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**Critical Periods in Cognitive and Socioemotional Development:
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JEL Codes: I15, I24, I31, I3, J13, J24, O1, O12, O15, Q54

Keywords: Critical period, Human capital, Early childhood development,
Dynamic complementarity



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

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Abstract

A large literature points towards the importance of early life circumstance in determining long-run human capital and wellbeing outcomes. This literature often justifies a focus on the very early years by citing the first 1000 days of life as a ‘critical period’ for child development, but this notion has rarely been directly tested. In a setting in which 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 similar critical period for socioemotional development. The impacts of the shocks are likely to be taking place through nutritional and agricultural income channels. These 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*

Keywords: *critical period, human capital, early childhood development, dynamic complementarity*

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1 Introduction

Cognitive and socioemotional skills are fundamental measures of an individual's human capital, and are highly predictive of adult labour market outcomes and multiple dimensions of well-being (Cunha & Heckman, 2007, 2009; Grantham-McGregor et al., 2007; Heckman et al., 2006; Attanasio, 2015). A broad literature has demonstrated that circumstances in early life may have strong impacts on the development of these skills, and therefore on economic welfare (Almond et al., 2018). 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 (including in utero) are key for determining adult capacity, with younger ages being increasingly sensitive within that window (Currie & Almond, 2011; Almond et al., 2018). Other literature cites 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, primarily because 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 something of a convention. It is sometimes justified by suggestive evidence that adult outcomes improve linearly with increasing exposure to beneficial policies only in (approximately) this window (e.g., see Hoynes et al., 2016). Direct causal evidence supporting a narrower focus on the first 1000 days is also sparse. Sometimes this focus is based on the neurodevelopmental literature, which suggests that the brain is most vulnerable when it is developing rapidly (Isaacs et al., 2008), and that brain volume grows most rapidly in the first 2 or so years of life (Gilmore et al., 2018). Alternatively, some studies showing that growth-faltering for disadvantaged children is most pronounced before age 2 (Victoria et al., 2010; Aiyar & Cummins, 2017) and that stunting is associated with poor cognitive development (Perkins et al., 2017). These studies are together taken as evidence that the first 1000 days is critical for cognitive development. But none of this evidence directly implies a *causal* relationship between age at exposure and adult outcomes (Leroy & Frongillo, 2019), and other factors may complicate the seemingly simple implications of each story.¹

In this paper, therefore, I take advantage of an empirical setting in which individuals are subject to repeated, uncorrelated, exogenous shocks throughout their entire childhood and use it to carry out a fine-grained test for the existence of critical periods in both cognitive and socioemotional development. I examine the effects of weather variation at every age from in utero to age 15 on adult cognitive and socioemotional outcomes. The data comes from individuals in the Indonesia Family Life Survey (IFLS) who were born in rural areas between 1988 and 2000. Such individuals experience the weather variation as a shock to nutritional investments, plausibly driven by changes in household economic welfare. My

¹For example, adult cognitive performance may be strongly influenced by the development of the prefrontal cortex, an area of the brain which undergoes significant changes well after the 2nd birthday (Fiske & Holmboe, 2019; Sapolsky, 2017). And a number of studies now suggest that there is a non-negligible possibility of catch-up growth after the first 24 months (Prentice et al., 2013), suggesting that shocks after the 2nd birthday may also be important for determining adult height-for-age and cognitive skills.

approach therefore provides some of the first causal evidence on whether the timing of such shocks matters for adult human capital.

My main results show evidence of a critical period at age 2 for the effect of weather variation on adult cognitive ability. A 1 standard deviation increase in my primary weather shock 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 effect at age 2 appears to be stronger for boys. This is in line with previous literature showing that boys may be more vulnerable to disruptions to development in utero and in very early childhood (Kraemer, 2000; Eriksson et al., 2010). This age 2 effect is highly robust to different empirical specifications, and I use placebo shocks to demonstrate that such a strongly significant result is extremely unlikely to be the result of artefacts in the data. By contrast, socioemotional outcomes show no positive evidence for the existence of a critical period, with either null effects, or effects that 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 and household agricultural income. The initial aggregate weather shock measure I use has large effects, but it is difficult to pin down exactly *how* and *when* it impacts household welfare, and therefore cognitive development. To understand the mechanisms at play in more detail, I therefore develop a complementary “predicted harvest” weather shock.² I show that the predicted harvest shock has a significant impact on household expenditure and child nutritional investment. These effects can be isolated to 3-8 months after harvest, thus allowing me to pin down the timing of the shock impacts. The shock also has an effect on children’s height-for-age. Using this secondary shock, I corroborate my earlier results. I show that the effect on adult cognitive skills is particularly strong in the second half of the year after the 2nd birthday (especially for boys). Together this evidence suggests, therefore, that the critical period at age 2 is likely to be operating through agricultural income and nutritional investment channels.

A key advantage of my empirical strategy for testing for critical periods is the use of 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, Fenske, & Nyshadham, 2019). Such settings present greater challenges when trying to test for the timing of effects.

The IFLS data provides unique opportunities for testing for critical periods. 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, and contains a rich set of measures. This richness offers at least 3 key advantages over other datasets when testing for critical periods. First, all adult respondents are asked for a detailed migration history. This, along with very low attrition

²This shock index is constructed by examining several weather measures taken from the climatology literature and combining those that best predict rice harvest yields in the IFLS data.

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. Second, the IFLS provides an uncommonly broad range of outcome data that includes measures of depression, personality, wellbeing, and cognitive ability. This allows me to test for critical periods in all of these domains. And third, the long term panel provides contemporaneous data on many individuals from during 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.

Indonesia is an ideal setting for testing the timing of the effects of weather shocks. First, 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](#)). Second, Indonesia is a lower-middle-income country with a large rural population and large agricultural sector ([World Bank, 2018](#)). This population are likely to experience weather shocks as agricultural income shocks that affect children through changes in nutrition and other investment channels,³ allowing me to test for economically-relevant critical periods.

My paper contributes in a variety of ways to the literature on human capital accumulation. This literature often centres around the ideas of the Cunha-Heckman framework ([Cunha & Heckman, 2007, 2008](#); [Cunha et al., 2010](#)), which acts as a “workhorse model”. A central claim of this model is that parental investment is a key determinant of human capital accumulation, and that the *timing* of this investment matters for adult outcomes. The current study can thus be seen as a test of this central claim. As noted above, we have little direct causal evidence on the question of timing. A notable exception is [Barham et al. \(2013\)](#), who examine the effect of conditional cash transfers received between in utero and age 2 as compared to ages 2 to 5 in Nicaragua on cognitive and health outcomes. They show that boys exposed to the program between in utero and age 2 have cognitive scores (measured at age 10) that are approximately 0.15 standard deviations higher than boys exposed to the program between 2 and 5. My work contributes relative to this paper by providing a more disaggregated test of timing (yearly and 6-monthly), by testing a wider age-range and broader set of outcomes, and by testing longer term effects into adulthood. [Cunha et al. \(2010\)](#) is a second study that examines the question of timing. The authors find that the elasticity of substitution of cognitive skills with respect to investment declines sharply with age, whereas socioemotional skills remain malleable for longer.⁴ Their finding is based on a calibrated model of the human capital production function that relies on a number of parametric assumptions, and does not make use of exogenous variation resulting from a shock or an intervention. I therefore contribute

³For 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.

⁴In fact, they suggest that the elasticity of substitution for socioemotional skills may even increase with age. Such a picture is consistent with biological evidence showing that the pre-frontal cortex, which governs “higher-order” cognitive function and socioemotional behaviour, develops later than the areas of the brain that govern visual, spatial, and language capabilities (see [Grantham-McGregor et al., 2007](#) or [Sapolsky, 2017](#) for more detail).

by providing causal estimates of the importance of timing that require weaker assumptions. In addition to the question of timing, I am able to provide evidence on a number of other key claims in the human capital accumulation literature. A key novelty of this study is that I am able to test of many these (often untested) claims *in one setting*. The work therefore complements a recent literature that aims to adapt the Cunha-Heckman framework (originally developed based on data from the US) to a developing country setting ([Attanasio, Cattan, et al., 2020](#); [Attanasio, Meghir, & Nix, 2020](#)).⁵ In particular, I contribute in the following four ways.

First, I contribute to the literature on dynamic complementarity that provides evidence on whether investments in earlier periods may increase the productivity of later investments. Dynamic complementarity is a key element of the Cunha-Heckman framework. I show suggestive evidence that there may be a positive interaction effect for shocks at ages 1 and 2 for boys, in keeping with the implications of dynamic complementarity. It has been noted that the empirical challenge when estimating dynamic complementarity is the need to have two uncorrelated exogenous shocks (two “lightning strikes”) ([Almond & Mazumder, 2013](#)).⁶ Typically, papers solve this problem by using two different *types* of shocks or interventions, and examining the interaction effects between the two ([Adhvaryu et al., 2018](#); [Gunnsteinsson et al., 2014](#); [Rossin-Slater & Wüst, 2016](#); [Malamud et al., 2016](#); [Johnson & Jackson, 2019](#)). To my knowledge, my results are the first that make use of the *same type* of shock repeated at different ages in order to test for dynamic complementarity. I therefore supplement existing evidence by testing a novel type of interaction effect (on repeated investments) that may play an important role in human capital accumulation.

Second, I inform the debate on the differences between the accumulation of cognitive and socioemotional skills. Recent literatures point at the importance of socioemotional skills ([Heckman & Kautz, 2013](#); [Alan et al., 2019](#); [Ashraf et al., 2020](#); [Blattman et al., 2017](#); [Edmonds et al., 2020](#)), and how they may be influenced by early life circumstance ([Adhvaryu, Fenske, & Nyshadham, 2019](#); [Adhvaryu et al., 2017](#); [Pasha et al., 2018](#); [Singhal, 2019](#); [Persson & Rossin-Slater, 2018](#); [Krutikova & Lilleør, 2015](#); [Evans & English, 2002](#)). Results from calibrated production function models suggest that socioemotional skills may be malleable for longer than cognitive skills ([Cunha et al., 2010](#)), and that cognitive and socioemotional skills may respond differently to different types of parental investment ([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 such critical period for socioemotional development, adding to the evidence that human capital cannot be considered as a single “unidimensional object” ([Attanasio, 2015](#)).

Third, I contribute to the literature on the importance of parental investment for early childhood. The Cunha-Heckman model assumes that parental investment is one of the key determinants of human capital, and a number of empirical studies in developing countries

⁵Instead of calibrating a full structural model, I make fewer assumptions about the underlying model and instead use reduced-form estimates to understand the relevancy of the Cunha-Heckman model.

⁶An alternative approach to examining complementarities is to calibrate a dynamic production function model. For example, [Attanasio, Meghir, & Nix \(2020\)](#) use this approach to examine human capital accumulation in India, and show strong complementarity between prior outcomes and investments.

appear to support this claim ([Adhvaryu & Nyshadham, 2016](#); [Attanasio, Cattan, et al., 2020](#); [Attanasio, Meghir, & Nix, 2020](#); [Adhvaryu, Bednar, et al., 2019](#); [Carneiro et al., 2020](#)). I contribute to this literature by showing that shocks to household economic welfare can have a strong impact on children’s nutritional investment, and that this is a plausible mechanism for the effects on cognitive development.

Fourth, I show that the effects of the weather shocks on adult cognitive skills are latent during middle childhood: there are no significant impacts of the shocks at age 2 on cognitive scores at ages 7 to 14, and controlling for cognitive ability at age 7-14 does not attenuate the effects at age 2 on adult cognitive score. Due to the lack of evidence on this period, later childhood has been called the “missing middle” ([Almond et al., 2018](#)). Much of the literature on early interventions in the US find that treatment effects “fade out” by aged 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 do not really dissipate, but are hard to observe during this middle childhood period and so are only detectable 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.

The results found in this paper may have important policy implications. I have been able to isolate the impact of weather shocks on cognitive development to the year after the second birthday. By contrast, no such critical period appears to exist for socioemotional development. To the extent that the effects of such weather shocks occur through economic and health-related channels that can be manipulated by policy, this implies that early-childhood interventions focusing on cognitive development may be optimally targeted on the “critical period” after the second birthday. We should, however, be cautious when extrapolating the results on weather shocks to policy recommendations. Even if policies and shocks operate through similar channels, there are of course many reasons why their effects may differ.

The rest of the paper is organised as follows. Section 2 describes a theoretical grounding for the results based on Heckman’s human capital production function framework, including definitions for critical and sensitive periods. Section 3 describes the data sources used and the latent factor model used to measure adult cognitive and socioemotional outcomes. Section 4 outlines the empirical strategy, while Section 5 reports the results on cognitive and socioemotional outcomes. Section 6 reports the results on potential mechanisms, including the effects on household expenditure, indexes of investment, and child height-for-age. It also describes the construction of the secondary shock measure and the accompanying results

making use of that measure. Section 7 concludes with a discussion of the results.

2 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.⁷ 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 (\mathbf{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 .⁸ 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:

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

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 15.⁹ I therefore assume that adult skills settle by age 16, and will not be affected by any changes thereafter. Whereas equation 1 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 (\mathbf{h}) as a function of initial endowments (from before birth, e.g. genetics) and all past investments and shocks:

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

Or for a specific skill k (e.g. cognitive ability), adult skills h_k are¹⁰:

$$h_k = m_k\left(\mathbf{h}^P, \boldsymbol{\theta}_{-2}, (I_{-2} + \mu_{-2}), (I_{-1} + \mu_{-1}), \dots, (I_{15} + \mu_{15})\right)$$

⁷Full details of the model, including exact timings, examples of the parental investment maximisation programme, and other detailed definitions, can be found in the references.

⁸This is similar to the adaptation seen in [Currie & Almond \(2011\)](#); [Almond et al. \(2018\)](#).

⁹The 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".

¹⁰Papers in the literature often follow [Cunha & Heckman \(2007\)](#) and specify a flexible CES functional form for the investment technology, denoted $g(\cdot)$, which allows for elasticity of substitution between investment and shocks in each period $\sigma = 1/(1 - \phi)$ to vary:

$$\mathbf{h} = \mathbf{m}\left(\mathbf{h}^P, \boldsymbol{\theta}_1, g(\mathbf{I}, \boldsymbol{\mu})\right)$$

where $g(\mathbf{I}, \boldsymbol{\mu}) = \left[\sum_{t=-2}^{T=15} \gamma_t (I_t + \mu_t)^\phi \right]^{1/\phi}$

There are two quantities of interest when examining the effects of weather shocks on adult human capital. The first is $\partial m_k(\cdot)/\partial \mu_t$, 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 $dm_k(\cdot)/d\mu_t$, 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 (see the model in Appendix Section E.1 for a simple formalisation of this idea).

Corresponding to these two definitions of effects, we can define two notions of critical periods (building on the definitions seen in [Cunha & Heckman \(2007\)](#)).¹¹ 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:

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

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

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

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 .

In this paper, I estimate the reduced-form effect of shocks in each period, thereby testing for reduced-form critical periods. Indeed, the coefficients of interest β_j in my main specification (see Section 4) can be thought of as identifying $dm_k(\cdot)/d\mu_j$ for weather shocks at different ages. I do not estimate the direct effects of shocks. Estimating the direct effect of an early-life shock on adult human capital is extremely challenging because it would require controlling for *all* subsequent investment responses by parents in every later period. These later investment responses are highly endogenous and are likely to be difficult to measure exhaustively; my empirical setting is therefore not sufficient to estimate the direct effect.

The fact that I estimate the reduced-form effect is important for the interpretation of my results. Much of the literature on child development and nutrition sees critical periods as a “biological” phenomenon ([Knudsen, 2004](#); [Knudsen et al., 2006](#)). This corresponds

Here, the CES shares $\gamma_t \in [0, 1]$ can be thought of as “skill-multipliers” that describe the productivity of investment in period t via its direct effect and via the increased productivity of future investments. And $\phi \in (-\infty, 1]$ describes the degree of complementarity or substitutability between early and late investments in producing skills.

¹¹Because I am focusing on the effects of weather shocks in this paper, I define the notions relative to the exogenous shock μ_t instead of the endogenous investment I_t .

more closely to the *direct effect* definition above. My empirical setting is not well-suited for detecting biological critical periods. The long lag between early life shocks and the measurement of adult outcomes creates a longer window during which parents can respond with compensatory or reinforcing parental investments after a shock. Any subsequent parental investments would generate a disparity between the direct effect of the shock and the reduced-form effect. However, I do 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 investment responses are unlikely to be driving reduced-form effects, so that the reduced form and direct effects might be empirically similar. This evidence should be interpreted with caution, however, since I do not rule out investment responses more than 2 years after the shocks, or investment responses along other dimensions.

Instead, my results inform an important non-biological question: what is the long-run impact of a shock at each age, *given* how parents respond to shocks in the rural Indonesian context? These reduced-form impacts are welfare-relevant, since the welfare impacts of a shock depend on whether parents respond by compensating or reinforcing. A simple model (Appendix Section E.2) shows that the direct effect on h determines welfare only in cases that are unlikely to hold in practice—namely when the shocks μ are marginal and when parents have perfect knowledge of the human capital production function¹². The reduced form effect has welfare implications in more general settings.

3 Data and Measurement System

3.1 IFLS data

My main source of outcome variable data is the Indonesia Family Life Survey (IFLS) (RAND, 1994, 1997, 2000, 2008, 2015). This is a comprehensive longitudinal survey that includes 5 waves between 1993 and 2015, containing detailed information on over 30,000 individuals. Individuals come from 13 of the 27 provinces and are representative of 83% of the Indonesian population. Later waves include questions that assess cognitive ability and other socioemotional dimensions, including depression, subjective wellbeing, personality, and emotional affect. 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. Questions regarding the positive and negative emotions the respondent felt in the last day are used to measure emotional affect. Personality questions are based on the "Big 5" personality traits (Rammstedt & John, 2007), and depression is measured using the CES-D10 scale (Radloff, 1977). Both of these protocols are extensively used in the psychology and economics literature, including in developing contexts (e.g. Das et al., 2009; de Quidt & Haushofer, 2019; Rietveld et al., 2015; Dal Bó et al., n.d.; 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. These are then used as the

¹²See e.g. Dizon-Ross (2019); Attanasio et al. (2019); Cunha et al. (2013) for evidence that parents have poor knowledge of the human capital production function.

dependent variables in my main specification.¹³

The rich IFLS data allows me to test for various mechanisms. There are measures of household expenditure, childhood nutritional and parental-time investment, and child height-for-age. I use these as additional outcome variables to understand whether they could explain the results on cognitive development. I also use gender, religion, and parental education measures as controls in my specification.

I construct a year-by-year history of each individual's location using the IFLS. First, I use retrospective data on an individual's location at birth, and a full migration history that tracks an individual's location at age 12 and every migration thereafter. Second, I combine this with contemporaneous data on respondents' location at each of the five IFLS waves (in 1993, 1997, 2000, 2007, and 2015). I use information on whether the individual was born in a rural household to restrict to only the rural population, under the assumption that these are the households for whom weather shocks are likely to have a significant effect on household welfare through changes in nutrition and in agricultural income.¹⁴

More detail on the measures used in the IFLS data can be found in Appendix Section A.1.

3.2 *District, weather, and crop data*

The primary weather variable I use in the paper is the Standardised Precipitation Evapotranspiration Index (SPEI), a state-of-the-art drought index developed by [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 in turn affected by multiple features of the environment, including temperature, latitude, wind-speed, and the number of sunlight hours. Because the SPEI combines information on all these features, it may capture crop growing conditions more thoroughly than solely precipitation- or temperature-based measures. In keeping with this, it has been shown to be a better predictor of crop yields and other ecological and hydrological variables than other climate indexes in a variety of climactic contexts ([Beguería et al., 2014](#)). The measure 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. This monthly district SPEI is used to construct the initial weather shock variable, $SPEI_{i(t+j)}$ (or *SPEI growing season*) by calculating the average district SPEI over the growing season of

¹³This process is described further in Section 3.3 and in Appendix Section C.

¹⁴In keeping with this assumption, Appendix Table J1 shows that there are no significant effects (after adjusting for multiple hypothesis testing) on adult cognitive ability for individuals born in urban areas, in contrast to the results on those born in rural areas.

the main crop of that district in that period.¹⁵ ¹⁶ This 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 higher compared to the local long-run average (1961-2015). For the main specification, I match this shock back to individuals using the constructed year-by-year record of each individual's location described above. For example, the variable $SPEI_{i(t+2)}$ for an individual i born in t would denote the normalised average SPEI during the growing season of the main crop of the district where i spent the year of her life after her 2nd birthday.

To complement this variable, I construct a secondary “predicted harvest” weather shock that more readily allows me to pin down both the timing and channels of the weather shock. This shock is a composite index of variables that are most predictive of rice yields in the IFLS data (including, among them, the SPEI index). To construct it, I make use of daily data on precipitation and temperature to generate a number of additional climatological measures frequently used in the climate change literature, including growing degree days (Schlenker & Roberts, 2006; Schlenker et al., 2006), delay in the wet season (Naylor et al., 2007), longest dry spell (Tebaldi et al., 2006), and number of rainy days (May, 2004; Fishman, 2016, 2018).¹⁷ After developing these additional climate indicators, I then generate the predicted harvest index by regressing rice harvest yields from the IFLS data on the wider set of climatological measures (including SPEI), and using the significant coefficients as weights for the construction of the index. This process is described further in Section 6.1.

3.3 Measurement of skills

I use the latent factor model seen in Heckman et al. (2013) to combine individual measures into indexes. This technique is common in the psychometric literature. It helps to reduce measurement error by explicitly accounting for classical measurement error.¹⁸ It also reduces the dimensionality of the set of outcome variables, accounting for the fact that two highly correlated survey measures are best conceptualised as two proxy measures of a single psychological trait (e.g. (i) “I see myself as someone who is outgoing and sociable” and (ii) “I see myself as someone who is talkative” both measure extraversion).

The process and results used to generate factor scores is described in detail in Appendix

¹⁵The growing season and crop data used here are taken from district-level data, described in more detail in Appendix Section A.2.

¹⁶Although 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.

¹⁷Full descriptions of these measures, their construction, and the related literature that motivates them can be found in Appendix Section B.

¹⁸Psychological or skill measures tend to be “riddled with measurement error” (Cunha & Heckman, 2009; Heckman et al., 2013). If such error is classical, it may lead to imprecise estimates of causal effects. If it is non-classical, then it may bias the estimated impact of weather shocks on psychological outcome variables. Such error may be even more severe in low- and middle-income country contexts (Laajaj & Macours, 2019; Laajaj et al., 2019).

Section C, and the results are summarised in Table 1. For cognitive, there is a single factor by all the cognitive measures available in the data. For socioemotional, I detect 3 latent factors. The measures in each of the latent factors align relatively closely with the survey module structure¹⁹. The first I interpret as “affect / wellbeing”. This is mostly composed of measures from the Positive-Negative Affect module of the IFLS survey, which asks about which emotions the individual felt in the past week, and life-evaluation questions such as the Cantrill Ladder. The second factor is “personality”, composed of questions from the Big 5 personality test. The interpretation of this factor is less clear. It combines questions which are intended to identify distinct personality traits, such as extraversion and conscientiousness.²⁰ The third factor “depression”, is exclusively composed of questions from the CES-D depression scale. A fuller discussion of the interpretation of each factor is found in Appendix Section C. Having generated the factors, I then have factor scores for each individual which are used as dependent variables in the main results of the paper. These factors are always to be interpreted “positively”, in line with previous literature which sees these traits as skills. For example, a higher depression factor score will mean *better* mental health or *less* depression. Scores are normalised to have a mean of 0 and a standard deviation of 1 to ease interpretation.

Table 1: Latent Factors and their corresponding measures

	Socioemotional		
	“Affect / Wellbeing”	“Personality”	“Depression”
Cognitive			
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 (Cantrill Ladder)		
	Wellbeing: Assessment of situation		
	CES-D: I was happy		

Notes: Each column represents a single factor, containing a list of all the measures which are deemed to load on that factor. Full description of each of the variables, methodology for the creation of each factor, and factor loadings tables are all found in Appendix Section C.

3.4 Samples and summary statistics

In order to make full use of the wealth of the IFLS data in order to understand both the effects of weather shocks and the mechanisms through which they can affect adult outcomes, I run analyses on a number of different samples with different units of observation. For clarity, these samples are summarised in Table 2. All samples are restricted to rural only, and the

¹⁹The full list of questions associated with each socioemotional measure can be found in Appendix Table A1.

²⁰The results indicating that the factor structure deviates from the “Big 5” factors in this context are in keeping with Laajaj & Macours (2019) and Laajaj et al. (2019). The five personality traits in the Big 5 are based on factor analyses of populations in upper-income countries. The authors show that these traits are less likely to show up in the factor structure in lower-income contexts, and surveys often point towards a single “personality” factor.

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	Household Expenditure	11571	Household x Wave	IFLS1-4	Rural farming households
	Rice production	4653	Household x Wave	IFLS4-5	Rural farming households, most recent main crop was rice
	Investment Indexes	4247	Individual x Wave	IFLS3-5	Living in rural farming households, ages 0-5
	Height-for-age	9396	Individual x Wave	IFLS1-5	Living in rural farming households, ages 2-6

Notes: This describes the various samples used in the results sections, 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.

contemporaneous mechanism samples are also restricted to only farming households. This restriction is based on the assumption that urban and non-farming households are unlikely to be affected by weather shocks, while rural farming households are likely to be impacted by these shocks through changes in agricultural incomes. The “main sample” used in Sections 5.1 and 5.2 includes all the individuals born after 1988 in the IFLS data for whom there is either socioemotional or cognitive outcome data available. Individuals in this sample were therefore at most 5 years old at the time of the first wave of the IFLS data in 1993. This means that my analysis of potential mechanisms using the earliest IFLS data (in particular, child anthropometrics and household expenditure) is still relevant for the early childhood period of my main sample.^{21 22} The main sample is at the level of the individual.²³ For the mechanisms results, I include individuals outside the main sample to increase power. For early life investment indexes I focus on all children aged 0-5, while for the height-for-age analyses I focus on a similar age-group but slightly “lagged” (ages 2-6) in order to allow time for weather shocks to have a detectable impact on height.

Appendix Table D1 presents summary statistics for individuals in the main sample. Factor scores are normalised so that by construction, the mean is 0 and the standard deviation is 1.²⁴ Roughly half of the sample (48%) were born during the growing season of the main crop in their district. The main weather shock variables are the SPEI growing season from 2 years before birth up to age 15. This is also standardised to have a mean of 0 and standard deviation

²¹The 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.

²²It also makes it more likely that my definition of a weather shock (which is based on the growing season for the main crop in terms of harvested area, based on data from 2000) is most relevant to agricultural yield.

²³This was appropriate since many cognitive and socioemotional variables are only available in the most recent wave, IFLS5 (2015), meaning that there was typically one observation of the outcome variable per person. In cases where individuals had cognitive or socioemotional outcomes measured in both IFLS4 and IFLS5, I generated combined factor scores by taking the unweighted mean of the factor score from both waves.

²⁴Individuals 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.

of 1 at the district \times year level for all Indonesian districts in the period 1961-2015. A 1 unit increase can therefore be interpreted as a 1SD improvement in weather conditions during the growing season, relative to the long-run average. The sample mean of SPEI growing season is above 0 for all years after birth, suggesting that on average, the weather conditions experienced by members of the main sample after birth were slightly more favourable than the long-run average from 1961 to 2015. The within-sample standard deviation is slightly lower than 1, reflecting the fact that my sample only covers a subset of the years and districts used to standardise. The main sample is restricted to only include individuals born after 1988 and the median individual is born in 1993. 53% of the main sample are female. The highest level of education reached by a parent of sample members is typically elementary (52%), while 20% have a parent that reached Junior High School, 19% have a parent that reached Senior High, and 8% have a parent that reached university.

4 Empirical Strategy

To test for the effect of early-life weather shocks on adult outcomes, I estimate the following equation:

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

Here, Y_{irt} denotes the adult outcome variable of interest for an individual i born in region r at time t .²⁵ In Section 5.1, I use the factor score for cognitive skills, while in Section 5.2 I use the three socioemotional factor measures: affect/wellbeing, personality, and depression. My weather shock variable is $SPEI_{i(t+j)}$. This is a shock variable based on the SPEI climate indicator as described in Section 3, and matched back to individuals so that $SPEI_{i(t+j)}$ describes the average SPEI over the growing season of the main crop in the district where i was located in the year after their j th birthday, according to the constructed location history I described in Section 3.1.²⁶ \mathbf{X}_{ir} is a vector of individual-level controls, that (in the preferred specification) includes dummies for the highest level of education achieved by a parent of i , dummies for religion, a dummy indicating whether individual i was born during the growing season of their birth district r , and a female dummy. δ_r and μ_t are birth-region and birth-year fixed effects.

The coefficients of interest in this specification are β_j , $j \in \{-2, -1, \dots, 15\}$. These allow me to test for the effects of weather shocks at different stages of life on adult outcomes. In particular, I can look at the different effects of weather conditions separately for every year from 2 years before birth all the way to age 15. A key advantage of my empirical setting when trying to make such distinctions is that the serial correlation of weather shocks in each year is very low.²⁷ This means that there is independent variation in the weather shocks year-on-year, thereby allowing for fine-grained distinctions between effects in each year.

²⁵What I here call “region” corresponds to an Indonesian *kabupaten*. There are individuals from 187 regions in the main sample.

²⁶For years before birth, the district of birth is used. More details on the construction of this variable is in Appendix Section A.2.

²⁷For example, the empirical correlation in the main sample between $SPEI_{i(t+s)}$ and $SPEI_{i(t+s-1)}$ (that is, the correlation between a shock and the 1 period lag) is only 0.076 (95% confidence interval: [0.071, 0.081]). Appendix Table D2 and Figure D3 show the full correlation matrix in the main sample.

The birth-year fixed effects in the specification 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 conditional on these birth-year and birth-region fixed effects, the SPEI shocks are exogenous.²⁸

One threat to the main identification strategy based on birth-region and birth-year fixed effects would be if there are endogenous migration reactions to weather shocks that confound the causal effect of weather shocks on adult outcomes. Suppose, for example, that some families are able to migrate within a given year to areas with favourable weather, and families of higher cognitive ability are more likely to do so. In this case, the selection effect resulting from a positive correlation between $SPEI_{i(t+j)}$ and adult cognitive ability would confound the causal effect of a shock. In general, the type of migration that threatens my estimation occurs when individuals migrate into areas based on (i) the current weather patterns (in the same year as the migration), or (ii) future weather patterns.²⁹ The migrant must be either rapid or have foresight, in addition to being selective. Although migration is relatively common in the sample, I show in Column (2) of Appendix Table I2 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.

Another type of bias could arise due to selective mortality. For example, if extreme negative weather shocks (such as drought) lead to the death of children, and these deaths are concentrated upon those children who would otherwise have developed poorly, then any positive relationship between weather shocks and adult outcomes would be biased downwards. I test for such an effect in Appendix Section I, and show that while there may be a positive impact of SPEI shocks in utero on infant mortality, the magnitude is small and appears not to affect the probability of inclusion in my main sample.³⁰ This implies that selection bias will be close to 0, although it cannot be ruled out entirely.

An additional concern with my two-way fixed effect empirical strategy comes from a recent econometric literature that has pointed out that fixed effect specifications can lead to a biased estimate of the true treatment effect in the presence of heterogeneous treatment effects (Goodman-Bacon, 2018; de Chaisemartin & D’Haultfoeuille, 2018; de Chaisemartin & d’Haultfoeuille, 2020). The concern arises when the fixed-effect estimator gives a higher (lower) weight to district-cohort groups with a higher average treatment effect on the treated

²⁸In some additional specifications I also make of sibling fixed effects, which are identified under the assumption that within-family variation in weather shock exposure is not correlated to factors that also affect adult cognitive or socioemotional skills.

²⁹By contrast, migration responses based on *past* weather patterns should rightly be thought of as one of the potential channels through which weather impacts adult outcomes. Nevertheless, the results in Column (1) of Appendix Table I2 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.

³⁰Moreover, 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.

(ATT), leading to an upward (downward) bias on the overall estimate. The weight assigned to each district-cohort group depends on their treatment status. However, in the current context, since the weather shocks I examine are plausibly as-good-as-random, they are likely to be uncorrelated with the (heterogeneous) ATTs across different districts and cohorts. In Appendix Section G 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.

As noted in the introduction, one key advantage of the IFLS data is that it includes full migration histories and thus allows me to construct a year-by-year record of the location of each individual (and then match each individual to a shock). I make use of retrospective survey questions that ask about location of birth and subsequent migrations. There may be non-negligible measurement error in the retrospective migration histories given by respondents. It may be difficult for respondents to remember the year in which they migrated if it was a long time ago, especially if they were young at the time. If such measurement error is classical, it will lead to attenuation bias on the coefficients estimated in the main specification.³¹ However, since my main sample was born between 1988 and 2000, many individuals were children in IFLS households during IFLS survey-wave years (1993, 1997, 2000, 2007, 2015). Therefore, to construct the year-by-year record I combine the retrospective questions with the contemporaneous data on current location of individuals in each of the survey years. This is likely to mitigate much of the measurement error stemming from retrospective migration history.

To test for the existence of critical periods in early childhood development, I need be able to answer two questions. First, I need to test whether there is an overall effect of early childhood weather shocks on adult outcomes (regardless of the timing). To do this, I make use of F-tests that test the joint null hypothesis $H_0 : \beta_{-2} = \dots = \beta_{15} = 0$. A significant result on this test provide evidence for an overall effect of early life weather shocks on adult outcomes.

Second, I need to test whether the effect is concentrated on any specific periods. To do this, I need to test the individual coefficients on specific years of life, i.e. test $H_j : \beta_j = 0$. This involves running 17 hypothesis tests simultaneously, so I account for multiple hypothesis testing by calculating the sharpened q-values from [Anderson \(2008\)](#) for the set of β_j in my main specification. These q-values are p-values adjusted to control for the false discovery rate (FDR), which describes the expected proportion of false rejections out of all rejections. (More detail on the process and the assumptions behind it are found in Appendix Section H.) Intuitively, a q-value of 0.05 indicates that we can reject the null hypothesis if we are willing to accept a false discovery rate (the average probability that any significant result is a false positive) of 5%.³²

³¹Note too, that attenuation bias may vary by age. First, birth locations and years are likely to be more accurate than the year of migration, so attenuation bias may be smaller for years close to birth than in later years. On the other hand, more recent migrations may be remembered more accurately than more distant ones, which would imply that later years are less attenuated. The net effect is ambiguous.

³²Using the q-value will lead to more conservative inference than the standard t-test and reduce the probability of Type I errors. The advantage of this is that any significant effects of weather shocks at a certain age can be confidently asserted to be true effects rather than artefacts of the testing procedure, and thus allow me to test for the existence of critical periods in early childhood.

5 Main Results

5.1 Cognitive outcomes

Table 3 shows the results of running the main specification with adult cognitive factor z-score as the outcome variable Y_{irt} , and a corresponding summary of results is shown in Figure 1. In column (1), there is a strong and statistically significant positive coefficient on SPEI growing season at age 2 (0.063). The q-value for SPEI growing season at age 2 is 0.002. This implies that the probability that the observed coefficient is a false positive is below 1%, even after adjusting for multiple hypothesis testing. I show the F-statistic and corresponding p-value for the joint hypothesis test of $H_0 : \beta_{-2} = \dots = \beta_{15} = 0$. The p-value of 0.001 in column (1) implies that we can strongly reject the null here as well. None of the coefficients in column (1) other than that of age 2 has a q-value below 0.1, suggesting that the reduced-form effect of SPEI growing season is particularly strong at age 2. Comparing columns (2) and (3) shows that the effect at age 2 may be somewhat stronger for males than for females, with a coefficient of 0.071 for males and 0.047 for females. This is in keeping with evidence from the biomedical literature that, both in utero and in infancy, males may be more vulnerable than females to shocks such as malnutrition (Kraemer, 2000; Eriksson et al., 2010).

The magnitude of the coefficient at age 2 is relatively large given the ‘mild’ nature of the shock, and given the fact that outcomes are measured at least 13 years after the second birthday for any given individual. Increasing the SPEI growing season index at age 2 by one standard deviation relative to the long-run average leads to an average increase of 0.063 standard deviations in adult cognitive score. I show later that a key mechanism driving this increase is likely to be increased nutritional investment. A useful point of comparison is therefore Maluccio et al. (2009), who show that a protein-rich nutritional intervention in Guatemala that targeted children during the period from 0 to 36 months of age led to a 0.25SD increase in reading and non-verbal cognitive ability in adulthood. The effect size on SPEI growing season is smaller than this, which is to be expected given that (i) the weather shock only changes nutrition for a shorter period (6 months, rather than 36 months), as I show in Sections 6.3 and 6.2, and that (ii) the effect of a weather shock on nutrition is likely to be significantly weaker than an intervention that focuses solely on improving nutrition.

The results presented here can be interpreted as strong evidence in favour of a reduced-form critical period in early childhood for cognitive development. Specifically, the fact that there is a large positive effect of weather shocks that exists only two years after birth suggests that shocks in this time interval have a *particularly strong* effect on adult cognitive skills, whereas there is no evidence that shocks outside of the time interval have any effect. This early-life critical period for cognitive development is in keeping with previous literature in economics (Heckman & Mosso, 2014; Barham et al., 2013) that suggests the early years are the most sensitive.³³

On the other hand, such literature typically cites the *entire* first 1000 days of childhood as a critical period, and often with earlier years being more sensitive within this window. In light

³³The lack of effect later in life is also consistent with biological evidence suggesting that areas of the brain associated with spatial reasoning (important for the Raven’s matrices tests used as measures of cognitive ability in the IFLS data) develop in the first 2-3 years of childhood (Grantham-McGregor et al., 2007).

of this, it is surprising that the coefficients at age 0 and 1 are not significantly different from 0. There are two possible interpretations for this result. First, the *direct effect* of the shocks might be null at ages 0 and 1. There are plausible biological mechanisms that could explain this result.³⁴ Alternatively, compensating parental investment responses may dampen any positive direct effects at ages 0 and 1. For example, negative weather shocks may lead to poor nutrition at ages 0 and 1, but parents make up for this in later good years by investing in better nutrition. I further examine these potential explanations in Section 7.

To understand 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 J1). I show that the coefficient at age 2 remains strongly positive, with a q-value below 0.05, when I expand my sample to include older individuals (column (1)), use siblings fixed effects and birth order fixed effects instead of birth district fixed effects (column (2), see also Appendix Figure J1), and use a different version of the SPEI weather variable (column (3)). I also show that the coefficients are highly stable when including age fixed effects as controls in the regression (Appendix Table J4). None of these specifications yields a coefficient with a q-value of less than 0.05 on the coefficient for SPEI growing season at any other age. In columns (4) and (5), the strong coefficient at age 2 reduces in magnitude and loses statistical significance when running the same estimation on only people born in urban areas. This is consistent with later evidence suggesting that weather is likely to have an effect through nutritional investment and agricultural incomes.

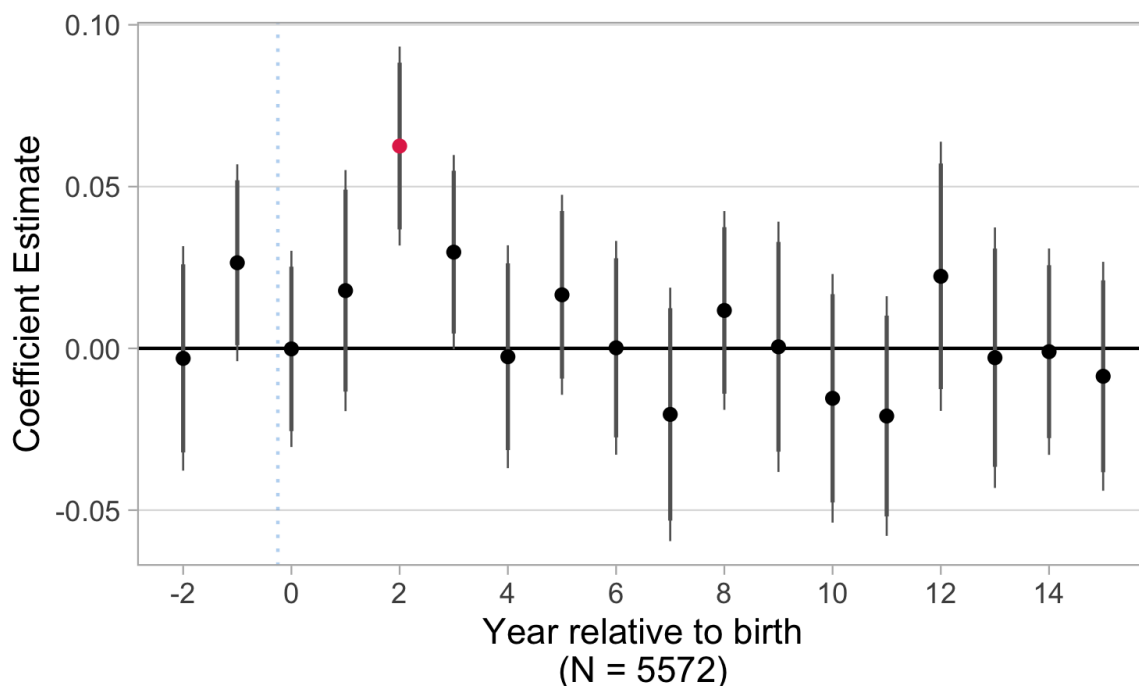
Second, I show in Appendix Table J2 that coefficients on early life shocks are not biased by the inclusion of later shocks in the specification. A priori, there may be an interaction term between shock variables at different ages (for example due to dynamic complementarity in investments). Since these interaction terms are omitted from my main specification, this could lead to an omitted variable bias on the coefficient estimates of earlier shocks. Intuitively, the coefficients on earlier shocks could “pick up” some of the interaction effect. Such an omitted variable bias would be 0 when (i) shocks across ages are independent, and (ii) the mean value of all the shocks is 0.³⁵ Since the correlation between shocks at different ages is weak but not 0 (see Appendix Table D2), and the mean value of all the shocks is slightly positive in most cases, missing interaction effects may therefore cause some bias on my coefficients. However, Appendix Table J2 shows that any bias is empirically close to 0, since the coefficient at age 2 remains highly stable when removing later SPEI growing season variables from the regression.³⁶

³⁴For example, brain areas associated with “higher” cognitive function (e.g. the pre-frontal cortex) develop significantly after the first year of life (Grantham-McGregor et al., 2007). The null effects at age 0 and 1 may thus be consistent with biological evidence if the cognitive factor score picks up differences in higher cognitive ability. The cognitive measures from the IFLS include tasks such as “word recall” and written maths, which may be determined in large part by an individual’s *executive function*, for example through his/her working memory, ability to task switch, and attention. Executive function is typically seen as driven by the prefrontal cortex (Little et al., 2014).

³⁵To see this, denote D as the value of the shock and consider that $Cov(D_{i(t+j)}, D_{i(t+j)} \times D_{i(t+k)}) = E[D_{i(t+j)}^2]E[D_{i(t+k)}] - E[D_{i(t+j)}]^2E[D_{i(t+k)}]$. A sufficient condition for this to be 0 is (i) $E[D_{i(t+j)}] = 0$ for all j , and (ii) $D_{i(t+j)} \perp D_{i(t+k)}$.

³⁶In columns (3) to (5) of this table I enforce assumption (ii) above by demeaning all SPEI growing season variables. This yields no major change in the estimated coefficients.

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 (not adjusted for multiple testing). Points highlighted in red denote coefficients that have a q-value less than 0.05, implying that they are significantly different from 0 after adjusting for multiple testing.

Third, I relax the assumption of linear effects that is built into my main specification (Equation 2). 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 K1). Appendix Section K shows further results using alternative specifications, including binary shocks with different thresholds, different linear effects for positive and negative values, and squared term specification.

Fourth, Section 5.3 presents the results of two types of placebo tests. I make use of (i) shocks from before birth, 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 lends credit to the claim that my main result is picking up true variation, rather than just artefacts due to random noise.

5.2 Socioemotional outcomes

Table 4 and Figure 2 show the results of estimating Equation 2 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, signifying weak evidence that the shocks together are causing variation in the adult factor score. This is

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 reported in parentheses and are clustered by birth district. The table shows the result of running Equation 2 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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

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

The positive effect on depression in utero is in keeping with recent evidence suggesting the importance of economic shocks before birth on adult mental health ([Adhvaryu, Fenske, & Nyshadham, 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. Appendix Table L1 shows that these negative effects are stronger among, and sometimes isolated to, girls. For example, better nutrition in the early teenage years has been associated with *earlier* fertility or menarche for females,³⁷. This could have a negative impact on adult wellbeing.³⁸ Second, the effects on socioemotional scores might be due to noise. The coefficients are only weakly significant, and they are not robust to alternative specifications. When I include siblings fixed effects (Appendix Table L2), none of the coefficients are significant at the 10% level after multiple hypothesis testing, and the previously significant coefficients at age -1 and 10 for depression are very close to 0 and are not significant even before multiple hypothesis testing. This suggests that the coefficients in the main specification may not 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 development of socioemotional outcomes in rural Indonesia. While weather shocks in early life appear to have no significant effect on adult personality outcomes, the results suggest that similar weather shocks may have some influence on adult affect/wellbeing and depression outcomes. The fact that it is difficult to isolate the timing of this influence reflects the fact that there is not a single critical period, but potentially multiple ages in which affect/wellbeing and depression outcomes are weakly malleable (or malleable only for girls).

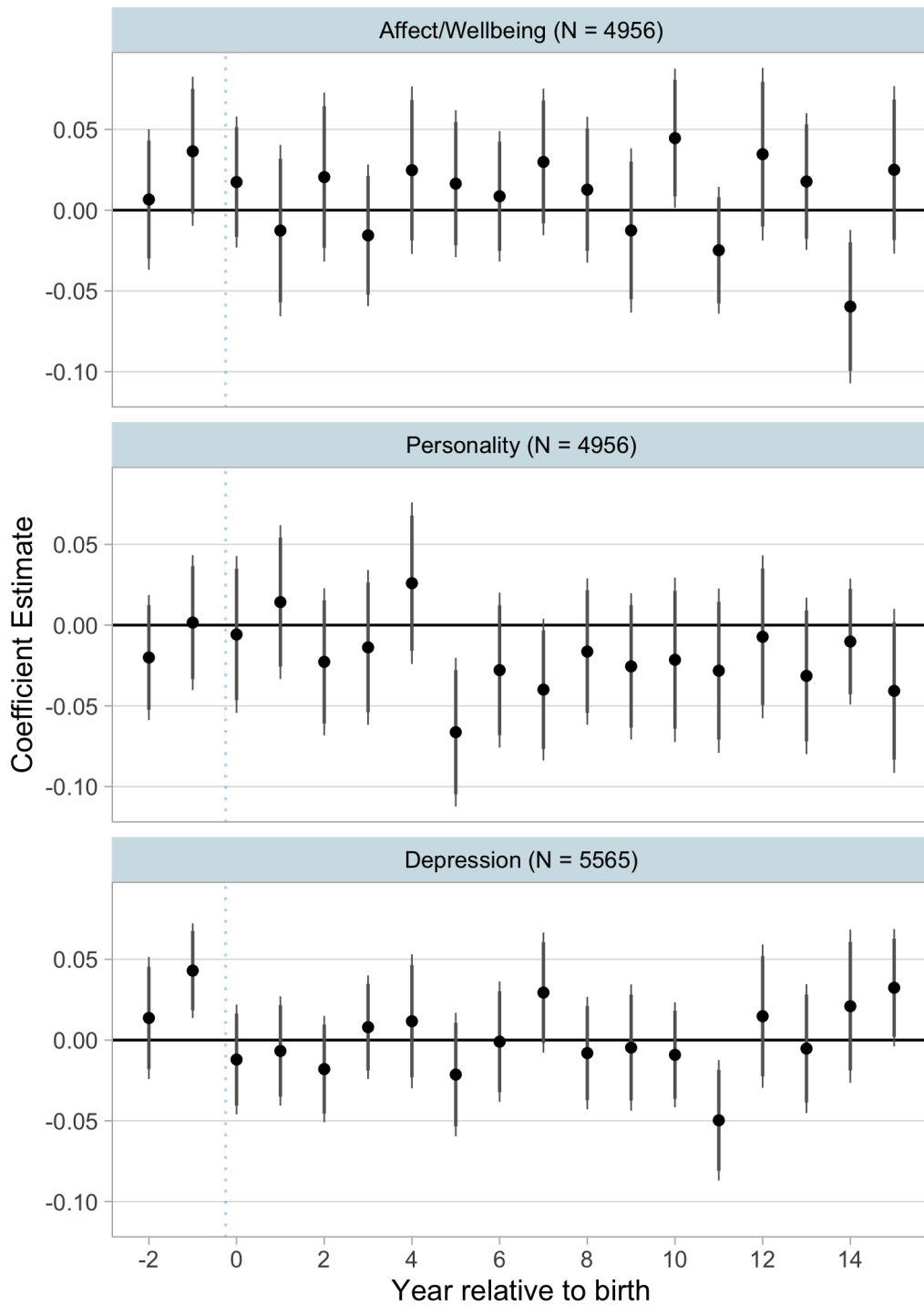
5.3 Cognitive placebo tests

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

³⁷For evidence on earlier menarche and the link to nutrition, see e.g. [Belachew et al. \(2011\)](#); [Hochberg & Belsky \(2013\)](#). Such channels have been shown to operate as the mechanisms that explain some of the impacts of conditional cash transfers in Nicaragua ([Barham et al., 2018](#)).

³⁸Appendix Table L4 displays a simple test of this proposition, in which I use a variation of my main specification with an indicator of whether a female respondent has ever given birth as an outcome variable. This shows no significant effect of shocks in teenage years on the probability to have given birth, implying that fertility is unlikely to be a key mechanism for the negative impacts on socioemotional scores in teenage years. I am unable to test whether the age of menarche could be a potential explanatory channel that is isolated to females.

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 (not adjusted for multiple testing). Points highlighted in red denote coefficients that have a q-value less than 0.05, implying that they are significantly different from 0 after adjusting for multiple testing.

Table 4: Effect of SPEI growing season on socioemotional factor scores of individual born in t

	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 shows the result of running Equation 2 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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

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:

1. *Before-birth 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 2 with adult cognitive score as the dependent variable. 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.
2. *Within-lifetime iterations*. I randomly “reshuffle” the within-lifetime shocks.³⁹ Separately for each individual, the shock values for ages $\{-2, -1, \dots, 15\}$ are reassigned to a different year in the set $\{-2, -1, \dots, 15\}$. 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 2. 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 (i.e. critical periods).

The results of both placebo tests are found in Table 5. A more rigorous description of the placebo methodology, along with some additional presentations of the results, are contained in Appendix Section F. 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 5.1 are unlikely to be driven by artefacts in the data. The before-birth 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.⁴⁰ 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

³⁹This strategy is based on the same intuition as randomisation inference, see ?.

⁴⁰Since the model for my main results (Section 5) 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.

0.002) is capturing a true phenomenon rather than random noise.

Table 5: Results of placebo tests

Placebo Type	Test Type	Total Tests	# Significant	Prop Significant
Before-birth shocks	p - by coefficient	90000	70	0.001
Before-birth shocks	p - at least one	5000	69	0.014
Before-birth shocks	q - by coefficient	90000	0	0.000
Before-birth shocks	q - at least one	5000	0	0.000
Before-birth shocks	F	5000	0	0.000
Within-lifetime, random	p - by coefficient	90000	2182	0.024
Within-lifetime, random	p - at least one	5000	1763	0.353
Within-lifetime, random	q - by coefficient	90000	52	0.001
Within-lifetime, random	q - at least one	5000	50	0.010
Within-lifetime, random	F	5000	4574	0.915

Notes: The “before-birth 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 2. 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 2. 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. The placebo test methodology is described fully in Appendix Section F.

5.4 Cognitive: ages 7-14

The main results in Section 5.1 focus on adult cognitive ability as an outcome. Here, I examine effects on cognitive ability, as measured between the ages of 7 and 14 years. This middle childhood period has been widely referred to as the “missing middle,” as there is limited available evidence on how human capital evolves in this period (Almond et al., 2018). The evidence we do have suggests a common pattern of *fade-out*, where initially strong effects disappear during middle childhood (Currie & Almond, 2011). In contrast to this, I show evidence that long-term effects may simply be hard to detect in middle childhood.

Table 6 shows evidence that the impact of early life weather shocks on cognitive score cannot be detected in middle childhood. I make use of the fact that 75% of my main sample also have measured cognitive outcomes at earlier ages between the ages of 7 and 14.⁴¹ First, columns

⁴¹Only 75% of the main sample is included. This raises concerns that the selection of this sample is driving some of the results. 84% of the missing values are due to these individuals not being included in the IFLS sample when at the appropriate ages (7-14). These individuals enter the IFLS sample only in later waves. This pattern will occur if a new individual enters a household that includes an original IFLS member. While it is possible that these individuals are systematically different to our main sample, it seems unlikely that selection into IFLS (rather than non-IFLS) households is driven strongly by early life circumstance. The results in Column (3) are highly similar to the main results in Section 5.1, with a strong positive effect at age 2. This lends support to the claim that the results on adult cognitive score are not being driven by the differences between the main sample and this subsample.

(1) and (2) show no evidence of any impact of the SPEI growing season on cognitive scores at ages 7-14.⁴² The F-tests on both specifications are insignificant, and the strong effect at age 2 seen in the main results is not “picked up” when measured at this earlier age. Second, columns (3) and (4) present suggestive evidence that the impact of the shock at age 2 that we see in the main results is not *mediated* by the cognitive score at age 7-14. Both regressions show the effect of early life shocks on adult cognitive ability, analogous to the main specification of the paper. Comparing the two columns, we see that adding a control for cognitive score aged 7-14 in the regression has almost no impact on the coefficients for *SPEI growing season*. This is true despite the fact that there is a very strong correlation between cognitive score at age 7-14 and cognitive score at adulthood (seen in the last coefficient of column (4)). Taken together, this evidence fits with a recurrent story seen in the “missing middle” literature, in which early life shocks have latent effects that fade out but then reappear in adulthood. The existing literature has largely been centred upon interventions in developed country contexts⁴³. My results indicate that the latent-effect phenomenon may also be relevant for early life shocks in developing countries. To the extent that the weather shocks I examine are proxies for factors like nutrition (that are themselves manipulable by policy), this finding could be relevant for the evaluation of policy. In particular, it would imply that measuring cognitive scores in middle childhood is unlikely to be a “sufficient statistic” (or adequate surrogate)⁴⁴ for the overall impacts of early life circumstance on adult human capital.

5.5 Interaction effects (dynamic complementarity)

If early investments are complementary with later investments, then the returns to investments in later periods depend on investment in early periods, providing an additional reason why the timing of investment can matter.⁴⁵ Using the framework seen in Section Section 2, we can define this type of *dynamic complementarity* as holding when:

$$\frac{\partial h_k}{\partial \mu_t \partial \mu_{t'}} > 0 \quad (t' > t)$$

In other words, when (a shock on) investment in an earlier period t increases the returns to (a shock on) investment in a later period t' , we say there is dynamic complementarity.⁴⁶ Many papers in the literature test for dynamic complementarity by examining the interaction effects on *different* types of shocks (Adhvaryu et al., 2018; Gunnsteinsson et al., 2014; Rossin-Slater & Wüst, 2016; Malamud et al., 2016; Johnson & Jackson, 2019). By contrast, I use the same

⁴²The results do not change qualitatively when split by gender, see Appendix Table J3.

⁴³One notable exception is the seminal Jamaica experiment, see Grantham-McGregor et al. (1991); Walker et al. (2005); Gertler et al. (2021); Walker et al. (2021).

⁴⁴See the idea of sufficient statistics in Chetty (2009). Surrogates are described further in Athey et al. (2019).

⁴⁵Contrast this to the case in which early and late investments are perfect substitutes. If this holds, and if the “skill-multipliers” are equal across time (i.e. $\gamma_t = \bar{\gamma}$ where $\bar{\gamma}$ is a constant for all t in the terminology of Section 2), then the timing of investment will not matter and adult human capital will depend only on the *total* level of investment.

⁴⁶Note that there are two definitions for dynamic complementarity found in the literature. The more common variant (see e.g. Cunha & Heckman (2007); Currie & Almond (2011); Almond et al. (2018)) states that dynamic complementarity holds when:

$$\frac{\partial h_k}{\partial \theta_t \partial \mu_t} > 0$$

Table 6: 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 (0.019)	0.010 (0.026)	0.037** (0.018)	0.032* (0.018)
SPEI growing season, Age = 0	0.003 (0.021)	0.040 (0.028)	0.004 (0.016)	0.003 (0.015)
SPEI growing season, Age = 1	0.005 (0.021)	0.023 (0.028)	0.020 (0.019)	0.019 (0.018)
SPEI growing season, Age = 2	0.028 (0.022)	0.035 (0.031)	0.074*** (0.019)	0.067*** (0.018)
SPEI growing season, Age = 3	0.027 (0.021)	0.044* (0.027)	0.030* (0.015)	0.023 (0.014)
SPEI growing season, Age = 4	-0.022 (0.018)	-0.004 (0.028)	-0.015 (0.019)	-0.009 (0.018)
SPEI growing season, Age = 5	-0.002 (0.017)	-0.012 (0.026)	0.008 (0.016)	0.008 (0.015)
SPEI growing season, Age = 6	0.013 (0.018)	0.043* (0.025)	0.002 (0.017)	-0.001 (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 2 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. 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. F-statistic and F-test are for the joint hypothesis test of the null that all the shown coefficients in the model are equal to 0.

type of shock to investment (the weather shocks denoted by μ_t) and examine the interaction effects over multiple periods of childhood.

To increase power on the interaction terms, I focus only on the very earliest periods, and I test for the interaction effect between the shock at age 2 and the shocks in all other early-life periods. Table 7 shows the results of these estimations. There are no significant interaction effects for females, implying no evidence for dynamic complementarity. On the other hand, there appears to be (somewhat weak) evidence of dynamic complementarity for boys only, with a significant interaction effect of weather variation at ages 1 and 2 at the 5% level (Column (2)). The coefficient on this interaction effect is 0.058. Experiencing weather during the growing season 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. The results in Section 6 suggest that nutritional investment may be a key channel. If true, then Table 7 is suggestive evidence that nutritional investment is dynamically complementary over early childhood periods. Better nutritional investment at age 1 may increase the *productivity* of nutritional investment at age 2.

That is, dynamic complementarity is defined as holding if and only if the returns to investment (or an investment shock) are increasing in contemporaneous skills θ_t . When we make the standard assumptions of (i) *self-productivity* ($\partial h_k / \partial \theta_t > 0$) and (ii) productive investments ($\partial h_k / \partial \mu_t > 0$), this first definition implies the definition seen in the text. The variant used in the text is described as the definition of “dynamic complementarity” in [Heckman & Mosso \(2014\)](#).

Table 7: Cognitive interaction (dynamic complementarity)

	Dep Var: Adult Cog Z-score			
	Both (1)	Male (2)	Female (3)	Male (1 x 2 only) (4)
SPEI growing season, age -1	0.026 (0.016)	0.033 (0.021)	0.023 (0.024)	0.038* (0.020)
SPEI growing season, age 0	-0.001 (0.014)	0.014 (0.021)	-0.013 (0.019)	0.014 (0.022)
SPEI growing season, age 1	0.018 (0.017)	0.011 (0.025)	0.025 (0.020)	0.013 (0.026)
SPEI growing season, age 2	0.069*** (0.015)	0.079*** (0.024)	0.052** (0.021)	0.078*** (0.024)
SPEI growing season, age 3	0.035** (0.014)	0.051** (0.021)	0.016 (0.023)	0.053** (0.021)
SPEI growing season, (age -1 x age 2)	0.005 (0.013)	-0.018 (0.017)	0.028 (0.021)	
SPEI growing season, (age 0 x age 2)	0.000 (0.016)	-0.019 (0.021)	0.005 (0.020)	
SPEI growing season, (age 1 x age 2)	0.028* (0.015)	0.058** (0.025)	0.006 (0.018)	0.056** (0.025)
SPEI growing season, (age 3 x age 2)	-0.016 (0.014)	-0.002 (0.024)	-0.028 (0.023)	
Birth Year Fixed Effects	Yes	Yes	Yes	Yes
Birth District Fixed Effects	Yes	Yes	Yes	Yes
F statistic	1.212	2.525	1.178	5.002
p-value for F-test	0.307	0.043	0.322	0.027
R ²	0.211	0.230	0.254	0.230
N	5572	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 a version of Equation 2, but using as explanatory variables only SPEI growing seasons from age -1 to age 3 and the interactions between SPEI growing season at age 2 with all other weather variables. All columns use cognitive factors 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) includes all individuals, columns (2) and (4) only males, and column (3) only females. *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. 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. F-statistic and F-test are for the joint hypothesis test of the null that all the shown coefficients in the model are equal to 0.

6 Mechanisms

To understand whether the weather variation examined in this paper is working through economically relevant channels, I examine the mechanisms of the effects. I also use these mechanisms to understand how *quickly* the shock has an effect on economic conditions and therefore pin down more precisely the timing of the critical period on cognitive development.

I am more effectively able to do this with a complementary shock measure, the *predicted harvest index*. This secondary measure is constructed by combining the weather measures that best predict *rice* harvests in the IFLS districts. The advantage of this secondary measure is that I can clearly pin down the mechanisms and the precise timing of impacts, because it has a clear impact on nutritional investment and household expenditure that can be isolated to 3-8 months after harvest. By contrast, the original shock only has an impact on nutritional investment, so the mechanisms at play are less clear. On the other hand, the *SPEI growing season* is likely to have greater power overall because it is based on the main crop of each district, rather than solely on rice. Further, the aggregate crop data used to construct SPEI growing season comes from 2000, whereas the rice harvest data used for the predicted harvest index is only available for the two latest waves of the IFLS survey (in 2007 and 2015). The SPEI growing season may therefore more accurately reflect crop conditions during earlier childhood periods for my main sample, who were born between 1988 and 2000. As these factors would suggest, confidence intervals are typically smaller for SPEI growing season.

6.1 Construction of predicted harvest measure

To construct the predicted harvest index, I first take a number of climatic 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. This process is described in detail in Appendix Section B. Appendix Table B1 indicates 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 (a measure of heat exposure widely used to predict crop yield (Schlenker et al., 2006)), and (iii) delay in the arrival of the wet season (Naylor et al., 2007). I use column (3) to construct a “predicted harvest index” for every year-district pair by taking the predicted value from this regression and normalising it to have a mean of 0 and standard deviation of 1. The index can thus be thought of as a summary index for the weather features that predict high rice yields. I use this predicted harvest index as an explanatory variable to complement the *SPEI growing season* measure used thus far.⁴⁷

6.2 Investment indexes

I here show evidence that the weather variation I use has a positive effect on investment for under-5s in IFLS households, lending support to the claim that both weather shocks are likely to be having an effect on cognitive development through nutritional channels. 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 relating to

⁴⁷I 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.

whether and how much the father and mother work).⁴⁸ Together these constitute two of the most plausible channels through which increases in agricultural income could improve early childhood development. I examine the effects of weather shocks corresponding to the last 2 years of harvest on these contemporaneous investments for children under 5 years old.

I first use the following empirical specification, that tests the effects of the weather corresponding to the current year's harvest and the previous year's harvest:

$$I_{iry} = \alpha + \beta_0 \text{Weather}_{ry} + \beta_1 \text{Weather}_{r,y-1} + \pi_r + \mu_y + \varepsilon_{iry} \quad (3)$$

where I_{iry} is the investment index for an under-5 individual i in region r matched to the harvest in year y ,⁴⁹ 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.

I can further use dummy variables for *when* each household was measured relative to harvest to understand the timing of impacts in more detail. In particular, I define two 6-month periods during the year.⁵⁰ Let $\mathbb{1}\{\text{AfterHarvest}\}_{iry}$ be an indicator such that:

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

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

$$\begin{aligned} I_{iry} = & \alpha + \beta_0 \text{Weather}_{ry} + \beta_1 \text{Weather}_{r,y-1} + \delta \cdot \mathbb{1}\{\text{AfterHarvest}\}_{iry} + \\ & (\gamma_0 \cdot \mathbb{1}\{\text{AfterHarvest}\}_{iry} \cdot \text{Weather}_{ry}) + (\gamma_1 \cdot \mathbb{1}\{\text{AfterHarvest}\}_{iry} \cdot \text{Weather}_{r,y-1}) \\ & + \pi_r + \mu_y + \varepsilon_{iry} \end{aligned} \quad (4)$$

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.⁵¹

Columns (1)-(4) of Table 8 show the results from estimating Equation 3, while columns (5) and (6) are estimated using Equation 4. Both the weather measures positively impact

⁴⁸The survey questions used are described in Appendix Section A.1. The construction of the indexes is described in Appendix Section C.6.

⁴⁹If the weather variation affects household welfare and childhood investment primarily through an agricultural income channel, then we expect this effect to be strongest some time around the time of harvest. To reflect this, I match households to weather shocks by assigning them to the harvest in year y when they were interviewed between 3 months before and 8 months after that harvest.

⁵⁰In Appendix Figure N1 I examine the timing of weather effects at a more granular monthly level. The *predicted harvest index* appears to lead increases in household expenditure for the period approximately between 3 and 8 months after harvest, thus motivating the 6-month periods chosen here.

⁵¹The effects of interest that are reported in Table 8 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.

nutritional investment. SPEI growing season has a positive and statistically significant impact of 0.065 standard deviations in the year of harvest. While the coefficient on predicted harvest across the whole year of the harvest is not significantly different from 0, this disguises a significant and positive effect that is isolated to between 3 and 8 months after harvest. None of the coefficients on the parental time index is significant at the 10% level. The coefficients are not precisely estimated. However, this still alleviates the concern that weather improvements could 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.

Table 8: *Impact of weather shocks on indexes of investment for u5s*

Outcome measured in:		SPEI growing season		Predicted harvest			
		Nutrition (1)	Parent (2)	Nutrition (3)	Parent (4)	Nutrition (5)	Parent (6)
SPEI growing season	Year 0	0.065*** (0.024)	-0.008 (0.037)				
SPEI growing season	Year 1	0.009 (0.021)	-0.002 (0.022)				
Predicted harvest index	Year 0			0.028 (0.022)	-0.036 (0.027)		
Predicted harvest index	Year 1			0.005 (0.021)	0.003 (0.021)		
Predicted harvest index	Months -3 to 2 after harvest					-0.013 (0.036)	0.013 (0.044)
Predicted harvest index	Months 3 to 8 after harvest					0.058** (0.024)	-0.032 (0.039)
Predicted harvest index	Months 9 to 14 after harvest					0.029 (0.024)	-0.015 (0.027)
Predicted harvest index	Months 15 to 20 after harvest					-0.013 (0.032)	0.004 (0.038)
Year FEs		No	No	Yes	Yes	Yes	Yes
District FEs		Yes	Yes	Yes	Yes	Yes	Yes
Age (Month) FEs		Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean		-0.050	-0.003	-0.050	-0.003	-0.052	-0.012
R ²		0.139	0.131	0.145	0.148	0.129	0.124
N		4247	4247	4247	4247	4246	4246

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 \times wave). The dependent variable in columns (1), (3), (5) is nutritional investment index for children under 5 years old (composed of food frequency and dietary diversity measures). The dependent variable in columns (2), (4), and (6) 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 C.6. 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 B.2.1). “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 4 (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.

6.3 Household expenditure

To complement the results showing that weather variation has an effect on nutritional investment, I here examine whether this is driven by changes in aggregate household welfare. I examine the effects of weather shocks corresponding to the last 2 years of harvest on contemporaneous log household per capita expenditure. I show that better predicted harvests increase household expenditure in the period between 3 and 8 months after harvest, mirroring the results on investment, while SPEI growing season variation does not predict expenditure.

The results, presented in Table 9, are based on specifications analogous to Equations 3 and 4, but using log household expenditure as the outcome variable.⁵² Columns (1) and (2) show that the impact of SPEI growing season is not significantly different from 0. This shock nevertheless has an impact on nutritional investment: a plausible explanation for this is that good harvests increase the diversity of food available to households without requiring an increase in expenditure. The predicted harvest index has a significant impact on both total and food expenditures. The 0.068 coefficient on total expenditure implies that a one standard deviation increase in the predicted harvest index increases household per capita expenditure by an average of 6.5% in the year of the harvest. Using the interaction specification in Equation 4, this effect can be isolated to the *after harvest* period, that is, 3-8 months after the district harvest date (columns (5) and (6)). During this time period, a one standard deviation increase in the predicted harvest index for the most recent harvest increases total household per capita expenditure by an average of 10.4% (column (5)). But in the periods outside this window, there is no significant effect of the predicted harvest index on expenditures. This result and the results on the nutritional investment index provide a clear demarcation of the timing of the effect on household economic welfare. I use the result later in this section. I assume that the shock only “bites” in the window 3-8 months after harvest. This allows me to use more granular 6-month windows to analyse the effects of weather shocks on cognitive development.

6.4 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 10 displays the results of running a version of Equation 2 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 6.⁵³ Panel A displays the results when using SPEI growing season as the main treatment variable. Although the previous section indicated that the SPEI growing season increases nutritional investment, 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 testing.

⁵²I use household expenditure adjusted for inflation at the province, rural-urban, year level (the third definition as described in Appendix Section A.1). This is only available for IFLS waves 1-4. I show in Appendix Section N that the results are robust to other definitions of the expenditure variable.

⁵³I 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.

Table 9: Effect of weather variation on log household per capita expenditure

		Dep Var: ln(Household Expenditure p.c.)					
		Total (1)	Food (2)	Total (3)	Food (4)	Total (5)	Food (6)
	Outcome measured in:						
SPEI growing season	Year 0	0.014 (0.019)	0.017 (0.018)				
SPEI growing season	Year 1	0.001 (0.025)	0.010 (0.023)				
Predicted harvest index	Year 0			0.068** (0.028)	0.066** (0.027)		
Predicted harvest index	Year 1			-0.001 (0.023)	-0.002 (0.022)		
Predicted harvest index	Months -3 to 2 after harvest					-0.021 (0.039)	-0.016 (0.038)
Predicted harvest index	Months 3 to 8 after harvest					0.099*** (0.031)	0.094*** (0.030)
Predicted harvest index	Months 9 to 14 after harvest					-0.009 (0.029)	-0.017 (0.028)
Predicted harvest index	Months 15 to 20 after harvest					-0.002 (0.026)	0.004 (0.025)
Year FEs		Yes	Yes	Yes	Yes	Yes	Yes
District FEs		Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean		12.728	12.210	12.728	12.210	12.728	12.210
R ²		0.120	0.103	0.118	0.101	0.120	0.103
N		11561	11571	11561	11571	11557	11567

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 \times 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), the dependent variable is total expenditure calculated in this way. For columns (2), (4), and (6), 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 B1 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. 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 B.2.1). "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 4 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.

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.⁵⁴ 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.

6.5 Predicted harvest index on cognitive

Here I present results examining the effect of the predicted harvest index on adult cognitive skills. This allows me to corroborate the main results from Section 5 with results on the new shock, and to examine the timing of the cognitive critical period at a more granular 6-monthly level.⁵⁵ First, examining Panel A of Table 11, and the left half of Figure 3, there is a strongly significant effect at age 2 for boys of 0.095 standard deviations (with a q-value of 0.005). There is no such effect for girls, for whom the coefficient is 0.011 and is not significant at the 10% level. The existence of a critical period for boys at age 2 corroborates the results seen using the SPEI growing season measure in Section 5.1. Two weather shocks, constructed in different ways, lead to a similar coefficient that can be isolated to period 2. This is strong evidence of a reduced-form critical period for cognitive development at this age. Given that the predicted harvest index appears to have a clear effect on household expenditure, nutritional investment, and child anthropometrics, we can be more confident that this is a critical period that arises at least partly due to nutritional and economic factors.

Besides corroboration of the previous results, the predicted harvest index also allows me to pin down the *timing* of the critical period at a more granular level. The results in Sections 6.2 and 6.3 showed that the impact of the predicted harvest index on nutritional investment and household expenditure could be isolated to a window between 3 and 8 months after harvest. Using this fact, I can analyse the effect of these shocks at a 6-monthly level, rather than at an annual level. I assign every 6-month interval in an individual's lifetime *either* to the 6-month period when any shock will "bite" (3 to 8 months after harvest) *or* to the 6-month period when the shock has no effect (3 months before harvest to 2 months after harvest). This assignment will depend on when the individual is born relative to harvest.⁵⁶

⁵⁴In Appendix Table O1, I use the methodology described in Appendix Section B.2.4 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).

⁵⁵For these results, I increase power by focusing only on the first 5 years of life. In Appendix Table P1 I show that the strong effect of the predicted harvest at age 2 on adult cognitive scores is largely unchanged by including later ages in the regression (the coefficient goes from 0.084 to 0.082 with a standard error of 0.028), although the increased number of hypotheses tested contributes to a larger q-value of 0.067.

⁵⁶For example, if an individual is born 3 months after harvest, then the first 6-month period of their life (age 0-5 months inclusive) will be assigned to the shock that "bites" in that period, while the second 6-month period of their life (age 6-11 months) will be assigned to a value of 0 (because the shock has no detectable effect in this period). This methodology is described in detail in Appendix Section B.2.4.

Table 10: 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 (0.024)	[1]	-0.019 (0.018)	[1]	0.014 (0.037)	[0.879]	-0.049* (0.026)	[0.444]	-0.028 (0.035)	[1]	0.001 (0.030)	[1]
SPEI Shock, Age = 0	-0.003 (0.026)	[1]	-0.001 (0.020)	[1]	-0.017 (0.033)	[0.879]	-0.041 (0.028)	[0.444]	0.017 (0.029)	[1]	0.028 (0.029)	[1]
SPEI Shock, Age = 1	-0.035* (0.021)	[0.406]	0.001 (0.018)	[1]	-0.054* (0.028)	[0.21]	0.017 (0.024)	[0.604]	-0.014 (0.034)	[1]	0.003 (0.027)	[1]
SPEI Shock, Age = 2			0.015 (0.023)	[1]			0.040 (0.033)	[0.449]			-0.011 (0.030)	[1]
SPEI Shock, Age = 3			0.014 (0.017)	[1]			0.001 (0.025)	[0.631]			0.027 (0.025)	[1]
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 (0.033)	[1]	0.054 (0.033)	[0.343]	-0.009 (0.038)	[1]	0.052 (0.035)	[0.582]	0.030 (0.049)	[1]	0.048 (0.051)	[0.713]
Predicted Harvest Index, Age = 0	-0.004 (0.026)	[1]	0.039 (0.028)	[0.343]	-0.041 (0.037)	[1]	0.005 (0.036)	[1]	0.046 (0.041)	[1]	0.060 (0.043)	[0.5]
Predicted Harvest Index, Age = 1	-0.034 (0.031)	[1]	0.043* (0.025)	[0.343]	-0.030 (0.035)	[1]	0.006 (0.033)	[1]	-0.034 (0.041)	[1]	0.088** (0.035)	[0.072]
Predicted Harvest Index, Age = 2			0.022 (0.026)	[0.372]			0.022 (0.032)	[1]			0.030 (0.038)	[0.713]
Predicted Harvest Index, Age = 3			0.014 (0.025)	[0.372]			0.055 (0.038)	[0.582]			-0.016 (0.035)	[0.713]
Birth Year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
(Current) District FEs	Yes		Yes		Yes		Yes		Yes		Yes	
District x Birth Month 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 B1 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Panel B of Table 11 and the right half of Figure 3 show the results of the estimations with 6-month intervals. There is a strong and significant positive effect at age 30-35 months when pooling both genders of 0.84 standard deviations (q value = 0.041). This seems to be driven solely by males, with a high coefficient of 0.161 standard deviations at this age. There is also some indication of other sensitive periods (24-29 months, 48-53 months), but the coefficient on both of these periods is not significant after adjusting for multiple hypothesis testing. In keeping with the annual results, there are no significant effects at any age for females, and coefficients are typically close to 0. Broadly, these results indicate that in the rural Indonesian context, weather shocks that are likely to improve harvest yields can lead to a large (reduced form) increase in male adult cognitive ability *specifically* when they impact household welfare during a very narrow age window of 30-35 months. This can be interpreted as strong evidence in favour of a reduced-form critical period, in line with the results seen in Section 5.1.

6.6 Discussion of mechanisms

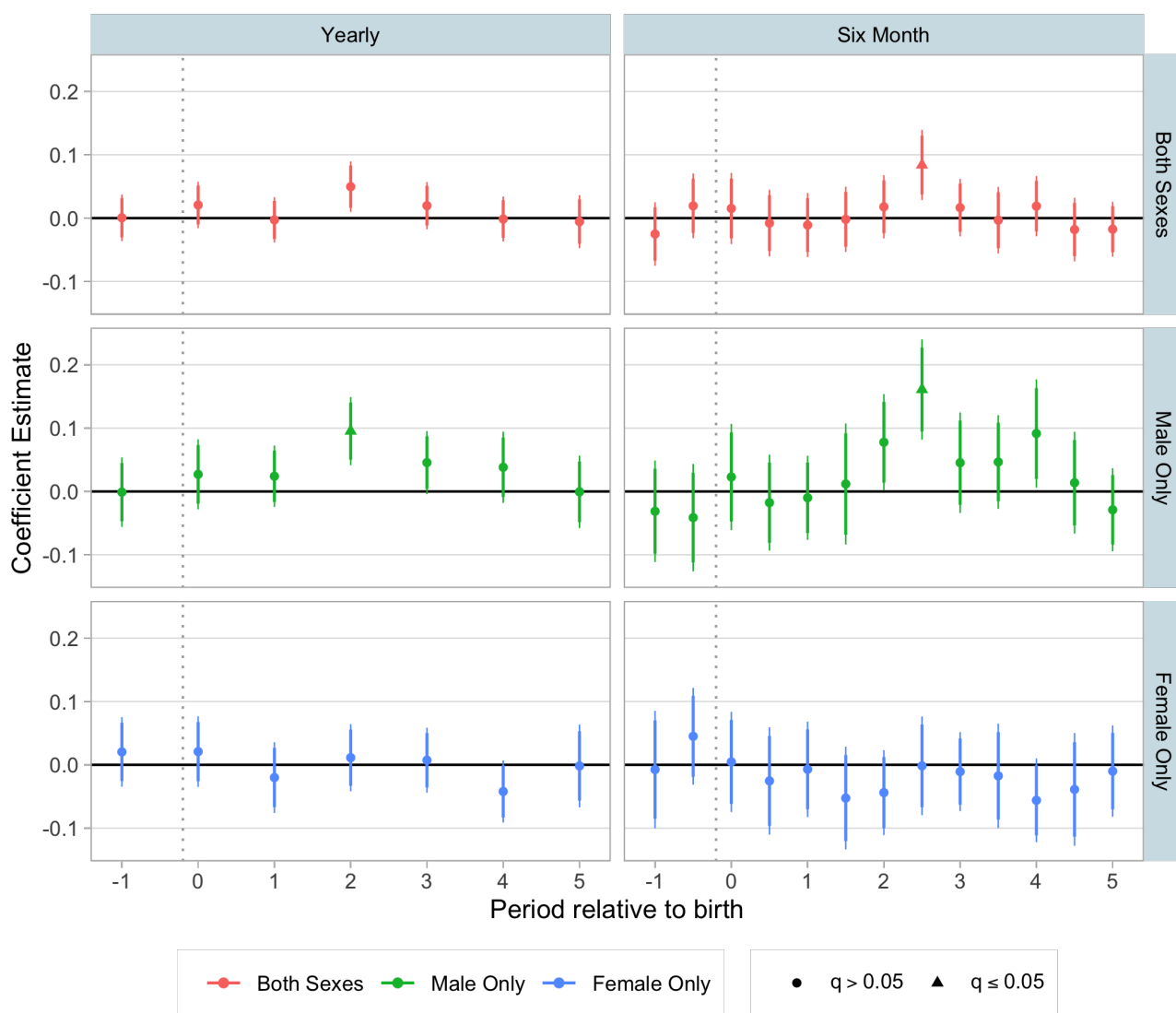
The results suggest that early-life weather variation is likely to have an effect on adult cognitive ability through two interlinked channels, namely (i) increases in nutritional investment for young children, and (ii) increases in household expenditure due to increased agricultural income. There are a number of other mechanisms that could also explain the effects of early life weather on cognitive scores. I cannot rule these out, but there are reasons to suggest that they are not the key drivers of the main results.

First, wetter weather may increase the risks of floods or may lead to a worse early-life disease environment and worse cognitive development. These mechanisms suggest a *negative* relationship between rainfall and cognitive development. The story thus has difficulty explaining the strongly positive relationship between SPEI at age 2 and cognitive scores. If floods were important, heavy rainfall (and large positive SPEI shocks) would have negative effects on cognitive development. Appendix Section K also shows no consistent evidence for this claim. Furthermore, it seems unlikely that purely rainfall-driven mechanisms underlie the main results, since the effect at age 2 on cognitive score persists when using the predicted harvest index, which is composed of multiple weather measures not based on rainfall such as temperature and season timing.

Second, parents may spend less time with children when harvests are plentiful, thus leading to a negative effect of crop-friendly weather on cognitive development. Table 8 showed that parental time investments are unaffected by the weather.

Finally, there may be general equilibrium effects of weather shocks in local areas. For example, weather variation may change the prices of food in the local area, affecting the welfare of households who do not farm. I cannot rule this channel out. However, it can be thought of as an extension of the main mechanism I have proposed, since it will likely affect cognitive development primarily through changes in nutritional investment and economic welfare.

Figure 3: Effect of predicted harvest index on cognitive



Notes: Each point corresponds to a coefficient from Table 11, so represents the effect of the predicted harvest index at each age on cognitive factor z-score in adulthood. All coefficients control for birth-year fixed effects and individual-level controls (dummies for highest level of parental education, sex, and religion). 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 B.2.4 for details.) Error bars are 90% and 95% confidence intervals (not adjusted for multiple testing).

Table 11: Effect of predicted harvest index on adult cognitive Z-scores**Panel A: Yearly**

	Predicted Harvest Index					
	Both Sexes (1)	q value (1)	Male Only (2)	q value (2)	Female Only (3)	q value (3)
Age = -1	0.001 (0.019)	[1]	-0.001 (0.028)	[0.885]	0.020 (0.028)	[1]
Age = 0	0.021 (0.019)	[1]	0.027 (0.028)	[0.505]	0.021 (0.028)	[1]
Age = 1	-0.003 (0.018)	[1]	0.024 (0.025)	[0.505]	-0.020 (0.028)	[1]
Age = 2	0.050 (0.020)**	[0.116]	0.095 (0.027)***	[0.005]	0.011 (0.027)	[1]
Age = 3	0.020 (0.019)	[1]	0.046 (0.025)*	[0.279]	0.007 (0.026)	[1]
Age = 4	-0.001 (0.018)	[1]	0.038 (0.028)	[0.433]	-0.042 (0.025)*	[1]
Age = 5	-0.006 (0.021)	[1]	-0.001 (0.029)	[0.885]	-0.002 (0.033)	[1]
Birth Year FEs	Yes		Yes		Yes	
Birth District FEs	Yes		Yes		Yes	
District x Month of Birth FEs	No		No		No	
F statistic	1.047		2.416		0.769	
p-value for F-test	0.400		0.022		0.614	
R ²	0.209		0.232		0.250	
N	5572		2601		2971	

Panel B: 6 month age-intervals

	Predicted Harvest Index					
	Both Sexes (1)	q value (1)	Male Only (2)	q value (2)	Female Only (3)	q value (3)
Age = -12 to -7 months	-0.025 (0.026)	[1]	-0.031 (0.041)	[1]	-0.008 (0.047)	[1]
Age = -6 to -1 months	0.019 (0.026)	[1]	-0.041 (0.043)	[1]	0.045 (0.039)	[1]
Age = 0 to 5 months	0.015 (0.029)	[1]	0.023 (0.042)	[1]	0.005 (0.040)	[1]
Age = 6 to 11 months	-0.008 (0.027)	[1]	-0.018 (0.038)	[1]	-0.025 (0.043)	[1]
Age = 12 to 17 months	-0.011 (0.026)	[1]	-0.010 (0.034)	[1]	-0.007 (0.038)	[1]
Age = 18 to 23 months	-0.002 (0.026)	[1]	0.012 (0.048)	[1]	-0.052 (0.041)	[1]
Age = 24 to 29 months	0.018 (0.025)	[1]	0.078 (0.038)**	[0.22]	-0.044 (0.034)	[1]
Age = 30 to 35 months	0.084 (0.028)***	[0.041]	0.161 (0.040)***	[0.002]	-0.002 (0.039)	[1]
Age = 36 to 41 months	0.017 (0.023)	[1]	0.045 (0.040)	[1]	-0.011 (0.032)	[1]
Age = 42 to 47 months	-0.003 (0.027)	[1]	0.047 (0.037)	[1]	-0.017 (0.042)	[1]
Age = 48 to 53 months	0.019 (0.024)	[1]	0.091 (0.043)**	[0.22]	-0.056 (0.034)*	[1]
Age = 54 to 59 months	-0.018 (0.026)	[1]	0.014 (0.041)	[1]	-0.039 (0.045)	[1]
Age = 60 to 65 months	-0.018 (0.022)	[1]	-0.029 (0.033)	[1]	-0.010 (0.037)	[1]
Birth Year FEs	Yes		Yes		Yes	
Birth District FEs	No		No		No	
District x Month of Birth FEs	Yes		Yes		Yes	
F statistic	1.493		2.278		1.030	
p-value for F-test	0.113		0.009		0.425	
R ²	0.421		0.570		0.550	
N	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. 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 B1 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 B.2.4. 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 B.2.4 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

7 Discussion & Conclusion

In this paper I present new evidence for the existence of a critical period for cognitive development as a result of weather shocks in early childhood, and I am able to isolate this period to the year after the second birthday. I show that 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 such impact. This effect appears to be strongest among boys. 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 further show evidence that the observed effects on cognitive development are consistent with an economic channel in which weather affects aggregate household expenditure, nutritional investment, and infant health outcomes (as proxied by anthropometrics), leading to impacts on cognitive development that persist into adult life.

These results may have important potential policy implications. In particular, the existence of a critical period at age 2 for cognitive development, but the absence of such a critical period for socioemotional development, can inform the optimal timing of early-childhood interventions. To the extent that reduced-form critical periods for weather shocks mirror the reduced-form critical periods for such interventions, the results suggest that interventions aiming to improve cognitive development should optimally be targeted at 2-year-olds. My results imply that targeting at this age may be even more effective than interventions targeted at 0- or 1-year-olds, contrary to previous literature suggesting that the entire first 1000 day period is “critical”. By contrast, my results suggest no such critical window for socioemotional development. This is consistent with previous claims socioemotional programmes need not prioritise the first 1000 days in the same way.

The particularly strong effect of weather shocks at around 24-36 months is surprising given the literature in child development that proposes the first 1000 days as the “critical period” for cognitive development. This claim comes from sources in the neurodevelopmental literature based on brain volume growth ([Isaacs et al., 2008](#); [Gilmore et al., 2018](#)) and the nutritional literature based on stunting ([Victora et al., 2010](#); [Aiyar & Cummins, 2017](#); [Perkins et al., 2017](#)). However, my results are consistent with a recent review of these literatures that concluded: “the evidence does not identify the early years as the as the sole sensitive time period within which to have a significant influence upon development” ([Wachs et al., 2014](#)). There are, for example, a number of studies showing positive effects of early preschool programmes at ages 3-4 on later cognitive scores, suggesting that cognitive development is not “set in stone” by 24 months after birth ([Dean & Jayachandran, 2020](#); [Schweinhart & Weikart, 1981](#); [Reynolds et al., 2011](#)).

Moreover, there are at least three plausible explanations for the difference between my results and the two literatures outlined above. First, the impacts I describe are *reduced-form* impacts of early-life weather shocks. They are measured at least 13 years after shocks at age 2, and incorporate the effects of subsequent parental investments. This contrasts to the biological framing of critical periods in the neurodevelopmental literature that places less emphasis on investment responses. Second, my results are causally identified, whereas the

correlational results in previous studies may be confounded by omitted factors. Third, the stylised facts in the existing literatures often do not account for complexities in the relevant biological mechanisms. These include catch-up growth, which could explain the effects of later nutritional shocks (Prentice et al., 2013); and the late development of the prefrontal cortex and other fronto-parietal networks, which are important for cognitive development (Hanson et al., 2013; Ferrer, 2009; Little et al., 2014; Buss & Spencer, 2014; Buss et al., 2014; Buss & Spencer, 2018; Fiske & Holmboe, 2019). 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.

Other interesting questions remain. How generalisable is the critical period discovered here? What types of interventions can successfully make use of it, and what are the resulting gains in cost-effectiveness and efficiency? What drives the “missing middle” latent effect of early life shocks that disappears and then reappears in later life? What is the source of the heterogeneity across genders? Answering any of these questions will drive a deeper understanding of the process of early-life human capital accumulation.

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Online Appendix

A Data Appendix

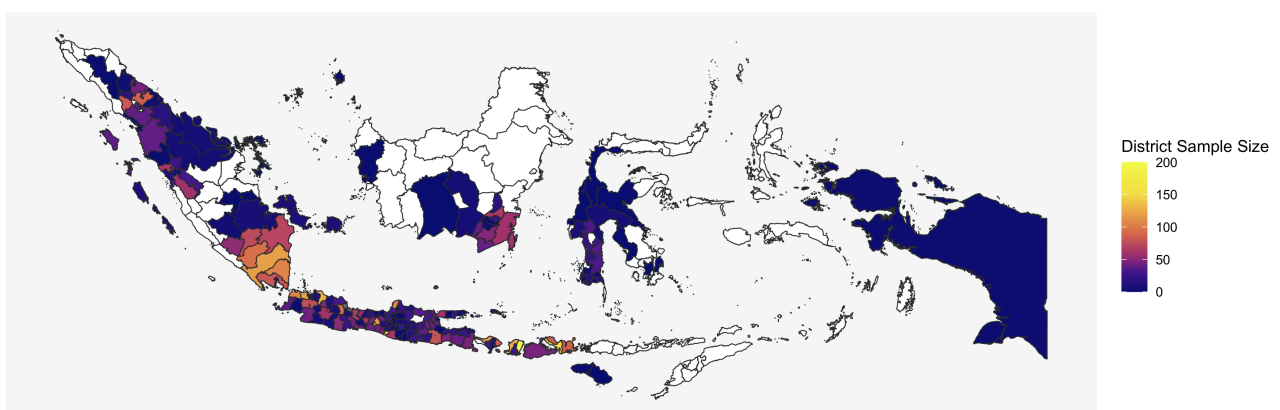
A.1 IFLS data

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 5.4.

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 homeowners. 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 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 Section 6.1 include all harvests where the main crop was rice. I construct a measure of yield by dividing the amount harvested by the area harvested.

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	Extraversion - 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)

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 6.2:

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 C).
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 C).

Parental time-use. I make use of the following variables to construct the parental time-use index seen in Section 6.2: (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 4 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, BPS (?).

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.⁵⁷ 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.

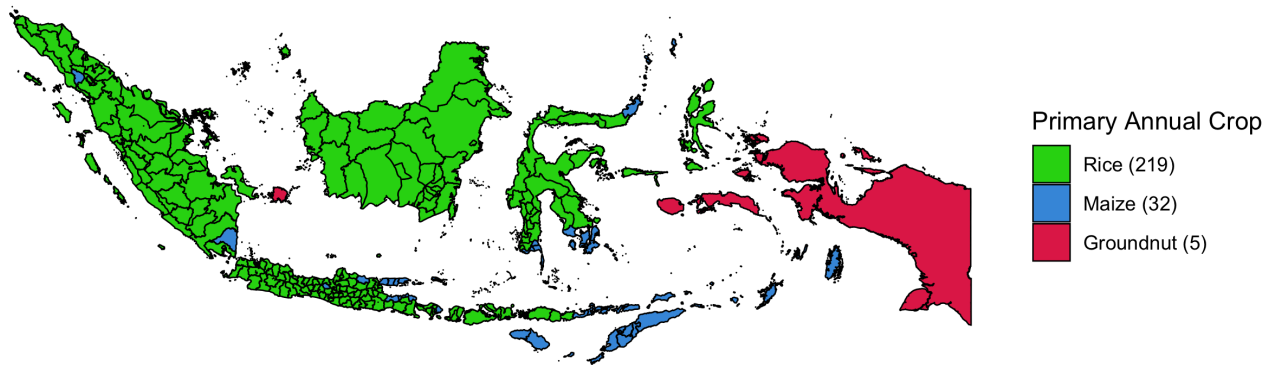
Aggregate crop harvest data. Crop harvested-area data comes from Monfreda et al. (2008), who combine national, state, and county level census data to create a global data set that describes the harvested area for 175 crops on a 5 minute by 5 minute (approximately 10km by 10km) grid, based on the closest 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.⁵⁸ 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 growing season in each district, I make use of crop calendar data from the University of Wisconsin-

⁵⁷Their station-level rainfall data comes from Global Historical Climatology Network (GHCN) Precipitation and Temperature Data (Version 2) and the Badan Meteorologi Dan Geofisika (BMG) agency in Indonesia.

⁵⁸I 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



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

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 predicted harvest measure

B.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:

$$IHS(RiceYield)_{jhrt} = \alpha + \sum_k \gamma_k WeatherRice_{jhrt,k} + \mathbf{X}'_{ht}\delta + \mathbf{Z}'_{jt}\lambda + \pi_r + \mu_t + \varepsilon_{jhrt} \quad (5)$$

$Weather_{jhrt,k}$ 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 B1 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. 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. A fuller description of the construction of the predicted harvest measure is found in the next section.

B.2 Detail of construction

The main aim of the predicted harvest measure is to pin down the timing of the impacts of weather variations. To that end, there are three main changes in the way I use the available data to construct the shock:

1. I use daily temperature and precipitation data to calculate a richer set of weather variations that are likely to predict harvest, that I can then use alongside the SPEI.
2. I use the IFLS data on rice farming to calculate the typical growing season (planting and harvest dates) at a more disaggregated level. In particular this allows me to estimate the day, rather than month, of planting/harvest, and also allows me to estimate at the sub-district (*kecamatan*) level.

Table B1: 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 (0.048)	0.050** (0.025)	0.040* (0.024)	0.043* (0.025)	0.036 (0.024)		0.040 (0.024)
Wet Season Delay (Z)	-0.052** (0.024)	-0.054** (0.023)	-0.059** (0.023)	-0.050** (0.023)	-0.054** (0.023)	-0.058** (0.023)	
Longest Dry Spell (Z)	-0.062* (0.034)	-0.041* (0.021)		-0.026 (0.021)			
SPEI (0-2m before rice planting)	0.109*** (0.040)	0.116*** (0.039)	0.103** (0.040)			0.099** (0.040)	0.097** (0.040)
SPEI (rice planting to rice harvest)	-0.057 (0.061)						
Num. Rainy Days (Z)	-0.035 (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	3.482	4.868	4.794	3.524	4.217	5.616	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 B. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

3. I use the results from a regression of rice yields on the set of weather variables to create a “predicted harvest” measure, and then use this measure as the main explanatory variable in the results.

B.2.1 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. \(2019\)](#).
- **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.

B.2.2 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 $WeatherRice_{jhr,t,k}$ where j is a rice crop farmed by household h in subdistrict r and in survey-wave t , and $k = \{1, 2, \dots, K\}$ 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.⁵⁹

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 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, $DD_{min} = 8^{\circ}C$ and $DD_{max} = 32^{\circ}C$. The growing degree days measure is then calculated as the sum of the $g(x)$ measure for the

⁵⁹For 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.

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.

B.2.3 Construction of predicted harvest measure

I use the results in Table B1 to construct a predicted harvest index $PredHarvest_{ry}$ for each district r and analysis year y in the following way:

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

where W_{ry} denotes the vector of weather variables defined at the district \times year level seen in Table B1, and $\hat{\gamma}$ is the vector of predicted coefficients on the weather variables seen in Table B1. 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.

B.2.4 Matching individuals to shock measures

Based on the results seen in the expenditure section, the weather variation captured by $PredHarvest_{ry}$ “bites” and affects household expenditure 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 height-for-age and 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:

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 :

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

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, $\mathcal{A}(i, 1) = \{\text{Jan 2001, Feb 2001, ..., Dec 2001}\}$. For individual i at age a residing in district r :

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

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 Predicted Harvest 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.⁶⁰

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 $PredHarvestYear_{ry}$ when in the second bucket.

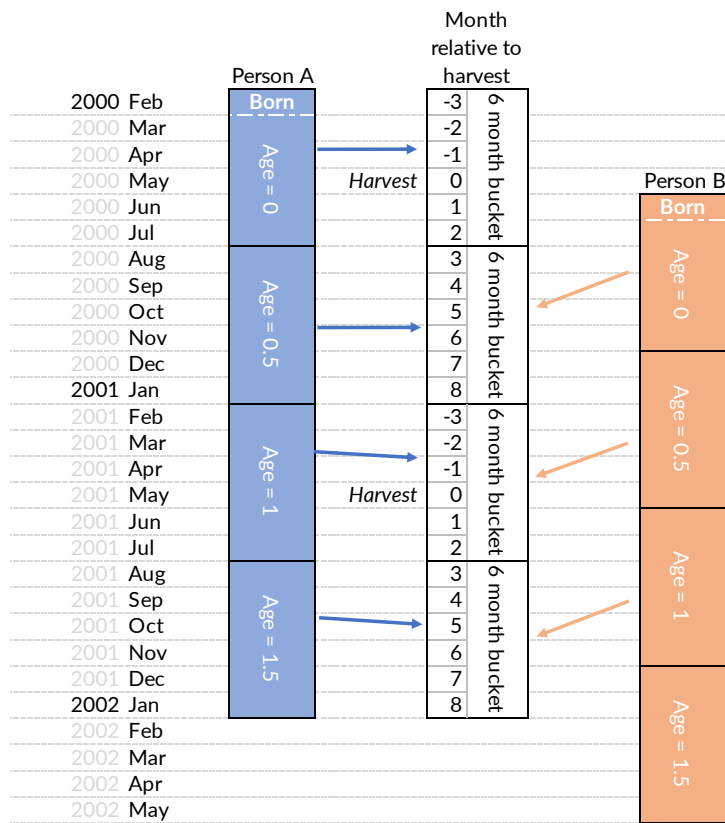
Then, for every 6-month life-period for every individual, I match it to the *single* 6-month weather bucket for that district, where the matching weather bucket will be the one that overlaps the most with the 6-month life period. Figure B1 gives an example of this approach. In the district of analysis, 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

⁶⁰Simulations 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.

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 B1, 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 robustness checks (Appendix Tables O2 and P2) 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.

Figure B1: 6-month bucket assignment process



C Construction of indexes

As discussed in Section 3.3, 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.

C.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:⁶¹

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.

C.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:

$$Y_i = \alpha + \mathbf{X}_i' \beta + \varepsilon_i \quad (6)$$

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 6, 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:

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

⁶¹The '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 appears to have led to a very different pattern of response bias (see Figure ??), 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.

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.

C.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 C1 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 of factors in IFLS4 reflects this. For IFLS4, the scree plot (see Fig. C1a), 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. C1b). 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 C1: 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 C1a and C1b. Each method recommends fewer factors for IFLS4 than IFLS5 because IFLS4 contains fewer socioemotional questions than IFLS 5 (see Table A1 for details).

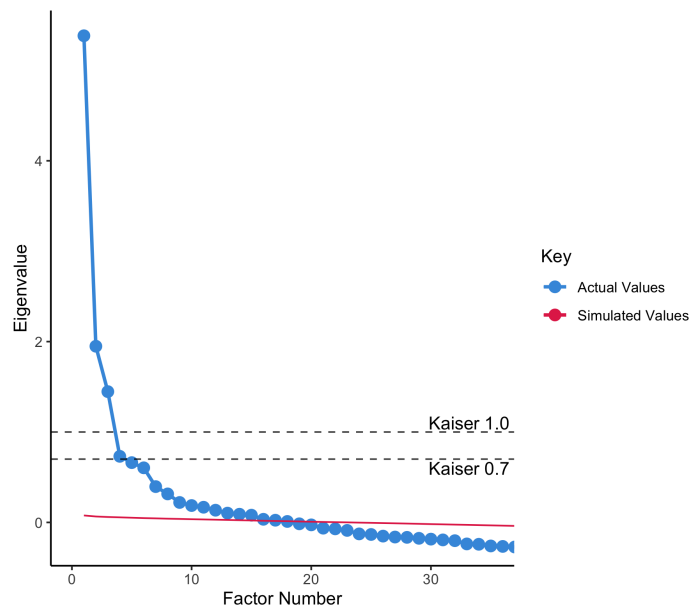
C.4 Estimating the factor analysis model

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 residuals⁶², 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

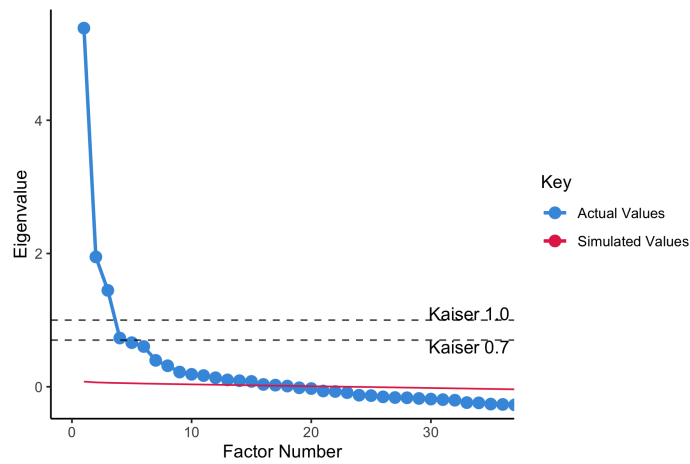
⁶²This has been shown to give unbiased estimates of factor loadings in the context of ordinal variables such as those used here, see [Lee et al., 2012](#).

Figure C1: 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 \(1966\)](#).

assumption that factors are uncorrelated⁶³. 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.

Table C3 shows the factor loadings for the socioemotional measures available in IFLS5, and Table C4 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 C3 and C4 where the value meets this condition.

The factor loadings seen in Table C3 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 C2) 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 C4) 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 C2: *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 C3 and C4

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 ‘Extroversion - Outgoing’ (0.543).

⁶³This 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.

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 C5](#) shows the cognitive factor loadings for IFLS4, and [Table C6](#) 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 \(2019\)](#).

C.5 *Generating factor scores*

I use the factor loadings from Tables C3–C6 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 C3, C4, C5 and C6.
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).⁶⁴ 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 C2. By construction, all the distributions are centred around 0, and they all appear to be approximately symmetrical.

C.6 *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 C.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

⁶⁴Mediator variables, on the other hand, are already combined across waves as described in Step 2.

Table C3: 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 C4: 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 C5: 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

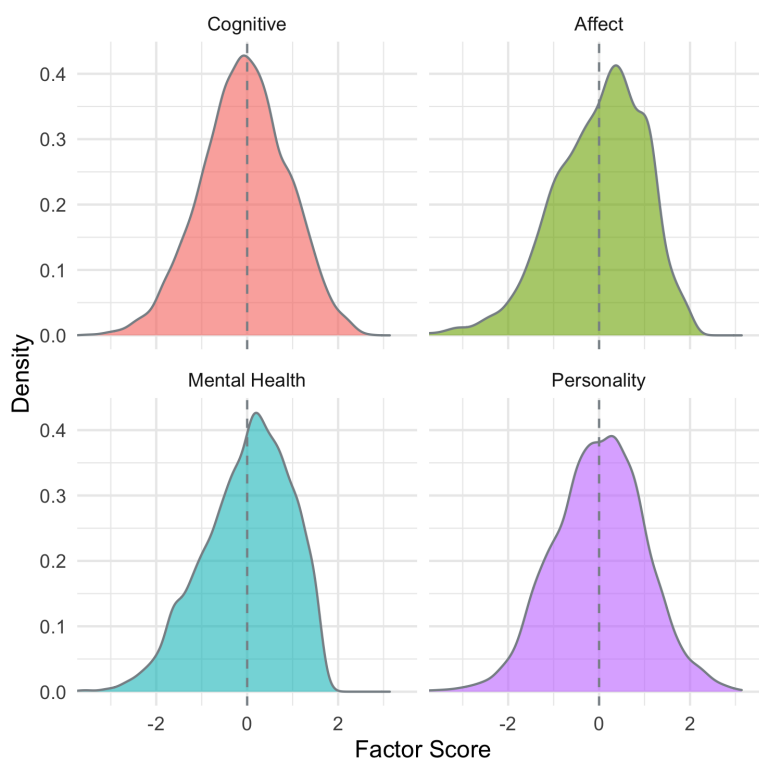
Notes: Cells highlighted in blue have an absolute value of greater than 0.3.

Table C6: 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.

Figure C2: Kernel density of each of the factor scores



factor analysis and generating indexes based on the factor loadings. Table C7 shows the weights on each measure when constructing the indexes.

Table C7: 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

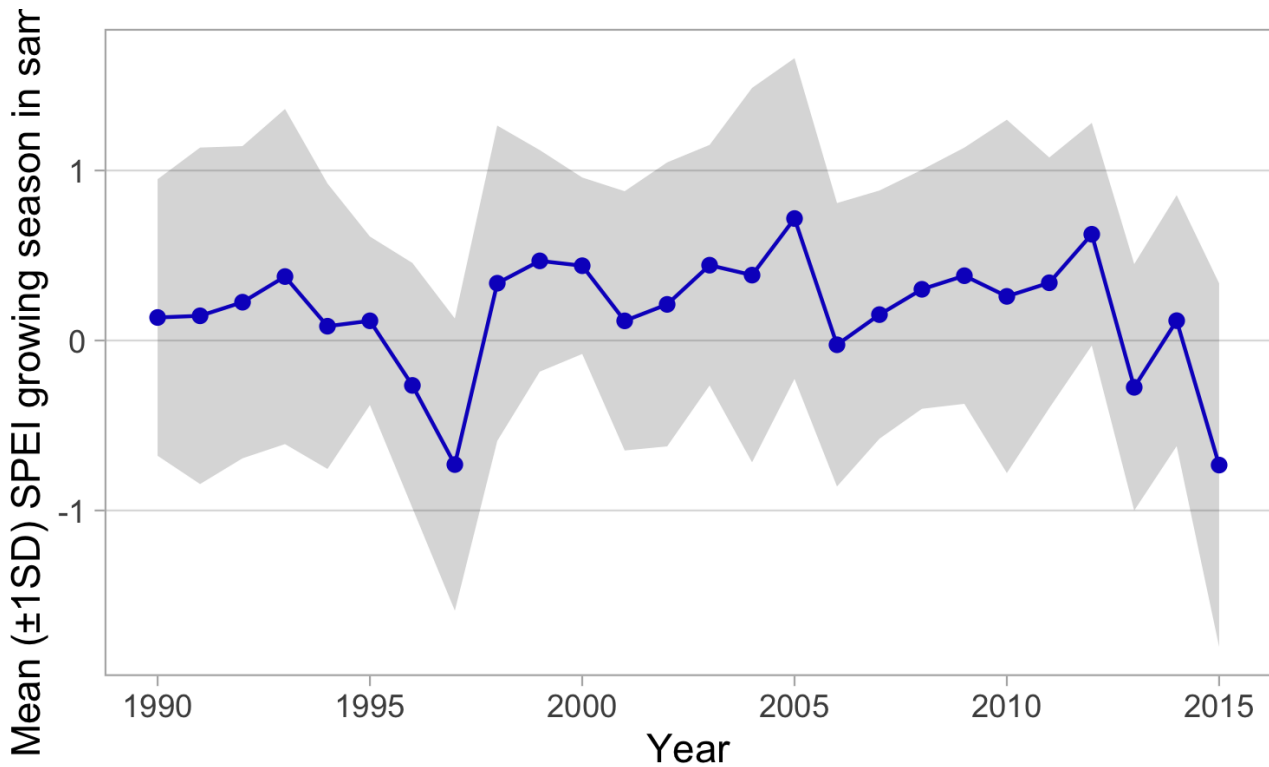
D Descriptive statistics

Table D1: 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 education - Elementary (=1)	5572	0.52	0.50	0	1	1
Highest level of parent education - Junior High (=1)	5572	0.20	0.40	0	0	1
Highest level of parent education - Senior High (=1)	5572	0.19	0.40	0	0	1
Highest level of parent education - 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. The number of observations is lower for affect/wellbeing and personality factors because these were not measured in IFLS3 or IFLS4.

Figure D1: SPEI growing season over each year



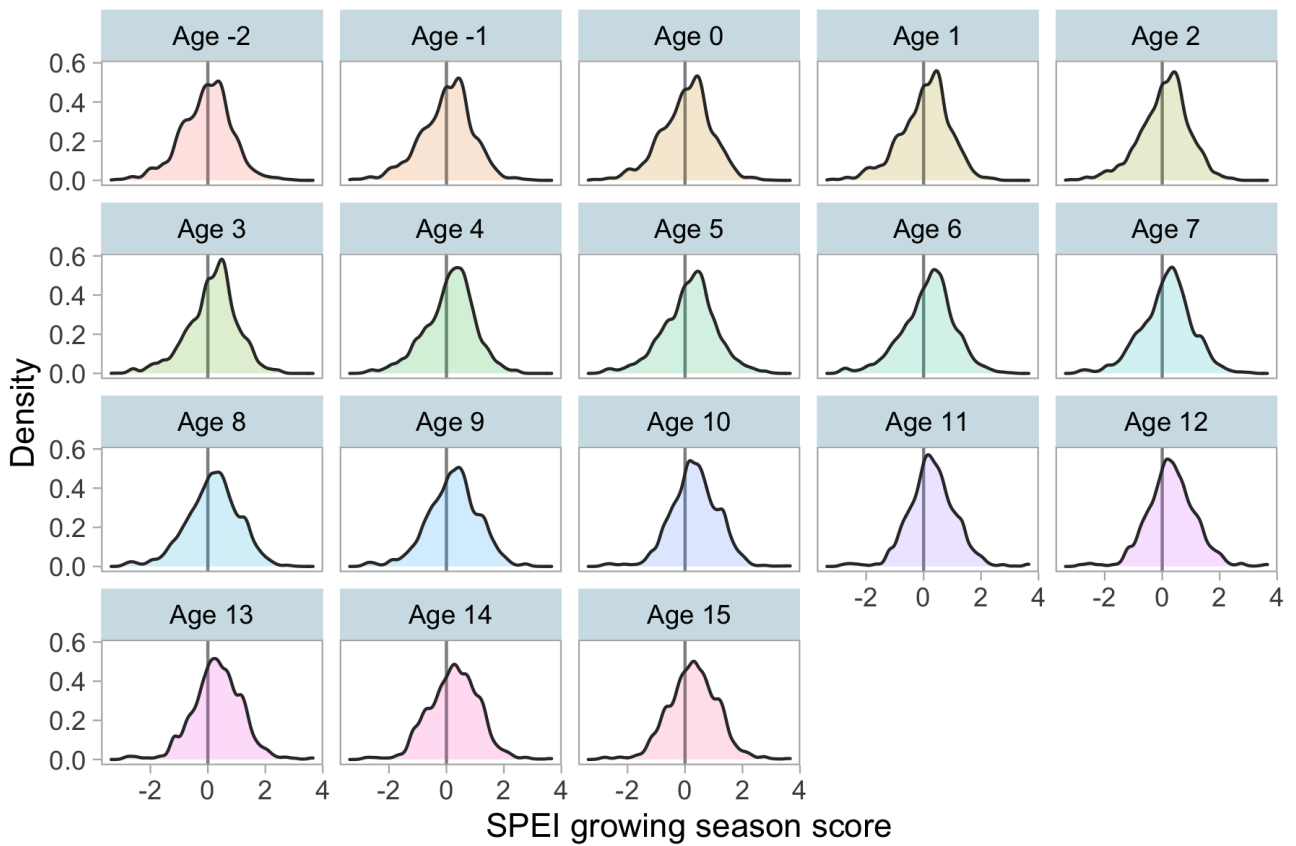
Notes: This shows the yearly mean and ± 1 SD shaded intervals for the value of SPEI growing season experienced in each year for the individuals in the main sample. A negative spike is seen in 1997, which was when severe drought struck much of Indonesia.

Table D2: 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

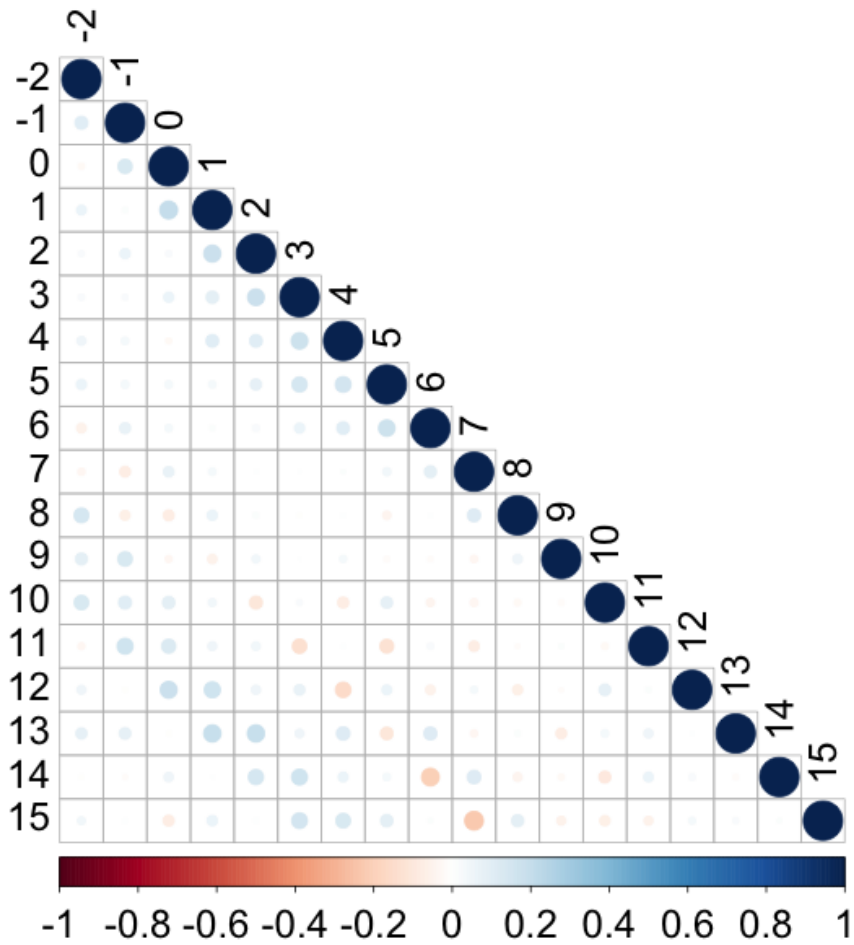
Notes: This is the correlation matrix for the values of SPEI growing season at different ages for individuals in the main sample. The x - and y -axes describe the age of the shock. The absolute value of the correlation between shocks in different periods is low, with no such correlation exceeding 0.2.

Figure D2: *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 D1. This is because individuals in the sample are born in different years.

Figure D3: Correlation between SPEI growing season at different ages in the main sample



Notes: This is a visual representation of Figure D2, 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.

E Extensions to the conceptual framework

E.1 Simple model with investment responses

To reflect this, investment in $t + 1$ can be written as a function of all previous shocks and investments.⁶⁵

$$I_{t+1} = z_{t+1}(I_t, I_{t-1}, \dots, I_{-2}, \mu_t, \mu_{t-1}, \dots, \mu_{-2})$$

This implies that in general the full reduced form estimates of the impact of a shock μ_t will not be equal to the partial equilibrium effects, that is:

$$\frac{dm_k(\cdot)}{d\mu_t} \neq \frac{\partial m_k(\cdot)}{\partial \mu_t}$$

To illustrate this, consider a simplified model which has only two childhood periods $t = \{1, 2\}$, and where I_1 has already been chosen by parents to be \bar{I}_1 . Then we can rewrite adult skills h_k as:⁶⁶

$$h_k = m_k\left(\mathbf{h}^P, \boldsymbol{\theta}_1, g(\mu_1, \mu_2, \bar{I}_1, I_2(\mu_1))\right)$$

If we assume for simplicity that $m(\cdot)$ is additively separable in \mathbf{h}^P , $\boldsymbol{\theta}_1$, and $g(\cdot)$, then the reduced-form effect of a change in μ_1 will be:

$$\begin{aligned} \frac{dm_k}{d\mu_1} &= \frac{dm_k}{dg} \times \frac{dg}{d\mu_1} \\ &= \frac{dm_k}{dg} \left[\frac{\partial g}{\partial \mu_1} + \frac{\partial g}{\partial I_2} \cdot \frac{dI_2}{d\mu_1} \right] \end{aligned}$$

whereas the direct effect will be:

$$\frac{\partial m_k}{\partial \mu_1} = \frac{dm_k}{dg} \frac{\partial g}{\partial \mu_1}$$

So the total reduced-form effect can be written as the direct effect plus a term that is some positive function⁶⁷ of the investment change of I_2 in response to the shock μ_1 :

$$\underbrace{\frac{dm_k}{d\mu_1}}_{\text{reduced form}} = \underbrace{\frac{\partial m_k}{\partial \mu_1}}_{\text{"direct" effect}} + \underbrace{\frac{dm_k}{dg} \cdot \frac{\partial g}{\partial I_2} \cdot I_2'(\mu_1)}_{\text{investment response effect}}$$

Thus, depending on whether the investment response to μ_1 is *compensating* ($I_2'(\mu_1) < 0$) or *reinforcing* ($I_2'(\mu_1) > 0$), the reduced form will understate or overstate the "direct" effect of the shock. The main results found in this paper identify the reduced form impacts of weather shocks in each period. Indeed, the coefficients of interest β_j in my main specification (see Section 4) can be thought of as identifying $dm_k(\cdot)/d\mu_j$ for weather shocks at different ages. As noted, these coefficients are of direct policy relevance themselves. But it is also important to understand the mechanisms behind such reduced-form effects, and whether direct effects may be driven or dampened by later investment. Therefore in Section 6 I attempt to understand to what degree my results might be explained by different channels and investment responses.

⁶⁵The functional form of $z_{t+1}(\cdot)$ will depend on the exact optimisation programme faced by the parents. See the different suggestions in Cunha & Heckman (2007) or Currie & Almond (2011) and Almond et al. (2018).

⁶⁶I rewrite $I_2(\bar{I}_1, \mu_1)$ as $I_2(\mu_1)$ since I_1 is fixed.

⁶⁷Skills are naturally assumed to be a positive function of investment, so $dm_k/dg > 0$ and $\partial g/\partial I_2 > 0$.

E.2 Simple model with welfare

This simple model expands upon the discussion in Section 2. It notes briefly 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 2, 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} .

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

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

$$Y = C + p\bar{I}_1 + \frac{pI_2}{(1+r)}$$

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

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 \tilde{I}_2 and the welfare impact will be:

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

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

We can get an expression for the welfare impact of μ_1 , 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 \tilde{I}_2 instead of I_2^* , then the welfare impacts will be:

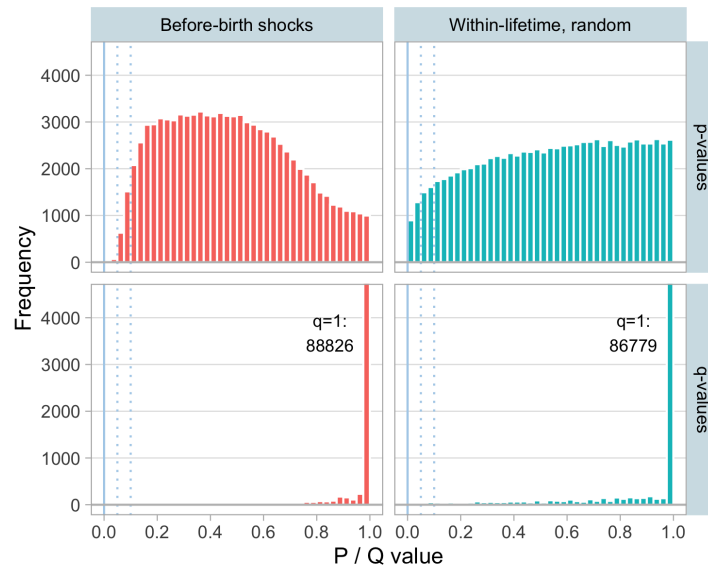
$$\frac{dW}{d\mu_1} = (1 - \alpha) \frac{1}{C} \frac{dC}{d\mu_1} + \alpha \frac{1}{h} \frac{dh}{d\mu_1}$$

F Placebo tests

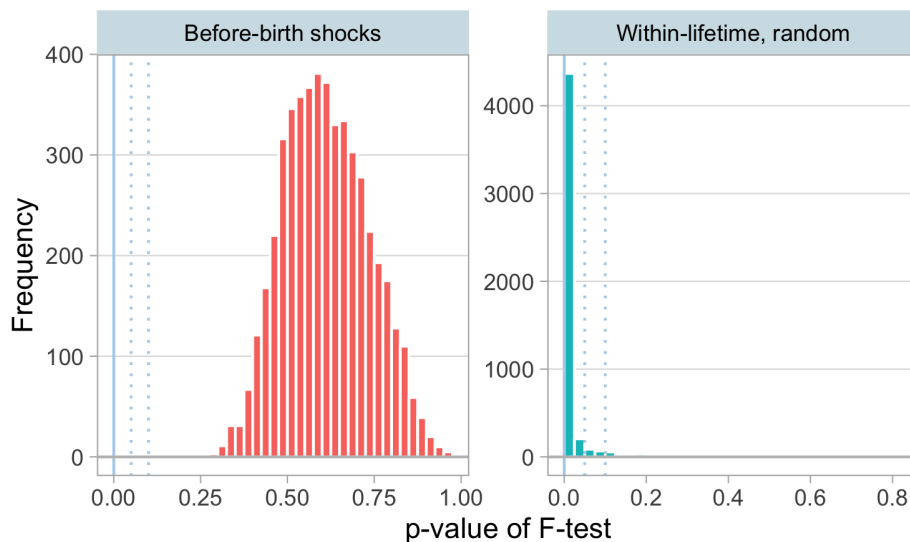
Figure F1 displays the results of the placebo tests in more detail. The rest of this section describes in detail the methodology used to run the placebo tests seen in Section 5.3. I run two different types of placebo tests, which I call “Before-birth shocks” and “Within-lifetime iterations” .

Figure F1: *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*



Before-birth 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 2. 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 j th 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-birth 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 $\mathcal{J}_{\text{hist}} = \{-27, -26, \dots, -3\}$.⁶⁸
2. For iteration $k = 1$:
 - (a) Randomly select (without replacement) a subset \mathcal{Z}_k of length 18 from the set $\mathcal{J}_{\text{hist}}$.⁶⁹
 - (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 $k \in \{2, 3, \dots, 1000\}$.

Within-lifetime iterations. I randomly "reshuffle" the within-lifetime shocks. Separately for each individual, the shock values for ages $(-2, -1, \dots, 15)$ is reassigned to a different year in the set $\{-2, -1, \dots, 15\}$. 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 2. 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 $\mathcal{J} = (-2, -1, \dots, 14, 15)$ be the (ordered) list of time periods used in the main specification. Let j_p be the p th 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 p th element of $\mathcal{Q}_i^{\text{reordered}}$. For example, if 5 is the 1st element of $\mathcal{Q}_i^{\text{reordered}}$, then $q_1 = 5$.

⁶⁸ -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*).

⁶⁹ 18 values are chosen because there are 18 coefficients in my main specification.

- 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 $i \in \{2, \dots, N\}$, 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:

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

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

G 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:

1. *Homogenous effects*. The ATT of weather variation at a given age is constant across all (birth-district, birth-year) cells.
2. *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 2) 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 G1 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 G1: *No significant correlation between the weights given to a (year × 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	451.27	997.14	0.65	1463
	1	-60.92	664.49	0.93	1463
	2	-276.16	433.07	0.52	1463
Proportion of adults with completed primary school	0	-0.10	0.09	0.27	1463
	1	-0.07	0.07	0.33	1463
	2	-0.01	0.05	0.87	1463
Proportion Rural	0	0.18	0.19	0.35	1463
	1	0.11	0.16	0.50	1463
	2	0.11	0.08	0.19	1463

Notes: The results in this table are calculated as follows. First, I run a fixed-effects regression (Equation 2) 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 $w_{r,t}^a$ 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 $w_{r,t}^a$ 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.

H Multiple Testing Adjustment

The False Discovery Rate (FDR) is the expected proportion of false rejections from testing a set of null hypotheses H_1, \dots, 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 $\beta_j, j \in \{-2, -1, \dots, 15\}$, get the corresponding p-values from the primary specification (denoted $p_{-2}, p_{-1}, \dots, p_{15}$)
2. Sort the p-values in ascending order so we have $p_{(1)} \leq p_{(2)} \leq \dots \leq p_{(17)}$
3. To test whether β_j is rejected at the significance level α :
 - (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 $p_{(1)}, \dots, p_{(k)}$
4. 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 $p_{-2}, p_{-1}, \dots, p_{15}$. 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 $FDR \lesssim \alpha_0 / \ln(n) = \alpha_0 / \ln(17)$. 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.

I 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.⁷⁰ 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 I1 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 5.⁷¹ The coefficient of 0.018 on $SPEI_{t-1}$ suggests that an increase in SPEI growing season of 1 standard deviation 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 (?). If in utero SPEI does indeed have a positive effect on the

⁷⁰I match pregnancies to districts using data on the mother's migration history.

⁷¹This appears to be driven mostly by an increase in the probability of a still birth.

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 5.1.

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 I1: 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 (0.023)			0.012 (0.033)		
SPEI growing season, Age = -1		0.018*** (0.005)	0.009		-0.015 (0.012)	1
SPEI growing season, Age = 0		-0.004 (0.006)	1		0.011 (0.007)	1
SPEI growing season, Age = 1		0.003 (0.007)	1		0.004 (0.010)	1
SPEI growing season, Age = 2		-0.003 (0.006)	1		0.015 (0.009)	1
SPEI growing season, Age = 3		-0.005 (0.006)	1		0.003 (0.010)	1
SPEI growing season, Age = 4		0.005 (0.006)	1		-0.009 (0.008)	1
SPEI growing season, Age = 5		-0.005 (0.005)	1		-0.003 (0.009)	1
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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

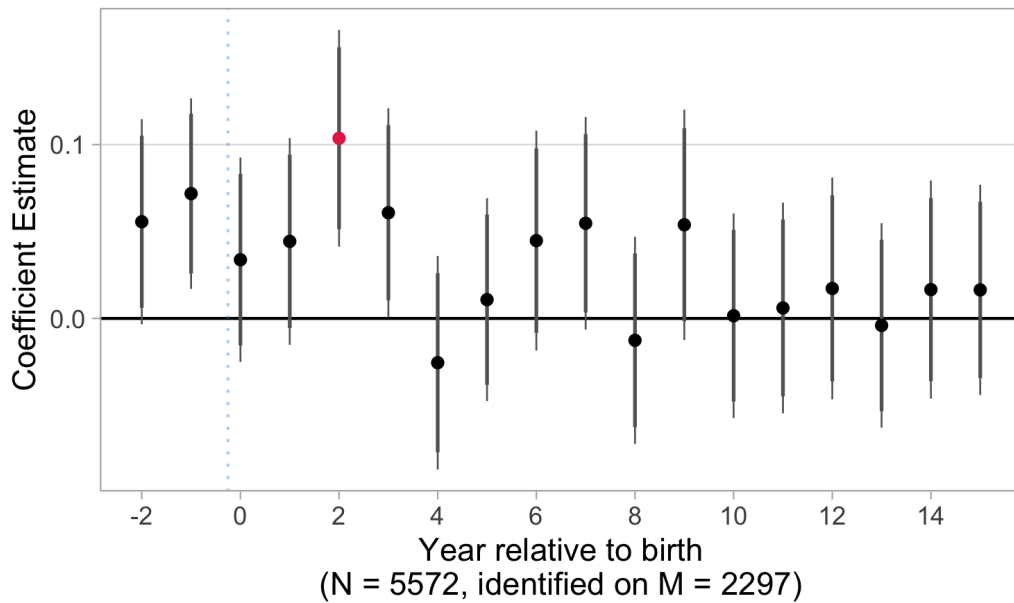
Table I2: Evidence against selective migration

	Dep Var: Individual Migrates in Year t		Dep Var: Probability that migration destination at t is district d	
	SPEI in starting district (1)	q value (1)	SPEI in destination district (2)	q value (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 .

J Additional tables: Cognitive outcomes (Main specification)

Figure J1: Effect of SPEI variation at different stages of childhood on cognitive factor scores using siblings fixed effects



Notes: Each point corresponds to a coefficient from column (2) of Table J1, so represents the effect of SPEI growing season at each age on cognitive factor z-score in adulthood. The model controls for siblings fixed effects and birth order effects as defined in Appendix Section A.1, and individual-level controls (dummies for highest level of parental education, sex, and religion). Error bars are 90% and 95% confidence intervals (not adjusted for multiple testing). Points highlighted in red denote coefficients that have a q-value less than 0.05, implying that they are significantly different from 0 after adjusting for multiple testing.

Table J1: Cognitive robustness

	Sample 1985-2000 (1)	q value (1)	Sibling FEs (2)	q value (2)	SPEI 4 month (3)	q value (3)	Urban (4)	q value (4)	Urban Siblings FEs (5)	q value (5)
SPEI growing season, Age = -2	-0.009 (0.014)	[0.826]	0.056 (0.030)*	[0.341]	-0.012 (0.019)	[1]	-0.013 (0.020)	[0.676]	0.008 (0.037)	[1]
SPEI growing season, Age = -1	0.024 (0.013)*	[0.24]	0.072 (0.028)**	[0.096]	0.022 (0.014)	[1]	-0.030 (0.020)	[0.594]	0.007 (0.036)	[1]
SPEI growing season, Age = 0	-0.006 (0.013)	[0.882]	0.034 (0.030)	[0.532]	-0.006 (0.017)	[1]	0.020 (0.028)	[0.676]	0.080 (0.042)*	[0.412]
SPEI growing season, Age = 1	0.020 (0.014)	[0.458]	0.044 (0.030)	[0.401]	0.017 (0.018)	[1]	0.025 (0.024)	[0.594]	0.005 (0.040)	[1]
SPEI growing season, Age = 2	0.042 (0.013)**	[0.027]	0.104 (0.032)**	[0.022]	0.057 (0.017)**	[0.016]	0.043 (0.024)*	[0.594]	0.075 (0.043)*	[0.412]
SPEI growing season, Age = 3	0.029 (0.014)**	[0.155]	0.061 (0.031)**	[0.337]	0.031 (0.017)*	[1]	0.021 (0.021)	[0.594]	-0.017 (0.042)	[1]
SPEI growing season, Age = 4	0.020 (0.016)	[0.501]	-0.025 (0.031)	[0.713]	-0.006 (0.016)	[1]	-0.029 (0.022)	[0.594]	0.006 (0.043)	[1]
SPEI growing season, Age = 5	0.034 (0.013)**	[0.106]	0.011 (0.030)	[0.913]	0.014 (0.017)	[1]	0.011 (0.031)	[0.676]	0.010 (0.044)	[1]
SPEI growing season, Age = 6	-0.006 (0.014)	[0.882]	0.045 (0.032)	[0.401]	-0.006 (0.017)	[1]	-0.048 (0.028)*	[0.594]	-0.007 (0.047)	[1]
SPEI growing season, Age = 7	-0.001 (0.015)	[1]	0.055 (0.031)*	[0.341]	-0.024 (0.018)	[1]	-0.017 (0.027)	[0.676]	-0.022 (0.045)	[1]
SPEI growing season, Age = 8	0.021 (0.013)	[0.358]	-0.013 (0.030)	[0.913]	-0.008 (0.014)	[1]	0.023 (0.023)	[0.594]	-0.036 (0.040)	[0.866]
SPEI growing season, Age = 9	0.013 (0.015)	[0.769]	0.054 (0.034)	[0.396]	-0.005 (0.018)	[1]	-0.013 (0.026)	[0.676]	-0.073 (0.045)	[0.426]
SPEI growing season, Age = 10	-0.017 (0.016)	[0.638]	0.002 (0.030)	[1]	-0.007 (0.019)	[1]	0.039 (0.024)	[0.594]	0.031 (0.045)	[1]
SPEI growing season, Age = 11	-0.004 (0.015)	[0.928]	0.006 (0.031)	[1]	-0.021 (0.018)	[1]	0.012 (0.029)	[0.676]	-0.043 (0.046)	[0.866]
SPEI growing season, Age = 12	0.031 (0.014)**	[0.155]	0.017 (0.033)	[0.868]	0.027 (0.018)	[1]	-0.030 (0.027)	[0.594]	-0.080 (0.045)*	[0.412]
SPEI growing season, Age = 13	0.012 (0.014)	[0.769]	-0.004 (0.030)	[1]	0.018 (0.019)	[1]	-0.046 (0.028)*	[0.594]	-0.102 (0.041)**	[0.328]
SPEI growing season, Age = 14	-0.002 (0.013)	[1]	0.017 (0.032)	[0.868]	0.003 (0.015)	[1]	-0.045 (0.025)*	[0.594]	-0.084 (0.044)*	[0.412]
SPEI growing season, Age = 15	-0.010 (0.014)	[0.769]	0.016 (0.031)	[0.868]	0.004 (0.017)	[1]	-0.030 (0.022)	[0.594]	-0.059 (0.040)	[0.446]
Birth Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth District FEs	Yes	Yes	No	No	Yes	Yes	Yes	No	No	No
Siblings FEs	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes
Birth Order FEs	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes
F statistic	3.362		1.740		1.979		1.749		1.113	
p-value for F-test	0.000		0.028		0.013		0.035		0.334	
R ²	0.195		0.879		0.212		0.262		0.906	
N	7309		5572		5572		3416		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 2 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 siblings fixed effects and birth order fixed effects instead of birth district fixed effects. Column (3) uses a definition of SPEI based on a 4-month average, rather than the 1-month average used in the main specification. Column (4) uses a different sample of individuals who are equivalent to the main sample, but were born in urban areas instead of in rural areas. Column (5) uses this same urban sample but with sibling and birth order fixed effects. *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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table J2: 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	Yes	Yes	Yes	Yes	Yes
Birth District FEs	Yes	Yes	Yes	Yes	Yes	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 2 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. This specification may avoid bias that can arise if there are interaction effects on shock variables that are omitted in the specification (see discussion in Footnote ??). *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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table J3: 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 (0.026)	0.023 (0.024)	0.025 (0.023)	0.022 (0.023)	0.045* (0.024)	0.040* (0.024)
SPEI growing season, Age = 0	-0.023 (0.027)	0.030 (0.027)	0.004 (0.023)	0.010 (0.022)	0.007 (0.024)	-0.001 (0.022)
SPEI growing season, Age = 1	-0.001 (0.025)	0.021 (0.026)	0.031 (0.022)	0.031 (0.021)	0.006 (0.028)	0.000 (0.026)
SPEI growing season, Age = 2	0.024 (0.025)	0.033 (0.032)	0.062** (0.024)	0.056** (0.024)	0.074** (0.029)	0.066** (0.027)
SPEI growing season, Age = 3	0.026 (0.027)	0.030 (0.026)	0.018 (0.023)	0.011 (0.023)	0.053** (0.023)	0.045** (0.020)
SPEI growing season, Age = 4	-0.020 (0.026)	-0.019 (0.027)	-0.007 (0.031)	-0.001 (0.029)	-0.012 (0.024)	-0.007 (0.022)
SPEI growing season, Age = 5	0.024 (0.024)	-0.029 (0.024)	0.008 (0.024)	0.001 (0.023)	-0.005 (0.022)	0.003 (0.021)
SPEI growing season, Age = 6	0.006 (0.027)	0.008 (0.024)	0.021 (0.025)	0.019 (0.024)	-0.009 (0.024)	-0.011 (0.023)
Cog score (aged 7-14)				0.256*** (0.026)		0.251*** (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 2 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. 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. F-statistic and F-test are for the joint hypothesis test of the null that all the shown coefficients in the model are equal to 0.

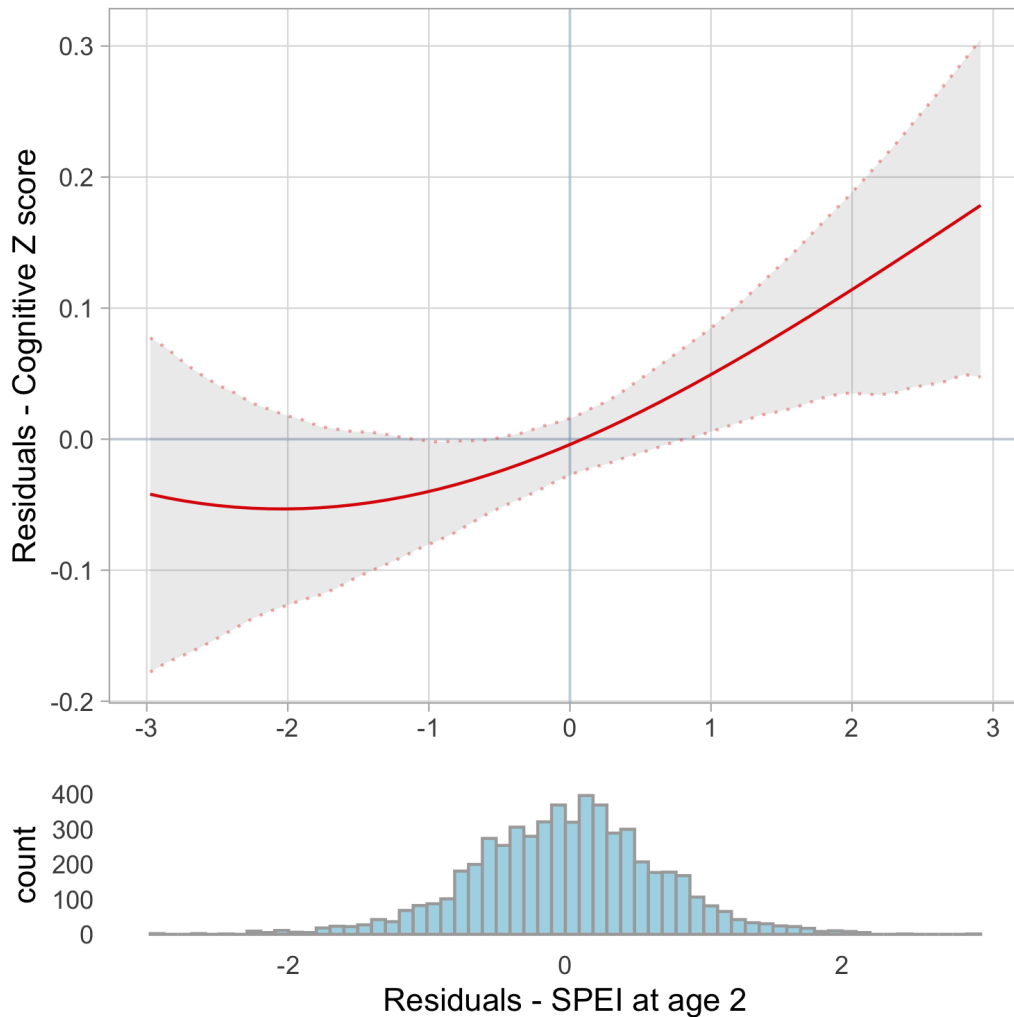
Table J4: Cognitive outcomes are robust to inclusion of age fixed effects

	Dep Var: Adult Cognitive Score			
	Main spec (1)	q value (1)	Age FEs (2)	q value (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 2 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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

K Additional tables: Alternative non-linear models

Figure K1: 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 K1: 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 2 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. 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. F-statistic and F-test are for the joint hypothesis test

Table K2: 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 2 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. 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. F-statistic and F-test are for the joint hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table K3: 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 2 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 $\mathbb{1}\{SPEI_{i(t+j)} < -2\}$ where $\mathbb{1}\{\cdot\}$ 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. 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. F-statistic and F-test are for the joint hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table K4: 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 2 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 $\mathbb{1}\{SPEI_{i(t+j)} > 2\}$ where $\mathbb{1}\{\cdot\}$ 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. 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. F-statistic and F-test are for the joint hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table K5: 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 2 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. 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. F-statistic and F-test are for the joint hypothesis test of the null that all the shown coefficients in the model are equal to 0.

L Additional tables: Socioemotional outcomes

Table L1: *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* (0.029)	[0.416]	-0.042 (0.036)	[1]	-0.045 (0.030)	[0.527]	-0.003 (0.031)	[1]	0.015 (0.023)	[1]	0.016 (0.031)	[1]
SPEI growing season, Age = -1	0.065** (0.032)	[0.416]	0.017 (0.031)	[1]	0.013 (0.028)	[1]	0.002 (0.031)	[1]	0.044* (0.024)	[0.664]	0.041 (0.025)	[1]
SPEI growing season, Age = 0	0.030 (0.030)	[0.463]	-0.007 (0.039)	[1]	-0.024 (0.027)	[0.853]	-0.004 (0.037)	[1]	-0.000 (0.023)	[1]	-0.018 (0.030)	[1]
SPEI growing season, Age = 1	-0.050 (0.032)	[0.427]	0.028 (0.037)	[1]	0.011 (0.033)	[1]	0.015 (0.035)	[1]	-0.005 (0.024)	[1]	0.001 (0.028)	[1]
SPEI growing season, Age = 2	0.053* (0.029)	[0.416]	-0.004 (0.039)	[1]	-0.030 (0.024)	[0.711]	-0.012 (0.040)	[1]	-0.032 (0.023)	[0.989]	-0.004 (0.029)	[1]
SPEI growing season, Age = 3	0.010 (0.025)	[0.68]	-0.036 (0.035)	[1]	-0.010 (0.027)	[1]	-0.027 (0.034)	[1]	-0.008 (0.025)	[1]	0.026 (0.028)	[1]
SPEI growing season, Age = 4	0.049 (0.033)	[0.427]	0.006 (0.034)	[1]	0.028 (0.038)	[0.864]	0.028 (0.033)	[1]	0.006 (0.031)	[1]	0.018 (0.031)	[1]
SPEI growing season, Age = 5	-0.049 (0.032)	[0.427]	0.087** (0.034)	[0.256]	-0.074** (0.031)	[0.4]	-0.045 (0.030)	[1]	-0.056** (0.027)	[0.664]	0.021 (0.028)	[1]
SPEI growing season, Age = 6	-0.027 (0.028)	[0.463]	0.025 (0.030)	[1]	-0.060* (0.031)	[0.4]	0.013 (0.037)	[1]	-0.013 (0.025)	[1]	0.001 (0.029)	[1]
SPEI growing season, Age = 7	0.011 (0.031)	[0.68]	0.048 (0.038)	[1]	0.006 (0.029)	[1]	-0.074** (0.035)	[0.445]	0.034 (0.026)	[0.989]	0.023 (0.031)	[1]
SPEI growing season, Age = 8	-0.017 (0.033)	[0.654]	0.032 (0.034)	[1]	0.001 (0.025)	[1]	-0.020 (0.035)	[1]	-0.025 (0.026)	[1]	0.004 (0.028)	[1]
SPEI growing season, Age = 9	-0.019 (0.031)	[0.654]	-0.007 (0.045)	[1]	-0.030 (0.035)	[0.853]	-0.005 (0.039)	[1]	0.001 (0.029)	[1]	-0.001 (0.035)	[1]
SPEI growing season, Age = 10	0.038 (0.036)	[0.463]	0.053* (0.032)	[1]	-0.027 (0.029)	[0.853]	0.004 (0.042)	[1]	0.016 (0.026)	[1]	-0.018 (0.026)	[1]
SPEI growing season, Age = 11	-0.055* (0.029)	[0.416]	-0.002 (0.030)	[1]	-0.044 (0.030)	[0.527]	-0.019 (0.042)	[1]	-0.052* (0.028)	[0.664]	-0.046 (0.029)	[1]
SPEI growing season, Age = 12	0.018 (0.033)	[0.654]	0.044 (0.044)	[1]	-0.066* (0.035)	[0.4]	0.064* (0.035)	[0.562]	0.001 (0.030)	[1]	0.021 (0.035)	[1]
SPEI growing season, Age = 13	-0.017 (0.032)	[0.654]	0.054 (0.036)	[1]	-0.012 (0.036)	[1]	-0.028 (0.038)	[1]	0.008 (0.029)	[1]	-0.010 (0.031)	[1]
SPEI growing season, Age = 14	-0.102*** (0.039)	[0.199]	-0.032 (0.040)	[1]	-0.057* (0.030)	[0.4]	0.022 (0.035)	[1]	0.016 (0.032)	[1]	0.019 (0.033)	[1]
SPEI growing season, Age = 15	0.015 (0.032)	[0.654]	0.029 (0.040)	[1]	0.026 (0.033)	[0.854]	-0.098*** (0.036)	[0.144]	0.034 (0.026)	[0.989]	0.034 (0.026)	[1]
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 2 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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table L2: 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 2 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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table L3: Effect of SPEI growing season on socioemotional factor scores with age fixed effects

	Affect		Personality		Depression	
	Age FEs (1)	q value (1)	Age FEs (2)	q value (2)	Age FEs (3)	q value (3)
SPEI growing season, Age = -2	0.006 (0.022)	[1]	-0.022 (0.020)	[1]	0.005 (0.020)	[1]
SPEI growing season, Age = -1	0.036 (0.023)	[1]	0.001 (0.021)	[1]	0.042 (0.015)***	[0.093]
SPEI growing season, Age = 0	0.017 (0.021)	[1]	-0.007 (0.025)	[1]	-0.016 (0.017)	[1]
SPEI growing season, Age = 1	-0.012 (0.027)	[1]	0.014 (0.024)	[1]	-0.011 (0.019)	[1]
SPEI growing season, Age = 2	0.019 (0.026)	[1]	-0.024 (0.023)	[1]	-0.024 (0.018)	[1]
SPEI growing season, Age = 3	-0.015 (0.022)	[1]	-0.013 (0.024)	[1]	-0.001 (0.017)	[1]
SPEI growing season, Age = 4	0.023 (0.027)	[1]	0.026 (0.025)	[1]	0.013 (0.019)	[1]
SPEI growing season, Age = 5	0.013 (0.023)	[1]	-0.064 (0.023)***	[0.131]	-0.027 (0.019)	[1]
SPEI growing season, Age = 6	0.007 (0.020)	[1]	-0.028 (0.025)	[1]	-0.013 (0.019)	[1]
SPEI growing season, Age = 7	0.030 (0.023)	[1]	-0.041 (0.022)*	[1]	0.013 (0.018)	[1]
SPEI growing season, Age = 8	0.008 (0.023)	[1]	-0.020 (0.023)	[1]	-0.015 (0.017)	[1]
SPEI growing season, Age = 9	-0.016 (0.025)	[1]	-0.026 (0.023)	[1]	-0.002 (0.019)	[1]
SPEI growing season, Age = 10	0.044 (0.022)**	[0.662]	-0.023 (0.026)	[1]	-0.004 (0.017)	[1]
SPEI growing season, Age = 11	-0.025 (0.020)	[1]	-0.028 (0.026)	[1]	-0.046 (0.018)***	[0.093]
SPEI growing season, Age = 12	0.036 (0.027)	[1]	-0.008 (0.026)	[1]	0.012 (0.021)	[1]
SPEI growing season, Age = 13	0.017 (0.021)	[1]	-0.032 (0.024)	[1]	-0.006 (0.019)	[1]
SPEI growing season, Age = 14	-0.060 (0.024)**	[0.316]	-0.012 (0.020)	[1]	0.010 (0.023)	[1]
SPEI growing season, Age = 15	0.023 (0.027)	[1]	-0.041 (0.026)	[1]	0.033 (0.018)*	[0.544]
Birth Year FEs	Yes		Yes		Yes	
Birth District FEs	Yes		Yes		Yes	
Age (Year) FEs	Yes		Yes		Yes	
Sample Mean	0.003		-0.006		0.012	
F statistic	1.628		0.985		2.322	
p-value for F-test	0.057		0.479		0.003	
R ²	0.070		0.072		0.079	
N	4956		4956		7090	

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 2 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. Instead of taking the average adult cognitive score when it is measured in multiple waves, I here leave 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 for depression score, which is measured in two survey waves (IFLS4 and IFLS5). 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. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table L4: Effect of SPEI growing season on female's fertility

	Dep Var: Individual Has Given Birth (=1)	
	(1)	q value (1)
SPEI growing season, Age = 10	0.009 (0.012)	[0.72]
SPEI growing season, Age = 11	0.016 (0.012)	[0.72]
SPEI growing season, Age = 12	0.020* (0.012)	[0.72]
SPEI growing season, Age = 13	0.015 (0.012)	[0.72]
SPEI growing season, Age = 14	0.008 (0.012)	[0.72]
SPEI growing season, Age = 15	0.009 (0.011)	[0.72]
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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

M Additional tables: Rice production

Table M1: Rice production - robustness to different fixed effect specifications

	Dep Var: IHS(Harvest Output / hectare)			
	(1)	(2)	(3)	(4)
Growing Degree Days (Z)	0.050** (0.025)	0.046* (0.027)	0.050** (0.021)	0.044* (0.023)
Wet Season Delay (Z)	-0.054** (0.023)	-0.052** (0.025)	-0.053* (0.029)	-0.042 (0.028)
SPEI (0-2m before rice planting)	0.116*** (0.039)	0.118*** (0.041)	0.084** (0.041)	0.085** (0.042)
Longest Dry Spell (Z)	-0.041* (0.021)	-0.043* (0.023)	-0.037 (0.026)	-0.034 (0.029)
District FEs	Yes	Yes	No	No
Sub-district FEs	No	No	Yes	Yes
Wave FEs	Yes	No	Yes	No
Year FEs	No	Yes	No	Yes
Sample Mean	9.079	9.078	9.080	9.078
F statistic	4.868	4.145	3.214	2.336
p-value for F-test	0.001	0.003	0.013	0.054
R ²	0.189	0.189	0.301	0.302
N	4653	4636	4649	4636

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 B. The dependent variable in all columns is the inverse hyperbolic sine transformation of rice harvest output (in kg) divided by the area harvested. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table M2: Rice production - using measures of harvest output and value as an outcome

	IHS(Harvest Output)		IHS(Harvest Value)		IHS(Harvest Value / hectare)	
	(1)	(2)	(3)	(4)	(5)	(6)
Growing Degree Days (Z)	0.041*	0.035*	0.033	0.027	0.042	0.031
	(0.021)	(0.021)	(0.023)	(0.023)	(0.029)	(0.027)
Wet Season Delay (Z)	-0.028	-0.030	-0.029	-0.032	-0.054	-0.059*
	(0.024)	(0.023)	(0.033)	(0.033)	(0.033)	(0.034)
SPEI (0-2m before rice planting)	0.086***	0.078**	0.071**	0.063*	0.100**	0.086**
	(0.033)	(0.031)	(0.034)	(0.035)	(0.042)	(0.042)
Longest Dry Spell (Z)	-0.023		-0.026		-0.044*	
	(0.019)		(0.029)		(0.023)	
Wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sample Mean	7.378	7.378	15.208	15.208	16.909	16.909
F statistic	2.630	2.953	1.704	1.839	3.087	3.575
p-value for F-test	0.037	0.035	0.152	0.143	0.018	0.016
R ²	0.394	0.394	0.464	0.464	0.250	0.249
N	4709	4709	4708	4708	4652	4652

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 B. The dependent variable is the inverse hyperbolic sine of the total harvest output (in kg) in columns (1) and (2), the inverse hyperbolic sine of the total harvest value (in) in columns (3) and (4), and the inverse hyperbolic sine of the harvest value per hectare in columns (5) and (6). 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

N 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 3). 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 $\mathcal{K} = \{-3, -2, \dots, 8\}$ 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:

$$\begin{aligned} Exp_{hry} = & \alpha + \beta_0 Weather_{ry} + \beta_1 Weather_{r,y-1} + \sum_{k \in \mathcal{K}} \delta_k Month_k \\ & + \sum_{k \in \mathcal{K}} \gamma_{0,k} Weather_{ry} + \sum_{k \in \mathcal{K}} \gamma_{1,k} Weather_{r,y-1} + \pi_r + \mu_y \end{aligned} \quad (7)$$

with all the other terms defined as in Equation 3.

The coefficients seen in Figure N1 are *sums* of coefficients from Equation 7. For example, the reported coefficient for “Month 3” will be τ_3 where τ_j is defined as below. There are two cases:

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

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:

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

The 6-month coefficients and standard errors in Table 9 are calculated in an analogous way.

Table N1: 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 N1: Household expenditure results are robust to different price adjustments and weather indexes (continued)

Panel D: Index Construction: GDD + SPEI Index

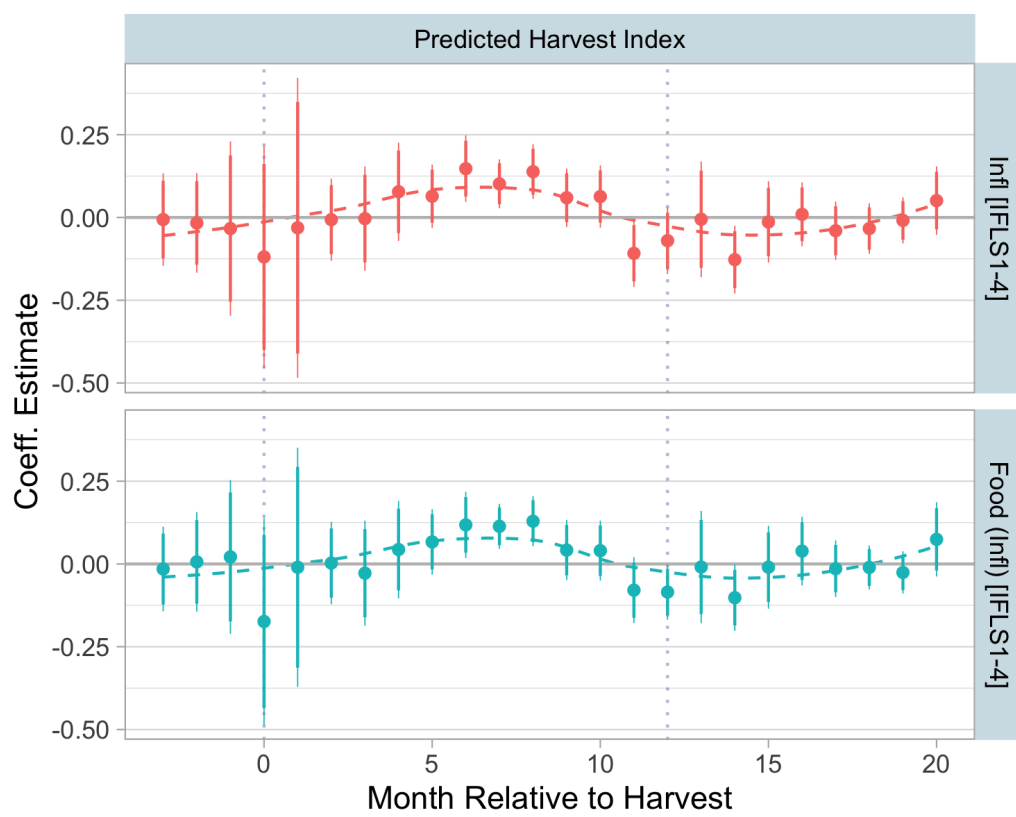
	Nominal		Infl [IFLS1-4]		Real [IFLS2/3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Year 0	0.037 (0.018)**		0.047 (0.022)**		0.073 (0.033)**	
Year 1	-0.003 (0.014)		0.001 (0.020)		0.003 (0.029)	
Months -3 to 2		0.008 (0.025)		-0.027 (0.028)		0.007 (0.055)
Months 3 to 8		0.048 (0.023)**		0.076 (0.028)***		0.097 (0.037)**
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 B1, 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 B1). Panel C uses an index constructed from column (5) of Table B1, Panel D uses an index constructed from column (7) of Table B1, and Panel E uses an index constructed from column (6) of Table B1. The harvest date is defined as the average harvest date of rice in that district based on IFLS harvest data (see Section B.2.1). “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 N1: *Effect of predicted harvest indexes on log household per capita expenditure (monthly)*



Notes: Results of the estimation process from Equation 7.

O Additional tables: Anthropometrics

Table O1: *Effect of predicted harvest index on HAZ in 6-monthly age intervals*

	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 = -12 to -7 months	-0.051 (0.040)	[1]	0.008 (0.034)	[1]	-0.099 (0.064)	[1]	-0.008 (0.054)	[1]	0.011 (0.065)	[1]	0.019 (0.051)	[1]
Predicted Harvest Index, Age = -6 to -1 months	0.025 (0.039)	[1]	0.071** (0.036)	[0.372]	-0.022 (0.063)	[1]	0.093* (0.054)	[0.681]	0.048 (0.068)	[1]	0.009 (0.059)	[1]
Predicted Harvest Index, Age = 0 to 5 months	-0.015 (0.040)	[1]	0.007 (0.037)	[1]	-0.042 (0.060)	[1]	-0.033 (0.058)	[0.947]	-0.020 (0.068)	[1]	-0.010 (0.059)	[1]
Predicted Harvest Index, Age = 6 to 11 months	0.005 (0.039)	[1]	-0.012 (0.032)	[1]	-0.023 (0.065)	[1]	-0.064 (0.050)	[0.681]	0.051 (0.064)	[1]	0.006 (0.052)	[1]
Predicted Harvest Index, Age = 12 to 17 months	-0.012 (0.036)	[1]	0.055* (0.032)	[0.372]	-0.020 (0.058)	[1]	-0.005 (0.049)	[1]	0.016 (0.061)	[1]	0.114** (0.054)	[0.12]
Predicted Harvest Index, Age = 18 to 23 months			0.038 (0.033)	[0.513]			-0.040 (0.052)	[0.947]			0.112** (0.049)	[0.12]
Predicted Harvest Index, Age = 24 to 29 months			0.055* (0.031)	[0.372]			0.085* (0.050)	[0.681]			0.105** (0.047)	[0.12]
Predicted Harvest Index, Age = 30 to 35 months			0.015 (0.032)	[1]			-0.015 (0.051)	[1]			0.094* (0.052)	[0.124]
Predicted Harvest Index, Age = 36 to 41 months			0.035 (0.032)	[0.513]			0.062 (0.050)	[0.681]			0.031 (0.045)	[0.981]
Birth Year FEs	Yes		Yes		Yes		Yes		Yes		Yes	
(Current) District FEs	No		No		No		No		No		No	
District x Birth Month 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		1.665	
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 B.2.4. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table B1 and calculating the predicted rice yields from this model for each year × district. It is standardised 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Figure O1: Impact on height-for-age z-scores by gender (yearly)

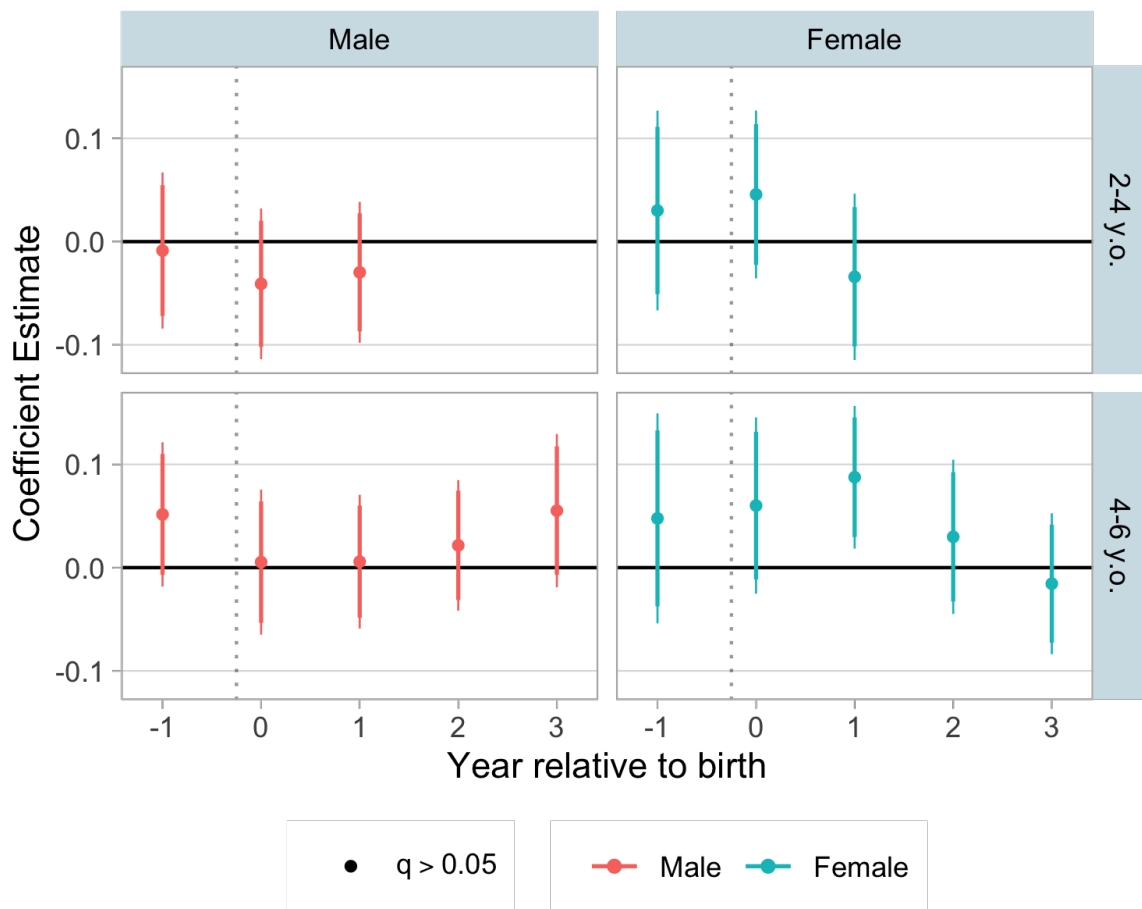


Figure O2: Impact on height-for-age z-scores by gender (6-month buckets)

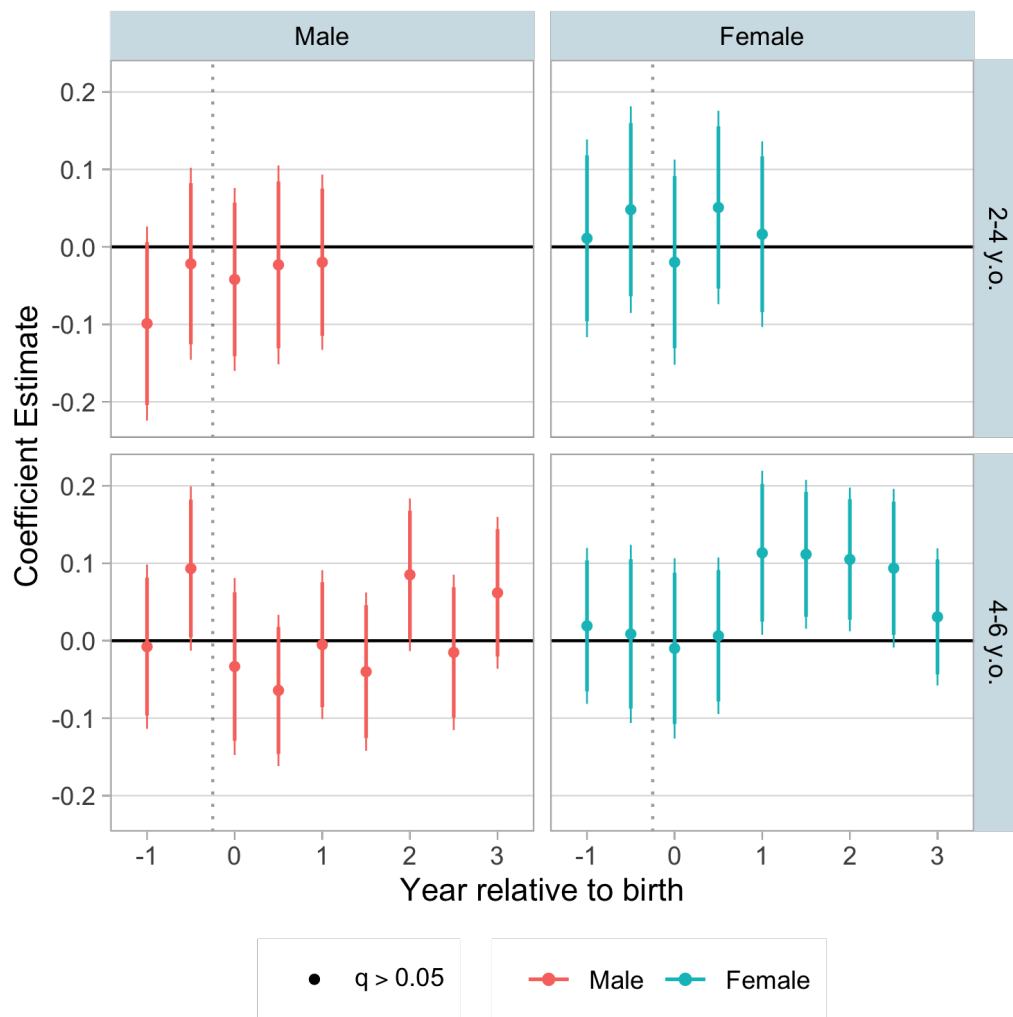


Table O2: HAZ results are robust to using adjusted shock measure (weighted to account for differential exposure to shocks)

	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 = -12 to -7 months	-0.053 (0.051)	[1]	0.006 (0.044)	[0.733]	-0.102 (0.086)	[1]	-0.018 (0.072)	[1]	0.003 (0.084)	[1]	0.016 (0.067)	[0.994]
Predicted Harvest Index, Age = -6 to -1 months	0.021 (0.050)	[1]	0.090* (0.047)	[0.313]	-0.025 (0.083)	[1]	0.131* (0.072)	[0.901]	0.075 (0.085)	[1]	0.016 (0.077)	[0.994]
Predicted Harvest Index, Age = 0 to 5 months	-0.025 (0.050)	[1]	-0.003 (0.048)	[0.733]	-0.040 (0.079)	[1]	-0.044 (0.071)	[0.901]	-0.044 (0.087)	[1]	-0.011 (0.084)	[0.994]
Predicted Harvest Index, Age = 6 to 11 months	-0.014 (0.050)	[1]	-0.012 (0.042)	[0.733]	-0.045 (0.080)	[1]	-0.081 (0.063)	[0.901]	0.016 (0.080)	[1]	-0.015 (0.066)	[0.994]
Predicted Harvest Index, Age = 12 to 17 months	-0.020 (0.045)	[1]	0.071* (0.040)	[0.313]	-0.043 (0.076)	[1]	-0.006 (0.061)	[1]	0.007 (0.081)	[1]	0.158** (0.070)	[0.098]
Predicted Harvest Index, Age = 18 to 23 months			0.062 (0.042)	[0.313]			-0.044 (0.062)	[0.901]			0.140** (0.064)	[0.098]
Predicted Harvest Index, Age = 24 to 29 months			0.069* (0.039)	[0.313]			0.086 (0.069)	[0.901]			0.132** (0.060)	[0.098]
Predicted Harvest Index, Age = 30 to 35 months			0.008 (0.043)	[0.733]			-0.053 (0.066)	[0.901]			0.106 (0.066)	[0.196]
Predicted Harvest Index, Age = 36 to 41 months			0.059 (0.038)	[0.313]			0.091 (0.060)	[0.901]			0.042 (0.060)	[0.925]
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	
Sample Mean	-1.848		-1.716		-1.850		-1.771		-1.845		-1.661	
F statistic	0.374		1.625		0.398		1.260		0.244		1.783	
p-value for F-test	0.867		0.103		0.851		0.255		0.943		0.067	
R ²	0.316		0.332		0.483		0.472		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 B.2.4. 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. *Predicted harvest index* is a weather index constructed by taking the coefficients from model (2) in Table B1 and calculating the predicted rice yields from this model for each year × district. It is standardised 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

P Additional tables: Cognitive outcomes, predicted harvest shock

Table P1: 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)*	[0.752]
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)*	[0.752]
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 B1 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 B.2.4. 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table P2: Cognitive results using the predicted harvest index are robust to using adjusted shock measure (weighted to account for differential exposure to shocks)

	Predicted Harvest Index					
	Both Sexes (1)	q value (1)	Male Only (2)	q value (2)	Female Only (3)	q value (3)
Age = -12 to -7 months	-0.023 (0.033)	[1]	-0.026 (0.053)	[1]	-0.010 (0.060)	[1]
Age = -6 to -1 months	0.030 (0.033)	[1]	-0.037 (0.053)	[1]	0.055 (0.052)	[1]
Age = 0 to 5 months	0.033 (0.037)	[1]	0.042 (0.054)	[1]	0.011 (0.048)	[1]
Age = 6 to 11 months	-0.006 (0.035)	[1]	-0.012 (0.048)	[1]	-0.041 (0.056)	[1]
Age = 12 to 17 months	-0.014 (0.034)	[1]	-0.010 (0.046)	[1]	-0.013 (0.048)	[1]
Age = 18 to 23 months	0.003 (0.033)	[1]	0.021 (0.061)	[1]	-0.051 (0.052)	[1]
Age = 24 to 29 months	0.016 (0.033)	[1]	0.089* (0.053)	[0.543]	-0.050 (0.043)	[1]
Age = 30 to 35 months	0.110*** (0.036)	[0.03]	0.203*** (0.054)	[0.003]	0.017 (0.054)	[1]
Age = 36 to 41 months	0.024 (0.031)	[1]	0.069 (0.053)	[0.712]	-0.009 (0.042)	[1]
Age = 42 to 47 months	0.002 (0.034)	[1]	0.076 (0.052)	[0.679]	-0.018 (0.055)	[1]
Age = 48 to 53 months	0.042 (0.032)	[1]	0.132** (0.055)	[0.122]	-0.045 (0.042)	[1]
Age = 54 to 59 months	-0.010 (0.032)	[1]	0.015 (0.052)	[1]	-0.035 (0.058)	[1]
Age = 60 to 65 months	-0.020 (0.029)	[1]	-0.031 (0.046)	[1]	-0.013 (0.046)	[1]
Birth Year FEs	Yes		Yes		Yes	
Birth District FEs	No		No		No	
District x Month of Birth FEs	Yes		Yes		Yes	
F statistic	1.605		2.118		0.708	
p-value for F-test	0.077		0.016		0.754	
R ²	0.422		0.570		0.550	
N	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. 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 B1 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 B.2.4. 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 B.2.4 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.

Table P4: Cognitive results are robust to other weather indexes (6 month intervals)

	CDD + Wet			CDD + SPEI			Wet + SPEI			CDD + Wet + SPEI + Dry Spell			
	Both Sexes	Male Only	Female Only	Both Sexes	Male Only	Female Only	Both Sexes	Male Only	Female Only	Both Sexes	Male Only	Female Only	
	q value	q value	q value	q value	q value	q value	q value	q value	q value	q value	q value	q value	
Age = -12 to -7 months	-0.000 (0.024)	-0.015 (0.042)	[1]	-0.032 (0.024)	-0.037 (0.040)	[1]	-0.030 (0.040)	-0.033 (0.040)	[1]	-0.025 (0.025)	-0.039 (0.043)	[1]	-0.006 (0.044)
Age = -6 to -1 months	0.018 (0.029)	-0.048 (0.044)	[1]	0.019 (0.025)	-0.028 (0.039)	[1]	0.021 (0.025)	-0.035 (0.041)	[1]	0.017 (0.026)	-0.042 (0.045)	[1]	0.050 (0.038)
Age = 0 to 5 months	0.034 (0.029)	0.013 (0.054)	[1]	0.012 (0.026)	0.027 (0.038)	[1]	0.011 (0.028)	0.026 (0.040)	[1]	0.015 (0.026)	0.009 (0.040)	[1]	0.020 (0.036)
Age = 6 to 11 months	-0.042 (0.028)	-0.062 (0.043)	[0.924]	-0.051 (0.049)	0.003 (0.038)	[1]	-0.019 (0.040)	-0.006 (0.038)	[1]	-0.015 (0.026)	-0.027 (0.038)	[1]	-0.015 (0.040)
Age = 12 to 17 months	0.014 (0.025)	-0.001 (0.035)	[1]	-0.016 (0.025)	-0.014 (0.035)	[1]	-0.002 (0.036)	-0.012 (0.035)	[1]	-0.025 (0.025)	-0.019 (0.033)	[1]	-0.026 (0.036)
Age = 18 to 23 months	-0.020 (0.027)	0.008 (0.048)	[1]	-0.000 (0.046)	0.003 (0.037)	[1]	-0.028 (0.037)	0.007 (0.039)	[1]	0.000 (0.026)	0.022 (0.045)	[1]	-0.051 (0.040)
Age = 24 to 29 months	0.016 (0.027)	0.056 (0.043)	[1]	-0.026 (0.041)	-0.026 (0.041)	[1]	-0.036 (0.031)	0.074** (0.037)	[0.208]	0.005 (0.025)	0.068* (0.039)	[0.429]	-0.063* (0.034)
Age = 30 to 35 months	0.089*** (0.028)	0.160*** (0.041)	[0.022]	0.071*** (0.027)	0.130*** (0.041)	[0.115]	0.024 (0.034)	0.146*** (0.041)	[0.098]	0.076*** (0.028)	0.149*** (0.040)	[0.004]	-0.001 (0.039)
Age = 36 to 41 months	-0.025 (0.025)	0.012 (0.043)	[1]	0.026 (0.022)	0.039 (0.037)	[1]	0.024 (0.034)	0.044 (0.038)	[1]	-0.001 (0.023)	0.038 (0.038)	[1]	-0.036 (0.027)
Age = 42 to 47 months	-0.001 (0.031)	0.064 (0.047)	[1]	-0.026 (0.044)	0.023 (0.034)	[1]	-0.004 (0.040)	0.033 (0.035)	[1]	-0.011 (0.026)	0.038 (0.034)	[1]	-0.027 (0.039)
Age = 48 to 53 months	-0.002 (0.026)	0.079 (0.052)	[1]	0.026 (0.023)	0.084** (0.036)	[0.154]	0.024 (0.032)	0.089** (0.039)	[0.171]	0.011 (0.023)	0.096** (0.042)	[0.159]	-0.067** (0.030)
Age = 54 to 59 months	-0.008 (0.029)	0.012 (0.043)	[1]	-0.016 (0.024)	0.009 (0.037)	[1]	-0.039 (0.040)	0.012 (0.038)	[1]	-0.021 (0.025)	-0.007 (0.037)	[1]	-0.038 (0.041)
Age = 60 to 65 months	-0.048* (0.025)	-0.066* (0.039)	[0.525]	-0.040 (0.035)	-0.016 (0.031)	[1]	0.006 (0.036)	-0.021 (0.031)	[1]	-0.014 (0.022)	-0.014 (0.031)	[1]	-0.008 (0.033)
Birth Year FEs	Yes	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	No
District x Month of Birth FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F statistic	2.029	2.887	1.627	1.306	1.787	1.389	1.963	1.963	1.332	1.532	1.943	1.536	1.336
p-value for F-test	0.016	0.082	0.202	0.049	0.049	0.157	0.027	0.027	0.187	0.029	0.029	0.196	0.196
R ²	0.422	0.570	0.421	0.421	0.568	0.421	0.569	0.569	0.421	0.421	0.570	0.551	0.551
N	5569	2600	2969	5572	2601	2971	2601	2601	5572	5572	2601	2971	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 three columns use an index constructed in an analogous way to the predicted harvest index but based on just using Wet Season 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 B1). Columns (4)-(6) use an index constructed from column (5) of Table B1, columns (7)-(9) use an index constructed from column (7) of Table B1, and columns (10)-(12) use an index constructed from column (6) of Table B1. Individuals are matched to values of predicted harvest index using the process described in B.2.4. 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 B.2.4 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 hypothesis test of the null that all the shown coefficients in the model are equal to 0.*