of educational investment during middle school.

Table 6: *Cognitive interaction (dynamic complementarity)*

	Dep Var: Adult Cog Z-score					
	Both (1)	Male (2)	Female (3)	Both (4)	Both (5)	Both (6)
SPEI growing season, age 0	−0.002	0.014	−0.016			
	(0.014)	(0.021)	(0.019)			
SPEI growing season, age 1	0.015	0.009	0.023			
	(0.017)	(0.026)	(0.019)			
SPEI growing season, age 2	0.068***	0.075***	0.051**			
	(0.015)	(0.025)	(0.021)			
SPEI growing season, age 3	0.031**	0.046**	0.013			
	(0.014)	(0.021)	(0.023)			
SPEI growing season, (age 0 x age 2)	0.000	−0.016	0.006			
	(0.016)	(0.022)	(0.019)			
SPEI growing season, (age 1 x age 2)	0.027*	0.057**	0.003			
	(0.015)	(0.025)	(0.018)			
SPEI growing season, (age 3 x age 2)	−0.016	0.003	−0.032			
	(0.014)	(0.024)	(0.022)			
SPEI growing season, ages 0-3				0.127***	0.080**	0.091**
				(0.035)	(0.037)	(0.041)
SPEI growing season, ages 10-12				−0.021		
				(0.033)		
SPEI growing season, (ages 0-3 x ages 10-12)				−0.051		
				(0.053)		
SPEI growing season, ages 13-15					0.013	
					(0.033)	
SPEI growing season, (ages 0-3 x ages 13-15)					0.081**	
					(0.039)	
SPEI growing season, ages 10-15						−0.010
						(0.059)
SPEI growing season, (ages 0-3 x ages 10-15)						0.056
						(0.054)
Birth year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.211	0.229	0.253	0.209	0.209	0.209
N	5572	2601	2971	5572	5572	5572

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running versions of Equation 1. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. All columns use cognitive factor score measured in adulthood (above aged 15) as the dependent variable. In columns (1) to (3) the explanatory variables are SPEI growing season from age -1 to age 3 *and* the interactions between SPEI growing season at age 2 with all other weather variables. Column (2) is only males, and column (3) is only females. *SPEI growing season, ages 0-3* denotes the mean value of SPEI growing season for an individual across ages 0, 1, 2, and 3. The age ranges 13-15 and 10-15 are defined analogously. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

5 Mechanisms

In this section I examine a number of potential mechanisms that could explain the effects on cognitive development. The results suggest that weather has an impact on nutritional investment between 3 and 8 months after harvest. I use this to show that effects on cognitive development are particularly strong in the *second* half of the year between the second and third birthday. I then show evidence that breastfeeding behaviour may be insulating children from shocks at earlier ages.

Throughout this section, I corroborate the results on *SPEI growing season* with an additional weather variable, the *predicted harvest index*. To construct it, I first regress rice yields from the IFLS data on a number of weather measures from the climatology literature. The index is the predicted value from this regression, normalised to have a mean of 0 and standard deviation of 1. It is thus a summary index for the weather features that predict high rice yields in the IFLS sample. See Appendix Section D for more details.

5.1 Investment indexes

This section provides evidence that weather variation has a positive effect on investment for under-5s in IFLS households, suggesting that weather shocks may be affecting cognitive development through nutritional channels.

I focus on two important channels through which increases in agricultural yields could affect early childhood development. I construct a *nutritional investment index* (composed of measures of food frequency and dietary diversity for young children) and a *parental time index* (composed of questions on whether and how much the father and mother work).[17]

First, I examine how weather from the last 2 years affects contemporaneous investments for children under 5 years old. The empirical specification is:

$$I_{iry} = \alpha + \beta_0 Weather_{ry} + \beta_1 Weather_{r,y-1} + \pi_r + \mu_y + \varepsilon_{iry} \tag{2}$$

where I_{iry} is the investment index for an under-5 individual i in region r measured in year y. $Weather_{ry}$ is the weather that corresponds to the harvest in year y (either SPEI growing season or predicted harvest index), and π_r and μ_y are district and year fixed effects.

Second, I use data on *when* each household was measured relative to harvest to understand the timing of impacts in more detail. Motivated by results disaggregated by month (Appendix Figure O1), I define two 6-month periods during the year: *around*

[17]The survey questions used are described in Appendix Section A.1. The construction of the indexes is described in Appendix Section B.7.

harvest (3 months before harvest to 2 months after), and *after harvest* (3 to 8 months after). Using the interaction of weather variation with an indicator of which period investment was measured in, the results indicate when the shocks "bite" and affect investment. Appendix Section E gives more details on the specification.

Table 7 shows the results. Both weather measures positively impact nutritional investment. SPEI growing season has a positive and statistically significant effect of 0.065 standard deviations in the year of harvest, which can be isolated to the period 3-8 months after harvest. The coefficient on predicted harvest across the whole year is not significantly different from 0, but this disguises a positive effect that is also isolated to between 3 and 8 months after harvest. Why might the effects on nutrition be focused on this period? Plausibly, the smaller yields of households that experience poor weather provide food stocks that run out after only 2-3 months. They may thus experience earlier, longer, and more severe lean seasons than households with normal or favourable weather conditions.

For the parental time index, none of the coefficients is significant at the 10% level. The coefficients are not precisely estimated, but this does suggest that weather improvements do not lead to reductions in parental time investment (for example, due to the labour requirements of good harvests) that might offset the positive effects on nutritional investment.

5.2 Household expenditure

To complement the results showing that weather variation affects nutritional investment, I here examine whether this is driven by changes in aggregate household welfare that would result from changes in harvest yields for rural households.

Table 8 shows the effect of weather shocks in the last 2 years on contemporaneous log household per capita expenditure. A 1 SD improvement in the SPEI growing season increases per capita expenditures by approximately 6% in the period between 3 and 8 months after harvest. Similarly, the predicted harvest index is associated with a 10.4% increase in total per capita expenditure in this period (corresponding to the coefficient on the log outcome of 0.099). Good weather and accompanying good harvests thus appear to improve aggregate household expenditure, which then translates to improved nutritional investment, specifically in the window 3 to 8 months

Table 7: *Impact of weather shocks on indexes of investment for u5s*

		Dep Var: Nutrition Index				Dep Var: Parental Time Index			
	Outcome measured in:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI growing season	Year 0	0.065***				−0.008			
		(0.024)				(0.037)			
SPEI growing season	Year 1	0.009				−0.002			
		(0.021)				(0.022)			
SPEI growing season	Months -3 to 2 after harvest		0.024				−0.006		
			(0.027)				(0.039)		
SPEI growing season	Months 3 to 8 after harvest		0.092***				0.035		
			(0.034)				(0.040)		
SPEI growing season	Months 9 to 14 after harvest		0.016				−0.011		
			(0.025)				(0.034)		
SPEI growing season	Months 15 to 20 after harvest		−0.012				−0.000		
			(0.026)				(0.022)		
Predicted harvest index	Year 0			0.028				−0.036	
				(0.028)				(0.028)	
Predicted harvest index	Year 1			0.005				0.003	
				(0.022)				(0.022)	
Predicted harvest index	Months -3 to 2 after harvest				−0.013				0.013
					(0.042)				(0.037)
Predicted harvest index	Months 3 to 8 after harvest				0.058*				−0.032
					(0.031)				(0.031)
Predicted harvest index	Months 9 to 14 after harvest				0.029				−0.015
					(0.027)				(0.028)
Predicted harvest index	Months 15 to 20 after harvest				−0.013				0.004
					(0.028)				(0.028)
Year FEs		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FEs		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age (month) FEs		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.139	0.139	0.145	0.129	0.131	0.135	0.148	0.124
N		4247	4247	4247	4246	4247	4247	4247	4246

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses. When the dependent variable is *SPEI growing season*, the standard errors are clustered by district. When the dependent variable is *predicted harvest index*, the standard errors are bootstrapped to account for the construction of the regressor, as described in Appendix Section E.3. The unit of observation is (individual × wave). The dependent variable in columns (1)-(4) is nutritional investment index for children under 5 years old (composed of food frequency and dietary diversity measures). The dependent variable in columns (5)-(8) is parental time investment index for children under 5 years old (composed of measures of time spent working for both parents, and whether their primary activity is working). The survey questions used are described in Appendix Section A.1. The construction of the indexes is described fully in Appendix Section B.7. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year × district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. For the SPEI growing season, the harvest date is defined as the average harvest date of the main crop grown in that district (as according to aggregate data, see description in Section A.2). For the Predicted Harvest Index, the harvest date is defined as the average harvest date of rice in that district based on IFLS harvest data (see Section D.2). "Year 0" is the period between 3 months before and 8 months after harvest (inclusive). Analogously, "Year 1" is the period 9 months and 20 months after harvest (inclusive). For the 6-monthly effects, the coefficients reported come from a version of Equation 6 (but with investment index as the dependent variable) and are β_0 for -3 to 2 months; $\beta_0 + \gamma_0$ for 3-8 months; β_1 for 9-14 months; $\beta_1 + \gamma_1$ for 15-20 months.

after harvest.[18] [19] These results are robust to different constructions of the household expenditure variable (Appendix Table O1).

In Appendix Section Q, I examine whether the changes in nutritional investment and household expenditure translate into improved height-for-age (as measured between ages 2 and 6, giving enough time for nutritional status to show up as changes in height). The predicted harvest index at age 1 has a positive effect on female height-for-age in early childhood, but there are no detectable effects of early-life SPEI growing season on height-for-age. One interpretation is that height-for-age is mostly determined by cumulative nutritional investments over the course of a longer window in early childhood (in contrast to the apparently strong critical period for cognitive development at age 2). This, along with noisy measures of height-for-age at ages 2-6 may make it harder to detect the effects of temporary changes in weather earlier in life.

5.3 Effects on cognitive development: 6 month intervals

The effects of weather on expenditure and nutritional investment are isolated to a window between 3 and 8 months after harvest, providing a clear demarcation of the timing of the effect of the variation. By assuming that shocks only "bite" in the window 3-8 months after harvest, I use this result to understand the timing of critical periods in cognitive development using more granular 6-month intervals.[20]

I assign every 6-month interval in an individual's lifetime *either* to the 6-month period when the weather shock will bite (3-8 months after harvest), *or* to the 6-month period when weather has no effect (3 months before to 2 months after harvest). This assignment will depend on when the individual is born relative to harvest. The shock will be more salient for some individuals than others, so I account for differences across

[18] There may be general equilibrium effects of weather shocks in local areas, for example, effects on the price of agricultural goods. This channel should be thought of as an extension of the main mechanism, since it will likely affect cognitive development primarily through changes in nutritional investment and economic welfare.

[19] Wetter weather may increase the risks of floods or may lead to a worse early-life disease environment. This is unlikely to be driving results, since (i) it would not explain a positive relationship between SPEI at age 2 and cognitive development, (ii) the results persist when using the predicted harvest index which includes multiple weather measures not based on rainfall, and (iii) large positive SPEI shocks (associated with heavy rainfall and flooding) do not have negative effects on cognitive development (Appendix Section M).

[20] The variation in harvest time across different regions implies that impacts will not be confounded by other cyclical shocks to nutrition, such as Ramadan (see Appendix Figure P1).

Table 8: *Effect of weather variation on log household per capita expenditure*

		SPEI growing season				Predicted Harvest Index			
	Outcome measured in:	Total (1)	Food (2)	Total (3)	Food (4)	Total (5)	Food (6)	Total (7)	Food (8)
SPEI growing season	Year 0	0.014	0.017						
		(0.019)	(0.018)						
SPEI growing season	Year 1	0.001	0.010						
		(0.025)	(0.023)						
SPEI growing season	Months -3 to 2 after harvest			−0.028	−0.051*				
				(0.031)	(0.029)				
SPEI growing season	Months 3 to 8 after harvest			0.058**	0.057**				
				(0.028)	(0.024)				
SPEI growing season	Months 9 to 14 after harvest			−0.021	0.005				
				(0.028)	(0.024)				
SPEI growing season	Months 15 to 20 after harvest			−0.013	−0.006				
				(0.019)	(0.019)				
Predicted harvest index	Year 0					0.068**	0.066**		
						(0.031)	(0.030)		
Predicted harvest index	Year 1					−0.001	−0.002		
						(0.029)	(0.028)		
Predicted harvest index	Months -3 to 2 after harvest							−0.021	−0.016
								(0.054)	(0.050)
Predicted harvest index	Months 3 to 8 after harvest							0.099**	0.094**
								(0.038)	(0.036)
Predicted harvest index	Months 9 to 14 after harvest							−0.009	−0.017
								(0.034)	(0.034)
Predicted harvest index	Months 15 to 20 after harvest							−0.002	0.004
								(0.035)	(0.034)
Year FEs		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FEs		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean		12.728	12.210	12.728	12.210	12.728	12.210	12.728	12.210
R^2		0.120	0.103	0.127	0.109	0.118	0.101	0.120	0.103
N		11561	11571	11529	11539	11561	11571	11557	11567

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. When the dependent variable is *SPEI growing season*, the standard errors are clustered by district. When the dependent variable is *predicted harvest index*, the standard errors are bootstrapped to account for the construction of the regressor, as described in Appendix Section E.3. The unit of observation is (household × wave). The dependent variable is based on log household per capita expenditure adjusted for inflation at the district and year level, which is available for IFLS waves 1-4 (see more on this in Appendix Section A.1). For columns (1), (3), and (5), and (7), the dependent variable is total expenditure calculated in this way. For the remaining columns, it is food expenditure only. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year × district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. For the SPEI growing season, the harvest date is defined as the average harvest date of the main crop grown in that district (as according to aggregate data, see description in Section A.2). For the Predicted Harvest Index, the harvest date is defined as the average harvest date of rice in that district based on IFLS harvest data (see Section D.2). "Year 0" is the period between 3 months before and 8 months after harvest (inclusive). Analogously, "Year 1" is the period 9 months and 20 months after harvest (inclusive). For the 6-monthly effects, the coefficients reported come from Equation 6 and are β_0 for -3 to 2 months; $\beta_0 + \gamma_0$ for 3-8 months; β_1 for 9-14 months; $\beta_1 + \gamma_1$ for 15-20 months.

individuals in shock exposure in a number of ways.[21]

Figure 3 shows the results.[22] For both SPEI growing season and predicted harvest index, we again see strong evidence of a critical period at age 2. The similarity of the results across both weather measures suggests that the critical period in cognitive development at age 2 is a robust finding. The 6-month interval specification shows the effects to be particularly concentrated in the *second* half of the year between the second and third birthdays. For both weather indexes, there are a strong effects of around 0.08 standard deviations at age 30-35 months, with p-values below 0.01. The q-value for SPEI growing season is below 0.05, while for the predicted harvest index I do not have the power to reject null effects after adjusting for multiple hypothesis testing.[23] At age 24-29 months, the evidence is more mixed. SPEI growing season yields a positive coefficient of 0.06 standard deviations that is only significant before adjusting for multiple hypothesis testing, and the coefficient on predicted harvest index is close to 0.

5.4 Breastfeeding

I find a surprising lack of evidence of an effect of weather variation *before* age 2. One potential explanation for this result is that children are protected from nutritional shocks at these ages because they are being breastfed. This is plausible, since the median weaning age for a child in the IFLS sample is 609 days old, shortly before the second birthday. Without a source of exogenous variation in breastfeeding choices, I cannot rigorously test whether breastfeeding mediates the effects of weather variation. However, two pieces of evidence suggest that it might play an offsetting role.

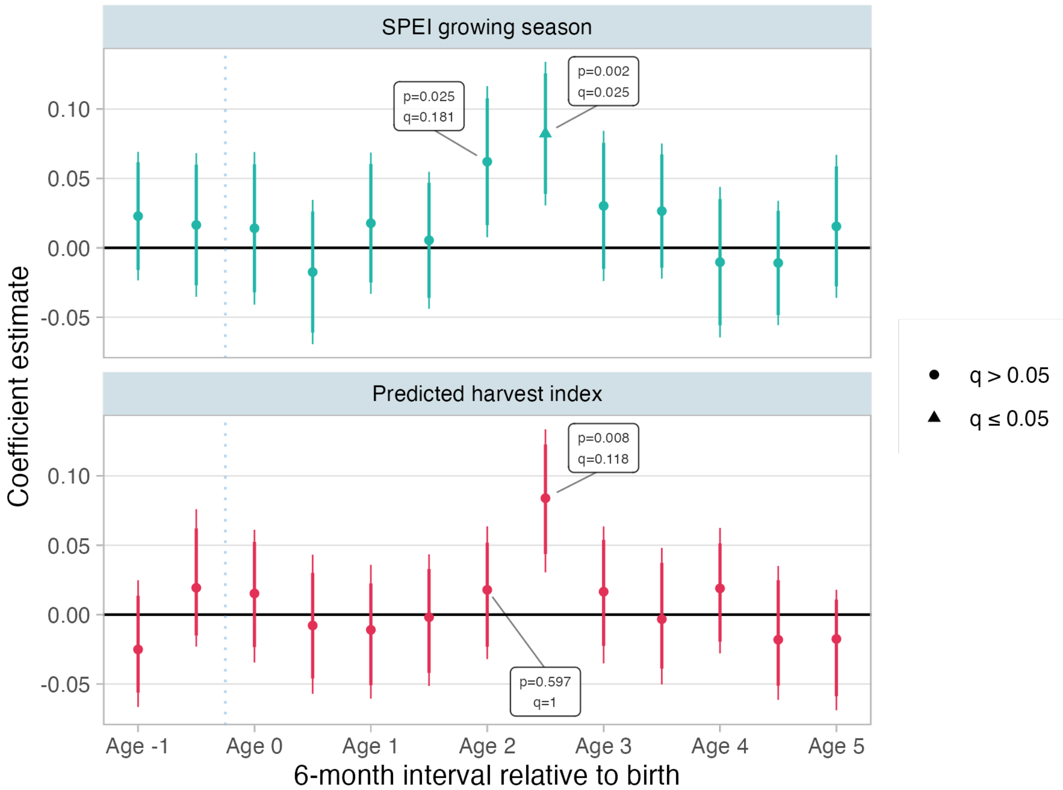
First, mothers change when they stop breastfeeding in a way that might offset the

[21] If an individual is born 3 months after harvest, then the first 6-month period of their life (age 0-5 months) is assigned the value of the shock that bites in that period, and the second 6-month period of their life (age 6-11 months) is assigned a value of 0 (because the shock has no detectable effect in this period). A person born 2 months later in the same district is assigned the same values, but will in reality be less exposed to the assigned shock. To control for this differing exposure to the shock variable, I include (district $\times$ birth-month-of-year) fixed effects, and show robustness to weighting the shock variable by an individual's exposure to the shock (Appendix Table L13). This methodology is described in detail in Appendix Section E.2.

[22] For these results, I increase power by focusing only on the first 5 years of life. Examining up to age 15 yields similar coefficients for age 2.5 across both indexes (Appendix Table L9). However, testing 35 hypotheses simultaneously reduces the power to detect effects after adjusting for multiple hypothesis testing. Appendix Table L10 shows the results by year for predicted harvest, which are qualitatively similar to the results with SPEI growing season. The results on the predicted harvest index are robust to different constructions of the index (Appendix Tables L11 and L12).

[23] Appendix Figure L1 shows that the coefficient estimates are larger for males, as they were for the main results.

Figure 3: *Effect of weather on cognitive development: 6-month intervals*



Notes: Each point represents the effect of weather variation in each 6-month age interval on adult cognitive z-score. The top chart uses SPEI growing season as the main explanatory variable, and the bottom chart uses the predicted harvest index. Error bars are 90% and 95% confidence intervals based on standard errors clustered at the district level (not adjusted for multiple testing). Error bars are 90% and 95% confidence intervals based on standard errors that are not adjusted for multiple testing. When the dependent variable is *SPEI growing season*, the standard errors are clustered by district. When the dependent variable is *predicted harvest index*, the standard errors are bootstrapped to account for the construction of the regressor, as described in Appendix Section E.3. A triangular point is used when the q-value is less than 0.05. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given specification. The dependent variable in all models is the adult cognitive factor score (measured after age 15), which is standardised to have 0 mean and standard deviation of 1. Individuals are matched to values of predicted harvest index using the process described in Section E.2. 6-monthly specifications control for (district × month-of-birth) fixed effects, to account for variation due to the timing of birth relative to the 6-month "bucket" individuals are assigned to (see Appendix Section E.2 for details). Both specifications also control for birth year fixed effects and individual-level controls (dummies for highest level of parental education, sex, and religion). All models use the individual-level attrition-corrected weights provided in the IFLS data.

effects of shocks at age 1. Using data on whether children are still being breastfed at the time of an IFLS survey, I measure whether this is affected by the most recent SPEI growing season, and how this effect depends on the age of the child (Figure 4). Around the most common weaning time (500-700 days old), increases in SPEI growing season are associated with a *decrease* in the probability of the child being breastfed. When harvests are bad around age 1, mothers prolong breastfeeding. This is likely to protect children from shocks at this age.[24]

Second, for the small subset of children who are never breastfed, there is a very strong positive effect of SPEI growing season at age 1 on cognitive development (Appendix Table P1), suggesting that they are particularly vulnerable to nutrition shocks due to changes in the weather. This second result should be interpreted with caution. Only 1.4% (N = 53) of the sample with available data are never breastfed, so the coefficient estimate is noisily estimated. The decision not to breastfeed is also endogenous, and may be affected by weather variation in a way that confounds the causal estimates. For example, the most common reason given for not breastfeeding is insufficient breastmilk, which could be caused by poor nutrition of the caretaker.

5.5 Discussion of mechanisms

The lack of effect before age 2 is surprising given the existing literature that proposes the first 1000 days as the critical period for cognitive development.[25] There are a number of factors that could explain this.

First, children may be protected from nutritional shocks when they are breastfeeding, as I discussed in Section 5.4. More generally, parental responses can offset the effects of negative shocks. This appeared to be the case for breastfeeding behaviour: parents responded to negative shocks by prolonging breastfeeding (and vice versa), thereby attenuating the effects of shocks before age 2. Parents may also be more willing to reduce other expenditures and maintain nutritional expenditures for younger children. Since the impacts I measure are *reduced-form*, measured at least 13 years after shocks at age 2, they incorporate the effects of any subsequent parental investments.

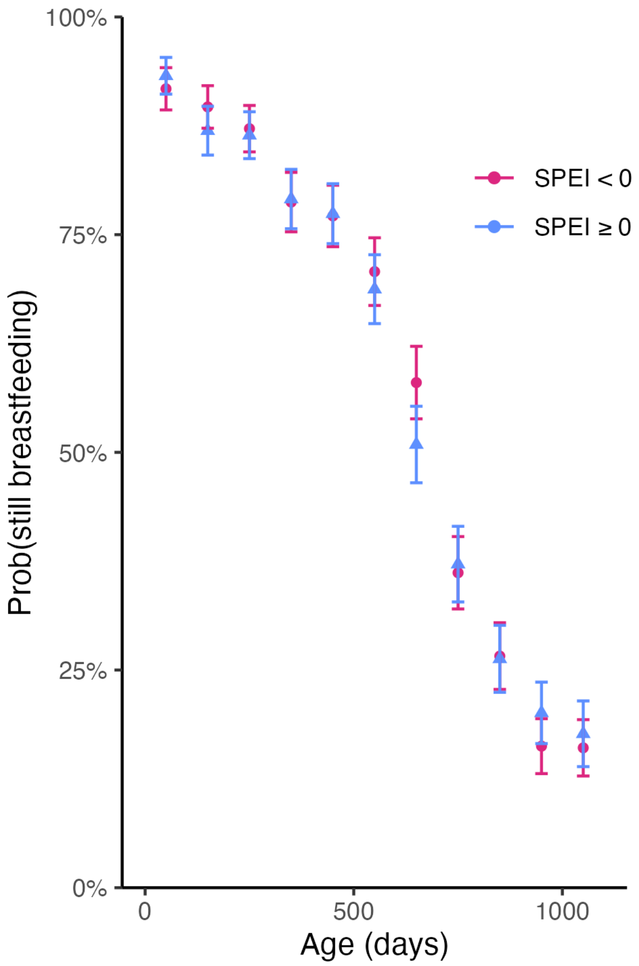
Another explanation for the discrepancy between my results and the literature could

[24] The protective effect of prolonging breastfeeding may be weaker if maternal nutrition also suffers. Appendix Table P2 shows some weak evidence that the predicted harvest index is positively correlated with maternal nutrition between 3 and 8 months after harvest, although the smaller sample of mothers makes it difficult to reject null effects.

[25] It does not preclude later effects, such as the one at age 30-35 months observed here: a review concluded that the earliest years are not the sole sensitive time period (Wachs et al., 2014), and studies show effects of preschool programmes at ages 3-4 on cognitive development (Dean & Jayachandran, 2020; Schweinhart & Weikart, 1981; Reynolds et al., 2011), suggesting that cognitive development is not "set in stone" by 24 months after birth.

Figure 4: *Breastfeeding timing*

(a) *Binary split*



(b) *Interaction specification*

	(1)
SPEI	0.008
	(0.015)
SPEI x (Age 100-200 days)	−0.033*
	(0.019)
SPEI x (Age 200-300 days)	−0.013
	(0.019)
SPEI x (Age 300-400 days)	−0.018
	(0.022)
SPEI x (Age 400-500 days)	−0.011
	(0.019)
SPEI x (Age 500-600 days)	−0.041*
	(0.021)
SPEI x (Age 600-700 days)	−0.060**
	(0.024)
SPEI x (Age 700-800 days)	−0.012
	(0.025)
SPEI x (Age 800-900 days)	−0.010
	(0.023)
SPEI x (Age 900-1000 days)	0.014
	(0.023)
SPEI x (Age 1000-1100 days)	0.011
	(0.020)
Year fixed effects	Yes
Birth district fixed effects	Yes
R^2	0.362
N	11656

Notes: Sample used is all children under the age of 3 years in rural farming households in the IFLS. For these children, mothers were asked whether they were still breastfeeding their child as of the date of interview. Panel **(a)** shows the raw probabilities of still being breastfed for each 100-day bin of age. The sample is split into those who experienced a positive SPEI growing season shock at the last harvest (SPEI $\geq$ 0) and those who experienced a negative SPEI growing season shock at the last harvest (SPEI $<$ 0). Panel **(b)** uses an interaction specification. SPEI growing season (as a linear variable, rather than a binary one) is interacted with each 100-day age bin. The outcome is a binary indicator of whether the child was still being breastfeed as of the date of interview. Standard errors are reported in parentheses and are clustered by birth district. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. All models use the individual-level attrition-corrected weights provided in the IFLS data. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

be that existing literature typically focuses on methods that do not make use of exogenous shocks. A neurodevelopmental literature shows a correlation between brain growth and cognitive development (Isaacs et al., 2008; Gilmore et al., 2018), while a literature in nutrition shows a correlation between stunting and cognitive development (Victora et al., 2010; Aiyar & Cummins, 2017; Perkins et al., 2017). While stunting and brain growth occur most rapidly before age 2, this does not directly imply that exogenous shocks at this time will have the biggest effect cognitive development in this period.

Indeed, there are a number of plausible mechanisms from the neurodevelopmental literature that could explain effects after age 2. First, even though brain volume growth is fastest before age 2, one study found it to be more sensitive to economic circumstance in the 24-36 month period than at earlier ages (Hanson et al., 2013).[26] Second, the prefrontal cortex is an important determinant of cognitive skills (Ferrer, 2009; Little et al., 2014), and this part of the brain follows a slower growth path, with important changes between ages 2 and 4 (Fiske & Holmboe, 2019). Third, connectivity between the frontal and parietal cortices may be important for cognitive ability, and later ages (after age 2) are key for the development of this connectivity (Buss & Spencer, 2014; Buss et al., 2014; Buss & Spencer, 2018; Fiske & Holmboe, 2019).[27] It remains an important avenue of research to explore the relative importance of such factors for explaining the effects of nutritional and economic shocks in low- and middle-income countries.

6 Discussion & conclusion

In this paper I present new evidence for the existence of a critical period at age 2 for cognitive development as a result of weather shocks in early childhood. Weather shocks at this age on individuals born in rural Indonesia between 1988 and 2000 have a long lasting effect on their cognitive ability as an adult, whereas weather shocks at other ages have no detectable impact. When examining similar evidence on adult socioemotional outcomes, I find no such evidence of a critical period for these weather shocks, with either null effects or effects that cannot be clearly isolated to single periods. I cannot rule out smaller positive impacts of less than 0.06 standard deviations for these null effects, but the results on cognitive development at age 2 suggest a particularly strong impact in this period.

[26](Hanson et al., 2013) show that the divergence in grey matter volume between US children in mid- and low-SES groups is somewhat starker in the 24–36 month period, suggesting heightened sensitivity.

[27]The studies indicate that the development of a stronger fronto-parietal network between the ages of 3 and 4.5 years underlies the development of visual working memory capacity, which has been shown to be correlated to performance on cognitive tests (Little et al., 2014).

The observed effects on cognitive development are consistent with an economic channel in which weather affects rural households' expenditure and nutritional investment, leading to impacts on cognitive development that persist into adult life. Caretakers partially compensate for shocks before age 2, in particular by prolonging breastfeeding. If breastfeeding is playing a protective role, this suggests the importance of improving insurance against shocks for families with children who have recently been weaned. More generally, the way parents react to shocks and interventions can play an important role in determining long-run impacts. Further research should seek to understand which behavioural factors lead to crowd-in or crowd-out of caretaker investment.

The results I present are most relevant to other contexts in which agricultural harvests play an important role in determining nutritional investments in children, and in which malnutrition is sufficiently severe that it can hamper the cognitive development of young children. By contrast, critical periods are likely to manifest differently in contexts with less agricultural dependency and nutritional vulnerability. Further research should investigate whether the critical periods found here exist for the effects of *policy interventions* that target nutrition and cognitive development in contexts similar to rural Indonesia. Intervening in such periods may yield large gains in cost-effectiveness.

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Online Appendix

Reset numbering for appendix

A Data Appendix

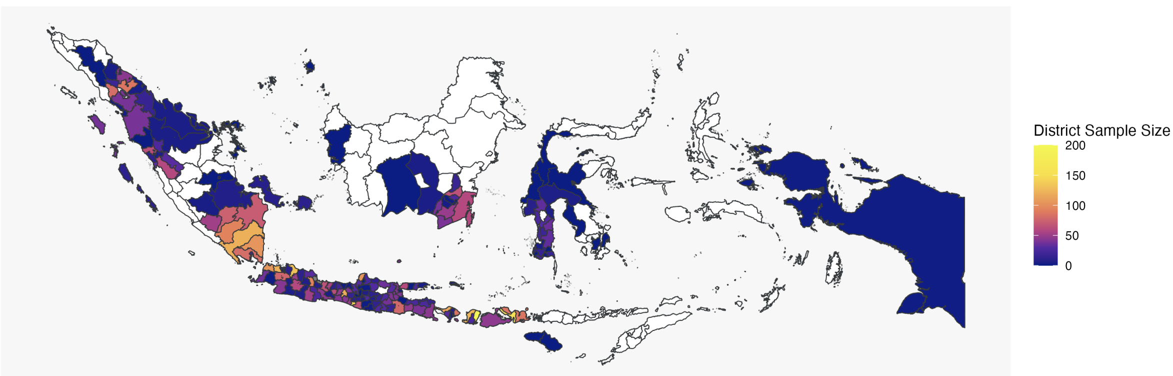
A.1 IFLS data

A summary of which outcome variables were available in each of the waves of IFLS (and the years of each survey) is found in Figure A1. Figure A2 shows the birth location of my main sample, which is concentrated in the 13 provinces covered by the IFLS data. The largest concentration of my sample is located in Western, Central, and Eastern Java.

Figure A1: *Summary of data availability for main outcome variables*

IFLS1 1993	IFLS2 1997	IFLS3 2000	IFLS4 2007	IFLS5 2015
HH Expenditure	HH Expenditure	HH Expenditure	HH Expenditure	HH Expenditure
Anthro	Anthro	Anthro	Anthro	Anthro
		Investment index (nutrition, parent)	Investment index (nutrition, parent)	Investment index (nutrition, parent)
		Cognitive (limited)	Cognitive	Cognitive
			Socioemotional (limited)	Socioemotional (full)

Figure A2: *Birth location of individuals in main sample*



Cognitive measures. All IFLS respondents above the age of 15 are asked a number of questions that are designed to test cognitive ability:

1. *Raven's progressive matrices* (Raven, 2000) - participants have to fill in the gaps of a visual matrix that follows a certain pattern. This is a common metric of "fluid intelligence".

2. *Maths - written* - participants have to answer 5 simple written maths questions.

3. *Word recall* - respondents were given a list of 10 words, and then asked to recall as many of the words as possible. They were asked to do this twice, once immediately after hearing the list, and another time 12-15 minutes later. (Score out of 10)

4. *Maths - oral* (IFLS5 only) - respondents were asked to serially subtract 7s from 100 (Score out of 10)

5. *Number series* (IFLS5 only) - participants are given a series of 3 numbers and are asked to fill in the fourth number in the series, e.g. *"2 4 6 ?"*. The IFLS data then uses a Rasch scoring model to create a Woodcock-Johnson score based on a participant's ability to answer questions of varying difficulty.

The easier questions in the Raven's test and the written maths test are also given to children in IFLS households between the ages of 7-14. I use these to generate the results seen in Section 4.3.

Socioemotional measures - the full set of socioemotional measures is found in Table A1. Depression measures are based on the CES-D scale. Personality measures are based on the Big 5 personality test.

Household expenditure. IFLS data contains detailed household expenditure data for each household. The categories asked are related to food, self-production, non-food, education, and rent (along with imputed rent). I impute the respondents' estimate of rent for home-owners. Total monthly expenditure is calculated by summing across all available categories. Total per capita monthly expenditure is calculated by dividing this by the reported household size. High quality price-adjustment data is not available for all waves of the IFLS data, so I use a variety of price-adjustments in the reported results:

1. *Nominal* - no price adjustment, available for all waves (IFLS1-5).

2. *"Real"* - the highest quality price adjustment available, from the IFLS data itself, that varies at the district (kabupaten) level, by rural/urban area, and by month-year. However this data is only available for IFLS2 and IFLS3.

3. *Inflation-adjusted ("Infl")* - a more comprehensive, but lower quality, price adjustment. It is less disaggregated than the "real" adjustment, and varies at the

Table A1: *Description of all socioemotional variables from IFLS*

Module	Question Name	Pre question	Full Question	Reverse coded?	Included in IFLS4	Answer Scale
Depression	Bothered	In the past week...	Bothered by things that usually don't bother me	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Concentration	In the past week...	I had trouble concentrating in what I was doing	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Depressed	In the past week...	I felt depressed	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Everything was an effort	In the past week...	I felt everything I did was an effort	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Hopeful	In the past week...	I felt hopeful about the future	-	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Fearful	In the past week...	I felt fearful	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Restless Sleep	In the past week...	My sleep was restless	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Happy	In the past week...	I was happy	-	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Lonely	In the past week...	I felt lonely	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Depression	Couldn't get going	In the past week...	I could not get going	Yes	Yes	1 to 4 ("Rarely" to "Most of the time")
Personality	Agreeableness - Forgiving	I see myself as someone who ...	Has a forgiving nature	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Agreeableness - Considerate and Kind	I see myself as someone who ...	Is considerate and kind to almost everyone	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Agreeableness - Rude	I see myself as someone who ...	Is sometimes rude to others	Yes	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Conscientiousness - Thorough	I see myself as someone who ...	Does a thorough job	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Conscientiousness - Lazy	I see myself as someone who ...	Tends to be lazy	Yes	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Conscientiousness - Efficient	I see myself as someone who ...	Does things efficiently	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Extraversion - Talkative	I see myself as someone who ...	Is talkative	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Extraversion - Reserved	I see myself as someone who ...	Is reserved	Yes	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Extraversion - Outgoing	I see myself as someone who ...	Outgoing, sociable	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Neuroticism - Relaxed	I see myself as someone who ...	Is relaxed, handles stress well	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Neuroticism - Worries	I see myself as someone who ...	Worries a lot	Yes	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Neuroticism - Gets Nervous	I see myself as someone who ...	Gets nervous easily	Yes	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Openness - Original	I see myself as someone who ...	Is original, comes up with new ideas	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Openness - Active Imagination	I see myself as someone who ...	Has an active imagination	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Personality	Openness - Artistic and Aesthetic	I see myself as someone who ...	Values artistic, aesthetic experiences	-	-	1 to 5 ("Disagree strongly" to "agree strongly")
Positive / Negative Affect	Frustrated	Yesterday, did you feel ...	Frustrated	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Sad	Yesterday, did you feel ...	Sad	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Enthusiastic	Yesterday, did you feel ...	Enthusiastic	-	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Lonely	Yesterday, did you feel ...	Lonely	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Content	Yesterday, did you feel ...	Content	-	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Worried	Yesterday, did you feel ...	Worried	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Bored	Yesterday, did you feel ...	Bored	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Happy	Yesterday, did you feel ...	Happy	-	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Angry	Yesterday, did you feel ...	Angry	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Tired	Yesterday, did you feel ...	Tired	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Stressed	Yesterday, did you feel ...	Stressed	Yes	-	1 to 5 ("Not at all" to "Very")
Positive / Negative Affect	Pain	Yesterday, did you feel ...	Pain	Yes	-	1 to 5 ("Not at all" to "Very")
Subjective Wellbeing	Life Satisfaction (Cantrill Ladder)	How satisfied are you with your life as a whole		-	-	1 to 5 ("Not at all" to "Completely satisfied")
Subjective Wellbeing	Assessment of current situation	All things together how are things these days		-	Yes	1 to 4 ("Very unhappy" to "Very happy")
Risk/Time Preferences	Gamble Tradeoff 1	Sure gain of 800k/month, or series of 50/50 gambles		Yes	Yes	1 to 5 (Least Risk Averse to Most Risk Averse)
Risk/Time Preferences	Gamble Tradeoff 2	Sure gain of 4m/month, or series of 50/50 gambles		Yes	Yes	1 to 5 (Least Risk Averse to Most Risk Averse)
Risk/Time Preferences	1 year time tradeoff	Receive 1m today or higher amount in 1 year		-	Yes	1 to 5 (Least Patient to Most Patient)
Risk/Time Preferences	5 year time tradeoff	Receive 1m today or higher amount in 1 year		-	Yes	1 to 5 (Least Patient to Most Patient)

province level, by rural/urban area, and by year. However it covers IFLS1-4, so the sample size is around double for that of "real". I use this quantity in the main results.

Anthropometrics. IFLS respondents (including children) had their height and weight measured. To calculate height-for-age and weight-for-age z-scores for children, I combine these measurements with WHO's child growth standards data (WHO & UNICEF, 2009). Following WHO recommendations, I remove all outliers with z-scores outside of the range $[-5, 5]$.

Rice production. Detailed rice production data is available for IFLS4 and 5. For all farming households, detailed data is available on the most recent crop farmed in the last 12 months, including the main crop farmed, the area harvested, the amount harvested, and the value of the harvest. The results shown in Appendix Table D1 include all harvests where the main crop was rice. I construct a measure of yield by dividing the amount harvested by the area harvested. To avoid dropping 0s, I use the inverse hyperbolic sine (IHS) transformation of the yield variables.

Early-life nutrition. I make use of the following variables to construct the nutrition index seen in Section 5.1:

1. Food frequency. Respondents are asked how often children eat (3+ times a day, 2 times a day, once a day, 5-6 times / week, 3-4 times / week, <3 times / week, or breastfeeding). When the response is breastfeeding, I assume this is equivalent to 3+ times / day. I transform this variable into an ordinal scale so that it can be age-standardised and converted to a Z-score according to the procedure described in Appendix Section B).

2. Vitamin-A frequency and iron frequency. The IFLS contains questions on the consumption of specific food groups, and I use these to construct measures of how often each child consumes (i) vitamin-A-rich foods (sweet potato, eggs, dairy, green leafy vegetables, papaya, carrot, and mango) and (ii) iron-rich foods (eggs, fish, meat, dairy). These categorisations are based on the FAO guidelines for constructing measures of dietary diversity Kennedy et al. (2011). This yields a measure from 0-7 indicating how many times in the week the child ate the relevant types of foods, which are also age-standardised and converted to a Z-score according to the procedure described in Appendix Section B).

Parental time-use. I make use of the following variables to construct the parental time-use index seen in Section 5.1: (i) primary activity is earning (mother), (ii) primary activity is earning (father), (iii) total weekly hours worked (mother), (iv) total weekly hours worked (father). All of these variables are also standardised according to the age of the child and converted to z-scores.

Birth location and migration history. IFLS contains data on all adults' birth district and migration history after the age of 12. I combine the data on district of birth, the district when surveyed, and migration history to construct a year-by-year history of the district each respondent has lived in since birth. This is subsequently used to match individuals to the SPEI values in each year of their life. The main specification in Section 3 also makes use of district location in the two years before birth. For these two years, individuals are matched to the location of their birth.

Birth date. I use the "best-guess" birth date from the IFLS data for each individual that incorporates information across multiple waves in cases of inconsistencies.

Sibling fixed effects. I combine information collected from both individuals and their parents in the IFLS survey to match individuals to their parents. This information is used to construct sibling fixed effects. These are dummies that denote individuals in the same "family group", defined here as sharing at least one parent. 96% of family groups share exactly one mother and one father, indicating that this definition is unlikely to be capturing patterns due to remarriage and non-nuclear families. I then use the best-guess birth date of each individual in a family group to construct the birth-order fixed effects.

Control variables. As controls I make use of data on the gender and religion of each individual. For individuals I construct a parental education variable, either by matching individuals back to their parents if they are also IFLS respondents, or by using the self-reported data on parental education. The variable used in the paper is the highest level of education reached by either of the parents. The possible levels are: no education, elementary school, junior high school, senior high school, or university. I also have data on the identity of the household head which I use to construct the household head education variable in a similar way.

A.2 District, Weather, and Crop Data

District data. District boundary data is taken from IPUMS International (Minnesota Population Center., 2018). This contains the shapefiles for the first-level regional boundaries (*province*) and the second-level district boundaries (*kabupaten*) used in the IFLS. There were multiple district boundary changes and splits (see e.g. Bazzi & Gudgeon, 2016) between the first and last waves of the IFLS. Since the IPUMS data is harmonized so that the geographical unit of analysis stays consistent over time, some split districts are kept together or combined into a larger unit in order to maintain consistency. The district (the main unit of analysis) used throughout the paper is thus the IPUMS 'harmonised' district. I also use the subdistrict (*kecamatan*) level for estimating the predicted-harvest shock, which was derived from data from the Indonesian government's statistics service (Statistik & SIAK, 2019).

Climate data - SPEI. The primary weather variable I use is the Standardised Precipitation Evapotranspiration Index (SPEI), a drought index developed recently by Vicente-Serrano et al. (2010). Although most of the economic literature on weather shocks focuses solely on precipitation and temperature, this neglects other features of the climate that can affect the growing cycle of a plant. In particular, the impact of rainfall on crop cycles depends on *potential evapotranspiration* (the ability of soil to retain water), which is in turn affected by multiple features of the environment, including temperature, latitude, windspeed, the number of sunlight hours. SPEI is a rich index that combines all of these features. It has been shown to be a better predictor of crop yields than other climate indexes Beguería et al. (2014). The methodology behind the construction of the SPEI index is described in more detail in Vicente-Serrano et al. (2010) and Beguería et al. (2014).

The Global SPEI database (Beguería & Vicente Serrano, 2017) uses precipitation and potential evaporation data to calculate monthly SPEI estimates in grids of 0.5 latitude by 0.5 longitude (corresponding to grids of approximately 50km by 50km at the equator). Monthly SPEI data is available for all years from 1900 to 2015. The index is standardised to have a mean of 0 and a standard deviation of 1 within each grid cell over the entire historical period (1900 to 2015), so that positive SPEI indexes generally represent good climactic conditions for crop-growing relative to the historical average, while negative SPEI indexes represent conditions more likely to lead to drought relative to the historical average. The data is fitted to a log-logistic distribution and can be normalised to a number of different time scales (e.g. 1, 2, 4, 6, 12 months, etc.). Since I am interested in the effect of weather conditions primarily through its effects on agriculture, I choose a short time frame (1-month) the SPEI calculation, while also showing robustness of my main results to the 4-month SPEI seen in Harari & Ferrara (2018). This means the SPEI will reflect short- and medium-run changes in moisture conditions that will be relevant for the seasonal changes that are important for crop yields.

In order to calculate the monthly district-level SPEI, I match each district to all the grid-squares with which it overlaps. I then use a weighted average of SPEI for all the matched grid-squares, where the weights are proportional to the area of the square that overlaps with the district. For example, if exactly half of district A sits inside grid-square s_1, and the other half sits inside grid-square s_2, then the estimated rainfall in district A would be the (unweighted) arithmetic mean of the rainfall in squares s_1 and s_2.

My approach for calculating the district-level weather patterns is likely to be preferable to that seen in previous estimates from Indonesia (Maccini & Yang, 2009; Bharati & Chin, 2016). Maccini & Yang (2009) use data on the latitude and longitude of the *centroid* of each district to match each district to the nearest weather station, and then use monthly rainfall data from this station directly.[28] This measurement is likely to induce non-negligible measurement error; while the median distance between the district centroid and weather station in their sample period is only 14km, the 95th percentile is 70km and the maximum is approximately 230km. The main advantage of the approach that I take is that I make use of district shapefiles rather than just data on the district centroid. This means that I accurately account for the different shapes and sizes of each district when calculating district-level weather.

Climate data - rainfall and temperature. When developing the predicted harvest shock measure, I make use of precipitation and temperature data from SA-OBS dataset (van den Besselaar et al., 2017). This data is highly disaggregated at both temporal and geographical levels, with daily observations at the 0.25 latitude by 0.25 longitude grid level. I aggregate the gridded observations to the district (*kabupaten*) level in the same way as the SPEI data, as described above.

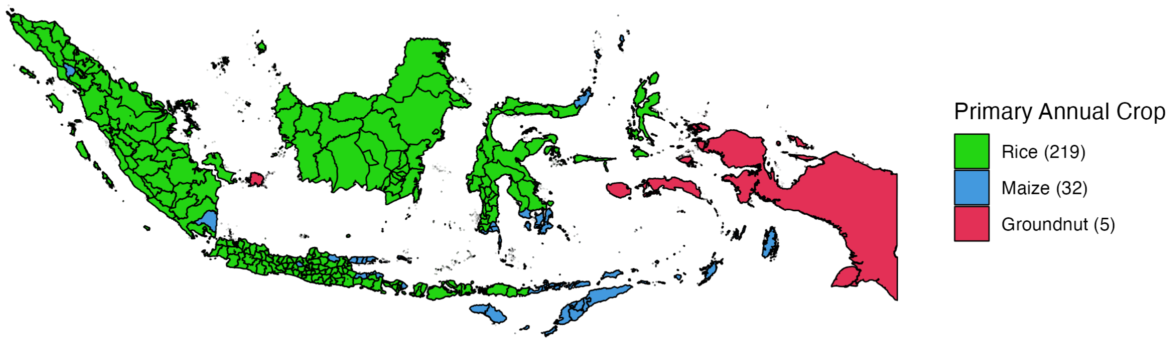
Aggregate crop harvest data. Crop harvested-area data comes from Monfreda et al. (2008), who combine national, state, and county level census data to create a global data set that describes the harvested area for 175 crops on a 5 minute by 5 minute (approximately 10km by 10km) grid, based on the closest available census data to the year 2000. Using this data, I calculate the primary annual crop in each district according to the total harvested area.[29] Figure A3 shows the primary annual crop in each district in the data. Rice is the primary annual crop for 219 out of 256 districts, with production particularly concentrated in many areas of Java. The primary annual crop for 32 districts is maize, and for 5 it is groundnut. The districts in which groundnut is the most harvested annual crop tend to have a lower proportion of harvested area overall, and since the IFLS sample is taken from the 13 provinces indicated above in the western areas of Indonesia, these areas are unlikely to be driving the results I show in the main body of the paper. For example, only 9 individuals in the IFLS sample were born in the large eastern island of Papua highlighted in green on the map.

Aggregate crop calendar data. In order to identify the aggregate-level primary grow-

[28] Their station-level rainfall data comes from Global Historical Climatology Network (GHCN) Precipitation and Temperature Data (Version 2) and the Badan Meterologi Dan Geofisika (BMG) agency in Indonesia.

[29] I exclude perennial crops such as oil palm from this calculation, since seasonal weather shocks are unlikely to affect production or yields.

Figure A3: *Primary Annual Crops (by harvested area) in each Indonesian district*



ing season in each district, I make use of crop calendar data from the University of Wisconsin-Madison's Nelson Institute (Sacks et al., 2010). This provides grid-cell level (0.5 x 0.5 degree) data for planting and harvesting dates of 19 different crops, including rice, maize, and groundnuts. I aggregate this to the district level by choosing the most common planting and harvesting dates over all the cells in the district.

A.3 SPEI growing season definition

Although growing season timings and crops vary across districts, some patterns are common across many districts. The main crop for the majority of districts in my final sample is rice (Figure A3). The majority of rice production occurs during the wet season, which typically takes place from around October to March in Indonesia (Food and Agriculture Organisation, 2005; Naylor et al., 2007) A secondary growing season for rice also occurs during the early dry season, but yields for this season are typically lower. I focus on the main growing season during the wet season for the rest of the paper.

Shock definition. In order to match individuals to shocks, I take the following steps, loosely following Maccini & Yang (2009). For individual i in year y:

1. Identify the district r that i was in during year y using the full migration history described above in Appendix Section A.1.

2. Identify the plant and harvest dates of the main crop in district r.

3. If i was born before the harvest date of y, assign i to the growing season in $y - 1$. If i was born after the harvest date of y, assign i to the growing season in y.

4. Generate $SPEI_{iy}$ as the average SPEI over the assigned growing season in region r.

This shock definition is based on the assumption that weather patterns during the growing season affect agricultural income at harvest time, meaning that the effects of the shock will be felt only after harvest. Individuals are therefore matched to the growing season of the most recent harvest.

B Construction of indexes

As discussed in Section 2.3, I use a latent factor model in the style of Cunha et al. (2010) to combine data from multiple measures of skills to a lower-dimensional set of traits. The latent factor model explicitly allows for measurement error and combines data from multiple measures in order to mitigate the problem of measurement error on psychological variables.

I carried out an exploratory factor analysis (EFA) exercise on the cognitive measures and the socioemotional measures used as outcomes. The EFA process used was similar across all of these measures. The process is described in detail throughout the rest of this section.

For the outcomes and mediation measures of interest, I took the following five steps to carry out the exploratory factor analysis:

1. Correct survey responses for acquiescence bias (for socioemotional measures only).
2. Standardise measures by age (where required).
3. Determine the number of latent factors underlying the set of measured variables.
4. Estimate the factor loadings for each measure.
5. Use the factor loadings to generate factor scores for each individual in the survey

I describe each of these steps below. Note that for the cognitive and socioemotional outcome measures (only available in IFLS4 and IFLS5), I carried out separate factor analyses for each wave of the survey, so that there are two different factor structures, one for the questions contained in IFLS4 and one for the questions contained in IFLS5. For the mediation measures, I pooled data available from all waves in the analysis.

B.1 Correcting for acquiescence bias (socioemotional only)

Acquiescence bias (also known as "yay-saying") is the tendency of a respondent to agree (or disagree) with a statement from the survey enumerator, even if doing so results in contradictory responses that are intended to capture the same trait. For example, a biased respondent may be likely to agree with both the statement "I see myself as someone who is talkative" *and* with the statement "I see myself as someone who is reserved", even though the two responses contradict each other. The acquiescence bias may be especially problematic given the lower-middle income context in Indonesia; cross-country evidence using the Big 5 personality tests tend to show higher acquiescence bias in lower income settings (Rammstedt & Farmer, 2013), and Laajaj & Macours (2019) find evidence of systematic measurement error related to acquiescence bias among farmers in western Kenya, which is more severe among the less educated. Using exploratory factor analysis without correcting for such bias can lead to misleading results, including the emergence of a factor that is an artefact of the response bias rather than underlying socioemotional variation. Laajaj & Macours (2019) further show that correcting for acquiescence bias substantially improves the reliability of socioemotional constructs, so I follow them and Laajaj et al. (2019) in carrying out a correction that is common in the psychometric literature (Soto et al., 2008; Rammstedt & Farmer, 2013). The correction makes use of the fact that for some socioemotional traits, there are some questions that are positively-coded, and some that are reverse-coded, and so we can detect the acquiescence pattern for a given individual. I take the following steps to correct for acquiescence on all socioemotional outcomes that use a Likert scale:[30]

1. Reverse the reverse-coded items. For example, for a scale that goes from 1 to 5, 1 will be recoded as 5, 2 as 4, etc.
2. For every personality trait that has at least one reverse-coded item and one positively-coded item:
   (a) Take the average of the positively-coded items for each individual i.
   (b) Subtract from this the average of the reverse-coded items for the same individual i.
   (c) Divide this by two.
3. Calculate the overall acquiescence score AS_i for individual i by averaging over the differences for all personality traits calculated in step 2.
4. Correct individual i's raw scores for acquiescence bias by adding AS_i to every reverse-coded item, and subtracting AS_i from every positively-coded item.

These corrected socioemotional scores are then used in all the steps below.

[30]The 'Personality', 'Positive / Negative Affect', and 'Depression' modules used a Likert scale and had both positive and reverse-coded items. Because the phrasing of the Likert scale on each of these modules was different (see Table A1), it led to a very different pattern of response bias, and so I generated separate acquiescence scores for each module and made one acquiescence correction for each module. In other words, I carried out steps 1-4 separately for each module, treating each Big 5 personality trait as a different trait in step 2, positive/negative affect as a single personality trait, and depression as a single personality trait.

B.2 Age standardisation

IFLS respondents are measured at different ages in adulthood, and both cognitive and socioemotional measures may vary by age. Therefore in order to get comparable measures of cognitive and socioemotional skills across different age groups I need to carry out some form of age standardisation. To do this, I make an internal standardisation following Rubio-Codina et al. (2015). To do this, I first compute the age-conditional mean of the cognitive / socioemotional measure using the fitted values of the regression:

$$Y_i = \alpha + \mathbf{X}_i' \beta + \varepsilon_i \tag{3}$$

where Y_i is the raw cognitive / socioemotional measure, and $\mathbf{X}_i$ is a polynomial of order 6 in age. To calculate the conditional standard deviation, I take the estimated residuals from Equation 3, denoted $\hat{\varepsilon}_i$, and regress them on the second order polynomial of age (A_i):

$$\hat{\varepsilon}_i = \pi_0 + \pi_1 A_i + \pi_2 A_i^2 + \nu_i$$

The estimated conditional standard deviation is then:

$$\widehat{SD}_i = \sqrt{\hat{\pi}_0 + \hat{\pi}_1 A_i + \hat{\pi}_2 A_i^2}$$

The age-specific z-score is then the result of taking the raw score, subtracting the age-conditional mean, and dividing by the age-conditional SD, as in:

$$ZScore_i = \frac{Y_i - (\hat{\alpha} + \mathbf{X}_i' \hat{\beta})}{\widehat{SD}_i}$$

As noted in Rubio-Codina et al. (2015), this form of standardisation gives results that are qualitatively similar to internal standardisation using the typical method (which involves calculating Z-scores within age-specific categories). The advantage here is that the approach is less sensitive to outliers and to having few observations within an age category than the standard method.

B.3 Determining the number of factors

In order to determine the number of factors that should be extracted from the data, I make use of 4 commonly-used methods that suggest how many factors to extract. The methods are as follows:

1. *Kaiser's criterion* (Kaiser, 1958). This rule-of-thumb suggests retaining all factors with an eigenvalue of above 1. The intuition that underlies this is that factors should only be kept if they explain as much variance as the equivalent of one original variable. This tends to suggest retaining a low number of factors; newer literature often suggests using a threshold value of 0.7 instead. I show results for both.

2. *Scree plot* (Cattell, 1966). This test is based on visual inspection of a plot of eigenvalues associated with the data. The proposed number of factors is equal to the number of factors before the 'elbow' of the scree plot; that is, the number before the which the smooth decrease of eigenvalues appears to level off towards the right of the plot.

3. *Minimum Average Partial (MAP)* (Velicer, 1976). This rule chooses the number of factors that minimises the unexplained partial correlation. The procedure iterates as follows. For $r = 1$, we run a full factor analysis with one factor, partial out this factor from the correlation matrix of the variables of interest, and calculate the average squared coefficient in the off-diagonals of this partial correlation matrix. Then, for $r = 2$, we run a similar process in which we partial out two factors, and calculate the average squared off-diagonal from the resulting matrix. This process is repeated up until $r = K - 1$ where K is the number of measurements. The recommended number of factors r^* is the value of r that minimises the average squared partial correlation. The intuition behind this process is that components are retained as long as the variance in the correlation matrix represents systematic variance. They are dropped when there is proportionately more unsystematic variance than systematic variance (see Attanasio, Cattan, et al., 2020, Appendix p. 15).

4. *Parallel Analysis* (Horn, 1965). Horn's test involves a Monte-Carlo procedure in which we simulate uncorrelated normal random variables of the same dimension as the actual data of interest. The eigenvalues derived from the actual data are then compared to the eigenvalues from the randomly generated data, and factors are kept if the eigenvalue is greater than the 95th percentile from the simulated data.

Cognitive and socioemotional. I carry out each of these methods first for all cognitive measures, and then for all socioemotional measures. All methods recommended one factor for cognitive measures in both IFLS4 and IFLS5. Table B1 shows the recommendation of the number of factors using each method for socioemotional measures. Each different method tends to give different recommendations, so some judgement is required in deciding how many factors to retain. Ledesma et al. (n.d.) suggest that Velicer's MAP criterion and Horn's Parallel Analysis tend to be more reliable, so the number of factors I retain for analysis is the number most commonly recommended from all the methods, with more weight placed on the parallel analysis and MAP criteria. Since there were fewer socioemotional questions asked in IFLS4 than in IFLS5 (see Table A1 for details), I expect there to be fewer factors for IFLS4; the fact that all methods suggest a smaller number pf factors in IFLS4 reflects this. For

IFLS4, the scree plot (see Fig. B1a), Kaiser criterion (1.0) and MAP all suggest that there is 1 factor. For IFLS5, the same set of methods suggest a value of 3 (see also Fig. B1b). In both cases, parallel analysis appears to overstate the number of latent factors. Based on this process, I retain 1 socioemotional factor for analysis in IFLS4, and 3 socioemotional factors in IFLS5.

I also carry out all of the above methods for each group of mediator variables that has three or more available measures (this therefore excludes parental education, which only has one measure). Based on the recommendations from each of the methods, I retain 2 factors for child health, 1 factor for early investment, 1 factor for parental health, and 2 factors for parental time use.

Table B1: *Recommendation of how many factors to retain from each method*

Method	IFLS4	IFLS5
Kaiser Criterion (1.0)	1	3
Kaiser Criterion (0.7)	2	4
Scree Plot	1	3
Parallel Analysis	8	17
Minimum Average Partial (MAP)	1	3
Retained for Analysis	1	3

Notes: Scree plots for each IFLS wave can be seen in Figures B1a and B1b. Each method recommends fewer factors for IFLS4 than IFLS5 because IFLS4 contains fewer socioemotional questions than IFLS 5 (see Table A1 for details).

B.4 Estimating the factor analysis model

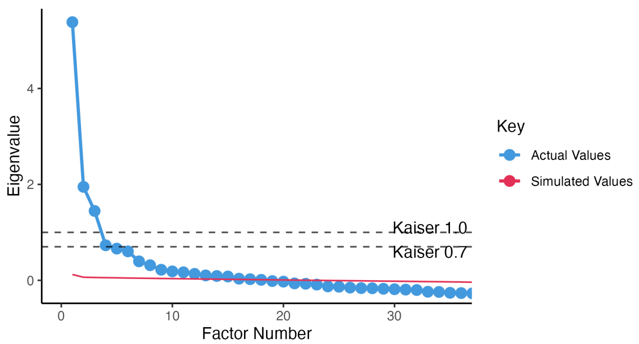
After identifying how many factors should be used in the factor analysis, I run an exploratory factor analysis (EFA) on measures (which have been corrected for acquiescence bias where relevant and age-standardised). The EFA estimates factor loadings by minimising the squared residuals[31], and then carries out a factor rotation that ensures that each measure primarily loads onto a single factor. I use an *oblimin* rotation to rotate factors; this has the advantage of being an *oblique* rotation rather than *orthogonal*, meaning that I do not have to make the strong assumption that factors are uncorrelated[32]. The aim of the rotation is to identify measures that primarily load onto a single factor, which can then be used as a 'dedicated' measure for that factor. Measures that load onto more than one factor, or onto no factors, will not be used in the measurement system.

[31] This has been shown to give unbiased estimates of factor loadings in the context of ordinal variables such as those used here, see Lee et al., 2012.

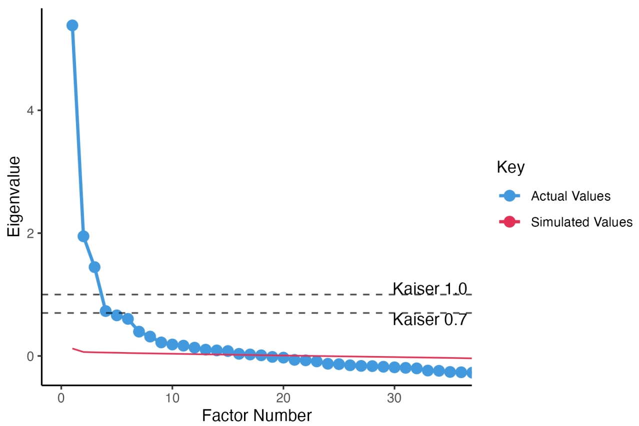
[32] This follows recent literature that also use oblique rotations, see Laajaj & Macours, 2019, Attanasio, Cattan, et al., 2020. Multiple methods for carrying out an oblique factor rotation are available, therefore as a robustness check I carried out the same exercise with both *geomin* and *quartimin* rotations and obtained similar results.

Figure B1: *Scree Plots for Exploratory Factor Analysis*

(a) *Socioemotional variables in IFLS4*



(b) *Socioemotional variables in IFLS5*



Notes: 'Actual values' denotes the eigenvalues from the true data. 'Simulated values' (in red) denotes the values from the 95th percentile of the randomly generated uncorrelated normal variables. The black horizontal dashed lines indicate the threshold points for the Kaiser criteria (1.0 and 0.7), and the solid black marks indicate possible positions for the 'elbow' of the scree plot in Cattell (1966).

Table B3 shows the factor loadings for the socioemotional measures available in IFLS5, and Table B4 shows the factor loadings for the socioemotional measures available in IFLS4. Following standard practice in the psychometric literature (Rammstedt & Farmer, 2013; Attanasio, Cattan, et al., 2020), I deem a measure to 'load' on a factor if the (absolute value of the) factor loading is greater than 0.3, and have highlighted cells in Tables B3 and B4 where the value meets this condition.

The factor loadings seen in Table B3 shows that the underlying latent variables coincide relatively closely with the survey modules in which they are used, and thus permit a clear interpretation for each factor (see Table B2) Factor 1 is loaded on strongly by all the questions in the Positive/Negative Affect (PNA) module, along with the two Subjective Well-being questions and the question from the Depression module relating to whether the individual felt happy in the last week. This factor can therefore be broadly interpreted as a measure of affect and well-being. Factor 3 has a similarly straightforward interpretation, being composed of all depression measurements apart from 'Everything was an effort', which does not load strongly (less than 0.3) on any factor. The factor loadings for the single factor in IFLS4 (Table B4) closely accord with the factor loadings of Factor 3 in IFLS5, with all depression measures loading except 'Everything was an effort'. This implies that the factor structure here is congruent across the two time periods and populations.

Table B2: *Dominant interpretation of each factor*

Factor	Wave	Interpretation
Factor 1	IFLS4	"Depression"
Factor 1	IFLS5	"Affect / Wellbeing"
Factor 2	IFLS5	"Personality"
Factor 3	IFLS5	"Depression"

Notes: Primary interpretations for each factor, based on the factor loadings seen in Tables B3 and B4

The factor loadings on Factor 2 in the personality module are less easily interpretable, as they do not conform with the 5-factor factor structure aligned with the "Big 5" personality traits. This result is in keeping with Laajaj & Macours (2019) and Laajaj et al. (2019), who show that factor structures tend to deviate from the Big 5 in low income contexts. The personality measures load onto a single factor, with the most consistent loadings coming from the *agreeableness*, *conscientiousness*, and *openness* traits, all of which have loadings around or above 0.3. Measures of *extroversion* and do not consistently load on Factor 2, despite a particularly strong factor loading for 'Extraversion - Outgoing' (0.543).

Notably, measures of risk and time preferences do not load onto any factor in either survey wave. This implies that such measures are subject to severe measurement error and would lead to misleading results if used as an outcome variable. This is in keeping with evidence that suggests self-reported responses for such measures that involve no real money at stake (unlike experimental measures of risk aversion or patience) tend to be highly unreliable (Binswanger, 1980; Chuang & Schechter, 2015).

There is little evidence of acquiescence bias in the socioemotional factor loadings: there is no discernible pattern where only reverse-coded or positively-coded items load onto a factor. Given that such patterns were observable when I ran the factor analysis without acquiescence correction (not shown), this implies that the acquiescence correction described above is effective. Notably when looking at the interpretations of Factors 1 and 2, very similar questions appear to load on different factors depending on the module they are in. For example, both the Positive-Negative Affect (PNA) and the Depression modules ask if the individual was lonely, but the measurements do not load on the same factor. There may be two main reasons for this. First, we may be worried that the responses to similar questions in different modules are biased in different ways due to changes in response pattern, possibly due to the different scales used, or the fact that the Depression module comes significantly later in the survey than the PNA module. This worry is mitigated somewhat by the acquiescence correction, which accounts for the proportion of bias that is due to "yay-saying". Alternatively, the difference could be due to the change in temporal scope in each module. In other words, since the PNA module asks about feelings yesterday, while the Depression module asks about feelings over the past week (see Table A1), respondents could give justifiably different answers. This consideration is confused somewhat by the fact that the subjective well-being questions (that target longer-term cognitive evaluation of happiness) tend to load alongside the short-term affect questions rather than the medium-term depression questions. One possible explanation may be that the long-term subjective well-being questions are interpreted by respondents as an evaluation of short-term happiness; this type of problem is well known in the literature on measuring well-being (see e.g. White, 2018; Benjamin et al., 2020).

Whichever explanation is true, the considerations above point towards the importance of running a factor analysis exercise on socioemotional measures, rather than naively interpreting each question to be measuring the trait it is nominally intended to measure. If the answer to a question about loneliness is so affected by seemingly extraneous factors such as the phrasing of the question or the position within the model, then the answer to such a question should not be taken 'at face value'. Instead, it is better to assume that it is a proxy for some underlying latent factor, and that this factor can in turn be recovered from multiple proxy measures. Nevertheless, we must be equally wary in interpreting the latent factors themselves: even though they are designed to pick up true variation (instead of measurement error), this true variation may still be at least partly due to seemingly extraneous factors like survey design and response biases, and so should be interpreted with caution.

Table B5 shows the cognitive factor loadings for IFLS4, and Table B6 shows the cognitive factor loadings for IFLS5. In both waves, all the cognitive measures load onto the same single factor, implying that this factor can be clearly interpreted as measuring cognitive ability. The written tests (Raven, Written Maths, and Number Series), have higher loadings in both waves than the oral tests (Word Recall and Oral Maths), suggesting that these capture more of the variation in the latent cognitive factor. Overall, the loadings for cognitive a clear interpretation of a single cognitive factor that is in keeping with previous literature Laajaj & Macours (2019).

B.5 Generating factor scores

I use the factor loadings from Tables B3–B6 to generate factor scores for each individual i. These factor scores represent the 'value' of that factor for each individual i. In order to generate the factor scores for factor k I carry out the following steps:

1. Assign each question to 'load' on factor k if and only if the (absolute value of) the factor loading is greater than or equal to 0.3 (following standard practice in the psychometric literature, see Rammstedt & Farmer, 2013; Attanasio, Cattan, et al., 2020). All other questions have their factor loadings set to 0.

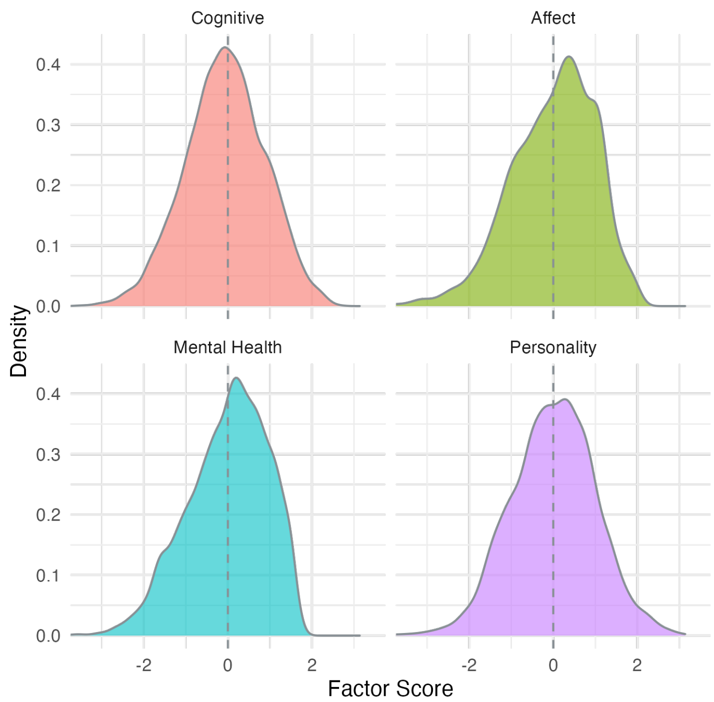
2. For each individual i, take a weighted mean of the questions that load onto factor k, where the weights correspond to the loadings obtained in Tables B3, B4, B5 and B6.

3. Standardise the factor scores so that each factor has a mean of 0 and a standard deviation of 1.

Using this method to obtain factor scores ensures that questions are only kept if they clearly load onto a particular factor, while questions with particularly weak loadings (such as the questions on risk and time preferences) are not included in the factor scores. Step 3 ensures that the factor scores are clearly interpretable. For example, if individual i has a factor score of 1 on Factor 2 ("Personality") in IFLS5, this means that her non-cognitive personality skills are 1 standard deviation above the sample mean.

The process described here generates a separate factor scores in each wave for the two outcome factors that are measured in both IFLS4 and IFLS5 (depression and cognitive).[33] The factor structures for these factors is strikingly similar across waves. I therefore construct the final outcome variables used in the main part of the paper by combining measurements across waves, in particular by taking a simple arithmetic mean of the factor score in IFLS4 and the factor score in IFLS5 for any individuals who were measured in both waves. The distribution of the finalised factor scores among my main sample are shown in Figure B2. By construction, all the distributions are centred around 0, and they all appear to be approximately symmetrical.

Figure B2: *Kernel density of each of the factor scores*



B.6 Measures of noise

Table B7 estimates two proxies for the amount of noise in each of the outcome variables, to act as a proxy for the likely degree of measurement error. First, I test for the correlation between the outcome for a given individual in 2008 and for the same individual in 2015. I can only calculate this measure for cognitive and depression scores, since these were the only outcomes available in 2008. The correlation is 0.52 for cognitive, suggesting strong correlation over the 7 year period. It is much lower for depression (0.15), which could be because this variable is measured with more error or simply because it varies more over time.

Second, I calculate the average inter-item correlation by taking the pairwise correlation between every measure used in an index, and then taking the mean for every pair.

[33]Mediator variables, on the other hand, are already combined across waves as described in Step 2.

Table B3: *Socio emotional factor Loadings for IFLS5*

Module	Question	Factor 1	Factor 2	Factor 3
Positive / Negative Affect	Frustrated (-)	0.607	-0.004	0.005
Positive / Negative Affect	Sad (-)	0.694	-0.021	-0.011
Positive / Negative Affect	Enthusiastic	0.332	0.041	0.008
Positive / Negative Affect	Lonely (-)	0.519	-0.017	0.046
Positive / Negative Affect	Content	0.632	-0.028	-0.034
Positive / Negative Affect	Worried (-)	0.467	0.005	0.039
Positive / Negative Affect	Bored (-)	0.594	0.087	-0.052
Positive / Negative Affect	Happy	0.557	0.020	0.025
Positive / Negative Affect	Angry (-)	0.581	0.030	0.007
Positive / Negative Affect	Tired (-)	0.363	0.028	-0.040
Positive / Negative Affect	Stressed (-)	0.673	-0.007	-0.027
Positive / Negative Affect	Pain (-)	0.301	0.000	0.026
Subjective Wellbeing	Assessment of current situation	0.365	0.008	0.029
Subjective Wellbeing	Life satisfaction (Cantrill ladder)	0.346	0.021	-0.019
Mental Health	Bothered (-)	0.089	-0.023	0.422
Mental Health	Concentration (-)	0.091	0.043	0.456
Mental Health	Depressed (-)	0.206	-0.038	0.511
Mental Health	Everything was an effort (-)	0.182	-0.011	0.198
Mental Health	Hopeful	-0.191	0.011	0.726
Mental Health	Fearful (-)	0.108	0.067	0.446
Mental Health	Restless sleep (-)	0.159	0.037	0.363
Mental Health	Happy	0.444	0.013	0.321
Mental Health	Lonely (-)	0.071	-0.024	0.495
Mental Health	Couldn't get going (-)	0.063	0.061	0.440
Personality	Agreeableness - forgiving	-0.001	0.534	-0.017
Personality	Agreeableness - considerate and kind	-0.032	0.608	-0.031
Personality	Agreeableness - rude (-)	0.020	0.386	-0.024
Personality	Conscientiousness - thorough	0.026	0.480	0.038
Personality	Conscientiousness - lazy (-)	-0.004	0.429	-0.039
Personality	Conscientiousness - efficient	0.050	0.290	0.072
Personality	Extroversion - talkative	-0.008	0.097	0.003
Personality	Extroversion - reserved (-)	-0.030	0.163	0.053
Personality	Extroversion - outgoing	0.014	0.543	0.005
Personality	Neuroticism - relaxed	0.071	0.295	0.098
Personality	Neuroticism - worries (-)	0.130	0.103	0.170
Personality	Neuroticism - gets nervous (-)	0.063	0.288	0.049
Personality	Openness - original	0.007	0.405	0.043
Personality	Openness - active imagination	-0.040	0.280	0.043
Personality	Openness - artistic and aesthetic	-0.031	0.392	0.016
Risk/Time Preferences	1 year time tradeoff	-0.025	0.008	0.033
Risk/Time Preferences	5 year time tradeoff	-0.004	0.009	0.009
N				5267

Notes: Cells highlighted in blue have an absolute value of greater than 0.3. '(-)' denotes a reverse-coded item.

Table B4: *Socio emotional factor Loadings for IFLS4*

Module	Question	Factor 1
Mental Health	Bothered (-)	0.635
Mental Health	Concentration (-)	0.533
Mental Health	Depressed (-)	0.613
Mental Health	Everything was an effort (-)	0.284
Mental Health	Hopeful	0.463
Mental Health	Fearful (-)	0.494
Mental Health	Restless sleep (-)	0.457
Mental Health	Happy	0.543
Mental Health	Lonely (-)	0.618
Mental Health	Couldn't get going (-)	0.634
Subjective Wellbeing	Assessment of current situation	0.243
Risk/Time Preferences	1 year time tradeoff	-0.035
Risk/Time Preferences	5 year time tradeoff	-0.042
N		2242

Notes: Cells highlighted in blue have an absolute value of greater than 0.3. '(-)' denotes a reverse-coded item.

Table B5: *Cognitive Factor Loadings (IFLS4)*

Module	Question	Factor 1
Cognitive	Raven (15-24)	0.573
Cognitive	Maths - written (15-24)	0.533
Cognitive	Word recall	0.402
N		3083

Notes: Cells highlighted in blue have an absolute value of greater than 0.3.

Table B6: *Cognitive Factor Loadings (IFLS5)*

Module	Question	Factor 1
Cognitive	Raven (15-24)	0.536
Cognitive	Maths - written (15-24)	0.545
Cognitive	Word recall	0.394
Cognitive	Maths - oral	0.380
Cognitive	Number series	0.603
N		8003

Notes: Cells highlighted in blue have an absolute value of greater than 0.3.

This indicates how interrelated the items in an index are, and therefore how likely they are to reliably measure the construct that they are intending to measure. The correlation takes a value of between 0.24 and 0.28 for cognitive, affect/wellbeing, and depression. This is between the recommended range of 0.15 and 0.5 (Clark & Watson, 1995). Personality has a lower inter-item correlation of 0.13, suggesting higher measurement error and possibly lower construct validity.

Table B7: *Indicators of noise*

Measure	Cognitive	Affect/Wellbeing	Personality	Depression
$corr(Y_{2008}, Y_{2015})$	0.52	-	-	0.15
N	2424			1593
Average inter-item correlation	0.24	0.26	0.13	0.28
N	7109	4964	4956	7090

Notes: $corr(Y_{2008}, Y_{2015})$ denotes the correlation between the measure for a given individual in 2008 and the same measure in 2015. This correlation is only available for cognitive and mental health scores. Average inter-item correlation denotes the mean of every pairwise correlation in the set of measures used in that index.

B.7 Investment indexes

The variables used in the investment indexes are constructed in a similar way to the cognitive and socioemotional scores. Age standardisation is performed as in Appendix Section B.2. Due to the small number of measures available, I assume that the nutrition variables constitute one index and the parental time measures constitute another and use Anderson (2008)'s invariance-covariance-weights to construct indexes, rather than performing an exploratory factor analysis and generating indexes based on the factor loadings. Table B8 shows the weights on each measure when constructing the indexes.

Table B8: *Inverse Covariance Weights for Investment Indexes*

Index	Measure	Inverse covariance weight
Nutrition index	Food frequency	0.353
	Vitamin A frequency	0.381
	Iron frequency	0.266
Parental time index	Primary activity is earning (mother)	0.247
	Total weekly hours spent working (mother)	0.195
	Primary activity is earning (father)	0.266
	Total weekly hours spent working (father)	0.292

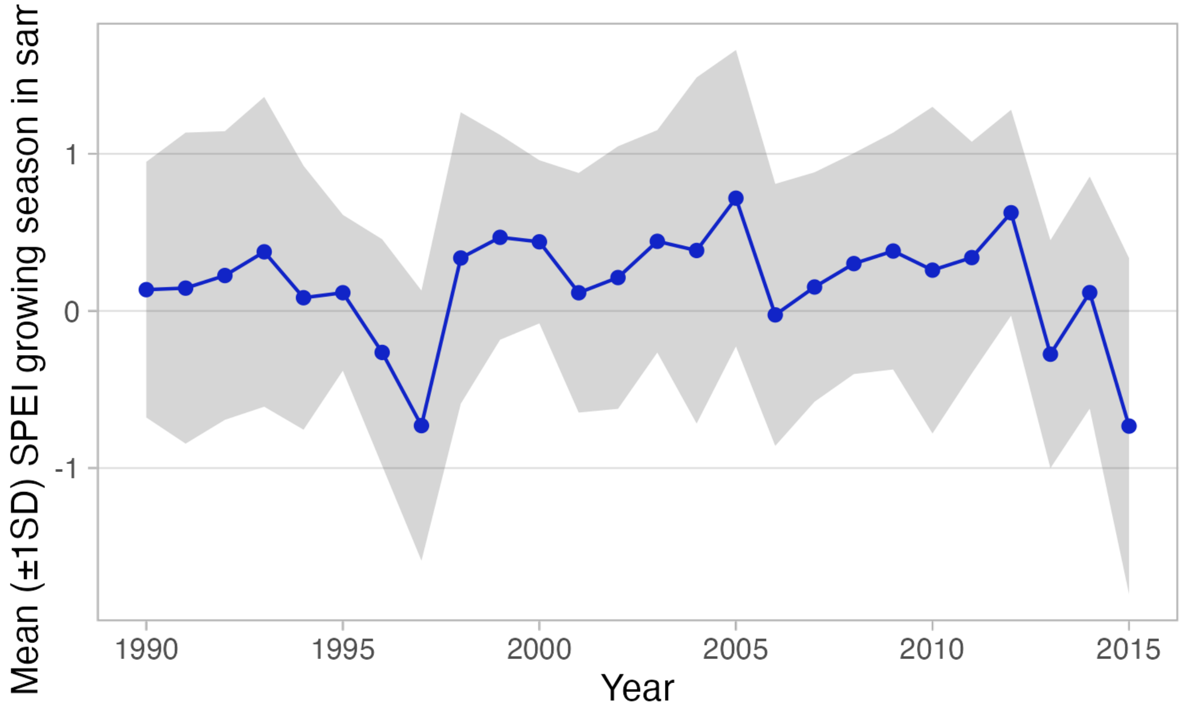
C Descriptive statistics

Table C1: *Summary Statistics - Main Sample*

Statistic	N	Mean	St. Dev.	Min	Median	Max
Factor score - cognitive	5572	0.00	1.00	−3.75	0.005	2.90
Factor score - affect/wellbeing	4956	−0.00	1.00	−4.35	0.13	2.05
Factor score - personality	4956	−0.00	1.00	−3.96	0.03	3.14
Factor score - depression	5565	0.00	1.00	−4.35	0.11	1.79
Born during the growing season (=1)	5572	0.48	0.50	0	0	1
SPEI growing season in t - 2	5572	−0.06	0.88	−3.33	−0.002	2.95
SPEI growing season in t - 1	5572	0.02	0.90	−3.37	0.09	3.01
SPEI growing season in t	5572	0.05	0.88	−3.20	0.12	3.01
SPEI growing season in t + 1	5572	0.06	0.87	−3.33	0.15	2.57
SPEI growing season in t + 2	5572	0.09	0.85	−3.20	0.17	2.57
SPEI growing season in t + 3	5572	0.16	0.87	−3.20	0.25	2.57
SPEI growing season in t + 4	5572	0.13	0.86	−3.03	0.21	2.57
SPEI growing season in t + 5	5572	0.16	0.92	−3.03	0.23	3.05
SPEI growing season in t + 6	5572	0.17	0.91	−2.90	0.27	3.05
SPEI growing season in t + 7	5572	0.17	0.89	−3.03	0.23	3.05
SPEI growing season in t + 8	5572	0.18	0.91	−2.90	0.22	3.05
SPEI growing season in t + 9	5572	0.23	0.89	−2.96	0.26	3.05
SPEI growing season in t + 10	5572	0.33	0.81	−2.87	0.32	3.66
SPEI growing season in t + 11	5572	0.29	0.82	−2.90	0.26	3.65
SPEI growing season in t + 12	5572	0.32	0.85	−2.96	0.31	3.66
SPEI growing season in t + 13	5572	0.32	0.85	−2.96	0.33	3.66
SPEI growing season in t + 14	5572	0.27	0.87	−2.90	0.28	3.66
SPEI growing season in t + 15	5572	0.28	0.86	−3.10	0.30	3.66
Female (=1)	5572	0.53	0.50	0	1	1
Year of birth	5572	1993.17	3.57	1988	1993	2000
Highest level of parent eduction - elementary (=1)	5572	0.52	0.50	0	1	1
Highest level of parent eduction - junior High (=1)	5572	0.20	0.40	0	0	1
Highest level of parent eduction - senior High (=1)	5572	0.19	0.40	0	0	1
Highest level of parent eduction - university (=1)	5572	0.08	0.28	0	0	1
Religion - muslim (=1)	5572	0.90	0.30	0	1	1
Religion - protestant (=1)	5572	0.04	0.19	0	0	1
Religion - hindu (=1)	5572	0.05	0.22	0	0	1
Religion - other (=1)	5572	0.01	0.11	0	0	1

Notes: Descriptive statistics for the "Main Sample" (row 1 in Table 2). This sample is at the individual level. Individuals who were born after 1988 were only tracked after moving household if they were part of the original sample from the first IFLS wave (1993), but will be missing if they were added in a later wave and moved households since IFLS4. Since Affect/Wellbeing and Personality were only measured in the 5th wave of IFLS (in 2015), any members interviewed only in IFLS4 (in 2007) have missing values for these variables. Therefore N is only 4956 for these factors.

Figure C1: *SPEI growing season over each year*



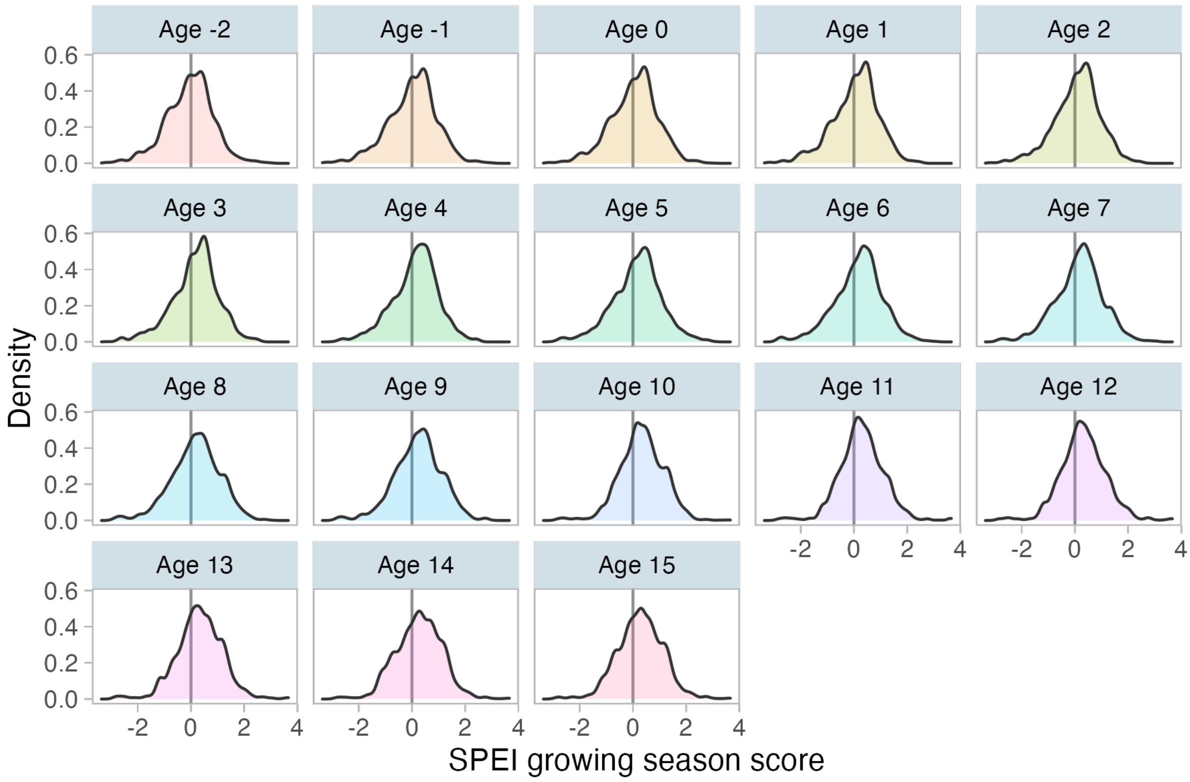
Notes: This shows the yearly mean and ±1 SD shaded intervals for the value of SPEI growing season experienced in each year for the individuals in the main sample. A negative spike is seen in 1997, which was when severe drought struck much of Indonesia.

Table C2: *Correlation between SPEI growing season at different ages in the main sample*

	Age -2	Age -1	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8	Age 9	Age 10	Age 11	Age 12	Age 13	Age 14	Age 15
Age -2	1.00	0.11	-0.02	0.06	0.02	0.03	0.05	0.07	-0.06	-0.03	0.14	0.09	0.14	-0.03	0.05	0.08	-0.01	0.04
Age -1	0.11	1.00	0.13	0.02	0.07	0.02	0.04	0.04	0.08	-0.07	-0.06	0.14	0.11	0.16	-0.01	0.09	-0.01	0.01
Age 0	-0.02	0.13	1.00	0.20	0.02	0.07	-0.02	0.04	0.04	0.07	-0.07	-0.03	0.10	0.13	0.18	-0.01	0.06	-0.08
Age 1	0.06	0.02	0.20	1.00	0.19	0.10	0.10	0.03	0.01	0.04	0.07	-0.06	0.04	0.05	0.17	0.19	0.00	0.07
Age 2	0.02	0.07	0.02	0.19	1.00	0.18	0.10	0.08	0.03	0.00	0.02	0.04	-0.11	0.05	0.05	0.19	0.15	0.01
Age 3	0.03	0.02	0.07	0.10	0.18	1.00	0.18	0.15	0.07	0.00	-0.01	0.00	0.02	-0.14	0.07	0.05	0.16	0.16
Age 4	0.05	0.04	-0.02	0.10	0.10	0.18	1.00	0.16	0.10	0.01	0.00	0.03	-0.08	0.00	-0.15	0.12	0.06	0.14
Age 5	0.07	0.04	0.04	0.03	0.08	0.15	0.16	1.00	0.17	0.04	-0.04	-0.02	0.09	-0.12	0.06	-0.10	0.04	0.10
Age 6	-0.06	0.08	0.04	0.01	0.03	0.07	0.10	0.17	1.00	0.09	-0.00	-0.01	-0.04	0.03	-0.06	0.11	-0.20	0.01
Age 7	-0.03	-0.07	0.07	0.04	0.00	0.00	0.01	0.04	0.09	1.00	0.11	-0.04	-0.04	-0.07	0.03	-0.03	0.12	-0.23
Age 8	0.14	-0.06	-0.07	0.07	0.02	-0.01	0.00	-0.04	-0.00	0.11	1.00	0.06	-0.03	-0.01	-0.07	0.02	-0.05	0.10
Age 9	0.09	0.14	-0.03	-0.06	0.04	0.00	0.03	-0.02	-0.01	-0.04	0.06	1.00	-0.02	0.01	-0.01	-0.07	-0.03	-0.05
Age 10	0.14	0.11	0.10	0.04	-0.11	0.02	-0.08	0.09	-0.04	-0.04	-0.03	-0.02	1.00	-0.03	0.09	0.04	-0.09	-0.07
Age 11	-0.03	0.16	0.13	0.05	0.05	-0.14	0.00	-0.12	0.03	-0.07	-0.01	0.01	-0.03	1.00	0.01	0.06	0.06	-0.05
Age 12	0.05	-0.01	0.18	0.17	0.05	0.07	-0.15	0.06	-0.06	0.03	-0.07	-0.01	0.09	0.01	1.00	-0.00	0.03	0.03
Age 13	0.08	0.09	-0.01	0.19	0.19	0.05	0.12	-0.10	0.11	-0.03	0.02	-0.07	0.04	0.06	-0.00	1.00	-0.02	0.02
Age 14	-0.01	-0.01	0.06	0.00	0.15	0.16	0.06	0.04	-0.20	0.12	-0.05	-0.03	-0.09	0.06	0.03	-0.02	1.00	0.01
Age 15	0.04	0.01	-0.08	0.07	0.01	0.16	0.14	0.10	0.01	-0.23	0.10	-0.05	-0.07	-0.05	0.03	0.02	0.01	1.00

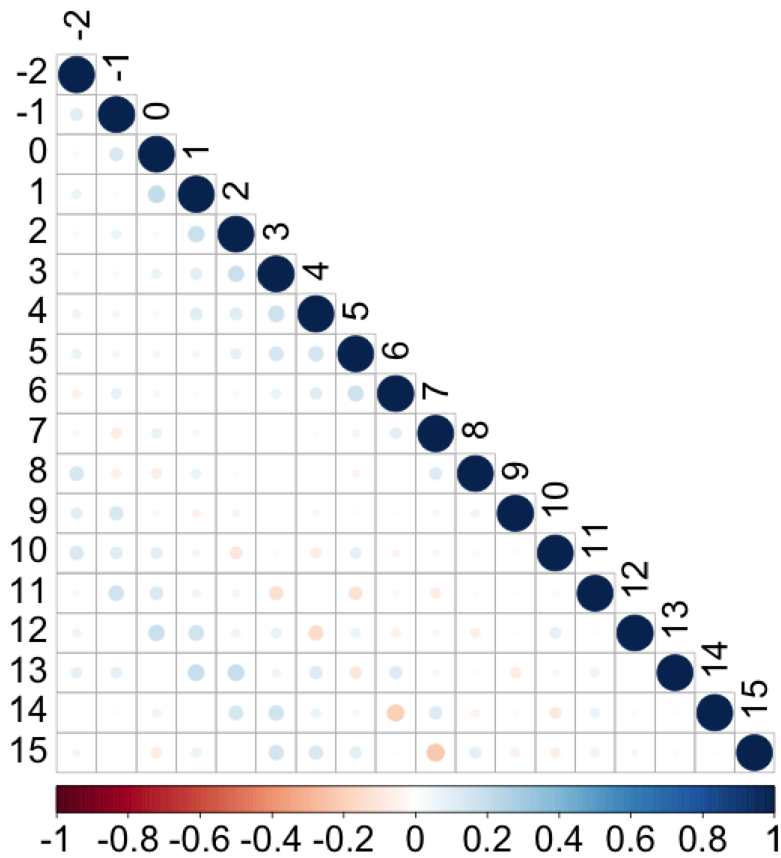
Notes: This is the correlation matrix for the values of SPEI growing season at different ages for individuals in the main sample. The x- and y-axes describe the age of the shock. The absolute value of the correlation between shocks in different periods is low, with no such correlation exceeding 0.2.

Figure C2: *The distribution of SPEI growing season is similar at each age*



Notes: This shows the distribution of shocks experienced at each age by individuals in the main sample. Notably, the distribution of shocks is very similar across ages, despite some "spikes" in the yearly variation seen in Figure C1. This is because individuals in the sample are born in different years.

Figure C3: *Correlation between SPEI growing season at different ages in the main sample*



Notes: This is a visual representation of Table C2, describing the correlation matrix for the values of SPEI growing season at different ages for individuals in the main sample. The x- and y-axes describe the age of the shock. The absolute value of the correlation between shocks in different periods is very low, with no such correlation exceeding 0.2.

D Construction of predicted harvest measure

To construct the predicted harvest index, I first take a number of climactic measures from the climatology literature that are likely to explain rice yields, and use them in as explanatory variables in a regression with rice yields from the IFLS data as an outcome.

D.1 Summary of process

To construct the predicted harvest index, I first take a number of climactic measures from the climatology literature that are likely to explain rice yields, and use them in as explanatory variables in a regression with rice yields from the IFLS data as an outcome. The explanatory variables include the SPEI index at two different periods (0-2 months before planting, and planting to harvest), along with growing degree days (a measure of heat exposure widely used to predict crop yield (Schlenker et al., 2006)), measures of rainfall (total rainfall and number of rainy days (May, 2004)), the length of the longest dry spell over the harvest season (Tebaldi et al., 2006), and the delay in the arrival of the wet season (Naylor et al., 2007). For a rice crop j farmed by household h in district r and in wave t, the estimating equation is:

$$IHS(RiceYield)_{jhrt} = \alpha + \sum_k \gamma_k WeatherRice_{jhrt,k} + \mathbf{X}'_{ht}\delta + \mathbf{Z}'_{jt}\lambda + \pi_r + \mu_t + \varepsilon_{jhrt} \quad (4)$$

$Weather_{jhrt,k}$ are the different weather-measure z-scores described above. $IHS(RiceYield)_{jhrt}$ is the inverse hyperbolic sine of the harvest yield, i.e. the harvest output in kg divided by the number of hectares of land harvested. The IHS specification allows me to include failed harvests, i.e. harvests with a yield of 0. $\mathbf{X}_{ht}$ is a vector of household controls that includes whether the household head is female and the religion of the household head. π_r are district fixed effects, and μ_t are wave fixed effects.

The results in Table D1 indicate that the main predictors of rice yields are (i) SPEI 0-2 months before average rice planting date, (ii) growing degree days over planting period, and (iii) wet season delay. Some models also show the longest dry spell to be significant. I use column (3) to construct a "predicted harvest index" for every year and district combination by taking the predicted value from this regression and normalising it to have mean 0 and standard deviation 1. The index can thus be thought of as a summary index for the weather features that predict high rice yields. show that using I use this predicted harvest index as an explanatory variable to complement the previous weather shock measure. I also use the models from columns (2) and (4)-(7) to construct alternative indexes that act as robustness checks for my results with the predicted harvest index. More details on the individual weather measures and the construction are given below.

Table D1: *Impact of different weather features on rice yields*

	IHS(harvest output / hectare)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Growing degree days (Z)	0.070	0.050**	0.040*	0.043*	0.036		0.040
	(0.048)	(0.025)	(0.024)	(0.025)	(0.024)		(0.024)
Wet season delay (Z)	−0.052**	−0.054**	−0.059**	−0.050**	−0.054**	−0.058**	
	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	
Longest dry spell (Z)	−0.062*	−0.041*		−0.026			
	(0.034)	(0.021)		(0.021)			
SPEI (0-2m before rice planting)	0.109***	0.116***	0.103**			0.099**	0.097**
	(0.040)	(0.039)	(0.040)			(0.040)	(0.040)
SPEI (rice planting to rice harvest)	−0.057						
	(0.061)						
Num. rainy days (Z)	−0.036						
	(0.092)						
Rain total (Z)	0.004						
	(0.068)						
Wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	9.079	9.079	9.079	9.079	9.079	9.079	9.079
F statistic	3.486	4.869	4.795	3.525	4.218	5.617	4.209
p-value for F-test	0.002	0.001	0.003	0.017	0.017	0.004	0.017
R^2	0.189	0.189	0.188	0.186	0.186	0.187	0.187
N	4653	4653	4653	4653	4653	4653	4653

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by district. The construction of each of the weather variables used is found in Appendix Section D. The dependent variable in all columns is the inverse hyperbolic sine transformation of rice harvest output (in kg) divided by the area harvested (in hectares). Rice production data is only available in the IFLS data in waves 4 and 5, corresponding to 2007 and 2015. All explanatory variables are standardised to have a mean of 0 and a standard deviation of 1 within each district over the period 1981-2015. Model (3) is the one that is used to construct the main predicted harvest index used in the paper. Other models are later used as robustness checks, with corresponding results presented in the Appendix. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

D.2 Weather definitions

In order to generate the richer set of weather measures, I use the following operational definitions:

- **Analysis year**. The analysis year starts on the 1st August, and finishes on 31st July the next year, following the approach seen in Naylor et al. (2007). The weather data available enable me to calculate measures for all the analysis years between 1981 and 2015.

- **Definition of start of wet season (yearly)**. The start of the wet season for a given district/subdistrict in a given analysis year is defined as the first day after August 1st that satisfies the following two conditions: (i) the cumulative rainfall for that analysis year is greater than 20cm (as in Naylor et al. (2007)); and (ii) the day is followed by at least 4 more consecutive rainy days (i.e. days with at least 0.1mm of rainfall), similar to the strategy seen in Macours et al. (2022).

- **Definition of end of wet season (yearly)**. The wet season is the first date for which at least 90% of cumulative rainfall in that analysis year has fallen, as in Naylor et al. (2007).

- **Average harvest/plant date**. For each district/subdistrict, I use the data on rice farming from IFLS4 and IFLS5 to calculate the average day on which rice is planted and harvested. To do this, I assign a given rice crop to be in the wet season if it was harvested earlier than the day that lies 2 months after the average end of the wet season (said average being taken over all years in that district/subdistrict). I then calculate the average harvest date for all crops in a given district/subdistrict that were assigned to the wet season.

D.3 Raw weather measures

Here I describe the weather measures used to predict rice yield, and then as inputs to the predicted harvest measure.

The following measures are calculated at two different levels. For the rice crops, I have more detailed location data, and so can calculate weather measures at the *kecamatan* (subdistrict) level. I generate a number of measures denoted as $WeatherRice_{jhrt,k}$, where j is a rice crop farmed by household h in subdistrict r and in survey-wave t, and $k = \{1, 2, ..., K\}$ denote the different weather measures. For individuals' historical shocks, I am only able to calculate weather measures at the *kabupaten* (district) level. To do this I calculate measures denoted as $WeatherDistrict_{ry,k}$, where r is the district, y is the analysis year, and k denotes the different measures. I use these to then calculate a series of shocks for each individual over their life-course based on the monthly-migration history constructed from the IFLS data.

- **Wet season delay**. The average wet season start is calculated by taking the number of days after 1st August for the start of the wet season in every year in the data, and then taking the mean of this value. "Wet season delay" is then calculated as the difference between the wet season start for that year relative to the district/subdistrict average over all years. Since rice planting decisions are typically based on reaching a set threshold of accumulated rainfall, a delay in the monsoon rains can delay rice planting and reduce yields (Maccini & Yang, 2009). Naylor et al. (2007) demonstrate that delays in the monsoon rains of 30 days or more in Java and Bali can have significant negative impacts on rice production during the main rice harvest season.[34]

  Rice crops are assigned to a given analysis year by assigning them to the most recent year for which the rice crop was planted *later than* the day lying exactly 2 months before the average start of the rainy season (in order to allow for variation in rice planting due to yearly variation in the start of the season.)

- **SPEI (0-2m before planting)**. This is the average SPEI index calculated over $\{0, 1, 2\}$ months before planting. This time window is likely to be important because there needs to be sufficient moisture before and around planting time in order to prepare the land for cultivation and to facilitate the early rooting of transplanted seedlings. However, excessive water at the vegetative growth stage soon after planting can hamper rooting and reduce yields (De Datta, 1981; Naylor et al., 2007).

- **SPEI (during growing)**. This is the mean SPEI index between the month after planting and the month of harvest. For rice crops this measure is calculated relative to the actual plant date of the crop measured, while for the individual/historical measure it is calculated relative to the average plant date of that district/subdistrict.

For all the following measures, they are defined in slightly different ways when applied to rice crops and when applied to individuals, given the differing data available for each observation type. When applying to rice crops, the measures are calculated using daily data from between the planting date *of that crop*, and the harvest date *of that crop*. Such a calculation is not possible when looking at the weather shocks experienced by individuals throughout their life course; instead, the measures are calculated using daily data from between the start and the end of the wet season for each year.

- **Growing degree days**. Following the climate change literature, growing degree

[34] For example, they show that a 30-day delay causes rice production between January and April to fall by an average of 11% in East Java / Bali, and by 6.5% in West/Central Java.

days are constructed using the number of days with temperature within certain bounds, i.e. according to the following function:

$$g(x) = \begin{cases} 0 & \text{if } x < DD_{min} \\ x - DD_{min} & \text{if } DD_{min} < x < DD_{max} \\ DD_{max} - DD_{min} & \text{if } x > DD_{max} \end{cases}$$

where x is the temperature on a given day, $DD_{min} = 8°C$ and $DD_{max} = 32°C$. The growing degree days measure is then calculated as the sum of the $g(x)$ measure for the relevant date ranges outlined above. Such a measure is commonly used in the climate change and agronomy literature as a measure of heat exposure that predicts crop yields in a wide variety of contexts (Schlenker & Roberts, 2006; Schlenker et al., 2006; Ritchie & Nesmith, 2015; Fishman, 2018).

- **Rain total**. Rain total is the sum of daily rainfall in mm, calculated over the relevant date ranges outlined above.
- **Number of rainy days**. The number of rainy days is the total number of days for which rain was greater than 0.1mm within the relevant date ranges outlined above. This measure is commonly used in the climate change literature, and, when included alongside the total rainfall, can be interpreted as a measure of the variability of daily rainfall *within* a rainy season (Fishman, 2016, 2018; May, 2004).
- **Longest dry spell**. The length in days of the longest dry spell (calculated as consecutive days with no rain (<0.1mm)), calculated over the relevant date ranges outlined above. This measure is also used in the climate change literature and captures a type of intraseasonal variability in rainfall that is correlated with droughts and crop stress (Fishman, 2016, 2018; Tebaldi et al., 2006).

All the above weather measures are then standardised at the district/subdistrict level by taking the deviation from the average and dividing by the standard deviation. These standardised measures are taken over the entire period for which data is available (1981 to 2015), and exclude the year for which the z-score is being calculated.

D.4 Construction of predicted harvest measure

I use the results in Table D1 to construct a predicted harvest index $PredHarvest_{ry}$ for each district r and analysis year y in the following way:

$$PredHarvest_{ry} := W'_{ry}\hat{\gamma} \tag{5}$$

where W_{ry} denotes the vector of weather variables defined at the district $\times$ year level seen in Table D1, and $\hat{\gamma}$ is the vector of predicted coefficients on the weather variables seen in Table D1. In the main specification (based on column (3)), $W_{ry} \in \mathbb{R}^3$ includes Growing Degree Days (Z), Wet Season Delay (Z), and SPEI measured 0-2 months before rice planting.

E Empirical specification for timing

E.1 *Contemporaneous timing tests*

In Sections 5.1 and 5.2 I test for the timing of the impact of weather variation on contemporaneous investments and expenditure using the specification described in this section. I define two 6-month periods during the year.[35] Let $\mathbb{1}\{AfterHarvest\}_{iry}$ be an indicator such that:

$$\mathbb{1}\{AfterHarvest\}_{iry} := \begin{cases} 0 & \text{when investment in } i \text{ is measured between 3 months before} \\ & \qquad \text{harvest and 2 months after (inclusive)} \\ 1 & \text{when investment in } i \text{ is measured between 3 and 8 months} \\ & \qquad \text{after harvest (inclusive)} \end{cases}$$

Using this variable I can run the following empirical specification that allows for a more granular test of timing at the 6-monthly level:

$$\begin{aligned} I_{iry} = \alpha + \beta_0 Weather_{ry} + \beta_1 Weather_{r,y-1} + \delta \cdot \mathbb{1}\{AfterHarvest\}_{iry} \; + \\ (\gamma_0 \cdot \mathbb{1}\{AfterHarvest\}_{iry} \cdot Weather_{ry}) \; + \; (\gamma_1 \cdot \mathbb{1}\{AfterHarvest\}_{iry} \cdot Weather_{r,y-1}) \\ + \; \pi_r + \mu_y + \varepsilon_{iry} \end{aligned} \tag{6}$$

Using the appropriate sums of the coefficients $\beta_0, \beta_1, \gamma_0,$ and γ_1 I can calculate the effect of yearly weather variation when measured in 4 six-month windows relative to the harvest, namely -3 to 2, 3 to 8, 9 to 14, and 15 to 20 months after harvest.[36]

E.2 *Effects on cognitive: 6-month intervals*

Based on the results seen in the expenditure section, weather variation "bites" and affects household expenditure and nutritional investment between 3 and 8 months after harvest for that year. I use this result when analysing the timing of the effect of early life weather shocks on adult cognitive score.

For these results, I match individuals to weather variation by first using the migration history described in Appendix Section A.1 to calculate the region of residence for each sample individual i in any given month m, call this $r(i, m)$. I then match individuals to weather variation at two levels, annual and 6-monthly. Each temporal level uses a slightly different approach:

[35] In Appendix Figure O1 I examine the timing of weather effects at a more granular monthly level. The predicted harvest index appears to lead increases in nutritional investment and household expenditure for the period approximately between 3 and 8 months after harvest, thus motivating the 6-month periods chosen here.

[36] The effects of interest that are reported in Table 7 are β_0 for -3 to 2 months; $\beta_0 + \gamma_0$ for 3-8 months; β_1 for 9-14 months; $\beta_1 + \gamma_1$ for 15-20 months.

Annual shock measures. I first define a *monthly* weather variation measure that accounts for the fact that the shock bites between 3 and 8 months after harvest. So for month m:

$$WeatherMonth_{rm} = \begin{cases} WeatherYear_{ry} & \text{if } m \text{ is between 3 and 8 months} \\ & \quad \text{after the avg. harvest month in year } y \\ 0 & \text{otherwise} \end{cases}$$

I then amalgamate these monthly shock measures to the annual level by taking the average shock value for each age. Consider an individual i. Let $\mathcal{A}(i,a)$ denote the set of months in which i is age a. For example, if i was someone born on 1st Jan 2000, $A(i,1) = \{$Jan 2001, Feb 2001, ..., Dec 2001$\}$. For individual i at age a residing in district r:

$$WeatherIndAnnual_{iar} = \frac{1}{12} \sum_{m \in \mathcal{A}(i,a)} WeatherMonth_{r(i,m),m}$$

Intuitively, I take the average value of the monthly shock variable over all the 12 months in which i has been age a.

6 month shock measures. The monthly weather shock takes the same value for 6 months at a time. This means that if I try to calculate a 6-monthly shock in the same way as the annual shock, there will be very high pseudo-serial correlation between shocks (i.e., high correlation between the value of i's shock for age a and $a-1$). This can generate artefacts in the results, including misleading alternating patterns in the data where a strong positive coefficient is followed by a strong negative coefficient.[37]

In order to avoid this problem, I instead assign individuals in a given period to a 6-month "bucket", in the following sense. Starting with an individual i's birth month, I split up their life into 6-month life-periods (I denote the period 1-6 months after birth as age 0, 7-12 months after birth as age 0.5, 13-18 months after birth as age 1, etc.) In a similar way, I split up the weather in a given district into 6-month buckets, where a month will be in the first bucket for that year if m is between 3 months before and 2 months after the average harvest month, and will be in the second bucket for that year if m is between 3 and 8 months after the average harvest month. The value of the predicted harvest measure will naturally take the value of 0 for the first bucket, and to $WeatherYear_{ry}$ when in the second bucket.

Then, for every 6-month life-period for every individual, I match it to the *single* 6-month weather bucket for that district, where the matching weather bucket will be

[37] Simulations confirm that such a pattern is likely to result when there is sufficient noise in the model, and when the shock variables are sufficiently serially correlated, even when such an alternating pattern does not exist in the data-generating process.

the one that overlaps the most with the 6-month life period. Figure E1 gives an example of this approach. In the district of analysis, the average harvest month is May. The 6-month weather buckets are thus defined by the white cells in the centre column. Person A was born in February 2000. Her life periods align perfectly with the weather buckets, so her "age = 0" period is assigned to the first bucket, "age = 0.5" is assigned to the second bucket, etc. Person B was born in June 2000. Because Person B's first life period ("age = 0") overlaps more with the second weather bucket (4 month overlap) than the first (2 month overlap), her first life period is assigned to the second weather bucket. Following similar logic, her "age = 0.5" life period is assigned to the third weather bucket, and "age = 1" is assigned to the fourth weather bucket, and so on.

One concern with this strategy is that this generates variation in shock-exposure even within a given bucket (and a given district). For example, in Figure E1, if we think that the shock "bites" in months 3-8 after harvest, then person A will get 6 months of exposure to the shock at age 0.5, while person B will only get 4-months of exposure to the shock at age 0, even though they are assigned the same value of the shock variable. I deal with this issue in two ways. First, I control for district-of-birth $\times$ birth-month-of-year fixed effects in all specifications with bucket-assigned shocks. This ensures that the treatment effects are not estimated using variation from individuals born in different months of the year within the same district. The cumulative effect of being born in a month with 4-months of exposure (for example), compared to being born in a month with 6-months of exposure, will be captured by the fixed effects and so won't confound the treatment effect estimates. Second, I run a robustness check (Appendix Table L13) in which I multiply individuals' shock variable by their level of "exposure" to the shock. For example, person A's shock would remain unchanged, while person B's shock would be multiplied by a factor of $\frac{4}{6}$ to account for the weaker level of exposure. These do not qualitatively change the results.

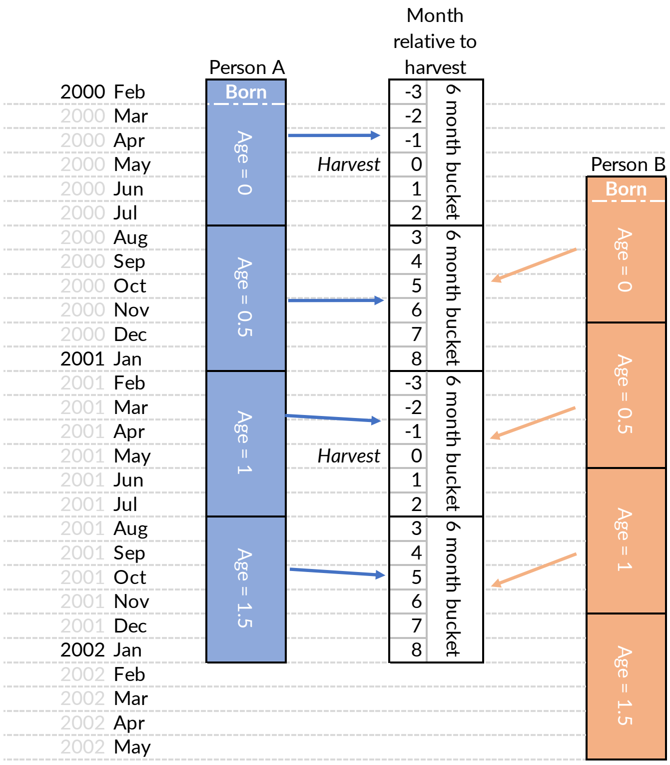
E.3 Bootstrapped standard errors for predicted harvest measure

For all results that make use of the predicted harvest measure, I bootstrap standard errors to take into account variation caused by the construction of the regressors. For example, to calculate the standard errors on the estimates of predicted harvest index on adult cognitive outcomes in Figure 3, I follow the process below:

1. I perform wild cluster resampling of the rice production sample. In other words, I resample at the district level, keeping all observations in a given district. I then calculate the effects of each weather measure $\hat{\gamma}$ using equation 4.

2. I construct $PredHarvest_{ry}$ using the calculated coefficients $\hat{\gamma}$.

Figure E1: *6-month bucket assignment process*



3. I construct 6-month shock measures based on the values of $PredHarvest_{ry}$ using the steps outlined in the previous section.
4. I match individuals in the main sample to these constructed shock measures.
5. I perform wild cluster resampling of the main cognitive sample, clustering at the district level.
6. I calculate the effect of these 6-month shock measures on adult cognitive scores in the bootstrapped sample.

I repeat this process 1000 times, and the standard errors reported in the tables are the standard deviations of the resampled treatment effects from the last step. The bootstrapped standard errors for the other tables using predicted harvest index are constructed in an analogous fashion.

F Conceptual framework

Here, I describe the theoretical framework on which my empirical results are founded. This framework allows me to give a precise definition of the concept of critical periods. It is based on the human capital production function model seen in Cunha & Heckman (2007) and Cunha et al. (2010) in which the timing of investment into human capital during childhood matters. Let $\boldsymbol{\theta}_t$ denote the vector of a child's stock of skills (including, for example, cognitive and socioemotional skills). In this model, skills evolve over the course of childhood in a way that depends on parental characteristics and human capital ($\boldsymbol{h}^P$), the child's existing stock of skills ($\boldsymbol{\theta}_t$), and parental investments in each period (I_t). Given my empirical setting, I add a variable μ_t that describes the exogenous weather shock to investment in period t.[38] I_t can be thought of as denoting the component of investment resulting from a variety of exogenous and endogenous factors, whereas μ_t captures the specific exogenous component of investment that is driven by weather shocks. The way skills evolve from one age-period to the next is described using:

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{f}_t(\boldsymbol{h}^P, \boldsymbol{\theta}_t, (I_t + \mu_t)) \tag{7}$$

All characters in boldface denote vectors. I assume for simplicity that investment and shocks are unidimensional scalars. In my empirical analysis, I allow for 17 distinct time periods to affect adult skills, ranging from 2 years before birth up to age 15.[39]

[38] This is similar to the adaptation seen in Currie & Almond (2011); Almond et al. (2018).

[39] The lower bound is based on evidence cited in the Introduction that suggests that cognitive traits are affected by shocks in utero. The upper bound is based on the fact that adult cognitive ability is measured for all adults above aged 15 in the IFLS data, and also based loosely on the discussion in Cunha & Heckman (2009, p. 331), which suggests that socioemotional skills in particular are "malleable until later ages".

I therefore assume that adult skills settle by age 16, and will not be affected by any changes thereafter. Whereas Equation 7 is written in recursive form, we can substitute in each equation for $\boldsymbol{\theta}_{15}, \boldsymbol{\theta}_{14}, \boldsymbol{\theta}_{13}$, etc. to get an expression for the adult stock of skills ($\boldsymbol{h}$) as a function of initial endowments (from before birth, e.g. genetics) and all past investments and shocks:

$$\boldsymbol{h} := \boldsymbol{\theta}_{16} = \boldsymbol{m}\Big(\boldsymbol{h}^P, \boldsymbol{\theta}_{-2}, (I_{-2} + \mu_{-2}), (I_{-1} + \mu_{-1}), ..., (I_{15} + \mu_{15})\Big)$$

Or for a specific skill k (e.g. cognitive ability), adult skills h_k are

$$h_k = m_k\Big(\boldsymbol{h}^P, \boldsymbol{\theta}_{-2}, (I_{-2} + \mu_{-2}), (I_{-1} + \mu_{-1}), ..., (I_{15} + \mu_{15})\Big)$$

There are two quantities of interest when examining the effects of weather shocks on adult human capital. The first is $\partial m_k(.)/\partial \mu_t$, which I will call the "direct effect". This is the direct impact of a change in investment on adult human capital, ignoring any subsequent investment responses by parents. The second is $dm_k(.)/d\mu_t$, which I will call the "reduced-form effect". This describes the overall impact on adult human capital h_k *while accounting for all parental responses*. In general, these two quantities will not be the same, because parents may react to early shocks by changing investments in later periods. If these later investments are reinforcing, the reduced-form effect will be larger than the direct effect; if they are compensating, the reduced-form effect will be smaller than the direct effect.

Corresponding to these two definitions of effects, we can define two notions of critical periods (building on the definitions seen in Cunha & Heckman (2007)). In particular, define C as a time interval lasting from t_{min} to t_{max}:

$$C = [t_{min}, t_{max}]$$

Then C is a *direct effect critical period* for skill k if and only if:

$$\frac{\partial m_k(.)}{\partial \mu_t} > 0 \quad \forall t \in C \qquad \text{and} \qquad \frac{\partial m_k(.)}{\partial \mu_t} = 0 \quad \forall t \notin C$$

And C is a *reduced-form critical period* for skill k if and only if:

$$\frac{dm_k(.)}{d\mu_t} > 0 \quad \forall t \in C \qquad \text{and} \qquad \frac{dm_k(.)}{d\mu_t} = 0 \quad \forall t \notin C$$

Intuitively, C is a critical period when *only* shocks within the time interval have a (direct or reduced-form) effect on adult skills h_k, while shocks outside of the time interval have no effect on adult skills h_k.[40]

[40]The biomedical literature typically uses a less restrictive definition, where effects in critical periods are stronger but effects outside critical periods need not be 0. This corresponds to the definition of "sensitive periods" in Cunha & Heckman (2007).

F.1 Simple model with welfare

The simplified model in this section shows that we can only write the welfare impacts of an early life shock in terms of the "direct effect" in the specific case where parents are optimising agents and have full knowledge of the human capital production function (which allows us to use the envelope conditions to ignore investment responses).

Assume a simpler version of the model in Section F, in which human capital is a scalar, there is only 1 shock variable μ_1 and we ignore h^P and θ_1 for simplicity. Parents can choose I_2 to react to the shock μ_1, and I_1 is fixed at $\bar{I}$.

$$h(I_2; \mu_1) = m\Big(\mu_1, \bar{I}_1, I_2(\mu_1)\Big)$$

Parental utility is determined by their lifetime consumption C, along with their child's human capital h. α determines their relative preference between these two factors:

$$U = (1-\alpha)\ln C + \alpha \ln h$$

The parental budget constraint is

$$\begin{aligned} Y &= C + p\bar{I}_1 + \frac{pI_2}{(1+r)} \\ \implies C(I_2) &= Y - p\left[\bar{I}_1 + \frac{I_2}{(1+r)}\right] \end{aligned}$$

where p is the relative price of investment, and r is the real exchange rate, and Y is (exogenous) income. We can substitute the budget constraint and technology into the utility function to get it solely in terms of I_2 and μ_1:

$$U(I_2; \mu_1) = (1-\alpha)\log\{C(I_2)\} + \alpha \log\{h(I_2; \mu_1)\}$$

If the prerequisites for the envelope conditions do not hold (e.g. because the parent does not optimise or doesn't have full knowledge of the human capital production function), then the parent chooses $\widetilde{I}_2$ and the welfare impact will be:

$$\frac{dU}{d\mu_1} = (1-\alpha)\frac{1}{C(\widetilde{I}_2)}\frac{dC(\widetilde{I}_2)}{d\mu_1} + \alpha\frac{1}{h(\widetilde{I}_2; \mu_1)}\frac{dh(\widetilde{I}_2; \mu_1)}{d\mu_1}$$

i.e. the welfare impact will be related to the *reduced form* impact of the shock μ_1 on h.

We can derive expression for the welfare impact of μ_1 in terms of the direct effect, but only in the specific case where we can assume that the envelope conditions hold, i.e. when the parent is maximising and has full knowledge of the human capital production function, and μ_1 is marginal. In this case, the agent will maximise to choose some optimal $I_2^*(\mu_1)$ and welfare (or indirect utility) will be:

$$W(\mu_1) = \max_{I_2}\{U(I_2;\mu_1)\}$$

Then the envelope conditions for I_2 allow us to simplify the expression for $dW/d\mu_1$:

$$\begin{aligned}
\frac{dW}{d\mu_1} &= \frac{dU(I_2^*(\mu_1),\mu_1)}{d\mu_1} \\
&= \underbrace{\frac{\partial U(I_2^*(\mu_1),\mu_1)}{\partial I_2}}_{=0} \cdot \frac{dI_2^*}{d\mu_1} + \frac{\partial U}{\partial \mu_1} = \frac{\partial U}{\partial \mu_1} = \frac{\partial U}{\partial h}\frac{\partial h}{\partial \mu_1} \\
\implies \frac{dW}{d\mu_1} &= \alpha \cdot \frac{1}{h} \cdot \frac{\partial h}{\partial \mu_1}
\end{aligned}$$

So in this specific case, to capture the full welfare effects of a change in μ_1 we only need to know the "direct effect" i.e. $\partial h/\partial t$, along with the parent's relative preference for human capital α.

If the policy maker has another objective altogether, such as maximising government revenue, the reduced form effect will also be the determinant of welfare. For example, suppose a representative agent model in which individuals earn hw and are taxed at an ad valorem rate of τ. Then government revenue will be:

$$G = hw(1-\tau)$$

And the impact of the shock on government revenue will be:

$$\frac{dG}{d\mu_1} = \frac{dh}{d\mu_1} \cdot w(1-\tau)$$

But if the prerequisites for the envelope conditions do not hold (e.g. because the parent does not optimise), and the parent chooses $\widetilde{I}_2$ instead of I_2^*, then the welfare impacts will be:

$$\frac{dW}{d\mu_1} = (1-\alpha)\frac{1}{C}\frac{dC}{d\mu_1} + \alpha\frac{1}{h}\frac{dh}{d\mu_1}$$

G Cognitive placebo tests

The effect of *SPEI growing season* on cognitive skills is isolated to a single spike at age 2. This raises concerns that the age 2 coefficient is the unexpected result of some artefact in the data or some aspect of the empirical strategy. For example, we might worry that shocks are correlated across- and within-individuals in just such a way that, by chance, random noise in the data "aligns" across individuals to create an apparently strong effect at a single age. Alternatively, the patterns of correlation between shocks across and within individuals may imply that inference using F-tests is not sufficiently conservative. To alleviate these concerns, I construct two simulated placebo tests of my empirical specification.

Before-conception shocks. I randomly select (without replacement) 18 years from the set of years between 27 and 3 years before birth. I use the 18 corresponding shock variables as explanatory variables in the main estimating equation 1. This acts as a check of the F-test, ensuring that random variation from *before* an individual's life cannot generate seemingly significant joint effects on adult cognitive skills.

$SPEI_{i(t+j)}$ denotes the weather experienced by individual i in the jth year after his/her birth in year t. When j is negative, let $SPEI_{i(t+j)}$ be the weather in i's district of birth $|j|$ years before he/she was born. For example, $SPEI_{i(t-10)}$ would be the SPEI index in i's district of birth from 10 years before i was born. The before-conception shocks placebo test is constructed as follows.

1. I construct a set $\mathcal{J}_{\text{hist}}$ of possible "historical" time periods from well before birth that should not affect adult outcomes. In this case, I choose $\mathcal{J}_{\text{hist}} = \{-27, -26, ..., -3\}$.[41]
2. For iteration $k = 1$:
   (a) Randomly select (without replacement) a subset $\mathcal{Z}_k$ of length 18 from the set $\mathcal{J}_{\text{hist}}$.[42]
   (b) Run the main specification but using the time periods from $\mathcal{Z}_k$, i.e. run
   $$Y_{irt} = \alpha + \sum_{z \in \mathcal{Z}_k} \beta_z SPEI_{i(t+z)} + \pi G_{ir} + \mathbf{X}_i' \gamma \; + \delta_r + \mu_t + \varepsilon_{irt}$$
3. Repeat step 2. for all iterations $k \in \{2, 3, ..., 1000\}$.

[41] -27 is the minimum value because the oldest individual in my sample was born in 1988, and my SPEI data ranges back to 1961. This means that the furthest back before birth I can construct shocks without generating missing values is 27 years before birth. -3 is the maximum value because it is the closest time period to the year of birth for which there is very unlikely to be any effects of weather on adult outcomes (-2 and -1 may have effects due to sensitivity to shocks *in utero*).

[42] 18 values are chosen because there are 18 coefficients in my main specification.

Within-lifetime iterations. I randomly "reshuffle" the within-lifetime shocks. Separately for each individual, the shock values for ages $(-2, -1, ..., 15)$ is reassigned to a different year in the set $\{-2, -1, ..., 15\}$. So for example, the shock value for age 0 might be reassigned to age 13, and the shock value for age 5 might be reassigned to age 1. The reassigned shock variables are then used as explanatory variables in equation 1. This can be seen as a verification of the q-value hypothesis tests, since it checks whether the chance alignment of noisy within-lifetime variation across individuals can generate patterns that look like strong effects in a single period (or critical periods). Let $\mathcal{J} = (-2, -1, ..., 14, 15)$ be the (ordered) list of time periods used in the main specification. Let j_p be the pth element of $\mathcal{J}$.

1. For iteration $k = 1$:
   (a) For individual $i = 1$:
      i. Create a new set $\mathcal{Q}_i^{\text{reordered}}$ by taking $\mathcal{J}$ and reordering the items randomly (such that none of the items are in the position they were originally at in $\mathcal{J}$). Let q_p denote the pth element of $\mathcal{Q}_i^{\text{reordered}}$. For example, if 5 is the 1st element of $\mathcal{Q}_i^{\text{reordered}}$, then $q_1 = 5$.
      ii. Define new placebo weather shock variables for individual i according to the elements in $\mathcal{Q}_i^{\text{reordered}}$ in the following way: $Placebo_{ip} = SPEI_{i(t+q_p)}$. Suppose, for example, that for the first placebo shock that $q_1 = 5$ as above, then $Placebo_{i,1} = SPEI_{i(t+5)}$. This will yield 18 different $Placebo_{i,p}$ variables for each individual.
   (b) Repeat step (a) for all individuals $i \in \{2, ..., N\}$, such that each of their placebo shock variables are iterated differently.
   (c) Run a regression, analogous to the main specification but using the placebo variables as the main treatment variables. In other words, run:

$$Y_{irt} = \alpha + \sum_{\{1,...,18\}} \beta_p Placebo_{i,p} + \pi G_{ir} + \mathbf{X}_i' \gamma + \delta_r + \mu_t + \varepsilon_{irt} \tag{8}$$

2. Repeat step 2. for all iterations $k \in \{2, 3, ..., 1000\}$.

Results: The results of both placebo tests are found in Table G1 and Figure G2. For both types of placebos, I run three types of hypothesis tests: (i) whether the p-value is less than $\alpha = 0.05$ for each shock *coefficient* in the model, (ii) whether the q-value is less than $\alpha = 0.05$ for each shock *coefficient* in the model, and (iii) whether the F-test is significant at the $\alpha = 0.05$ level (one test for each *model*). For the p- and q-value tests, I also report at the model level whether at least one p- or q-value is significant in the model. Each placebo test is re-run for 5000 models.

The results here confirm that my results from Section 4.1 are unlikely to be driven by artefacts in the data. The before-conception placebo generates some significant p-values, but no significant q-values. This suggests that the strongly significant results on adult cognitive ability are highly likely to be driven by true variation from within an individual's lifetime, rather than just chance alignment of random noise. The F-test is never significant, which indicates that the inference on the F-statistic is not insufficiently conservative. The within-lifetime placebo also generates results that support the methodology. A high proportion of simulations (35.3%) lead to at least one significant p-value, but only 0.1% of simulations include at least one significant q-value. This indicates that the FDR-controlled multiple hypothesis adjustment is effective at reducing the likelihood of false positives.[43] The low proportion of simulations that result in significant q-values, even at the 5% level, means that we can be highly confident that the strongly significant coefficient at age 2 in my main specification (with a q-value of 0.002) is capturing a true phenomenon rather than random noise.

Table G1: *Results of placebo tests*

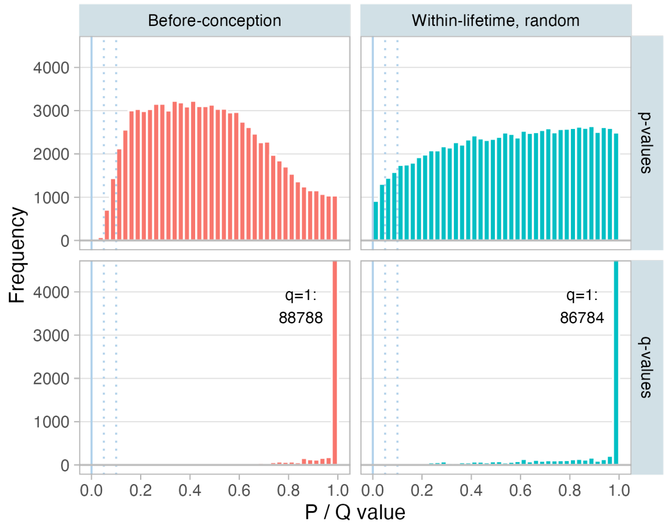
Placebo Type	Test Type	Total Tests	# Significant	Prop Significant
Before-conception	p - by coefficient	90000	79	0.001
Before-conception	p - at least one	5000	74	0.015
Before-conception	q - by coefficient	90000	0	0.000
Before-conception	q - at least one	5000	0	0.000
Before-conception	F	5000	0	0.000
Within-lifetime, random	p - by coefficient	90000	2225	0.025
Within-lifetime, random	p - at least one	5000	1812	0.362
Within-lifetime, random	q - by coefficient	90000	50	0.001
Within-lifetime, random	q - at least one	5000	50	0.010
Within-lifetime, random	F	5000	4551	0.910

Notes: The "before-conception shocks" placebo describes the results of randomly selecting 18 shocks from significantly before an individual was born (27-3 years before birth) as the explanatory variables in Equation 1. The "within-lifetime, random" placebo describes the results of randomly reordering the actual shocks experienced (separately for each individual in the sample) and using these synthetic placebo shocks as the explanatory variables in Equation 1. Each model is estimated 5000 times. All tests are tested at the significance level $\alpha = 0.05$. "p, by coefficient" describes how many *coefficients* have a p-value below 0.05 (yielding $18 \times 5000 = 90,000$ tests), while "p, at least one" describes how many models include at least one p-value below 0.05. "q, by coefficient" and "q, at least one" are defined similarly but use the q-values calculated using the sharpened FDR control procedure from Anderson (2008). The "F" rows describe how many models result in a rejected F-test at the 5% level.

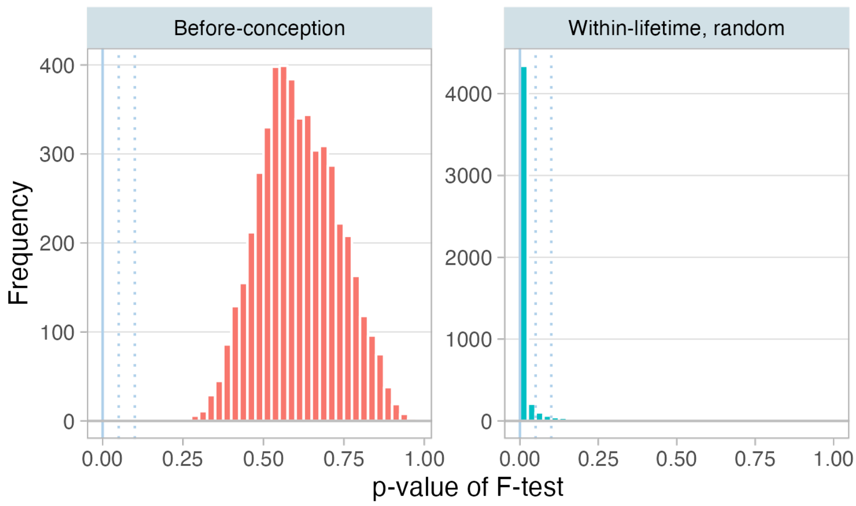
[43]Since the model for my main results (Section 4) leads to a rejection of the F-test, and the within-lifetime placebo test always uses the same variation but randomly "reshuffled", we also expect the F-test to be rejected in almost all cases, as indeed it is.

Figure G2: *Placebo test results*

(a) *Distribution of p- and q-values for individual coefficients after 1000 simulations of each placebo method*



(b) *Distribution of p-values for F-statistics on all coefficients after 1000 simulations of each placebo method*



H Power simulations

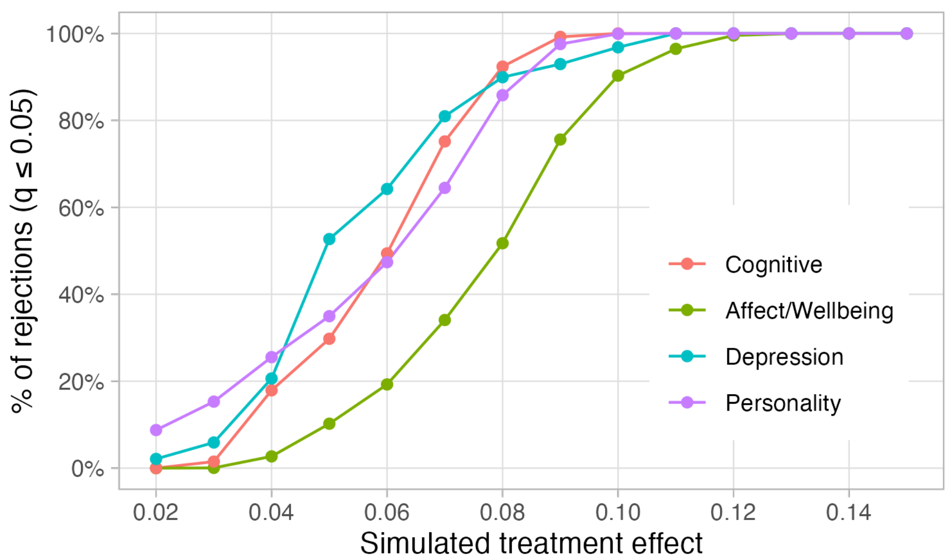
I run simulations to estimate the power of my test for critical periods. I take before-conception shocks for each outcome as a null distribution, and then simulate treatment effects of size κ. More specifically, for each outcome variable:

1. I use the methodology from Section G to generate simulated data that takes before-conception shocks as the main explanatory variables. I use the specification seen in equation 8. The distribution of the estimated treatment effects of the placebo shocks ($\hat{\beta}_p$) is a proxy for the distribution of treatment effects in the main specification (equation 1) under the null that $\beta_j = 0$ for all j.

2. For a randomly selected placebo shock, I simulate a linear treatment effect of that shock of κ.

3. I repeat this process 5000 times and count the proportion of simulations in which the randomly selected shock has a q-value of less than 0.05 (i.e., is rejected after adjusting for multiple hypothesis testing). This is the estimated power for the given level of κ.

Figure H3: *Simulated power: proportion of rejected q-values as a function of simulated treatment effect*



Notes: This shows the simulated power of each outcome at different levels of treatment effect κ, as described in the methodology in this section. The simulated data uses before-conception shocks as placebo shocks that proxy the null distribution, and then simulates an additional linear treatment effect on all individuals in the data of size κ for one randomly selected placebo shock. This simulation is repeated 5000 times for each point on the graph. Each point denotes the proportion of q-values below 0.05 for the shock with a simulated treatment effect.

I Heterogeneous effects

A recent body of literature (e.g. Goodman-Bacon, 2018; de Chaisemartin & d'Haultfoeuille, 2020) has pointed out that in the presence of heterogeneous treatment effects there may be difficulties with the interpretation of the type of fixed-effect regressions that I use in my main specification, namely those with multiple groups g and multiple time periods t. For example, (de Chaisemartin & d'Haultfoeuille, 2020) show that in a simple fixed-effects model with a common trends assumption, the coefficient on a fixed effect regression (β_{fe}) will estimate a *weighted* average of the (g, t)-cell-specific ATTs (average treatment effect on the treated). In general, the weights on each cell will not be equal, and some can be negative, implying that with heterogeneous treatment effects β_{fe} can even be of a different sign to all the cell-specific ATTs.

This framework implies that the coefficient estimates in my main results will only have a causal interpretation if one of the following two conditions hold:

- *Homogenous effects*. The ATT of weather variation at a given age is constant across all (birth-district, birth-year) cells.
- *Uncorrelated heterogeneous effects*. The ATT of weather variation at a given age may vary across (birth-district, birth-year) cells, but the weight attached to each (birth-district, birth-year) in the fixed effect regression is uncorrelated with the ATT in that cell.

The first condition is implausible in my context. There are many reasons why the ATT of weather variation may be higher in some districts and time periods than others, because for example they have a more educated population (which could change how parental investment reacts to shocks), because some districts are more suitable for growing crops that are more sensitive to weather variation, or because there is a greater rural population that is dependent on farming, thus altering changing the general equilibrium effects of weather shocks on the local economy.

On the other hand, the uncorrelated heterogeneous effects assumption is plausible. Note first that the weights attached to each cell depend on the treatment status of that cell (see e.g. Proposition 1 in (de Chaisemartin & d'Haultfoeuille, 2020)). This means that any correlation between the treatment status of a cell (i.e. the weather variation experienced) and the ATT of that cell will threaten the validity of my fixed-effect coefficient estimates. However, the main treatment variables I am examining are year-on-year weather variations (away from the historical average), which are plausibly as-good-as random, and thus exogenous to determinants of the ATT. For example, whether a district experiences a positive weather shock in a given year is determined by climatological factors and will thus be independent of factors like the proportion of adults who have completed a primary school in that district, the level of urbanisation in that district, the suitability of different crops, etc. that may influence the ATT. If this is true, then the fixed-effects estimates used in my main results can be interpreted causally. Note that the assumption required here is similar to the main identification assumption described in the empirical strategy, although here I require conditional exogeneity with respect to the ATT instead of to the outcome variable.

I am also able to show empirical evidence to suggest that the uncorrelated heterogeneous effects assumption is likely to hold. To do this, I first replicate my main empirical specification (Equation 1) with adult cognitive scores as an outcome, and use the framework in (de Chaisemartin & d'Haultfoeuille, 2020) to estimate the weights attached to each district-year cell. Table I1 then shows the results of regressing these weights on a number of observable characteristics that vary at the district-year level. None of the coefficients indicate a significant correlation between the estimated weights on SPEI growing season (at ages 0, 1, or 2) and any of the characteristics, which include the proportion of district area dedicated to rice farming, the population density, a measure of education (adult primary school completion), and the proportion of households in rural areas. The fact that these observable district characteristics are not correlated with the weights of the fixed-effect regression lends credence to the claim that the ATTs of each cell are also not correlated with the weights. This would imply that the fixed-effects regressions used in the main text successfully identify a meaningful causal effect.

Table I1: *No significant correlation between the weights given to a (year $\times$ district) cell and observable characteristics of the cell*

Variable	Treatment at age	Coefficient estimate	Std. error	p value	Number of cells
Area (proportion) dedicated to rice farming	0	0.05	0.20	0.80	1463
	1	0.18	0.13	0.17	1463
	2	-0.03	0.08	0.67	1463
Population density (persons per km^2)	0	465.25	988.62	0.64	1463
	1	58.71	670.22	0.93	1463
	2	-264.32	434.17	0.54	1463
Proportion of adults with completed primary school	0	-0.09	0.09	0.31	1463
	1	-0.07	0.08	0.36	1463
	2	-0.01	0.05	0.78	1463
Proportion rural	0	0.17	0.19	0.36	1463
	1	0.10	0.16	0.53	1463
	2	0.11	0.08	0.18	1463

Notes: The results in this table are calculated as follows. First, I run a fixed-effects regression (Equation 1) with adult cognitive score as the outcome variable. For the coefficients on SPEI growing season at ages 0, 1, and 2, I use the results in de Chaisemartin & d'Haultfoeuille, 2020 to calculate the weights attached to each (birth-district, birth-year) "cell" in this regression. Denote as $w^a_{r,t}$ the weight attached the cell (r,t) for coefficient on age $a \in \{0,1,2\}$, where r is a birth-district, and t is a birth-year. I then regress these weights $w^a_{r,t}$ on the variable in the first column. Apart from the area dedicated to rice farming, the measures in the first column are calculated using Indonesian census data (Minnesota Population Center, 2020), and are allowed to vary at the district-year level by matching the year of the treatment variable (i.e. birth-year + 0, birth-year + 1, birth-year + 2) to the closest census date and using the data from that census year. Proportion rural denotes the proportion of households that are in rural areas. Area dedicated to rice farming is calculated from the Monfreda et al. (2008) data, and is time invariant (based on data from 2000). The "p-value" column denotes the p-value of the t-test that the coefficient is significantly different from 0.

J Multiple testing adjustment

The false discovery rate (FDR) is the expected proportion of false rejections from testing a set of null hypotheses $H_1, ..., H_n$ i.e. $E(H_i \text{ is true}|\text{Test rejects } H_i)$. For each of the main results tables in the paper, I calculate the Benjamini & Hochberg (1995) FDR-adjusted p-values using the sharpened procedure below based on the one seen in Anderson (2008). The basic Benjamini-Hochberg procedure is as follows:

1. For each of the coefficients $\beta_j, j \in \{-2, -1, ..., 15\}$, get the corresponding p-values from the primary specification (denoted $p_{-2}, p_{-1}, ..., p_{15}$)
2. Sort the p-values in ascending order so we have $p_{(1)} \leq p_{(2)} \leq ... \leq p_{(17)}$
3. To test whether β_j is rejected at the significance level α:
4. (a) Find the largest k such that $p_{(k)} \leq k \times \alpha/17$
   (b) Reject all hypotheses with a lower p-value than $p_{(k)}$ i.e. the coefficients associated with the p-values $p_{(1)}, ..., p_{(k)}$
5. Repeat step 3 for all values α (starting from 1.000, then 0.999, then 0.998 etc.). The q-value q_j for β_j is the smallest value of α at which step 3 rejects the hypothesis for that coefficient.

The above procedure is actually over-conservative if the true (but unknown) number of false null hypotheses is greater than 0. Given that, it is possible to "sharpen" the procedure and increase power using the following steps:

1. Apply the above procedure at a significance level $q' = q/(1+q)$. Let c be the number of hypotheses rejected. If $c = 0$ then stop; otherwise go to step 2.
2. Let $\hat{m}_0 = M - c$.
3. Apply the above procedure at a level $q^* = q'M/\hat{m}_0$.

The degree to which the Benjamini & Hochberg (1995) procedure is conservative varies based on the dependency structure of the tested p-values $p_{-2}, p_{-1}, ..., p_{15}$. Suppose we set a significance threshold $\alpha_0 = 0.05$ such that we reject the null for β_j if $\beta_j \leq \alpha_0$. If the p-values are independent or positively dependent, then the procedure above will ensure that $FDR \leq \alpha_0$, implying that we are controlling for the false discovery rate at the desired level of 5%. If, on the other hand, any of the p-values are negatively dependent, the procedure is overly conservative as it ensures that $FDR \lessapprox \alpha_0/\ln(n) = \alpha_0/\ln(17)$. Since the right-hand side of this equation is smaller than α_0, this means we are controlling for a smaller FDR than intended, and being overly conservative in inferring significant effects. Given my empirical setting, the p-values are likely to be positively dependent (for example, the effect of weather shocks at age 1 is likely to be positively correlated with the effect of weather shocks at age 2). But if they are negatively dependent, I am still successfully controlling for Type I errors.

K Sample selection

A relevant worry in my empirical setting is whether the main sample I am using is subject to a selection effect that could bias causal estimates of the impact of early-life weather shocks on adult outcomes. Ideally, my main sample would be a random sample of all individuals born between 1988 and 2000 in rural Indonesia (in the provinces surveyed by the IFLS). However, we may be worried about two primary sources of selection that could lead to a non-random sample. First, there may be selective mortality. For example, it may be the case that extreme weather shocks such as drought lead to infant death, and that deaths are concentrated on infants with poor health. If poor health in infancy is negatively correlated with adult cognitive ability, this would lead to a positively biased estimate in my main specification. Second, children who were born in IFLS households are only tracked when they move households if they were part of one of the original households from the very first wave, IFLS1. If children who were only incorporated into the IFLS as a result of later waves non-randomly migrate out of their households, the sample of individuals in my main sample will be similarly non-random.

In order to test for such selection effects, I make use of the detailed pregnancy history taken of each women above aged 15 in the IFLS survey. Using this data, I have a record of every pregnancy and birth for IFLS respondents, which amounts to 9226 records.[44] 54.5% of these records (N = 5028) can be matched to individuals in the main sample used in the analysis. But the rest are missing from the main sample: for example, 16.2% (1493) die before the age of 5 or result in still birth, and so do not have their adult outcomes measured. If this attrition is non-random and correlated with early life weather shocks, this could lead to biased estimates in my main analysis. The test proposed will not detect all sources of attrition bias: in particular, it does not account for any individuals who are not recorded in the pregnancy history data, which could result from a mothers' recall bias or refusal to respond. On the other hand, the data available give me a unique opportunity to test for selective mortality directly. Table K1 shows the results of regressing measures of early life SPEI growing season on indicators for attrition, controlling as for the main analysis for birth-year and birth-district fixed effects.

In columns (1) and (2), I test whether early life SPEI affects the probability of dying before the age of 5 (or resulting in still birth). It appears that in utero $SPEI$ has a positive effect on the probability of dying before age 5.[45] The coefficient of 0.018 on $SPEI_{t-1}$ suggests that an increase in SPEI growing season of 1 standard devia-

[44] I match pregnancies to districts using data on the mother's migration history.

[45] This appears to be driven mostly by an increase in the probability of a still birth.

tion leads to an increase in the probability of dying before aged 5 by 1.8 percentage points, and the coefficient is significant at the 1% level. The direction of this effect is surprising given the main results in the paper: since SPEI is positively associated with household economic wellbeing and child anthropometrics, we would expect higher SPEI to have a negative impact on infant mortality. On the other hand, there may be non-economic explanations for such a result. For example, the impact shown here could possibly be explained by a change in the disease environment in utero. For example, wetter environments (higher SPEI) may lead to higher incidence of malaria and an increased risk of infant death (Kudamatsu et al., 2012). If in utero SPEI does indeed have a positive effect on the probability of infant death, this would likely lead to a positive bias on the results found in my main analysis: I would be missing weaker children (who are likely to have lower cognitive ability) that are subject to high SPEI from my analysis. However, this bias is likely to be isolated to the *in utero* period, rather than at age 2 where we see positive impacts of SPEI growing season on cognitive ability in the main results. The coefficient on $SPEI_{t-1}$ is also relatively small. Thus while I cannot rule out selection bias due to mortality, it is unlikely to explain the large effects seen on adult cognitive skills at age 2 in Section 4.1.

In columns (3) and (4), I run a similar test to see whether early life SPEI affects the overall probability to be included in my main sample. No coefficients on early life SPEI are significant at the 10% level, suggesting no evidence for any selective inclusion in the final sample. Despite the potential selective mortality seen in columns (1) and (2), I cannot reject that there is no selection effect of $SPEI_{t-1}$ overall, implying that selection bias in the sample is unlikely to drive the main results in the paper.

Table K1: *Testing for sample selection*

	Dep Var: Died before age 5			Dep Var: Included in the main sample		
	(1)	(2)	q value (2)	(3)	(4)	q value (4)
(Mean) SPEI growing season, ages -1 to 4	0.001			0.012		
	(0.023)			(0.033)		
SPEI growing season, age = -1		0.018***	0.009		−0.015	1
		(0.005)			(0.012)	
SPEI growing season, age = 0		−0.004	1		0.011	1
		(0.006)			(0.007)	
SPEI growing season, age = 1		0.003	1		0.004	1
		(0.007)			(0.010)	
SPEI growing season, age = 2		−0.003	1		0.015	1
		(0.006)			(0.009)	
SPEI growing season, age = 3		−0.005	1		0.003	1
		(0.006)			(0.010)	
SPEI growing season, age = 4		0.005	1		−0.009	1
		(0.006)			(0.008)	
SPEI growing season, age = 5		−0.005	1		−0.003	1
		(0.005)			(0.009)	
Birth year fixed effects	Yes	Yes		Yes	Yes	
Birth district fixed effects	Yes	Yes		Yes	Yes	
Sample mean	0.162	0.162		0.545	0.545	
F statistic	0.001	2.926		0.141	1.391	
p-value for F-test	0.975	0.006		0.714	0.294	
Adj. R^2	0.024	0.025		0.140	0.140	
N	9226	9226		9226	9226	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. Sample includes all children born between 1988 and 2000 whose mother was an IFLS respondent and gave a pregnancy history in at least one IFLS wave. "Died before age 5" is an dummy variable that takes the value 1 if pregnancy ended in still birth or miscarriage, or if child was born and died before 5th birthday. "Included in Main Sample" is an indicator variable for whether child is in the main sample used in the paper (see Table 2 and surrounding discussion). Mean SPEI growing season ages -1 to 4 takes the mean of the SPEI growing season an individual experiences across ages -1 to 4 inclusive. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

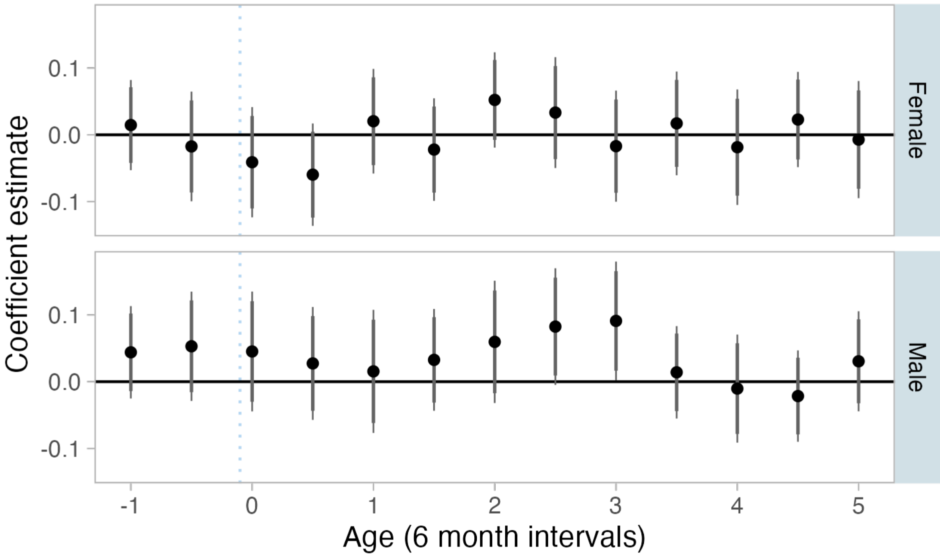
Table K2: *Evidence against selective migration*

	Dep Var: Individual Migrates in Year t		Dep Var: Probability that migration destination at t is district d	
	SPEI in starting district	q value	SPEI in destination district	q value
	(1)	(1)	(2)	(2)
SPEI growing season in t - 5	0.0002 (0.0017)	[1]	0.0015 (0.0011)	[1]
SPEI growing season in t - 4	−0.0050 (0.0037)	[1]	−0.0005 (0.0009)	[1]
SPEI growing season in t - 3	0.0041 (0.0034)	[1]	0.0009 (0.0009)	[1]
SPEI growing season in t - 2	−0.0008 (0.0034)	[1]	0.0007 (0.0005)	[1]
SPEI growing season in t - 1	−0.0046 (0.0069)	[1]	−0.0002 (0.0009)	[1]
SPEI growing season in t	0.0034 (0.0043)	[1]	0.0003 (0.0004)	[1]
SPEI growing season in t + 1	0.0002 (0.0021)	[1]	0.0010 (0.0008)	[1]
SPEI growing season in t + 2	0.0032 (0.0016)*	[1]	0.0013 (0.0008)	[1]
SPEI growing season in t + 3	−0.0100 (0.0071)	[1]	−0.0007 (0.0005)	[1]
SPEI growing season in t + 4	0.0010 (0.0047)	[1]	0.0001 (0.0006)	[1]
SPEI growing season in t + 5	0.0007 (0.0032)	[1]	−0.0001 (0.0005)	[1]
Individual FEs	Yes		No	
Year FEs	Yes		Yes	
Sample mean	0.0282		0.0054	
F statistic	1.5401		0.9695	
p-value for F-test	0.1869		0.5064	
R^2	0.1334		0.0940	
N	106375		3355	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by individual. Includes all individuals in the main sample. Column (1) uses a panel dataset with observations at the (Individual $\times$ year) level. The dependent variable is a dummy variable indicating whether the individual migrated in that year. The explanatory variables are the SPEI growing season in the starting district (pre-migration). Column (2) uses a dataset at the (District $\times$ year) level. The outcome variable is the probability that an individual in the sample chooses district d as their destination when migrating, calculated by taking the number of individuals who migrated to d in year t and dividing by the total number of individuals who migrated in year t.

L Additional tables: cognitive outcomes

Figure L1: *Effect of SPEI growing season on cognitive Z-score using 6-month intervals, by gender*



Notes: The dependent variable in all models is the adult cognitive factor score (measured after age 15). The cognitive factor score is standardised to have 0 mean and standard deviation of 1. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. Individuals are matched to values of predicted harvest index using the process described in Section E.2. All coefficients control for birth-year fixed effects and individual-level controls (dummies for highest level of parental education, sex, and religion). 6-monthly specifications control for (district × month-of-birth fixed effects), to account for variation due to the timing of birth relative to the 6-month "bucket" individuals are assigned to (see Appendix Section E.2 for details.) All models use the individual-level attrition-corrected weights provided in the IFLS data.

Table L1: *Cognitive robustness checks*

	Sample 1985-2000 (1)	q value (1)	Sample 1990-2000 (2)	q value (2)	Sibling FEs (3)	q value (3)	SPEI 4 month (4)	q value (4)	Anderson Index (5)	q value (5)	Mean Index (6)	q value (6)	Urban (7)	q value (7)
SPEI growing season, age = -2	−0.009 (0.014)	[0.826]	−0.005 (0.019)	[1]	0.056 (0.030)*	[0.341]	−0.012 (0.019)	[1]	−0.003 (0.016)	[1]	−0.001 (0.016)	[1]	−0.013 (0.020)	[0.676]
SPEI growing season, age = -1	0.024 (0.013)*	[0.24]	0.035 (0.016)**	[0.372]	0.072 (0.028)**	[0.096]	0.022 (0.014)	[1]	0.027 (0.015)*	[1]	0.027 (0.015)*	[1]	−0.030 (0.020)	[0.594]
SPEI growing season, age = 0	−0.006 (0.013)	[0.882]	0.003 (0.018)	[1]	0.034 (0.030)	[0.532]	−0.006 (0.017)	[1]	−0.002 (0.015)	[1]	−0.004 (0.015)	[1]	0.020 (0.028)	[0.676]
SPEI growing season, age = 1	0.020 (0.014)	[0.458]	0.021 (0.021)	[1]	0.044 (0.030)	[0.401]	0.017 (0.018)	[1]	0.020 (0.018)	[1]	0.019 (0.018)	[1]	0.025 (0.024)	[0.594]
SPEI growing season, age = 2	0.042 (0.013)***	[0.027]	0.057 (0.017)***	[0.017]	0.104 (0.032)***	[0.022]	0.057 (0.017)***	[0.016]	0.045 (0.014)***	[0.039]	0.048 (0.015)***	[0.023]	0.043 (0.024)*	[0.594]
SPEI growing season, age = 3	0.029 (0.014)**	[0.155]	0.016 (0.021)	[1]	0.061 (0.031)**	[0.337]	0.031 (0.017)*	[1]	0.018 (0.014)	[1]	0.019 (0.014)	[1]	0.021 (0.021)	[0.594]
SPEI growing season, age = 4	0.020 (0.016)	[0.501]	−0.019 (0.023)	[1]	−0.025 (0.031)	[0.713]	−0.006 (0.016)	[1]	−0.005 (0.016)	[1]	−0.005 (0.016)	[1]	−0.029 (0.022)	[0.594]
SPEI growing season, age = 5	0.034 (0.013)**	[0.106]	0.005 (0.022)	[1]	0.011 (0.030)	[0.913]	0.014 (0.017)	[1]	0.014 (0.015)	[1]	0.016 (0.015)	[1]	0.011 (0.031)	[0.676]
SPEI growing season, age = 6	−0.006 (0.014)	[0.882]	−0.005 (0.021)	[1]	0.045 (0.032)	[0.401]	−0.006 (0.017)	[1]	−0.007 (0.015)	[1]	−0.006 (0.015)	[1]	−0.048 (0.028)*	[0.594]
SPEI growing season, age = 7	−0.001 (0.015)	[1]	−0.020 (0.025)	[1]	0.055 (0.031)*	[0.341]	−0.024 (0.018)	[1]	−0.025 (0.017)	[1]	−0.024 (0.017)	[1]	−0.017 (0.027)	[0.676]
SPEI growing season, age = 8	0.021 (0.013)	[0.358]	−0.000 (0.021)	[1]	−0.013 (0.030)	[0.913]	−0.008 (0.014)	[1]	0.010 (0.015)	[1]	0.010 (0.015)	[1]	0.023 (0.023)	[0.594]
SPEI growing season, age = 9	0.013 (0.015)	[0.769]	−0.012 (0.026)	[1]	0.054 (0.034)	[0.396]	−0.005 (0.018)	[1]	−0.013 (0.017)	[1]	−0.009 (0.018)	[1]	−0.013 (0.026)	[0.676]
SPEI growing season, age = 10	−0.017 (0.016)	[0.638]	−0.030 (0.026)	[1]	0.002 (0.030)	[1]	−0.007 (0.019)	[1]	−0.018 (0.017)	[1]	−0.018 (0.017)	[1]	0.039 (0.024)	[0.594]
SPEI growing season, age = 11	−0.004 (0.015)	[0.928]	−0.039 (0.025)	[1]	0.006 (0.031)	[1]	−0.021 (0.018)	[1]	−0.020 (0.018)	[1]	−0.020 (0.018)	[1]	0.012 (0.029)	[0.676]
SPEI growing season, age = 12	0.031 (0.014)**	[0.155]	0.011 (0.025)	[1]	0.017 (0.033)	[0.868]	0.027 (0.018)	[1]	0.026 (0.020)	[1]	0.026 (0.020)	[1]	−0.030 (0.027)	[0.594]
SPEI growing season, age = 13	0.012 (0.014)	[0.769]	−0.013 (0.027)	[1]	−0.004 (0.030)	[1]	0.018 (0.019)	[1]	0.004 (0.019)	[1]	0.003 (0.019)	[1]	−0.046 (0.028)*	[0.594]
SPEI growing season, age = 14	−0.002 (0.013)	[1]	−0.008 (0.020)	[1]	0.017 (0.032)	[0.868]	0.003 (0.015)	[1]	0.008 (0.015)	[1]	0.009 (0.015)	[1]	−0.045 (0.025)*	[0.594]
SPEI growing season, age = 15	−0.010 (0.014)	[0.769]	−0.004 (0.022)	[1]	0.016 (0.031)	[0.868]	0.004 (0.017)	[1]	−0.010 (0.016)	[1]	−0.010 (0.016)	[1]	−0.030 (0.022)	[0.594]
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Birth district FEs	Yes		Yes		No		Yes		Yes		Yes		Yes	
Siblings FEs	No		No		Yes		No		No		No		No	
Birth Order FEs	No		No		Yes		No		No		No		No	
F statistic	3.362		2.036		1.740		1.979		2.122		2.180		1.749	
p-value for F-test	0.000		0.010		0.028		0.013		0.007		0.005		0.035	
R^2	0.195		0.216		0.879		0.212		0.207		0.210		0.262	
N	7309		4483		5572		5572		5572		5572		3416	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. Column (1) extends the sample by including individuals born between 1985 and 2000 (instead of just 1988 and 2000). Column (2) uses individuals born between 1990 and 2000. Column (3) uses siblings fixed effects and birth order fixed effects instead of birth district fixed effects. Column (4) uses a definition of SPEI based on a 4-month rolling average, rather than the 1-month average used in the main specification. Column (5) constructs the cognitive z-score using inverse covariance weighted indices from Anderson (2008). Column (6) uses cognitive indexes based on taking an unweighted sum of the z-scores for each sub-measure (Kling et al., 2007). Column (7) uses a different sample of individuals who are equivalent to the main sample, but were born in urban areas instead of in rural areas. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L2: *Cognitive results are robust to the exclusion of later shocks*

	Not demeaned				Demeaned SPEI					
	Up to age 2 (1)	q value (1)	Up to age 7 (2)	q value (2)	All ages (3)	q value (3)	Up to age 2 (4)	q value (4)	Up to age 7 (5)	q value (5)
SPEI growing season, age = -2	−0.004 (0.016)	[0.794]	−0.001 (0.017)	[1]	−0.003 (0.018)	[1]	−0.004 (0.016)	[0.794]	−0.001 (0.017)	[1]
SPEI growing season, age = -1	0.019 (0.015)	[0.548]	0.023 (0.016)	[0.438]	0.026 (0.015)*	[0.884]	0.019 (0.015)	[0.548]	0.023 (0.016)	[0.438]
SPEI growing season, age = 0	−0.003 (0.014)	[0.794]	0.001 (0.015)	[1]	−0.000 (0.015)	[1]	−0.003 (0.014)	[0.794]	0.001 (0.015)	[1]
SPEI growing season, age = 1	0.019 (0.017)	[0.548]	0.019 (0.017)	[0.615]	0.018 (0.019)	[1]	0.019 (0.017)	[0.548]	0.019 (0.017)	[0.615]
SPEI growing season, age = 2	0.063 (0.016)***	[0.001]	0.063 (0.016)***	[0.001]	0.063 (0.016)***	[0.002]	0.063 (0.016)***	[0.001]	0.063 (0.016)***	[0.001]
SPEI growing season, age = 3			0.032 (0.014)**	[0.121]	0.030 (0.015)*	[0.796]			0.032 (0.014)**	[0.121]
SPEI growing season, age = 4			−0.005 (0.018)	[1]	−0.003 (0.017)	[1]			−0.005 (0.018)	[1]
SPEI growing season, age = 5			0.019 (0.013)	[0.438]	0.017 (0.016)	[1]			0.019 (0.013)	[0.438]
SPEI growing season, age = 6			0.000 (0.017)	[1]	0.000 (0.017)	[1]			0.000 (0.017)	[1]
SPEI growing season, age = 7			−0.016 (0.017)	[0.615]	−0.020 (0.020)	[1]			−0.016 (0.017)	[0.615]
SPEI growing season, age = 8					0.012 (0.016)	[1]				
SPEI growing season, age = 9					0.000 (0.020)	[1]				
SPEI growing season, age = 10					−0.015 (0.019)	[1]				
SPEI growing season, age = 11					−0.021 (0.019)	[1]				
SPEI growing season, age = 12					0.022 (0.021)	[1]				
SPEI growing season, age = 13					−0.003 (0.020)	[1]				
SPEI growing season, age = 14					−0.001 (0.016)	[1]				
SPEI growing season, age = 15					−0.009 (0.018)	[1]				
Birth year FEs	Yes		Yes		Yes		Yes		Yes	
Birth district FEs	Yes		Yes		Yes		Yes		Yes	
F statistic	4.686		3.708		2.490		4.686		3.708	
p-value for F-test	0.000		0.000		0.001		0.000		0.000	
R^2	0.210		0.211		0.212		0.210		0.211	
N	5572		5572		5572		5572		5572	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. Columns (1) and (2) show that early coefficients are largely unchanged when removing later SPEI growing season variables. Columns (3) to (5) run a similar analysis but using a dataset in which all SPEI variables are demeaned so that the mean of each SPEI growing season variable is 0. By enforcing assumption (ii) in Footnote 12, this specification avoids the bias that can arise if there are omitted interaction effects on shock variables. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L3: *Cognitive "missing middle" by gender*

	Dep var: Cog at 7-14		Dep var: Cog at 15+			
	Female (1)	Male (2)	Female (3)	Female (4)	Male (5)	Male (6)
SPEI growing season, age = -1	0.014	0.023	0.025	0.022	0.045*	0.040*
	(0.026)	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)
SPEI growing season, age = 0	−0.023	0.030	0.004	0.010	0.007	−0.001
	(0.027)	(0.027)	(0.023)	(0.022)	(0.024)	(0.022)
SPEI growing season, age = 1	−0.001	0.021	0.031	0.031	0.006	0.000
	(0.025)	(0.026)	(0.022)	(0.021)	(0.028)	(0.026)
SPEI growing season, age = 2	0.024	0.033	0.062**	0.056**	0.074**	0.066**
	(0.025)	(0.032)	(0.024)	(0.024)	(0.029)	(0.027)
SPEI growing season, age = 3	0.026	0.030	0.018	0.011	0.053**	0.045**
	(0.027)	(0.026)	(0.023)	(0.023)	(0.023)	(0.020)
SPEI growing season, age = 4	−0.020	−0.019	−0.007	−0.001	−0.012	−0.007
	(0.026)	(0.027)	(0.031)	(0.029)	(0.024)	(0.022)
SPEI growing season, age = 5	0.024	−0.029	0.008	0.001	−0.005	0.003
	(0.024)	(0.024)	(0.024)	(0.023)	(0.022)	(0.021)
SPEI growing season, age = 6	0.006	0.008	0.021	0.019	−0.009	−0.011
	(0.027)	(0.024)	(0.025)	(0.024)	(0.024)	(0.023)
Cog score (aged 7-14)				0.256***		0.251***
				(0.026)		(0.024)
Birth year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Birth district FEs	Yes	Yes	Yes	Yes	Yes	Yes
Siblings FEs	No	No	No	No	No	No
Birth Order FEs	No	No	No	No	No	No
F statistic	0.694	0.791	1.783	1.361	2.171	1.961
p-value for F-test	0.696	0.612	0.085	0.218	0.033	0.055
R^2	0.218	0.203	0.286	0.326	0.231	0.275
N	2181	2189	2181	2181	2189	2189

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with only SPEI growing seasons from age -1 to age 6 as explanatory variables. The first two columns use the cognitive score measured between ages 7 and 14 as the dependent variable. Columns (3) to (6) use cognitive score measured in adulthood (above aged 15) as the dependent variable. The column titles indicate whether only females or males are included in the sample. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L4: *Cognitive outcomes are robust to inclusion of age fixed effects*

	Dep Var: Adult Cognitive Score			
	Main spec	q value	Age FEs	q value
	(1)	(1)	(2)	(2)
SPEI growing season, age = -2	0.007 (0.017)	[1]	0.007 (0.017)	[1]
SPEI growing season, age = -1	0.028 (0.016)*	[1]	0.030 (0.016)*	[0.941]
SPEI growing season, age = 0	−0.002 (0.015)	[1]	−0.001 (0.016)	[1]
SPEI growing season, age = 1	0.012 (0.019)	[1]	0.011 (0.018)	[1]
SPEI growing season, age = 2	0.065 (0.017)***	[0.003]	0.066 (0.017)***	[0.002]
SPEI growing season, age = 3	0.023 (0.015)	[1]	0.025 (0.015)*	[0.941]
SPEI growing season, age = 4	−0.005 (0.017)	[1]	−0.005 (0.017)	[1]
SPEI growing season, age = 5	0.012 (0.015)	[1]	0.010 (0.015)	[1]
SPEI growing season, age = 6	0.005 (0.017)	[1]	0.004 (0.016)	[1]
SPEI growing season, age = 7	−0.017 (0.020)	[1]	−0.015 (0.020)	[1]
SPEI growing season, age = 8	0.006 (0.015)	[1]	0.006 (0.015)	[1]
SPEI growing season, age = 9	−0.004 (0.019)	[1]	−0.005 (0.019)	[1]
SPEI growing season, age = 10	−0.018 (0.018)	[1]	−0.016 (0.018)	[1]
SPEI growing season, age = 11	−0.024 (0.018)	[1]	−0.025 (0.017)	[1]
SPEI growing season, age = 12	0.020 (0.021)	[1]	0.020 (0.021)	[1]
SPEI growing season, age = 13	−0.002 (0.019)	[1]	−0.001 (0.019)	[1]
SPEI growing season, age = 14	−0.004 (0.017)	[1]	−0.004 (0.018)	[1]
SPEI growing season, age = 15	−0.017 (0.017)	[1]	−0.019 (0.017)	[1]
Birth year FEs	Yes		Yes	
Birth district FEs	Yes		Yes	
Age (Year) FEs	No		Yes	
Sample mean	−0.003		−0.003	
F statistic	2.859		2.934	
p-value for F-test	0.000		0.000	
R^2	0.190		0.191	
N	7109		7109	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. Instead of taking the average adult cognitive score when it is measured in multiple waves, I here leave the observations at the (individual $\times$ wave) level to allow the inclusion of age fixed effects. Therefore, while the set of individuals is exactly the same as in the main results (e.g. Table 3), the number of observations is greater. Age fixed effects are dummies for each year of age. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L5: *Shocks in early life have weakly cumulative effects*

	Dep var: Adult Cognitive Score		
	Shock: SPEI≤-0.5	Shock: SPEI≤0	Shock: SPEI≤0.5
	(1)	(2)	(3)
# negative shocks = 1	-0.043	-0.025	0.034
	(0.030)	(0.030)	(0.064)
# negative shocks = 2	-0.069	-0.121^{***}	-0.028
	(0.047)	(0.045)	(0.063)
# negative shocks $\geq$ 3	-0.190^{**}	-0.143^{**}	-0.085
	(0.079)	(0.062)	(0.059)
Birth year FEs	Yes	Yes	Yes
Birth district FEs	Yes	Yes	Yes
R^2	0.208	0.209	0.209
N	5572	5572	5572

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The outcome variable is cognitive factor score measured in adulthood (above aged 15). Cognitive factor score is internally standardised, so the sample mean is 0 by construction. The table examines the effect of *how many* negative shocks are experienced in early life. *# negative shocks* is defined as the number of years between ages 1 and 3 that SPEI was below a certain threshold. Column (1) defines a negative shock as one where SPEI growing season is below -0.5, column (2) defines it as below 0, and column (3) as below 0.5. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data.

Table L6: *Dynamic complementarity in adolescence is mostly driven by males*

	Dep Var: Adult Cog Z-score					
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)
SPEI growing season, ages 0-3	0.073*	0.180***	0.053	0.101*	0.050	0.120*
	(0.043)	(0.058)	(0.043)	(0.059)	(0.047)	(0.062)
SPEI growing season, ages 10-12	−0.019	−0.006				
	(0.041)	(0.049)				
SPEI growing season, (ages 0-3 x ages 10-12)	−0.000	−0.113				
	(0.060)	(0.082)				
SPEI growing season, ages 13-15			−0.021	0.038		
			(0.046)	(0.046)		
SPEI growing season, (ages 0-3 x ages 13-15)			0.078	0.101**		
			(0.055)	(0.048)		
SPEI growing season, ages 10-15					−0.054	0.045
					(0.087)	(0.073)
SPEI growing season, (ages 0-3 x ages 10-15)					0.086	0.049
					(0.074)	(0.078)
Birth year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Birth district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.251	0.227	0.252	0.227	0.252	0.226
N	2971	2601	2971	2601	2971	2601

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running versions of Equation 1. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. All columns use cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Columns (1), (3) and (5) only include females, and other columns only include males. *SPEI growing season, ages 0-3* denotes the mean value of SPEI growing season for an individual across ages 0, 1, 2, and 3. The age ranges 13-15 and 10-15 are defined analogously. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L7: *Dynamic complementarity: effects on cognitive are not driven by changes in education*

Panel A: No interaction terms

	Dep Var: Years of schooling								
	Both (1)	Female (2)	Male (3)	Both (4)	Female (5)	Male (6)	Both (7)	Female (8)	Male (9)
SPEI growing season, ages 0-3	−0.092	−0.287*	0.097						
	(0.126)	(0.153)	(0.177)						
SPEI growing season, ages 10-12				−0.065	−0.049	−0.053			
				(0.106)	(0.140)	(0.132)			
SPEI growing season, ages 13-15							−0.169*	−0.225*	−0.185
							(0.096)	(0.120)	(0.140)
Birth year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	10.129	10.248	10.005	10.129	10.248	10.005	10.129	10.248	10.005
R^2	0.340	0.384	0.361	0.340	0.383	0.361	0.341	0.384	0.362
N	5010	2732	2278	5010	2732	2278	5010	2732	2278

Panel B: Interaction terms

	Dep Var: Years of schooling								
	Both (1)	Female (2)	Male (3)	Both (4)	Female (5)	Male (6)	Both (7)	Female (8)	Male (9)
SPEI growing season, ages 0-3	−0.144	−0.325*	0.041	−0.049	−0.316*	0.187	−0.071	−0.358*	0.173
	(0.138)	(0.190)	(0.179)	(0.142)	(0.160)	(0.213)	(0.163)	(0.200)	(0.223)
SPEI growing season, ages 10-12	−0.040	−0.020	−0.036						
	(0.109)	(0.143)	(0.135)						
SPEI growing season, (ages 0-3 x ages 10-12)	0.153	0.105	0.169						
	(0.181)	(0.219)	(0.283)						
SPEI growing season, ages 13-15				−0.164	−0.132	−0.239			
				(0.100)	(0.125)	(0.154)			
SPEI growing season, (ages 0-3 x ages 13-15)				−0.022	0.184	−0.112			
				(0.125)	(0.149)	(0.205)			
SPEI growing season, ages 10-15							−0.282	−0.199	−0.379
							(0.179)	(0.252)	(0.231)
SPEI growing season, (ages 0-3 x ages 10-15)							0.046	0.284	−0.075
							(0.219)	(0.282)	(0.299)
Birth year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth district fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean	10.129	10.248	10.005	10.129	10.248	10.005	10.129	10.248	10.005
R^2	0.341	0.384	0.361	0.341	0.385	0.362	0.341	0.385	0.362
N	5010	2732	2278	5010	2732	2278	5010	2732	2278

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running versions of Equation 1. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. All columns use *years of schooling* measured in above age 15 as the dependent variable. To control for age, age fixed effects are included. *SPEI growing season, ages 0-3* denotes the mean value of SPEI growing season for an individual across ages 0, 1, 2, and 3. The age ranges 13-15 and 10-15 are defined analogously. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L8: *Effect of SPEI growing season on cognitive: 2 year intervals*

	(1)	q value (1)
SPEI growing season, ages -2 to -1	0.022	[1]
	(0.024)	
SPEI growing season, ages 0 to 1	0.005	[1]
	(0.015)	
SPEI growing season, ages 2 to 3	0.064***	[0.001]
	(0.014)	
SPEI growing season, ages 4 to 5	0.006	[1]
	(0.014)	
SPEI growing season, ages 6 to 7	−0.004	[1]
	(0.015)	
SPEI growing season, ages 8 to 9	0.010	[1]
	(0.015)	
SPEI growing season, ages 10 to 11	−0.016	[1]
	(0.017)	
SPEI growing season, ages 12 to 13	0.023	[1]
	(0.019)	
SPEI growing season, ages 14 to 15	−0.001	[1]
	(0.015)	
F statistic	3.779	
p-value for F-test	0.000	
R^2	0.211	
N	5572	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are in parentheses and are clustered by birth district. The table uses a version of Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. *SPEI growing season, ages 2 to 3* is the mean SPEI growing season for the individual, taken across ages 2 and 3. Other age ranges are defined similarly. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L9: *Effect of weather on cognitive development, 6 month intervals and extended age range*

	Dep Var: Cognitive Z Score			
	SPEI growing season (1)	q value (1)	Predicted harvest index (2)	q value (2)
Age = -2	0.033 (0.029)	[1]	−0.003 (0.031)	[1]
Age = -1.5	−0.004 (0.025)	[1]	−0.015 (0.030)	[1]
Age = -1	0.028 (0.025)	[1]	−0.028 (0.028)	[1]
Age = -0.5	0.013 (0.028)	[1]	0.015 (0.030)	[1]
Age = 0	0.024 (0.029)	[1]	0.018 (0.031)	[1]
Age = 0.5	−0.021 (0.028)	[1]	−0.013 (0.029)	[1]
Age = 1	0.025 (0.028)	[1]	−0.027 (0.029)	[1]
Age = 1.5	−0.006 (0.027)	[1]	−0.006 (0.027)	[1]
Age = 2	0.057 (0.028)**	[1]	−0.002 (0.027)	[1]
Age = 2.5	0.079 (0.027)***	[0.149]	0.076 (0.029)***	[0.5]
Age = 3	0.036 (0.030)	[1]	0.017 (0.027)	[1]
Age = 3.5	0.016 (0.026)	[1]	−0.014 (0.030)	[1]
Age = 4	−0.004 (0.030)	[1]	0.015 (0.028)	[1]
Age = 4.5	−0.014 (0.024)	[1]	−0.029 (0.029)	[1]
Age = 5	0.029 (0.029)	[1]	−0.028 (0.028)	[1]
Age = 5.5	0.018 (0.026)	[1]	−0.013 (0.030)	[1]
Age = 6	−0.022 (0.032)	[1]	−0.032 (0.028)	[1]
Age = 6.5	0.010 (0.025)	[1]	−0.044 (0.032)	[1]
Age = 7	−0.005 (0.031)	[1]	−0.027 (0.031)	[1]
Age = 7.5	−0.017 (0.027)	[1]	−0.010 (0.029)	[1]
Age = 8	0.024 (0.030)	[1]	−0.015 (0.028)	[1]
Age = 8.5	−0.001 (0.026)	[1]	−0.038 (0.030)	[1]
Age = 9	0.045 (0.030)	[1]	−0.017 (0.031)	[1]
Age = 9.5	−0.039 (0.027)	[1]	−0.044 (0.032)	[1]
Age = 10	−0.055 (0.031)*	[1]	−0.011 (0.030)	[1]
Age = 10.5	−0.015 (0.029)	[1]	−0.038 (0.032)	[1]
Age = 11	−0.011 (0.033)	[1]	−0.004 (0.037)	[1]
Age = 11.5	−0.024 (0.031)	[1]	−0.038 (0.034)	[1]
Age = 12	0.008 (0.032)	[1]	−0.007 (0.033)	[1]
Age = 12.5	0.021 (0.034)	[1]	−0.035 (0.033)	[1]
Age = 13	−0.007 (0.033)	[1]	0.027 (0.033)	[1]
Age = 13.5	0.013 (0.033)	[1]	−0.036 (0.032)	[1]
Age = 14	0.022 (0.030)	[1]	0.040 (0.031)	[1]
Age = 14.5	−0.009 (0.029)	[1]	−0.003 (0.033)	[1]
Age = 15	−0.012 (0.031)	[1]	−0.005 (0.029)	[1]
Birth year FEs	Yes		Yes	
District x month-of-birth FEs	Yes		Yes	
R^2	0.424		0.424	
N	5572		5572	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The dependent variable in all models is the adult cognitive factor score (measured after age 15). The cognitive factor score is standardised to have 0 mean and standard deviation of 1. Column (1) uses the SPEI growing season as the main explanatory variable, and column (2) uses the predicted harvest index. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year × district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. Individuals are matched to values of predicted harvest index using the process described in Section E.2. 6-monthly specifications control for (district × month-of-birth fixed effects), to account for variation due to the timing of birth relative to the 6-month "bucket" individuals are assigned to (see Appendix Section E.2 for details.) All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L10: *Cognitive results using predicted harvest while including later ages*

	Dep Var: Adult Cognitive Score					
	Both (1)	q value (1)	Females Only (2)	q value (2)	Males Only (3)	q value (3)
Predicted Harvest Index, Age = -2	−0.012 (0.021)	[1]	−0.026 (0.037)	[1]	0.003 (0.033)	[1]
Predicted Harvest Index, Age = -1	−0.001 (0.020)	[1]	0.017 (0.030)	[1]	0.000 (0.029)	[1]
Predicted Harvest Index, Age = 0	0.015 (0.021)	[1]	0.018 (0.029)	[1]	0.016 (0.032)	[1]
Predicted Harvest Index, Age = 1	−0.014 (0.019)	[1]	−0.023 (0.029)	[1]	0.004 (0.025)	[1]
Predicted Harvest Index, Age = 2	0.038 (0.021)*	[0.956]	−0.001 (0.029)	[1]	0.082 (0.028)***	[0.067]
Predicted Harvest Index, Age = 3	0.020 (0.019)	[1]	0.001 (0.028)	[1]	0.051 (0.029)*	[0.751]
Predicted Harvest Index, Age = 4	−0.005 (0.019)	[1]	−0.043 (0.028)	[1]	0.032 (0.030)	[0.947]
Predicted Harvest Index, Age = 5	−0.023 (0.021)	[1]	−0.016 (0.034)	[1]	−0.020 (0.028)	[1]
Predicted Harvest Index, Age = 6	−0.040 (0.021)*	[0.956]	−0.027 (0.035)	[1]	−0.047 (0.026)*	[0.751]
Predicted Harvest Index, Age = 7	−0.008 (0.021)	[1]	0.001 (0.037)	[1]	−0.017 (0.028)	[1]
Predicted Harvest Index, Age = 8	−0.005 (0.020)	[1]	0.030 (0.035)	[1]	−0.037 (0.026)	[0.841]
Predicted Harvest Index, Age = 9	−0.015 (0.024)	[1]	−0.010 (0.033)	[1]	−0.036 (0.034)	[0.947]
Predicted Harvest Index, Age = 10	−0.023 (0.023)	[1]	−0.019 (0.031)	[1]	−0.025 (0.038)	[1]
Predicted Harvest Index, Age = 11	−0.035 (0.022)	[0.956]	−0.032 (0.035)	[1]	−0.044 (0.037)	[0.947]
Predicted Harvest Index, Age = 12	0.003 (0.019)	[1]	−0.023 (0.026)	[1]	0.015 (0.030)	[1]
Predicted Harvest Index, Age = 13	0.014 (0.021)	[1]	−0.017 (0.036)	[1]	0.040 (0.029)	[0.841]
Predicted Harvest Index, Age = 14	0.038 (0.023)*	[0.956]	0.038 (0.032)	[1]	0.043 (0.032)	[0.841]
Predicted Harvest Index, Age = 15	−0.017 (0.022)	[1]	0.010 (0.034)	[1]	−0.026 (0.034)	[1]
Birth year FEs	Yes		Yes		Yes	
Birth district FEs	Yes		Yes		Yes	
District x month-of-birth FEs	No		No		No	
F statistic	1.435		0.712		2.189	
p-value for F-test	0.120		0.796		0.005	
R^2	0.212		0.252		0.237	
N	5572		2971		2601	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The dependent variable in all models is the adult cognitive factor score (measured after age 15). The cognitive factor score is standardised to have 0 mean and standard deviation of 1. Column (1) includes both genders, column (2) only includes females, and column (3) only includes males. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year × district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. Individuals are matched to values of predicted harvest index using the process described in E.2. Yearly specifications control for birth district fixed effects. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L11: *Cognitive results are robust to other weather indexes (yearly intervals)*

	GDD + Wet						GDD + SPEI					
	Both Sexes (1)	q value (1)	Male Only (2)	q value (2)	Female Only (3)	q value (3)	Both Sexes (4)	q value (4)	Male Only (5)	q value (5)	Female Only (6)	q value (6)
Age = -1	0.004	[1]	0.011	[1]	0.012	[1]	−0.002	[1]	−0.010	[0.805]	0.023	[1]
	(0.020)		(0.031)		(0.028)		(0.018)		(0.024)		(0.028)	
Age = 0	0.020	[1]	0.024	[0.948]	0.019	[1]	0.018	[1]	0.026	[0.627]	0.018	[1]
	(0.019)		(0.029)		(0.030)		(0.018)		(0.025)		(0.028)	
Age = 1	0.002	[1]	0.037	[0.948]	−0.034	[1]	−0.005	[1]	0.010	[0.805]	−0.010	[1]
	(0.019)		(0.026)		(0.031)		(0.017)		(0.023)		(0.025)	
Age = 2	0.045**	[0.201]	0.067**	[0.1]	0.028	[1]	0.041**	[0.244]	0.085***	[0.016]	0.004	[1]
	(0.020)		(0.027)		(0.032)		(0.019)		(0.027)		(0.023)	
Age = 3	−0.015	[1]	0.027	[0.948]	−0.053*	[0.838]	0.027	[0.5]	0.038	[0.452]	0.031	[1]
	(0.019)		(0.026)		(0.029)		(0.017)		(0.023)		(0.025)	
Age = 4	−0.004	[1]	0.023	[0.948]	−0.039	[1]	−0.001	[1]	0.034	[0.512]	−0.036	[1]
	(0.022)		(0.033)		(0.029)		(0.016)		(0.025)		(0.024)	
Age = 5	−0.022	[1]	−0.025	[0.948]	−0.008	[1]	0.002	[1]	0.007	[0.805]	0.003	[1]
	(0.019)		(0.029)		(0.032)		(0.020)		(0.026)		(0.030)	
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Birth district FEs	Yes		Yes		Yes		Yes		Yes		Yes	
District x month-of-birth FEs	No		No		No		No		No		No	
F statistic	1.144		1.970		1.123		1.063		1.874		1.006	
p-value for F-test	0.338		0.062		0.351		0.389		0.077		0.429	
R^2	0.209		0.231		0.251		0.209		0.231		0.250	
N	5569		2600		2969		5572		2601		2971	

	Wet + SPEI						GDD + Wet + SPEI + Dry Spell					
	Both Sexes (7)	q value (7)	Male Only (8)	q value (8)	Female Only (9)	q value (9)	Both Sexes (10)	q value (10)	Male Only (11)	q value (11)	Female Only (12)	q value (12)
Age = -1	0.000	[1]	−0.005	[1]	0.022	[1]	−0.005	[1]	−0.015	[1]	0.019	[1]
	(0.018)		(0.025)		(0.028)		(0.019)		(0.028)		(0.027)	
Age = 0	0.020	[1]	0.026	[0.623]	0.021	[1]	0.013	[1]	0.013	[1]	0.022	[1]
	(0.018)		(0.026)		(0.028)		(0.018)		(0.026)		(0.028)	
Age = 1	−0.004	[1]	0.016	[0.659]	−0.013	[1]	−0.013	[1]	0.016	[1]	−0.034	[1]
	(0.018)		(0.024)		(0.026)		(0.018)		(0.025)		(0.029)	
Age = 2	0.047**	[0.141]	0.093***	[0.008]	0.007	[1]	0.039*	[0.598]	0.081***	[0.032]	0.001	[1]
	(0.020)		(0.028)		(0.025)		(0.020)		(0.028)		(0.026)	
Age = 3	0.025	[0.877]	0.042*	[0.319]	0.023	[1]	0.012	[1]	0.041*	[0.371]	−0.003	[1]
	(0.018)		(0.024)		(0.026)		(0.018)		(0.024)		(0.025)	
Age = 4	−0.001	[1]	0.037	[0.392]	−0.039	[1]	−0.013	[1]	0.027	[1]	−0.062***	[0.054]
	(0.017)		(0.026)		(0.024)		(0.017)		(0.028)		(0.023)	
Age = 5	−0.000	[1]	0.004	[1]	0.003	[1]	−0.005	[1]	0.002	[1]	−0.008	[1]
	(0.020)		(0.028)		(0.032)		(0.020)		(0.028)		(0.032)	
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Birth district FEs	Yes		Yes		Yes		Yes		Yes		Yes	
District x month-of-birth FEs	No		No		No		No		No		No	
F statistic	1.094		2.108		0.885		0.835		1.934		1.302	
p-value for F-test	0.369		0.046		0.520		0.559		0.068		0.252	
R^2	0.209		0.232		0.250		0.209		0.231		0.251	
N	5572		2601		2971		5572		2601		2971	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The dependent variable in all models is the adult cognitive factor score (measured after age 15). The cognitive factor score is standardised to have 0 mean and standard deviation of 1. The first column for each index includes both genders, the second column only includes females, and the third column only includes males. The first three columns use an index constructed in an analogous way to the predicted harvest index but based on just using Wet Season Delay and the SPEI to construct the index (column (2) of Table D1). Columns (4)-(6) use an index constructed from column (5) of Table D1, columns (7)-(9) use an index constructed from column (7) of Table D1, and columns (10)-(12) use an index constructed from column (6) of Table D1. The harvest date is defined as the average harvest date of rice in that district based on IFLS harvest data (see Section D.2). Individuals are matched to values of predicted harvest index using the process described in E.2. The yearly specifications control for birth district fixed effects. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table L12: *Cognitive results are robust to other weather indexes (6 month intervals)*

	GDD + Wet						GDD + SPEI						Wet + SPEI						GDD + Wet + SPEI + Dry Spell					
	Both Sexes (1)	q value (1)	Male Only (2)	q value (2)	Female Only (3)	q value (3)	Both Sexes (4)	q value (4)	Male Only (5)	q value (5)	Female Only (6)	q value (6)	Both Sexes (7)	q value (7)	Male Only (8)	q value (8)	Female Only (9)	q value (9)	Both Sexes (10)	q value (10)	Male Only (11)	q value (11)	Female Only (12)	q value (12)
Age = -12 to -7 months	−0.000	[1]	−0.015	[1]	−0.000	[1]	−0.032	[1]	−0.037	[1]	−0.007	[1]	−0.030	[1]	−0.033	[1]	−0.010	[1]	−0.025	[1]	−0.039	[1]	−0.006	[1]
	(0.024)		(0.042)		(0.039)		(0.024)		(0.040)		(0.046)		(0.025)		(0.040)		(0.047)		(0.025)		(0.043)		(0.044)	
Age = -6 to -1 months	0.018	[1]	−0.048	[0.689]	0.042	[1]	0.019	[1]	−0.028	[1]	0.044	[1]	0.021	[1]	−0.035	[1]	0.048	[1]	0.017	[1]	−0.042	[1]	0.050	[0.807]
	(0.029)		(0.044)		(0.043)		(0.025)		(0.039)		(0.038)		(0.025)		(0.041)		(0.038)		(0.026)		(0.045)		(0.038)	
Age = 0 to 5 months	0.034	[1]	0.013	[1]	0.013	[1]	0.012	[1]	0.027	[1]	0.007	[1]	0.011	[1]	0.026	[1]	0.002	[1]	0.015	[1]	0.009	[1]	0.020	[1]
	(0.029)		(0.054)		(0.044)		(0.026)		(0.038)		(0.036)		(0.028)		(0.040)		(0.038)		(0.026)		(0.040)		(0.036)	
Age = 6 to 11 months	−0.042	[0.924]	−0.062	[0.604]	−0.051	[1]	0.001	[1]	0.003	[1]	−0.019	[1]	0.001	[1]	−0.006	[1]	−0.015	[1]	−0.015	[1]	−0.027	[1]	−0.015	[1]
	(0.028)		(0.043)		(0.049)		(0.026)		(0.038)		(0.040)		(0.026)		(0.038)		(0.041)		(0.026)		(0.038)		(0.040)	
Age = 12 to 17 months	0.014	[1]	−0.001	[1]	0.011	[1]	−0.016	[1]	−0.014	[1]	−0.002	[1]	−0.014	[1]	−0.012	[1]	−0.006	[1]	−0.025	[1]	−0.019	[1]	−0.026	[1]
	(0.025)		(0.035)		(0.039)		(0.025)		(0.035)		(0.036)		(0.026)		(0.035)		(0.037)		(0.025)		(0.033)		(0.036)	
Age = 18 to 23 months	−0.020	[1]	0.008	[1]	−0.096**	[0.303]	−0.000	[1]	0.003	[1]	−0.028	[1]	0.001	[1]	0.007	[1]	−0.036	[1]	0.000	[1]	0.022	[1]	−0.051	[0.807]
	(0.027)		(0.048)		(0.046)		(0.025)		(0.046)		(0.037)		(0.026)		(0.047)		(0.039)		(0.026)		(0.045)		(0.040)	
Age = 24 to 29 months	0.016	[1]	0.056	[0.604]	−0.026	[1]	0.014	[1]	0.064*	[0.373]	−0.036	[1]	0.016	[1]	0.074**	[0.208]	−0.043	[1]	0.005	[1]	0.068*	[0.429]	−0.063*	[0.701]
	(0.027)		(0.043)		(0.041)		(0.024)		(0.036)		(0.031)		(0.024)		(0.037)		(0.032)		(0.025)		(0.039)		(0.034)	
Age = 30 to 35 months	0.089***	[0.022]	0.160***	[0.002]	0.030	[1]	0.071***	[0.115]	0.130***	[0.024]	−0.008	[1]	0.078***	[0.07]	0.146***	[0.008]	−0.005	[1]	0.076***	[0.098]	0.149***	[0.004]	−0.001	[1]
	(0.028)		(0.041)		(0.043)		(0.027)		(0.041)		(0.034)		(0.028)		(0.041)		(0.036)		(0.028)		(0.040)		(0.039)	
Age = 36 to 41 months	−0.025	[1]	0.012	[1]	−0.039	[1]	0.026	[1]	0.039	[1]	0.009	[1]	0.024	[1]	0.044	[1]	0.002	[1]	−0.001	[1]	0.038	[1]	−0.036	[0.807]
	(0.025)		(0.043)		(0.036)		(0.022)		(0.037)		(0.034)		(0.023)		(0.038)		(0.034)		(0.023)		(0.038)		(0.027)	
Age = 42 to 47 months	−0.001	[1]	0.064	[0.604]	−0.026	[1]	−0.005	[1]	0.023	[1]	−0.004	[1]	−0.005	[1]	0.033	[1]	−0.010	[1]	−0.011	[1]	0.038	[1]	−0.027	[1]
	(0.031)		(0.047)		(0.044)		(0.025)		(0.034)		(0.040)		(0.026)		(0.035)		(0.041)		(0.026)		(0.034)		(0.039)	
Age = 48 to 53 months	−0.002	[1]	0.079	[0.604]	−0.088**	[0.303]	0.026	[1]	0.084**	[0.154]	−0.033	[1]	0.024	[1]	0.089**	[0.171]	−0.042	[1]	0.011	[1]	0.096**	[0.159]	−0.067**	[0.472]
	(0.026)		(0.052)		(0.037)		(0.023)		(0.036)		(0.032)		(0.024)		(0.039)		(0.033)		(0.023)		(0.042)		(0.030)	
Age = 54 to 59 months	−0.008	[1]	0.012	[1]	−0.007	[1]	−0.016	[1]	0.009	[1]	−0.039	[1]	−0.018	[1]	0.012	[1]	−0.040	[1]	−0.021	[1]	−0.007	[1]	−0.038	[1]
	(0.029)		(0.043)		(0.054)		(0.024)		(0.037)		(0.040)		(0.024)		(0.038)		(0.042)		(0.025)		(0.037)		(0.041)	
Age = 60 to 65 months	−0.048*	[0.525]	−0.066*	[0.604]	−0.040	[1]	−0.004	[1]	−0.016	[1]	0.006	[1]	−0.009	[1]	−0.021	[1]	0.001	[1]	−0.014	[1]	−0.014	[1]	−0.008	[1]
	(0.025)		(0.039)		(0.035)		(0.021)		(0.031)		(0.036)		(0.021)		(0.031)		(0.036)		(0.022)		(0.031)		(0.033)	
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Birth district FEs	No		No		No		No		No		No		No		No		No		No		No		No	
District x month-of-birth FEs	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
F statistic	2.029		2.887		1.627		1.306		1.787		0.687		1.389		1.963		0.819		1.332		1.943		1.336	
p-value for F-test	0.016		0.001		0.082		0.202		0.049		0.774		0.157		0.027		0.639		0.187		0.029		0.196	
R^2	0.422		0.570		0.552		0.421		0.568		0.550		0.421		0.569		0.550		0.421		0.570		0.551	
N	5569		2600		2969		5572		2601		2971		5572		2601		2971		5572		2601		2971	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The dependent variable in all models is the adult cognitive factor score (measured after age 15). The cognitive factor score is standardised to have 0 mean and standard deviation of 1. The first column for each index includes both genders, the second column only includes females, and the third column only includes males. The first three columns use an index constructed in an analogous way to the predicted harvest index but based on just using Wet Season Delay and the SPEI to construct the index (column (2) of Table D1). Columns (4)-(6) use an index constructed from column (5) of Table D1, columns (7)-(9) use an index constructed from column (7) of Table D1, and columns (10)-(12) use an index constructed from column (6) of Table D1. Individuals are matched to values of predicted harvest index using the process described in E.2. The 6-monthly specifications control for (District × month of birth fixed effects), to account for variation due to the timing of birth relative to the 6-month "bucket" individuals are assigned to (see Appendix Section E.2 for details.) All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

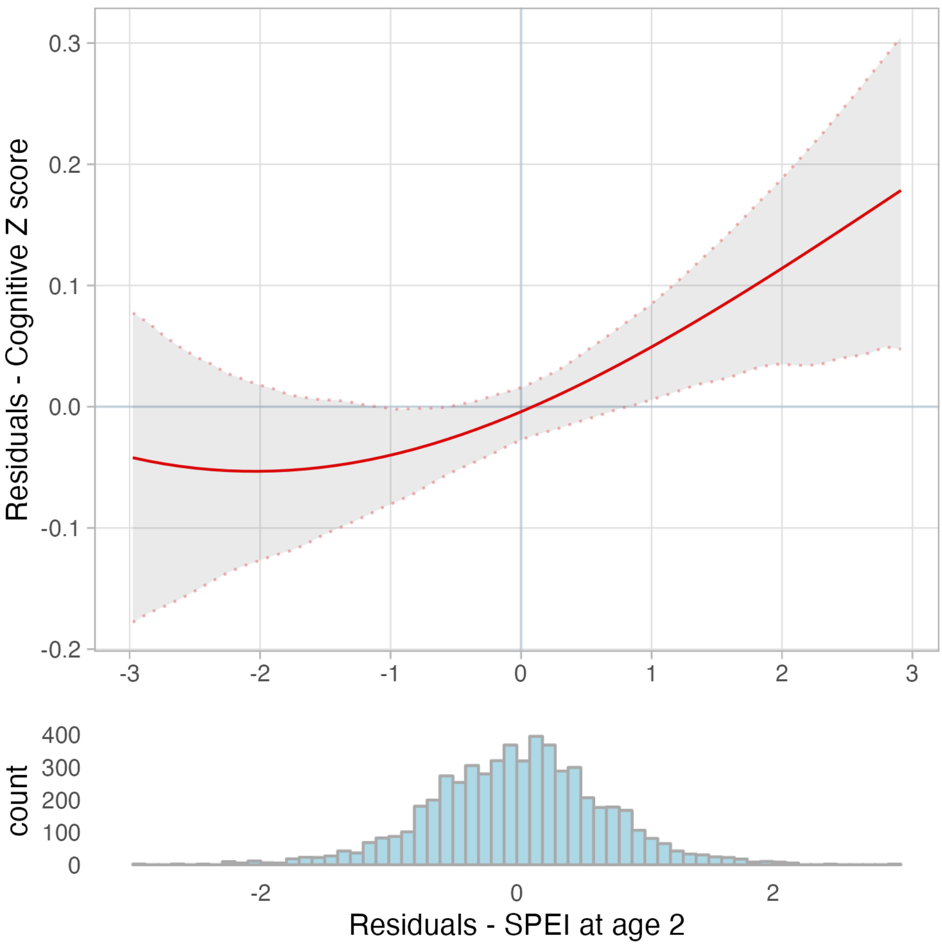
Table L13: *Cognitive results are robust to using adjusted shock measure (weighted to account for differential exposure to shocks)*

	Dep Var: Cognitive Z Score			
	SPEI growing season (1)	q value (1)	Predicted Harvest Index (2)	q value (2)
Age = -1	0.028 (0.031)	[1]	−0.023 (0.033)	[1]
Age = -0.5	0.029 (0.034)	[1]	0.030 (0.033)	[1]
Age = 0	0.007 (0.037)	[1]	0.033 (0.037)	[1]
Age = 0.5	−0.024 (0.035)	[1]	−0.006 (0.035)	[1]
Age = 1	0.024 (0.035)	[1]	−0.014 (0.034)	[1]
Age = 1.5	0.013 (0.033)	[1]	0.003 (0.033)	[1]
Age = 2	0.074 (0.037)**	[0.411]	0.016 (0.033)	[1]
Age = 2.5	0.108 (0.034)***	[0.021]	0.110 (0.036)***	[0.03]
Age = 3	0.027 (0.036)	[1]	0.024 (0.031)	[1]
Age = 3.5	0.039 (0.032)	[1]	0.002 (0.034)	[1]
Age = 4	−0.017 (0.037)	[1]	0.042 (0.032)	[1]
Age = 4.5	−0.012 (0.029)	[1]	−0.010 (0.032)	[1]
Age = 5	0.014 (0.034)	[1]	−0.020 (0.029)	[1]
Birth year FEs	Yes		Yes	
District x month-of-birth FEs	Yes		Yes	
F statistic	1.578		1.605	
p-value for F-test	0.085		0.077	
R^2	0.421		0.422	
N	5572		5572	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The dependent variable in all models is the adult cognitive factor score (measured after age 15). The cognitive factor score is standardised to have 0 mean and standard deviation of 1. Column (1) includes both genders, column (2) only includes females, and column (3) only includes males. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year $\times$ district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. Individuals are matched to values of predicted harvest index using the process described in E.2. All models in this table use an adjusted shock measure that accounts for differential exposure to shocks in each 6-month interval. For example, person *a* is born at the start of the shock-exposure period (3 months after harvest), so their first 6 months are exposed fully to the shock and the shock variable is not adjusted. However, person *b* is born in the middle of the shock-exposure period (say 5 months after harvest), and so only 4 out of the 6 first months of their life are exposed to the shock. I therefore adjust person *b*'s shock measure to be 2/3 as large as person *a*'s. The yearly specifications control for birth district fixed effects, while the 6-monthly specifications control for (District $\times$ month of birth fixed effects), to account for variation due to the timing of birth relative to the 6-month "bucket" individuals are assigned to (see Appendix Section E.2 for details.) All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

M Additional tables: alternative non-linear models

Figure M1: *Non-parametric kernel regression of $SPEI_{i(t+2)}$ on the residuals of cognitive factor score*



Notes: The red line denotes the estimates from a non-parametric kernel regression of $SPEI_{i(t+2)}$ on the residuals of cognitive factor score after conditioning for birth-year fixed effects, birth-district fixed effects, SPEI growing season from ages -2, -1, 0, 1, and 3-15, and individual controls (parental education, gender, and religion). The specification is a local-linear regression that uses a Gaussian kernel and chooses a bandwidth of 0.95 using a process of least-squares cross-validation. The dashed lines show the bootstrapped 95% confidence intervals. The light-blue histogram at the bottom of the chart shows the distribution of residuals in this sample.

Table M1: *Distinguishing between positive and negative shocks - linear model with different coefficients for positive and negative shocks*

	Dep Var: Adult Cog (1)
Negative:	
SPEI growing season $<$ 0, age = -2	0.003 (0.030)
SPEI growing season $<$ 0, age = -1	0.049 (0.028)*
SPEI growing season $<$ 0, age = 0	0.008 (0.029)
SPEI growing season $<$ 0, age = 1	0.016 (0.033)
SPEI growing season $<$ 0, age = 2	0.049 (0.033)
SPEI growing season $<$ 0, age = 3	0.014 (0.031)
SPEI growing season $<$ 0, age = 4	0.009 (0.033)
SPEI growing season $<$ 0, age = 5	0.007 (0.037)
SPEI growing season $<$ 0, age = 6	0.030 (0.036)
SPEI growing season $<$ 0, age = 7	−0.017 (0.040)
SPEI growing season $<$ 0, age = 8	0.009 (0.039)
SPEI growing season $<$ 0, age = 9	−0.014 (0.039)
SPEI growing season $<$ 0, age = 10	0.052 (0.049)
SPEI growing season $<$ 0, age = 11	−0.095 (0.053)*
SPEI growing season $<$ 0, age = 12	0.064 (0.056)
SPEI growing season $<$ 0, age = 13	−0.108 (0.051)**
SPEI growing season $<$ 0, age = 14	−0.044 (0.049)
SPEI growing season $<$ 0, age = 15	−0.021 (0.038)
Positive:	
SPEI growing season $\geq$ 0, age = -2	−0.001 (0.033)
SPEI growing season $\geq$ 0, age = -1	0.001 (0.031)
SPEI growing season $\geq$ 0, age = 0	0.001 (0.033)
SPEI growing season $\geq$ 0, age = 1	0.035 (0.038)
SPEI growing season $\geq$ 0, age = 2	0.080 (0.031)**
SPEI growing season $\geq$ 0, age = 3	0.052 (0.028)*
SPEI growing season $\geq$ 0, age = 4	0.000 (0.029)
SPEI growing season $\geq$ 0, age = 5	0.025 (0.027)
SPEI growing season $\geq$ 0, age = 6	−0.004 (0.029)
SPEI growing season $\geq$ 0, age = 7	−0.036 (0.033)
SPEI growing season $\geq$ 0, age = 8	0.039 (0.033)
SPEI growing season $\geq$ 0, age = 9	0.015 (0.037)
SPEI growing season $\geq$ 0, age = 10	−0.032 (0.032)
SPEI growing season $\geq$ 0, age = 11	0.005 (0.035)
SPEI growing season $\geq$ 0, age = 12	0.006 (0.037)
SPEI growing season $\geq$ 0, age = 13	0.042 (0.030)
SPEI growing season $\geq$ 0, age = 14	0.049 (0.034)
SPEI growing season $\geq$ 0, age = 15	0.001 (0.029)
Birth year fixed effects	Yes
Birth district fixed effects	Yes
F statistic	2.486
p-value for F-test	0.000
R^2	0.214
N	5572

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. The first set of coefficients (rows 1 to 18) describe the effect of a variable that takes the value of $SPEI_{i(t+j)}$ when $SPEI_{i(t+j)} < 0$, and 0 otherwise, so it describes the (linear) effect of $SPEI_{i(t+j)}$ when it is negative. Similarly, the second set of coefficients (rows 19 to 36) describe the effect of a variable that takes the value of $SPEI_{i(t+j)}$ when $SPEI_{i(t+j)} \geq 0$, and 0 otherwise, i.e. the (linear) effect of $SPEI_{i(t+j)}$ when it is positive. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table M2: *Distinguishing between positive and negative shocks - binary shock variables*

	Large positive shocks (>2 SD) (1)	q value (1)	Large negative shocks (<-2 SD) (2)	q value (2)	Binary shock (>0) (3)	q value (3)
SPEI growing season, age = -2	-0.210 (0.098)**	[0.255]	0.046 (0.100)	[1]	-0.004 (0.029)	[1]
SPEI growing season, age = -1	-0.055 (0.105)	[1]	-0.147 (0.094)	[0.43]	0.038 (0.027)	[1]
SPEI growing season, age = 0	0.115 (0.093)	[0.674]	-0.205 (0.091)**	[0.173]	-0.019 (0.029)	[1]
SPEI growing season, age = 1	-0.000 (0.072)	[1]	-0.175 (0.095)*	[0.345]	0.025 (0.034)	[1]
SPEI growing season, age = 2	0.088 (0.126)	[1]	-0.235 (0.090)**	[0.173]	0.103 (0.031)***	[0.018]
SPEI growing season, age = 3	0.155 (0.068)**	[0.255]	-0.207 (0.086)**	[0.173]	0.013 (0.031)	[1]
SPEI growing season, age = 4	-0.166 (0.090)*	[0.339]	-0.107 (0.151)	[1]	-0.021 (0.028)	[1]
SPEI growing season, age = 5	0.040 (0.092)	[1]	-0.092 (0.097)	[1]	-0.016 (0.030)	[1]
SPEI growing season, age = 6	-0.077 (0.116)	[1]	-0.097 (0.114)	[1]	-0.008 (0.031)	[1]
SPEI growing season, age = 7	-0.028 (0.086)	[1]	-0.016 (0.132)	[1]	-0.036 (0.036)	[1]
SPEI growing season, age = 8	-0.144 (0.114)	[0.674]	-0.032 (0.148)	[1]	-0.003 (0.030)	[1]
SPEI growing season, age = 9	0.053 (0.091)	[1]	-0.212 (0.123)*	[0.354]	-0.016 (0.034)	[1]
SPEI growing season, age = 10	-0.282 (0.113)**	[0.255]	-0.187 (0.201)	[1]	-0.018 (0.033)	[1]
SPEI growing season, age = 11	0.061 (0.086)	[1]	-0.059 (0.176)	[1]	-0.046 (0.028)*	[1]
SPEI growing season, age = 12	-0.017 (0.092)	[1]	-0.154 (0.231)	[1]	0.044 (0.036)	[1]
SPEI growing season, age = 13	0.140 (0.084)*	[0.411]	0.021 (0.175)	[1]	-0.023 (0.033)	[1]
SPEI growing season, age = 14	0.019 (0.087)	[1]	-0.010 (0.195)	[1]	-0.021 (0.030)	[1]
SPEI growing season, age = 15	-0.006 (0.102)	[1]	0.001 (0.117)	[1]	0.008 (0.026)	[1]
Birth year fixed effects	Yes		Yes		Yes	
Birth district fixed effects	Yes		Yes		Yes	
F statistic	4.540		2.451		1.644	
p-value for F-test	0.000		0.001		0.054	
R^2	0.212		0.209		0.212	
N	5572		5572		5572	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Column (1) shows the effect of large positive shocks (i.e. $SPEI_{i(t+j)} > 2$) , Column (2) shows the effect of large negative shocks (i.e. $SPEI_{i(t+j)} < -2$), and Column (3) shows the effect of a binary variable with the threshold at 0, (i.e. $SPEI_{i(t+j)} > 0$). Around 2% of the sample experience large positive shocks in a given year, and around 2% of the sample experience large negative shocks in a given year. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table M3: *Different thresholds for extreme negative shocks*

	<-2 SD (1)	q value (1)	<-1.5 SD (2)	q value (2)	<-1 SD (3)	q value (3)	<-0.5 SD (4)	q value (4)
SPEI growing season, age = -2	0.046 (0.100)	[1]	−0.046 (0.063)	[0.834]	0.051 (0.042)	[0.874]	−0.016 (0.036)	[1]
SPEI growing season, age = -1	−0.147 (0.094)	[0.43]	−0.083 (0.073)	[0.801]	−0.081 (0.041)**	[0.682]	−0.048 (0.029)	[0.684]
SPEI growing season, age = 0	−0.205 (0.091)**	[0.173]	−0.092 (0.074)	[0.801]	−0.060 (0.042)	[0.874]	0.014 (0.031)	[1]
SPEI growing season, age = 1	−0.175 (0.095)*	[0.345]	−0.130 (0.070)*	[0.801]	0.006 (0.043)	[1]	−0.004 (0.037)	[1]
SPEI growing season, age = 2	−0.235 (0.090)**	[0.173]	−0.131 (0.073)*	[0.801]	−0.062 (0.047)	[0.874]	−0.105 (0.033)***	[0.036]
SPEI growing season, age = 3	−0.207 (0.086)**	[0.173]	−0.100 (0.065)	[0.801]	−0.087 (0.049)*	[0.761]	−0.024 (0.034)	[1]
SPEI growing season, age = 4	−0.107 (0.151)	[1]	−0.035 (0.078)	[0.867]	−0.022 (0.047)	[1]	−0.002 (0.033)	[1]
SPEI growing season, age = 5	−0.092 (0.097)	[1]	−0.113 (0.078)	[0.801]	−0.052 (0.044)	[0.874]	−0.019 (0.039)	[1]
SPEI growing season, age = 6	−0.097 (0.114)	[1]	−0.156 (0.069)**	[0.801]	−0.004 (0.044)	[1]	0.006 (0.033)	[1]
SPEI growing season, age = 7	−0.016 (0.132)	[1]	0.011 (0.087)	[0.867]	−0.026 (0.063)	[1]	0.066 (0.037)*	[0.684]
SPEI growing season, age = 8	−0.032 (0.148)	[1]	−0.042 (0.076)	[0.867]	−0.038 (0.052)	[1]	−0.014 (0.034)	[1]
SPEI growing season, age = 9	−0.212 (0.123)*	[0.354]	−0.058 (0.069)	[0.801]	0.012 (0.051)	[1]	0.041 (0.039)	[1]
SPEI growing season, age = 10	−0.187 (0.201)	[1]	−0.037 (0.121)	[0.867]	−0.147 (0.062)**	[0.49]	0.007 (0.046)	[1]
SPEI growing season, age = 11	−0.059 (0.176)	[1]	0.032 (0.108)	[0.867]	0.014 (0.072)	[1]	0.054 (0.048)	[1]
SPEI growing season, age = 12	−0.154 (0.231)	[1]	−0.097 (0.184)	[0.867]	−0.145 (0.094)	[0.874]	−0.071 (0.045)	[0.684]
SPEI growing season, age = 13	0.021 (0.175)	[1]	0.168 (0.143)	[0.801]	0.046 (0.062)	[1]	0.045 (0.047)	[1]
SPEI growing season, age = 14	−0.010 (0.195)	[1]	−0.149 (0.091)	[0.801]	−0.010 (0.061)	[1]	0.056 (0.036)	[0.684]
SPEI growing season, age = 15	0.001 (0.117)	[1]	−0.105 (0.077)	[0.801]	−0.003 (0.057)	[1]	0.004 (0.040)	[1]
Birth year fixed effects	Yes		Yes		Yes		Yes	
Birth district fixed effects	Yes		Yes		Yes		Yes	
F statistic	2.451		1.205		1.912		2.347	
p-value for F-test	0.001		0.261		0.017		0.002	
R^2	0.209		0.210		0.211		0.212	
N	5572		5572		5572		5572	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. The column title indicates the threshold use to define the negative shock variable, e.g. column (1) shows the effect of negative shocks defined as $\mathbb{1}\left\{SPEI_{i(t+j)} < -2\right\}$ where $\mathbb{1}\{.\}$ is the indicator function. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table M4: *Different thresholds for extreme positive shocks*

	>2 SD (1)	q value (1)	>1.5 SD (2)	q value (2)	>1 SD (3)	q value (3)	>0.5 SD (4)	q value (4)
SPEI growing season, age = -2	-0.210 (0.098)**	[0.255]	-0.077 (0.056)	[1]	-0.021 (0.043)	[0.564]	0.021 (0.030)	[1]
SPEI growing season, age = -1	-0.055 (0.105)	[1]	0.026 (0.075)	[1]	0.047 (0.037)	[0.39]	-0.011 (0.029)	[1]
SPEI growing season, age = 0	0.115 (0.093)	[0.674]	-0.027 (0.056)	[1]	-0.053 (0.046)	[0.426]	0.001 (0.029)	[1]
SPEI growing season, age = 1	-0.000 (0.072)	[1]	0.134 (0.079)*	[1]	0.063 (0.045)	[0.39]	0.032 (0.034)	[1]
SPEI growing season, age = 2	0.088 (0.126)	[1]	0.090 (0.069)	[1]	0.089 (0.038)**	[0.176]	0.047 (0.028)*	[1]
SPEI growing season, age = 3	0.155 (0.068)**	[0.255]	0.136 (0.048)***	[0.103]	0.088 (0.040)**	[0.176]	0.036 (0.028)	[1]
SPEI growing season, age = 4	-0.166 (0.090)*	[0.339]	0.001 (0.075)	[1]	0.012 (0.043)	[0.615]	-0.003 (0.030)	[1]
SPEI growing season, age = 5	0.040 (0.092)	[1]	0.074 (0.063)	[1]	0.048 (0.037)	[0.39]	0.000 (0.029)	[1]
SPEI growing season, age = 6	-0.077 (0.116)	[1]	-0.036 (0.066)	[1]	-0.001 (0.038)	[0.705]	-0.002 (0.032)	[1]
SPEI growing season, age = 7	-0.028 (0.086)	[1]	0.010 (0.069)	[1]	-0.064 (0.044)	[0.39]	-0.045 (0.035)	[1]
SPEI growing season, age = 8	-0.144 (0.114)	[0.674]	0.027 (0.062)	[1]	0.080 (0.034)**	[0.176]	0.007 (0.032)	[1]
SPEI growing season, age = 9	0.053 (0.091)	[1]	0.088 (0.067)	[1]	0.030 (0.048)	[0.564]	-0.012 (0.036)	[1]
SPEI growing season, age = 10	-0.282 (0.113)**	[0.255]	-0.028 (0.068)	[1]	-0.019 (0.032)	[0.564]	-0.035 (0.033)	[1]
SPEI growing season, age = 11	0.061 (0.086)	[1]	0.054 (0.058)	[1]	0.011 (0.045)	[0.615]	-0.060 (0.035)*	[1]
SPEI growing season, age = 12	-0.017 (0.092)	[1]	-0.007 (0.060)	[1]	0.068 (0.038)*	[0.282]	0.022 (0.032)	[1]
SPEI growing season, age = 13	0.140 (0.084)*	[0.411]	0.015 (0.058)	[1]	0.027 (0.033)	[0.564]	0.048 (0.031)	[1]
SPEI growing season, age = 14	0.019 (0.087)	[1]	0.074 (0.057)	[1]	0.063 (0.030)**	[0.176]	0.003 (0.031)	[1]
SPEI growing season, age = 15	-0.006 (0.102)	[1]	-0.022 (0.052)	[1]	-0.043 (0.033)	[0.39]	-0.025 (0.031)	[1]
Birth year fixed effects	Yes		Yes		Yes		Yes	
Birth district fixed effects	Yes		Yes		Yes		Yes	
F statistic	4.540		1.551		2.313		2.011	
p-value for F-test	0.000		0.077		0.003		0.011	
R^2	0.212		0.210		0.213		0.211	
N	5572		5572		5572		5572	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. The column title indicates the threshold use to define the negative shock variable, e.g. column (1) shows the effect of negative shocks defined as $\mathbb{1}\left\{SPEI_{i(t+j)} > 2\right\}$ where $\mathbb{1}\{.\}$ is the indicator function. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table M5: *Effect of SPEI growing season on adult cognitive, with squared term specification*

	Model with squared terms (1)
SPEI growing season, age = -2	0.003 (0.018)
SPEI growing season, age = -1	0.026 (0.017)
SPEI growing season, age = 0	0.003 (0.016)
SPEI growing season, age = 1	0.018 (0.019)
SPEI growing season, age = 2	0.066 (0.017)***
SPEI growing season, age = 3	0.029 (0.017)*
SPEI growing season, age = 4	0.001 (0.019)
SPEI growing season, age = 5	0.015 (0.016)
SPEI growing season, age = 6	0.012 (0.017)
SPEI growing season, age = 7	−0.029 (0.020)
SPEI growing season, age = 8	0.025 (0.018)
SPEI growing season, age = 9	−0.003 (0.020)
SPEI growing season, age = 10	0.009 (0.022)
SPEI growing season, age = 11	−0.046 (0.022)**
SPEI growing season, age = 12	0.042 (0.026)*
SPEI growing season, age = 13	−0.027 (0.024)
SPEI growing season, age = 14	0.006 (0.019)
SPEI growing season, age = 15	−0.008 (0.019)
(SPEI growing season)^2, age = -2	−0.000 (0.012)
(SPEI growing season)^2, age = -1	−0.014 (0.011)
(SPEI growing season)^2, age = 0	−0.009 (0.012)
(SPEI growing season)^2, age = 1	−0.010 (0.013)
(SPEI growing season)^2, age = 2	0.011 (0.013)
(SPEI growing season)^2, age = 3	−0.000 (0.010)
(SPEI growing season)^2, age = 4	−0.003 (0.011)
(SPEI growing season)^2, age = 5	0.004 (0.012)
(SPEI growing season)^2, age = 6	−0.014 (0.012)
(SPEI growing season)^2, age = 7	−0.005 (0.014)
(SPEI growing season)^2, age = 8	−0.002 (0.013)
(SPEI growing season)^2, age = 9	0.003 (0.014)
(SPEI growing season)^2, age = 10	−0.025 (0.014)*
(SPEI growing season)^2, age = 11	0.022 (0.017)
(SPEI growing season)^2, age = 12	−0.017 (0.018)
(SPEI growing season)^2, age = 13	0.024 (0.015)
(SPEI growing season)^2, age = 14	0.009 (0.017)
(SPEI growing season)^2, age = 15	0.001 (0.012)
Birth year fixed effects	Yes
Birth district fixed effects	Yes
F statistic	2.520
p-value for F-test	0.000
R^2	0.214
N	5572

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

N Additional tables: socioemotional outcomes

Table N1: *Effect of SPEI growing season on socioemotional factor scores by gender*

	Affect/Wellbeing				Personality				Depression			
	Female (1)	q value (1)	Male (2)	q value (2)	Female (3)	q value (3)	Male (4)	q value (4)	Female (5)	q value (5)	Male (6)	q value (6)
SPEI growing season, age = -2	0.050*	[0.416]	−0.042	[1]	−0.045	[0.527]	−0.003	[1]	0.015	[1]	0.016	[1]
	(0.029)		(0.036)		(0.030)		(0.031)		(0.023)		(0.031)	
SPEI growing season, age = -1	0.065**	[0.416]	0.017	[1]	0.013	[1]	0.002	[1]	0.044*	[0.664]	0.041	[1]
	(0.032)		(0.031)		(0.028)		(0.031)		(0.024)		(0.025)	
SPEI growing season, age = 0	0.030	[0.463]	−0.007	[1]	−0.024	[0.853]	−0.004	[1]	−0.000	[1]	−0.018	[1]
	(0.030)		(0.039)		(0.027)		(0.037)		(0.023)		(0.030)	
SPEI growing season, age = 1	−0.050	[0.427]	0.028	[1]	0.011	[1]	0.015	[1]	−0.005	[1]	0.001	[1]
	(0.032)		(0.037)		(0.033)		(0.035)		(0.024)		(0.028)	
SPEI growing season, age = 2	0.053*	[0.416]	−0.004	[1]	−0.030	[0.711]	−0.012	[1]	−0.032	[0.989]	−0.004	[1]
	(0.029)		(0.039)		(0.024)		(0.040)		(0.023)		(0.029)	
SPEI growing season, age = 3	0.010	[0.68]	−0.036	[1]	−0.010	[1]	−0.027	[1]	−0.008	[1]	0.026	[1]
	(0.025)		(0.035)		(0.027)		(0.034)		(0.025)		(0.028)	
SPEI growing season, age = 4	0.049	[0.427]	0.006	[1]	0.028	[0.864]	0.028	[1]	0.006	[1]	0.018	[1]
	(0.033)		(0.034)		(0.038)		(0.033)		(0.031)		(0.031)	
SPEI growing season, age = 5	−0.049	[0.427]	0.087**	[0.256]	−0.074**	[0.4]	−0.045	[1]	−0.056**	[0.664]	0.021	[1]
	(0.032)		(0.034)		(0.031)		(0.030)		(0.027)		(0.028)	
SPEI growing season, age = 6	−0.027	[0.463]	0.025	[1]	−0.060*	[0.4]	0.013	[1]	−0.013	[1]	0.001	[1]
	(0.028)		(0.030)		(0.031)		(0.037)		(0.025)		(0.029)	
SPEI growing season, age = 7	0.011	[0.68]	0.048	[1]	0.006	[1]	−0.074**	[0.445]	0.034	[0.989]	0.023	[1]
	(0.031)		(0.038)		(0.029)		(0.035)		(0.026)		(0.031)	
SPEI growing season, age = 8	−0.017	[0.654]	0.032	[1]	0.001	[1]	−0.020	[1]	−0.025	[1]	0.004	[1]
	(0.033)		(0.034)		(0.025)		(0.035)		(0.026)		(0.028)	
SPEI growing season, age = 9	−0.019	[0.654]	−0.007	[1]	−0.030	[0.853]	−0.005	[1]	0.001	[1]	−0.001	[1]
	(0.031)		(0.045)		(0.035)		(0.039)		(0.029)		(0.035)	
SPEI growing season, age = 10	0.038	[0.463]	0.053*	[1]	−0.027	[0.853]	0.004	[1]	0.016	[1]	−0.018	[1]
	(0.036)		(0.032)		(0.029)		(0.042)		(0.026)		(0.026)	
SPEI growing season, age = 11	−0.055*	[0.416]	−0.002	[1]	−0.044	[0.527]	−0.019	[1]	−0.052*	[0.664]	−0.046	[1]
	(0.029)		(0.030)		(0.030)		(0.042)		(0.028)		(0.029)	
SPEI growing season, age = 12	0.018	[0.654]	0.044	[1]	−0.066*	[0.4]	0.064*	[0.562]	0.001	[1]	0.021	[1]
	(0.033)		(0.044)		(0.035)		(0.035)		(0.030)		(0.035)	
SPEI growing season, age = 13	−0.017	[0.654]	0.054	[1]	−0.012	[1]	−0.028	[1]	0.008	[1]	−0.010	[1]
	(0.032)		(0.036)		(0.036)		(0.038)		(0.029)		(0.031)	
SPEI growing season, age = 14	−0.102***	[0.199]	−0.032	[1]	−0.057*	[0.4]	0.022	[1]	0.016	[1]	0.019	[1]
	(0.039)		(0.040)		(0.030)		(0.035)		(0.032)		(0.033)	
SPEI growing season, age = 15	0.015	[0.654]	0.029	[1]	0.026	[0.854]	−0.098***	[0.144]	0.034	[0.989]	0.034	[1]
	(0.032)		(0.040)		(0.033)		(0.036)		(0.026)		(0.026)	
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Birth district FEs	Yes		Yes		Yes		Yes		Yes		Yes	
F statistic	2.165		1.801		1.427		1.764		1.639		1.050	
p-value for F-test	0.006		0.029		0.124		0.034		0.056		0.408	
R^2	0.107		0.106		0.099		0.116		0.129		0.111	
N	2717		2239		2717		2239		2967		2598	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running Equation 1 with the three socioemotional factors measured in adulthood (above aged 15) as the dependent variable for one gender at a time. Columns (1), (3), and (5) only include females in the sample, and columns (2), (4) and (6) only include males in the sample. All socioemotional scores are internally standardised, so the sample mean is 0 by construction. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table N2: *Effect of SPEI growing season on socioemotional factor scores with siblings fixed effects*

	Affect/Wellbeing (1)	q value (1)	Personality (2)	q value (2)	Depression (3)	q value (3)
SPEI growing season, age = -2	0.021 (0.044)	[1]	0.059 (0.043)	[0.658]	0.042 (0.035)	[0.672]
SPEI growing season, age = -1	0.029 (0.046)	[1]	−0.006 (0.045)	[1]	−0.009 (0.034)	[1]
SPEI growing season, age = 0	0.012 (0.046)	[1]	0.009 (0.041)	[1]	−0.065 (0.036)*	[0.384]
SPEI growing season, age = 1	0.017 (0.049)	[1]	−0.034 (0.046)	[0.846]	−0.010 (0.037)	[1]
SPEI growing season, age = 2	−0.012 (0.047)	[1]	−0.059 (0.044)	[0.658]	−0.100 (0.040)**	[0.205]
SPEI growing season, age = 3	−0.049 (0.045)	[1]	−0.052 (0.043)	[0.807]	−0.039 (0.035)	[0.672]
SPEI growing season, age = 4	0.002 (0.047)	[1]	0.009 (0.045)	[1]	−0.030 (0.042)	[1]
SPEI growing season, age = 5	−0.014 (0.049)	[1]	−0.107 (0.047)**	[0.265]	−0.070 (0.037)*	[0.384]
SPEI growing season, age = 6	−0.093 (0.047)*	[0.377]	−0.042 (0.048)	[0.807]	−0.045 (0.042)	[0.672]
SPEI growing season, age = 7	−0.059 (0.053)	[1]	0.004 (0.047)	[1]	0.001 (0.041)	[1]
SPEI growing season, age = 8	−0.030 (0.051)	[1]	−0.105 (0.043)**	[0.265]	−0.095 (0.040)**	[0.205]
SPEI growing season, age = 9	−0.019 (0.047)	[1]	0.039 (0.045)	[0.807]	−0.042 (0.040)	[0.672]
SPEI growing season, age = 10	0.057 (0.049)	[1]	−0.064 (0.046)	[0.658]	−0.011 (0.041)	[1]
SPEI growing season, age = 11	−0.064 (0.045)	[1]	−0.033 (0.049)	[0.846]	−0.019 (0.040)	[1]
SPEI growing season, age = 12	−0.125 (0.052)**	[0.306]	−0.072 (0.045)	[0.658]	−0.055 (0.041)	[0.672]
SPEI growing season, age = 13	−0.019 (0.047)	[1]	−0.023 (0.041)	[0.975]	−0.007 (0.040)	[1]
SPEI growing season, age = 14	−0.098 (0.044)**	[0.306]	−0.010 (0.046)	[1]	0.017 (0.041)	[1]
SPEI growing season, age = 15	−0.040 (0.044)	[1]	−0.065 (0.044)	[0.658]	0.059 (0.038)	[0.517]
Birth year FEs	Yes		Yes		Yes	
Birth district FEs	No		No		No	
Sibling FEs	Yes		Yes		Yes	
Birth Order FEs	Yes		Yes		Yes	
Sample mean	0.003		−0.006		0.009	
F statistic	1.240		1.702		1.400	
p-value for F-test	0.221		0.034		0.122	
R^2	0.835		0.843		0.820	
N	4956		4956		5565	

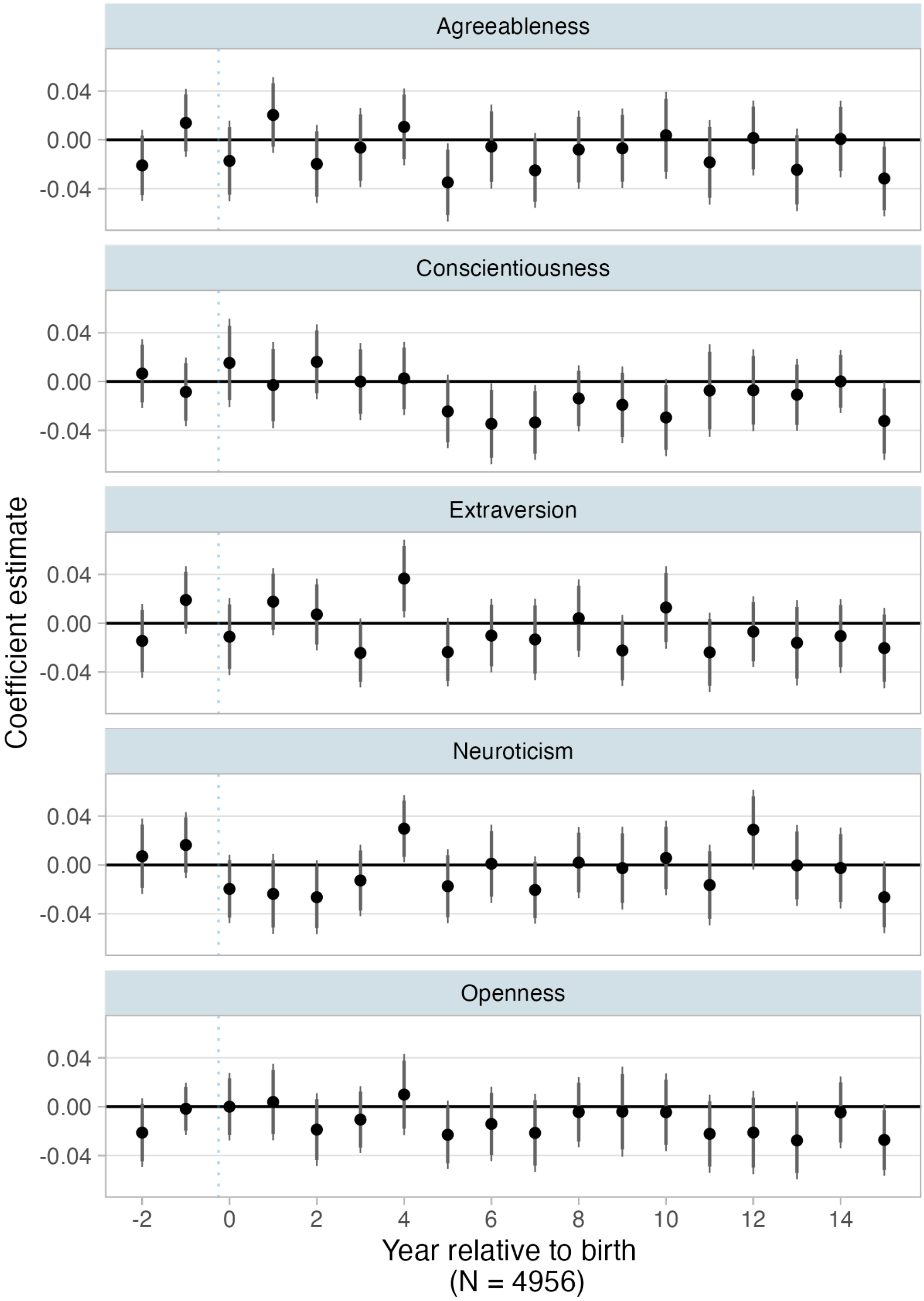
Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running Equation 1 with the three socioemotional factors measured in adulthood (above aged 15). All regressions include both sibling fixed effects and birth order fixed effects, as defined in Appendix Section A.1. All socioemotional scores are internally standardised, so the sample mean is 0 by construction. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table N3: *Effect of SPEI growing season on female's fertility*

	Dep Var: Individual Has Given Birth (=1)	q value
	(1)	(1)
SPEI growing season, age = 10	0.009	[0.72]
	(0.012)	
SPEI growing season, age = 11	0.016	[0.72]
	(0.012)	
SPEI growing season, age = 12	0.020*	[0.72]
	(0.012)	
SPEI growing season, age = 13	0.015	[0.72]
	(0.012)	
SPEI growing season, age = 14	0.008	[0.72]
	(0.012)	
SPEI growing season, age = 15	0.009	[0.72]
	(0.011)	
Birth year FEs	Yes	
Birth district FEs	Yes	
Sample mean	0.415	
F statistic	0.717	
p-value for F-test	0.637	
R^2	0.440	
N	2754	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The sample used is all females in the "main sample" for whom socioemotional variables are measured (as defined in Table 2). The dependent variable is an indicator for whether the individual has given birth by the survey in IFLS5. Since affect/wellbeing is only measured at one period in time (the 5th wave of IFLS in 2015), and I am controlling for birth-year fixed effects, I am effectively controlling for age fixed effects in this regression. All socioemotional scores are internally standardised, so the sample mean is 0 by construction. Additional controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Figure N1: *Effect of SPEI growing season on each Big 5 personality trait separately*



Notes: Each point represents the effect of an SPEI shock in the specific year relative to birth on the respective socioemotional Z-score in adulthood. Socioemotional measures are separated according to the "Big 5" personality traits, and combined using inverse-covariance-weighted indices (Anderson, 2008). All coefficients control for birth year fixed effects, birth district fixed effects, and individual-level controls (dummies for highest level of parental education, sex, and religion). Error bars are 90% and 95% confidence intervals based on standard errors clustered at the district level (not adjusted for multiple testing). Points are highlighted in red when the q-value is less than 0.05. . No points are highlighted because no coefficient has a q-value below 0.05.

O Additional tables: household expenditure

Monthly expenditure empirical strategy: Consider a household h in district r assigned to the harvest in year y (as in Equation 2). Let $Month_k$ be an indicator that takes the value 1 when the household was interviewed k months after the average harvest date for the district r, and 0 otherwise. Let $\mathcal{K} = \{-3, -2, ..., 8\}$ be the set of integers incorporating the values for months from -3 to 8 (that covers all the possible values for k). Then the monthly specification is:

$$\begin{aligned} Exp_{hry} = \alpha + \beta_0 Weather_{ry} + \beta_1 Weather_{r,y-1} + \sum_{k \in \mathcal{K}} \delta_k Month_k \\ + \sum_{k \in \mathcal{K}} \gamma_{0,k} Weather_{ry} + \sum_{k \in \mathcal{K}} \gamma_{1,k} Weather_{r,y-1} + \pi_r + \mu_y \end{aligned} \tag{9}$$

with all the other terms defined as in Equation 2. The coefficients seen in Figure O1 are *sums* of coefficients from Equation 9. For example, the reported coefficient for "Month 3" will be τ_3 where τ_j is defined as below. There are two cases:

$$\tau_j = \begin{cases} \beta_0 + \gamma_{0,j} & \text{if } j \in \{-3, -2, ..., 8\} \\ \beta_1 + \gamma_{1,j-12} & \text{if } j \in \{9, 10, ..., 20\} \end{cases}$$

τ_j captures the overall effect of the the predicted harvest measure in the month j relative to the harvest. For example, for $j = 3$ (3 months after harvest), I take the effect of the predicted harvest measure for the whole year around harvest (β_0), and add the coefficient specific to that month ($\gamma_{0,3}$). For $j = 15$, I take the coefficient for the effect of the predicted harvest measure from the previous year (β_1), and add it to the coefficient specific to that same month relative to harvest but from the previous year ($\gamma_{1,3}$). The standard errors of the τ_j coefficients are easily calculated using the variance covariance matrices of the β and γ coefficients, since:

$$Var(\tau_j) = \begin{cases} Var(\beta_0) + Var(\gamma_{0,j}) + 2Cov(\beta_0, \gamma_{0,j}) & \text{if } j \in \{-3, -2, ..., 8\} \\ Var(\beta_1) + Var(\gamma_{1,j-12}) + 2Cov(\beta_1, \gamma_{1,j-12}) & \text{if } j \in \{9, 10, ..., 20\} \end{cases}$$

The 6-month coefficients and standard errors in Table 8 are calculated in an analogous way.

Table O1: *Predicted harvest index expenditure results are robust to different price adjustments and index constructions*

Panel A: Index Construction: Predicted Harvest Index

	Nominal		Infl [IFLS1-4]		Real [IFLS2/3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Year 0	0.064 (0.022)***		0.068 (0.028)**		0.116 (0.043)***	
Year 1	−0.000 (0.016)		−0.001 (0.023)		−0.014 (0.034)	
Months -3 to 2		0.032 (0.028)		−0.021 (0.039)		0.026 (0.066)
Months 3 to 8		0.074 (0.026)***		0.099 (0.031)***		0.149 (0.048)***
Months 9 to 14		0.034 (0.020)*		−0.009 (0.029)		−0.064 (0.060)
Months 15 to 20		−0.028 (0.018)		−0.002 (0.026)		−0.027 (0.034)
R^2	0.802	0.802	0.118	0.120	0.123	0.126
N	15419	15415	11561	11557	5620	5619

Panel B: Index Construction: GDD + Wet Season Delay + SPEI + Dry Spell Index

	Nominal		Infl [IFLS1-4]		Real [IFLS2/3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Year 0	0.062 (0.022)***		0.071 (0.030)**		0.107 (0.040)***	
Year 1	0.011 (0.014)		0.002 (0.022)		−0.003 (0.029)	
Months -3 to 2		0.024 (0.029)		−0.009 (0.051)		0.001 (0.064)
Months 3 to 8		0.075 (0.024)***		0.095 (0.030)***		0.140 (0.040)***
Months 9 to 14		0.039 (0.017)**		−0.007 (0.028)		−0.063 (0.056)
Months 15 to 20		−0.013 (0.016)		0.004 (0.026)		−0.013 (0.029)
R^2	0.802	0.802	0.119	0.120	0.123	0.126
N	15419	15415	11561	11557	5620	5619

Panel C: Index Construction: GDD + Wet Season Delay Index

	Nominal		Infl [IFLS1-4]		Real [IFLS2/3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Year 0	0.073 (0.019)***		0.069 (0.027)**		0.209 (0.054)***	
Year 1	0.009 (0.019)		−0.005 (0.026)		−0.024 (0.045)	
Months -3 to 2		0.045 (0.028)		0.026 (0.055)		0.105 (0.093)
Months 3 to 8		0.083 (0.024)***		0.080 (0.026)***		0.243 (0.053)***
Months 9 to 14		0.021 (0.019)		−0.001 (0.026)		−0.071 (0.087)
Months 15 to 20		−0.004 (0.028)		−0.005 (0.035)		−0.020 (0.041)
R^2	0.802	0.802	0.119	0.119	0.128	0.131
N	15419	15415	11561	11557	5620	5619

Continued on next page...

Table O1: *Household expenditure results are robust to different price adjustments and weather indexes (**continued**)*

Panel D: Index Construction: GDD + SPEI Index

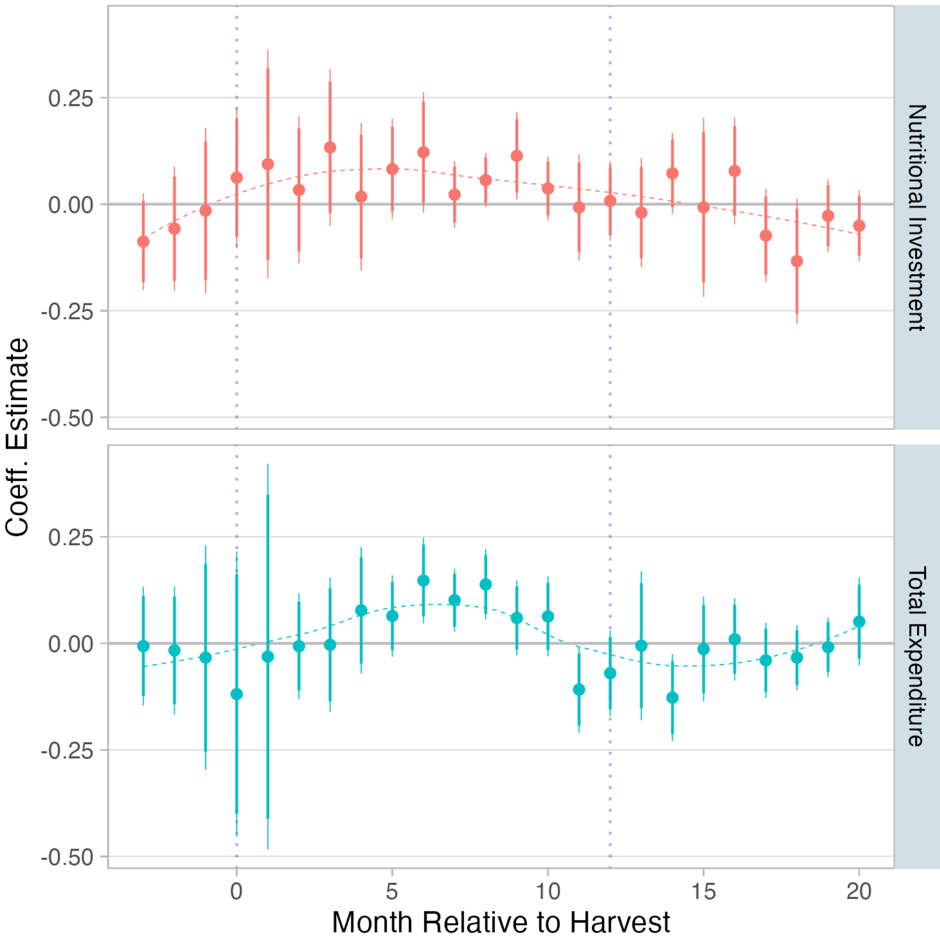
	Nominal		Infl [IFLS1-4]		Real [IFLS2/3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Year 0	0.037 (0.018)**		0.047 (0.022)**		0.073 (0.033)**	
Year 1	−0.003 (0.014)		0.001 (0.020)		0.003 (0.029)	
Months -3 to 2		0.008 (0.025)		−0.027 (0.028)		0.007 (0.055)
Months 3 to 8		0.048 (0.023)**		0.076 (0.028)***		0.097 (0.037)**
Months 9 to 14		0.037 (0.021)*		−0.010 (0.030)		−0.032 (0.052)
Months 15 to 20		−0.030 (0.015)**		−0.000 (0.023)		−0.008 (0.032)
R^2	0.801	0.802	0.117	0.119	0.121	0.123
N	15419	15415	11561	11557	5620	5619

Panel E: Index Construction: Wet Season Delay + SPEI Index

	Nominal		Infl [IFLS1-4]		Real [IFLS2/3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Year 0	0.050 (0.021)**		0.056 (0.025)**		0.091 (0.038)**	
Year 1	−0.003 (0.015)		0.000 (0.022)		−0.005 (0.031)	
Months -3 to 2		0.021 (0.028)		−0.029 (0.033)		0.015 (0.059)
Months 3 to 8		0.061 (0.025)**		0.088 (0.030)***		0.119 (0.042)***
Months 9 to 14		0.035 (0.020)*		−0.011 (0.031)		−0.060 (0.053)
Months 15 to 20		−0.030 (0.016)*		−0.001 (0.025)		−0.015 (0.033)
R^2	0.802	0.802	0.117	0.119	0.122	0.124
N	15419	15415	11561	11557	5620	5619

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by district. The unit of observation is (household × wave). The dependent variable is based on log total household expenditure. In columns (1) and (2) of all panels, the nominal expenditure is used (available for all IFLS waves 1-5). In columns (3) and (4), expenditure is adjusted for inflation at the district and year level (available for IFLS waves 1-4). In columns (5) and (6), expenditure is adjusted for inflation at the district and month-year level, but this is only available for IFLS2 and IFLS3 (see more on this in Appendix Section A.1). The explanatory variables used in Panel A are based on the predicted harvest index based on column (3) of Table D1, as in the main specification. Panel B uses an index constructed in an analogous way but based on just using Wet Season Delay and the SPEI to construct the index (column (2) of Table D1). Panel C uses an index constructed from column (5) of Table D1, Panel D uses an index constructed from column (7) of Table D1, and Panel E uses an index constructed from column (6) of Table D1. The harvest date is defined as the average harvest date of rice in that district based on IFLS harvest data (see Section D.2). "Year 0" is the period between 3 months before and 8 months after harvest (inclusive). Analogously, "Year 1" is the period 9 months and 20 months after harvest (inclusive).

Figure O1: *Effect of predicted harvest index on log household per capita expenditure and nutritional investment (monthly)*



Notes: Results of the estimation process from Equation 9.

P Additional tables: alternative mechanisms

Table P1: *SPEI at age 1 has strong effects on the small subsample who don't breastfeed*

	Dep Var: Cognitive Z Score
	(1)
SPEI growing season, age = 0	0.011
	(0.018)
SPEI growing season, age = 1	0.015
	(0.020)
SPEI growing season, age = 2	0.056**
	(0.022)
SPEI growing season, age = 3	0.014
	(0.017)
Never breastfed	−0.089
	(0.094)
(SPEI growing season, age = 0) x (Never breastfed)	−0.141
	(0.155)
(SPEI growing season, age = 1) x (Never breastfed)	0.240**
	(0.114)
(SPEI growing season, age = 2) x (Never breastfed)	0.038
	(0.138)
(SPEI growing season, age = 3) x (Never breastfed)	−0.031
	(0.142)
Birth year fixed effects	Yes
Birth district fixed effects	Yes
R^2	0.224
N	3690

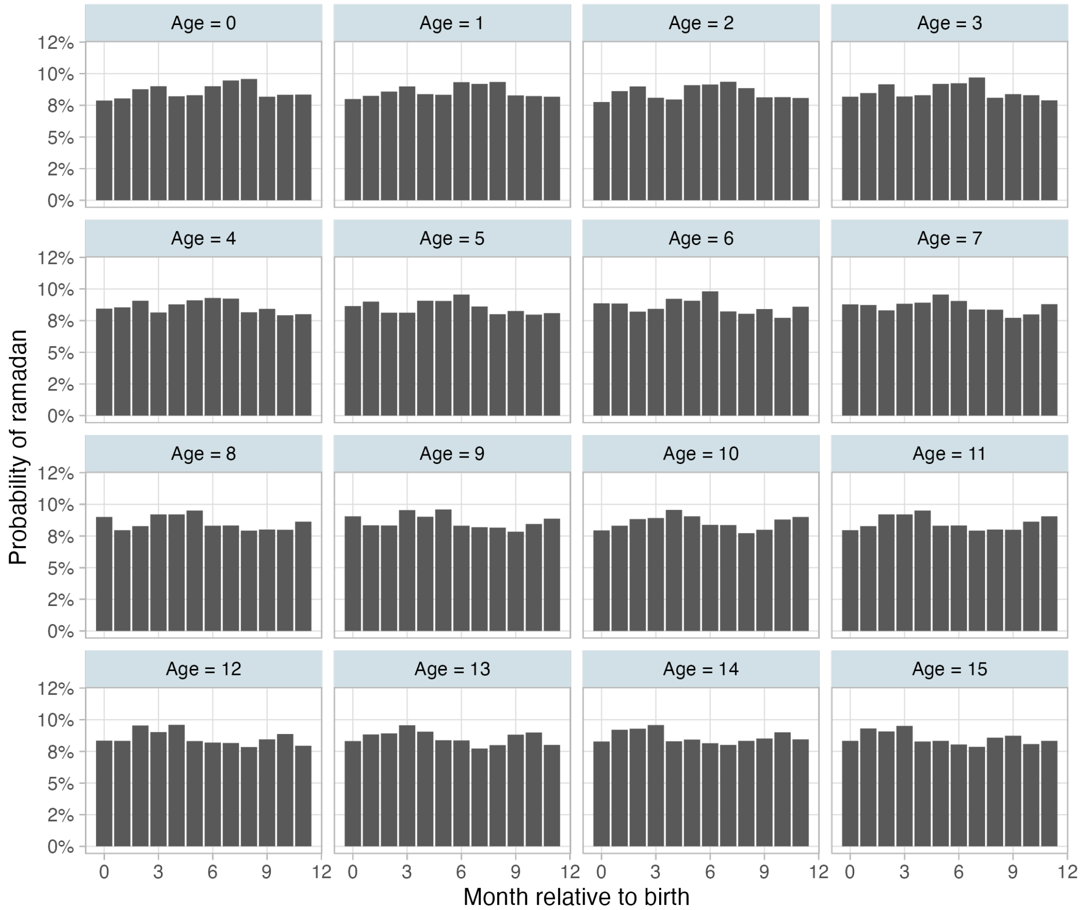
Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The table shows the result of running a version of Equation 1 with cognitive factor score measured in adulthood (above aged 15) as the dependent variable. Cognitive factor score is internally standardised, so the sample mean is 0 by construction. The sample used is all the main sample for whom the IFLS contains data on whether they were never breastfed. This sample includes all individuals whose mother was interviewed while the individual was a child. *Never breastfed* is an indicator variable that takes the value 1 if the caretaker never breastfed the child. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. Controls include dummies for the education level of the most-educated parent, dummies for religion, and a dummy for gender. All models use the individual-level attrition-corrected weights provided in the IFLS data.

Table P2: *Weather may also have an effect on maternal nutrition*

		Dep Var: Mother Nutrition Index			
	Outcome measured in:	(1)	(2)	(3)	(4)
SPEI growing season	Year 0	0.019			
		(0.021)			
SPEI growing season	Year 1	−0.020			
		(0.016)			
SPEI growing season	Months -3 to 2 after harvest		0.003		
			(0.025)		
SPEI growing season	Months 3 to 8 after harvest		0.044		
			(0.034)		
SPEI growing season	Months 9 to 14 after harvest		−0.028		
			(0.022)		
SPEI growing season	Months 15 to 20 after harvest		−0.001		
			(0.022)		
Predicted harvest index	Year 0			0.039	
				(0.027)	
Predicted harvest index	Year 1			−0.012	
				(0.026)	
Predicted harvest index	Months -3 to 2 after harvest				−0.007
					(0.039)
Predicted harvest index	Months 3 to 8 after harvest				0.069*
					(0.036)
Predicted harvest index	Months 9 to 14 after harvest				0.004
					(0.028)
Predicted harvest index	Months 15 to 20 after harvest				−0.025
					(0.033)
Year FEs		Yes	Yes	Yes	Yes
District FEs		Yes	Yes	Yes	Yes
Sample mean		0.065	0.065	0.065	0.065
R^2		0.167	0.168	0.172	0.173
N		3479	3479	3479	3478

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by district. The unit of observation is (individual × wave). The sample used is mothers of children under 5 in rural farming households. The dependent variable is a nutritional investment index for the mothers, composed of food frequency and dietary diversity measures in exactly the same way as the child nutrition index from the main results. The survey questions used are described in Appendix Section A.1. The construction of the indexes is described fully in Appendix Section B.7. *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year × district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. For the SPEI growing season, the harvest date is defined as the average harvest date of the main crop grown in that district (as according to aggregate data, see description in Section A.2). For the Predicted Harvest Index, the harvest date is defined as the average harvest date of rice in that district based on IFLS harvest data (see Section D.2). "Year 0" is the period between 3 months before and 8 months after harvest (inclusive). Analogously, "Year 1" is the period 9 months and 20 months after harvest (inclusive). For the 6-monthly effects, the coefficients reported come from a version of Equation 6 (but with investment index as the dependent variable) and are β_0 for -3 to 2 months; $\beta_0 + \gamma_0$ for 3-8 months; β_1 for 9-14 months; $\beta_1 + \gamma_1$ for 15-20 months.

Figure P1: *Timing of Ramadan is balanced across sample at different ages*



Notes: This graph shows the probability that Ramadan occurred at each month of age for the main sample. There are no notable differences between the timing of Ramadan at each age for the sample, suggesting that this cannot drive the impacts on cognitive development seen in the main results.

Q Height-for-age

The evidence suggests that weather variation leads to increased nutritional investment. I here examine whether this change in nutritional investment translates into improved height-for-age in early life. Table Q1 displays the results of running a version of Equation 1 with child height-for-age Z-scores as the outcome variable. Here, I use data for all children measured in the IFLS between the ages of 2 and 6.[46] Panel A displays the results when using SPEI growing season as the main treatment variable. Although Sections 5.1 and 5.2 indicate that the SPEI growing season increases nutritional investment and household expenditure, there is no apparent effect on early life height-for-age Z-scores, with no statistically significant coefficients across any age range and gender at the 5% level even before adjusting for multiple hypothesis test-

[46] I divide this group into two overlapping age ranges (2-4 year olds and 4-6 year olds inclusive). This helps me to retain a large enough sample size to maintain statistical power, while also being able to examine the effect of later shocks (at age 2 and 3) with the older group.

ing. Panel B shows some suggestive evidence that the predicted harvest index does have an effect on children's height-for-age. We see a strong positive coefficient of 0.088 for shocks at age 1 for females. The q-value for this coefficient is 0.072, indicating that it is weakly significant after adjusting for multiple hypothesis testing. No other coefficients are significant at the 5% level.[47] Taken together, the results suggest that the nutritional investment effects of the predicted harvest index can translate into health benefits for young children that can be detected in changes in height-for-age, although this effect is not ubiquitous or consistent across age-groups and gender.

[47]In Appendix Table Q2, I use the methodology described in Appendix Section E.2 to analyse the effects of shocks at a more granular level, namely at 6-month age intervals. This analysis indicates that the yearly results may be disguising some sensitive periods, as it suggests that there may be positive effects of an increased predicted harvest index for girls across a wide range of infant ages (from 12 months to 36 months), and that there may be some positive effect of weather before birth (on both sexes).

Table Q1: *Effect of early life weather on height-for-age Z scores*

Panel A: SPEI growing season

	Both Sexes				Male Only				Female Only			
	2-4 y.o. (1)	q value (1)	4-6 y.o. (2)	q value (2)	2-4 y.o. (3)	q value (3)	4-6 y.o. (4)	q value (4)	2-4 y.o. (5)	q value (5)	4-6 y.o. (6)	q value (6)
SPEI Shock, Age = -1	−0.007	[1]	−0.019	[1]	0.014	[0.879]	−0.049*	[0.444]	−0.028	[1]	0.001	[1]
	(0.024)		(0.018)		(0.037)		(0.026)		(0.035)		(0.030)	
SPEI Shock, Age = 0	−0.003	[1]	−0.001	[1]	−0.017	[0.879]	−0.041	[0.444]	0.017	[1]	0.028	[1]
	(0.026)		(0.020)		(0.033)		(0.028)		(0.029)		(0.029)	
SPEI Shock, Age = 1	−0.035*	[0.406]	0.001	[1]	−0.054*	[0.21]	0.017	[0.604]	−0.014	[1]	0.003	[1]
	(0.021)		(0.018)		(0.028)		(0.024)		(0.034)		(0.027)	
SPEI Shock, Age = 2			0.015	[1]			0.040	[0.449]			−0.011	[1]
			(0.023)				(0.033)				(0.030)	
SPEI Shock, Age = 3			0.014	[1]			0.001	[0.631]			0.027	[1]
			(0.017)				(0.025)				(0.025)	
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
(Current) District FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Age (Months) FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Sample mean	−1.848		−1.716		−1.850		−1.770		−1.845		−1.661	
F statistic	0.956		0.480		1.358		1.425		0.328		0.393	
p-value for F-test	0.415		0.791		0.258		0.218		0.805		0.853	
R^2	0.105		0.134		0.143		0.154		0.145		0.182	
N	5608		5781		2896		2889		2712		2892	

Panel B: Predicted Harvest Index

	Both Sexes				Male Only				Female Only			
	2-4 y.o. (1)	q value (1)	4-6 y.o. (2)	q value (2)	2-4 y.o. (3)	q value (3)	4-6 y.o. (4)	q value (4)	2-4 y.o. (5)	q value (5)	4-6 y.o. (6)	q value (6)
Predicted Harvest Index, Age = -1	0.012	[1]	0.054	[0.343]	−0.009	[1]	0.052	[0.582]	0.030	[1]	0.048	[0.713]
	(0.033)		(0.033)		(0.038)		(0.035)		(0.049)		(0.051)	
Predicted Harvest Index, Age = 0	−0.004	[1]	0.039	[0.343]	−0.041	[1]	0.005	[1]	0.046	[1]	0.060	[0.499]
	(0.026)		(0.028)		(0.037)		(0.036)		(0.041)		(0.043)	
Predicted Harvest Index, Age = 1	−0.034	[1]	0.043*	[0.343]	−0.030	[1]	0.006	[1]	−0.034	[1]	0.088**	[0.072]
	(0.031)		(0.025)		(0.035)		(0.033)		(0.041)		(0.035)	
Predicted Harvest Index, Age = 2			0.022	[0.372]			0.022	[1]			0.030	[0.713]
			(0.026)				(0.032)				(0.038)	
Predicted Harvest Index, Age = 3			0.014	[0.372]			0.055	[0.582]			−0.016	[0.713]
			(0.025)				(0.038)				(0.035)	
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
(Current) District FEs	Yes		Yes		Yes		Yes		Yes		Yes	
District x month-of-birth FEs	No		No		No		No		No		No	
Age (month) FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Sample mean	−1.848		−1.716		−1.850		−1.771		−1.845		−1.661	
F statistic	0.471		1.870		0.574		1.146		0.693		1.597	
p-value for F-test	0.703		0.102		0.633		0.339		0.558		0.164	
R^2	0.104		0.133		0.136		0.151		0.146		0.183	
N	5608		5782		2896		2890		2712		2892	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The dependent variable in all models is *height-for-age Z score*, calculated using the WHO's child growth standards data (WHO & UNICEF, 2009). *SPEI growing season* is constructed by taking the average value of the SPEI index over a district's growing season, standardised to have a standard deviation of 1 and a mean of 0 over the period 1961-2015. A full migration history for each individual is used to match individuals to the value of SPEI growing season that they experienced at every age. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year $\times$ district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.

Table Q2: *Effect of predicted harvest index on HAZ in 6-monthly age intervals*

	Both Sexes				Male Only				Female Only			
	2-4 y.o.	q value	4-6 y.o.	q value	2-4 y.o.	q value	4-6 y.o.	q value	2-4 y.o.	q value	4-6 y.o.	q value
	(1)	(1)	(2)	(2)	(3)	(3)	(4)	(4)	(5)	(5)	(6)	(6)
Predicted Harvest Index, Age = -12 to -7 months	−0.051	[1]	0.008	[1]	−0.099	[1]	−0.008	[1]	0.011	[1]	0.019	[1]
	(0.040)		(0.034)		(0.064)		(0.054)		(0.065)		(0.051)	
Predicted Harvest Index, Age = -6 to -1 months	0.025	[1]	0.071**	[0.372]	−0.022	[1]	0.093*	[0.681]	0.048	[1]	0.009	[1]
	(0.039)		(0.036)		(0.063)		(0.054)		(0.068)		(0.059)	
Predicted Harvest Index, Age = 0 to 5 months	−0.015	[1]	0.007	[1]	−0.042	[1]	−0.033	[0.947]	−0.020	[1]	−0.010	[1]
	(0.040)		(0.037)		(0.060)		(0.058)		(0.068)		(0.059)	
Predicted Harvest Index, Age = 6 to 11 months	0.005	[1]	−0.012	[1]	−0.023	[1]	−0.064	[0.681]	0.051	[1]	0.006	[1]
	(0.039)		(0.032)		(0.065)		(0.050)		(0.064)		(0.052)	
Predicted Harvest Index, Age = 12 to 17 months	−0.012	[1]	0.055*	[0.372]	−0.020	[1]	−0.005	[1]	0.016	[1]	0.114**	[0.12]
	(0.036)		(0.032)		(0.058)		(0.049)		(0.061)		(0.054)	
Predicted Harvest Index, Age = 18 to 23 months			0.038	[0.513]			−0.040	[0.947]			0.112**	[0.12]
			(0.033)				(0.052)				(0.049)	
Predicted Harvest Index, Age = 24 to 29 months			0.055*	[0.372]			0.085*	[0.681]			0.105**	[0.12]
			(0.031)				(0.050)				(0.047)	
Predicted Harvest Index, Age = 30 to 35 months			0.015	[1]			−0.015	[1]			0.094*	[0.124]
			(0.032)				(0.051)				(0.052)	
Predicted Harvest Index, Age = 36 to 41 months			0.035	[0.513]			0.062	[0.681]			0.031	[0.981]
			(0.032)				(0.050)				(0.045)	
Birth year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
(Current) District FEs	No		No		No		No		No		No	
District x month-of-birth FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Age (month) FEs	Yes		Yes		Yes		Yes		Yes		Yes	
Sample mean	−1.848		−1.716		−1.850		−1.771		−1.845		−1.661	
F statistic	0.543		1.469		0.517		1.214		0.260		1.664	
p-value for F-test	0.744		0.154		0.763		0.282		0.935		0.093	
R^2	0.325		0.340		0.483		0.473		0.510		0.519	
N	5608		5782		2896		2890		2712		2892	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are reported in parentheses and are clustered by birth district. The dependent variable in all models is *height-for-age Z score*, calculated using the WHO's child growth standards data (WHO & UNICEF, 2009). The calculation of predicted harvest in 6-month age intervals is described in Appendix Section E.2. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table D1 and calculating the predicted rice yields from this model for each year × district. It is standardised to so that within each district there is a mean of 0 and standard deviation of 1 over the period 1981-2015. All models use the individual-level attrition-corrected weights provided in the IFLS data. The q-value is the FDR-adjusted p-value, calculated according to the sharpened process seen in Anderson (2008) by pooling all coefficients in a given column. F-statistic and F-test are for the joint test of the null that all the shown coefficients in the model are equal to 0.