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The Effects of Prenatal Exposure to Plentiful Rainfall on Cognitive Development in Viet Nam

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Abstract: *We examine the impact of exposure to plentiful rainfall while in utero on the cognitive development of the same children from ages 5 to 15 from the Young Lives Project in Viet Nam. Using variations in the month and place of birth, we show that positive income shocks, proxied by above-average rainfall, are associated with better cognitive development up to age 8. The effect is more pronounced when positive shocks occurr early in gestation. However, we find that such positive effects are not sustained in the longer term and are completely absent at ages 10, 12, and 15. Our results call for effective and early policy interventions providing a sustained pathway for the cognitive development of children in weather disaster-prone regions.*

Keywords: early life shock, cognitive development, Viet Nam

JEL Classification: I15; I25

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1. Introduction

Human capital has many dimensions, ranging from education to health to general wellbeing. This not only determines individuals' future income and labour market outcomes (Schultz, 2003), but also plays a central role in economic development. Growing evidence suggests that the critical stage of human capital formation is in infancy or even in utero – this is known as the 'fetus origins hypothesis' (see Almond and Currie, 2011 for a review). Recent studies have further documented that exposure to weather-related shocks in utero has both short- and long-term effects on human capital formation (Maccini and Yang, 2009; Thai and Falaris, 2014; Shah and Steinberg, 2017; Carrillo, 2019; Shrestha, 2019; Zimmermann, 2020) and health (Abiona, 2017; Dinkelman, 2017; Rosales-Rueda, 2018).[1] In their seminal study, Maccini and Yang (2009) demonstrate the welcome effects of early-life positive rainfall on human capital formation: more early life rainfall is associated with higher test scores in school, especially for females. However, we still know relatively little about the *transitional stage* of those exposed during their lifespan, especially from early life to school age, as highlighted by Shah and Steinberg (2017). More importantly, the importance of the timing of rainfall shocks in utero is mostly omitted from analyses because of the lack of information about exact birth dates.

This study examines how prenatal exposure to rainfall shocks can shape cognitive development using data collected from the same children in Viet Nam drawn from the Young Lives survey.[2] We take advantage of this rich data source by tracking the cognitive development of the same children from preschool to school age. This empirical strategy exploits variations in monthly rainfall records from the historical average within the survey sites, combined with information about the exact time and place of birth, gender, parents' background, and schools to identify

[1] The literature is increasingly looking at the long-term effects of other forms of early-life shocks, such as that of Ramadan exposure in utero on cognitive skills (Almond, Mazumder, and R. Van Ewijk, 2015), radioactive fallout on education (Almond, Edlund, and Palme, 2009; Black et al., 2019), and commodity price shocks on mental health (Adhvaryu, Fenske, and Nyshadham, 2018).

[2] The Young Lives survey is designed to capture the complete lifespan of children born in rural areas and families that depend on farming for a living, either directly or indirectly. As rainfall shocks translate directly into incomes derived from farming, we argue that the negative impact of rainfall shocks can translate into higher food prices for workers in non-agricultural areas.

prevailing rainfall conditions during pregnancy. In essence, this method effectively compares later-life outcomes of individuals who were exposed to abnormal rainfall in utero to those of children who experienced normal rainfall conditions.

Two methodological strengths of this study should be highlighted. First, we examine the same rainfall shocks and track cognition at different stages of the lifecycle for the same children. In contrast, other studies usually examine cross-sectional cohorts available at each stage of the lifecycle (e.g. Maccini and Yang, 2009; Shah and Steinberg, 2017; Rosales-Rueda, 2018; Zimmermann, 2020).[3] Second, we construct rainfall exposure variables separately in each of the 9 months of pregnancy because the data follow the exact birthdates of the children.[4] Medical theory posits that fetal development progresses differently in each trimester (Glewwe, Jacoby, and King, 2001; Rosales-Rueda, 2018; Carrillo, 2019). For example, the fetal brain develops during the first trimester, while emotional and personality outcomes develop during the third trimester. Thus, individuals exposed to abnormal rainfall in different trimesters in utero may develop different cognitive outcomes compared to unexposed children. Constructing rainfall shocks by birth year as customarily done in the literature has the limitation of bundling those differently sensitive time windows together.

The main findings can be summarised as follows. First, exposure to above-average rainfall while in utero is associated with better cognitive development up to age 8. More importantly, this positive association is most evident when the rainfall shocks occur in the first two trimesters, but is absent in the last trimester. This finding is consistent with studies showing a positive association between incomes and high rainfalls, resulting in better nutritional intakes for pregnant mothers during the most sensitive period of fetal development. The second main finding, however, indicates that these short-term positive effects are not sustained: at ages 10, 12, and 15, these positive effects on cognitive development are absent.

[3] For example, Shah and Steinberg (2017) examine the effects of shocks in early life (in utero to age 2) on school-aged children's cognitive development at various stages (i.e. ages 5–16, 5–10, and 11–16) using cross-sectional data collected from children in rural India. This means that children exposed to prenatal rainfall may not be the same as the later sample collected to assess cognitive performance. This type of study commonly constructs prenatal weather patterns by the child's birthplace or current residence and birth month or year.

[4] This represents a departure from many studies that use the birth year to determine prenatal exposure to shocks. The data also include information on the children's birthplace, not their current residence.

Taken together, our results call for effective early policy interventions (e.g. investing in schools) to reinforce further investment in human capital sustainably.

Viet Nam provides an ideal case study to investigate the relationship between rainfall shocks and outcomes. As one of five countries deemed most affected by climate change, it has been suffering from a high frequency of natural disasters (Harvey, 2009). These extreme events pose a significant threat to large portions of the population living in rural areas, where agricultural production is the main source of income. At the same time, Viet Nam's performance in education is much higher than that of other low-income countries (Glewwe, 2004). However, there is a risk of education lag, manifested by the varying rate of school enrolment across rural areas and different demographic types. Rainfall variability and other weather-related shocks are projected to occur more frequently and to be more intense due to global warming. Hence, it is crucial for policymakers to understand how natural disasters disrupt the formation of human capital.

The rest of this paper is structured as follows. Section 2 presents the data used and followed by the study's empirical framework in Section 3. Section 4 discusses the results and policy implications. Section 5 concludes.

2. Data

The main data for this analysis are drawn from the Young Lives Project, an international study of childhood poverty following the lives of 12,000 children over 15 years in four developing countries: Ethiopia, India, Peru, and Viet Nam. [5] The Young Lives Project aims to investigate the drivers and impacts of child poverty and to generate evidence to help policymakers design programmes that benefit poor children and their families. It employs a multistage sampling design that represents a variety of social, geographic, and demographic groups. The children were randomly selected from 20 sentinel sites ('clusters').[6] In each country, the sample consists of two cohorts

[5] Data are available at https://www.younglives.org.uk/

[6] The concept of sentinel sites comes from health surveillance studies and is a form of purposive sampling where the site ('cluster') is deemed to represent a certain type of population, and is expected to reflect trends affecting those particular people or areas. For more details about the sampling design, see the Young Lives Project (2014).

of children: a younger cohort of 2,000 children born in 2001–2002, and an older cohort of 1,000 children born in 1994–1995. So far, the study has conducted five rounds of children and household surveys (for the years 2002, 2006, 2009, 2013, and 2016). This enables researchers to compare the same children at different ages to examine how their lives are changing; and different children at the same age to determine how their communities have changed over time. Young Lives is, although a unique and rich data source, not free from attrition. However, according to Outes-Leon and Dercon (2009), the project's attrition rate is low, reaching only 1.07% in Viet Nam in 2002–2006.

We extracted information from the original Young Lives surveys on Vietnamese children in the young cohort who were between 0 and 1 at the time of the first survey round in 2002.[7] This study uses the second, third, fourth, and fifth round of the survey on children and households. This information on children's cognitive development is supplemented by the school survey implemented in 2011 and 2016. The data cover five provinces: Lao Cai, Hung Yen, Da Nang, Phu Yen, and Ben Tre. Each province contains four sites, each comprising one or two communes. Our data cover all five provinces and 20 clusters to match the rainfall data (discussed below). We started with the young cohort of 2,000 children; however, the actual sample size in the empirical exercise is smaller because of missing information on cognitive measures.

Data on Cognitive Development

We use a wide range of cognitive skill measures. For preschool-aged children,[8] we use two indicators, the Peabody Picture Vocabulary Test (PPVT) and Cognitive Development Assessment (CDA) Quantity Test (derived from Round 2 of the Young Lives surveys in Viet Nam) as a proxy for the children's cognitive performance.

The PPVT is one of the most common measures of cognitive achievement (e.g. Özler et al., 2018; Sánchez and Singh, 2018; Singh, 2015). During the test, a child hears a simple word (e.g. 'boat', 'lamp', 'cow', or 'goat') and is then asked to identify which figure corresponds with the spoken word. The Young Lives staff then recorded

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[7] We excluded the older cohort of 1,000 children from our study since they were about 8 years old in the first round and, more importantly, we were unable to track their birthplaces to match them with rainfall shocks.

[8] In Viet Nam, formal schooling begins at age 6.

the PPVT score as the difference between the ceiling item and the total number of errors.[9] The CDA test measures children's understanding of quantity-related concepts, such as few, most, half, and many. The test contains 15 items and each correct answer is scored as one point, so that the minimum number of points a child can get is 0 and the maximum is 15. The Young Lives survey provides raw test scores as well as standardised scores.

We used the reading and writing assessment conducted in the third round of the Young Lives survey in 2009. The reading assessment evaluates the skill to read letters, a word, and a sentence; while the writing assessment examines the ability to write a short sentence. These tests are conducted during the interview and administered by Young Lives staff. The results are then recorded by the staff and measured by a categorical variable in the dataset. The reading variable is measured as (i) 'Can't read anything', (ii) 'Can read letters', (iii) 'Can read words', and (iv) 'Can read sentences'. The writing variable is measured as (i) 'Can't write', (ii) 'Can write with difficulty and errors', and (iii) 'Can write without difficulty and errors'. The results are drawn from the main children's survey, which includes children at school and those not at school.

We also compiled cognitive skills at school age (i.e. 8 years old) from the 2011 school survey, which complemented the children's survey and gathered data on children's experiences and achievements at school.[10] During the 2011–2012 school year, selected children completed a background questionnaire and were tested in mathematics and Vietnamese at both the start and end of the school year. Each test consisted of 30 multiple choice questions designed to test knowledge of the curriculum and contained several common (anchor) items to measure progress over the year. The questions were designed to reflect the national standard Grade 5 curriculum provided by the Ministry of Education. This allowed researchers to examine children's learning and learning progress, as well as the effectiveness of schools and teachers.

[9] The PPVT-III (204 items) was used in India and Viet Nam, and the PPVT-R (125 items) was used in Peru and Ethiopia. See Cueto et al. (2009) for details.

[10] Young Lives collected the original data from 3,284 Grade 5 pupils in 176 classes at 56 schools, or 92 school sites (when satellite sites are considered separately from the main school).

The school survey also included several measures of student behaviour as evaluated by their teachers. The assessment variables included the children's academic ability, motivation to succeed at school, and participation in class, scaled from 1 ('very low'), 2 ('low'), 3 ('medium'), 4 ('high'), and 5 ('very high'). These survey questions can shed light on general student attitudes and behaviour, possibly linked to some aspects of their non-cognitive development.[11] In addition, these measures have the advantage of being assessed by teachers, which can reduce reporting biases from other possible assessors, such as parents.

Rainfall Data

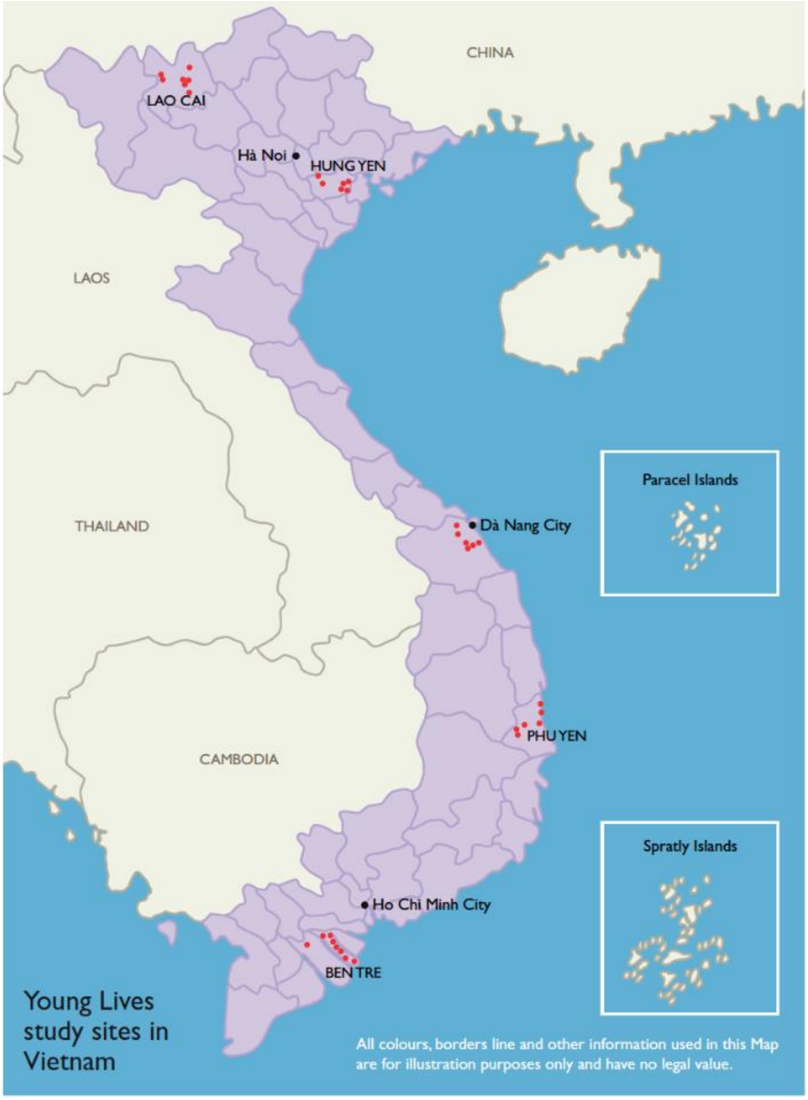
The study mainly collected rainfall data from Gridded Monthly Time Series Data (Version 4.01) provided by the National Oceanic and Atmospheric Administration. This dataset provides global historical estimates of precipitation for a grid of 0.5 degrees latitude by 0.5 degrees longitude for the period 1900–2017.[12] One of the advantages of using the National Oceanic and Atmospheric Administration dataset is that it can be disaggregated to low administrative units.

We then matched the rainfall data with each available Vietnamese province in the Young Lives dataset, and further to the month and year of birth for children in the young cohort. To assess the level of rainfall in a given month, we also obtain historical monthly average provincial rainfall for the period 1900–2017. The locations of the rainfall stations and Young Lives clusters are shown in Figure 1. The geographic coverage of the rainfall stations is expansive, covering Viet Nam's northern, central, and southern provinces.

[11] There is a strong positive link between noncognitive skills and labour market outcomes (Glewwe, Huang, and Part, 2017).

[12] This dataset has been widely used in the economic literature to measure climatic shocks and climate change (e.g. Dell, Jones, and Olken, 2012; Burke, Gong and Jones, 2015; Rocha and Soares, 2015; Sarsons, 2015).

Figure 1: Young Lives Study Sites in Viet Nam



Note: The Young Lives survey (Viet Nam) covers five provinces: Lao Cai, Hung Yen, Da Nang, Phu Yen, and Ben Tre.
Source: Young Lives. https://www.younglives.org.uk/

3. Identification Strategy

We estimate the impacts of rainfall shocks, defined as any deviation from the historical norm, in utero on the cognitive skills of affected children from age 5 to age 15. First, we explain the rainfall variable, followed by the regression specification that we apply to the data.

Rainfall Variable

We obtain abnormal rainfall as the deviation between the log of total rainfall and log of historical rainfall, as presented in Equation 1:

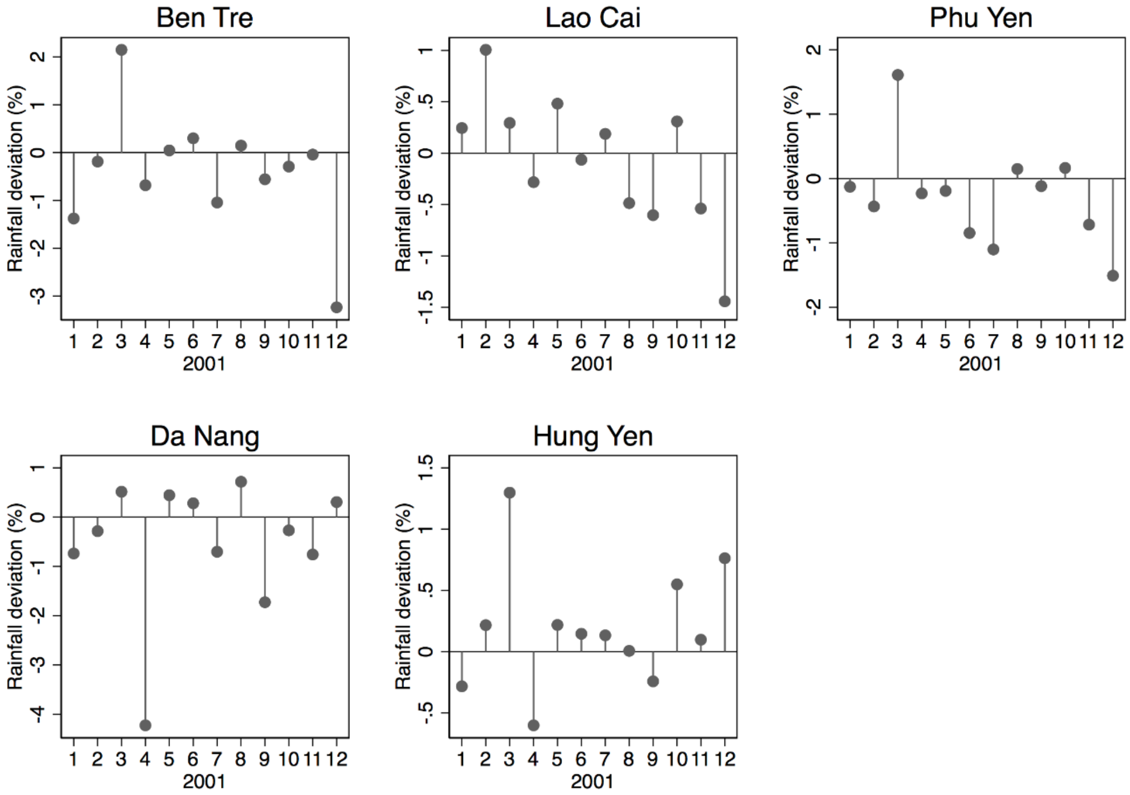
$$\Delta Rain\_utero_{i,j,m} = \log(R_{i,j,m}) - \log(\bar{R}_{i,j,m}) \quad (1)$$

where $R_{i,j,m}$ indicates total monthly rainfall in province *j* where child *i* was born and lives in year *t*, month *m* indicates the gestation month ($m = 1, \ldots 9$), [13] and $\bar{R}_{i,j,m}$ is the historical monthly average rainfall in the same birth province, *j*.[14] We also expanded our study period to 3 months before pregnancy to examine early exposure to rainfall shocks.

This relative measure of rainfall shocks has merit over an absolute measure of rainfall (as used in Jayachandran, 2006) because the same amount of rainfall may have different effects based on average rainfall levels (Adhvaryu, Fenske, and Nyshadham, 2018). Figure 2 shows monthly rainfall deviations in the three provinces covered by the Young Lives survey in 2001, when most of the children were born. Those born in February and March were likely to experience higher rainfall than usual, while the opposite is found for children born in December. The province of Ben Tre has less variation in rainfall than do the other two provinces, while Phu Yen had less rainfall than usual in 2011. It should also be noted that rainfall in the birth year (2001) in Viet Nam did not constitute extreme weather relative to the historical average (Figure 2). Accordingly, the rainfall shocks may not be as strong as in other cases, such as the 1997–1998 El Niño (Rosales-Rueda, 2018).[15]

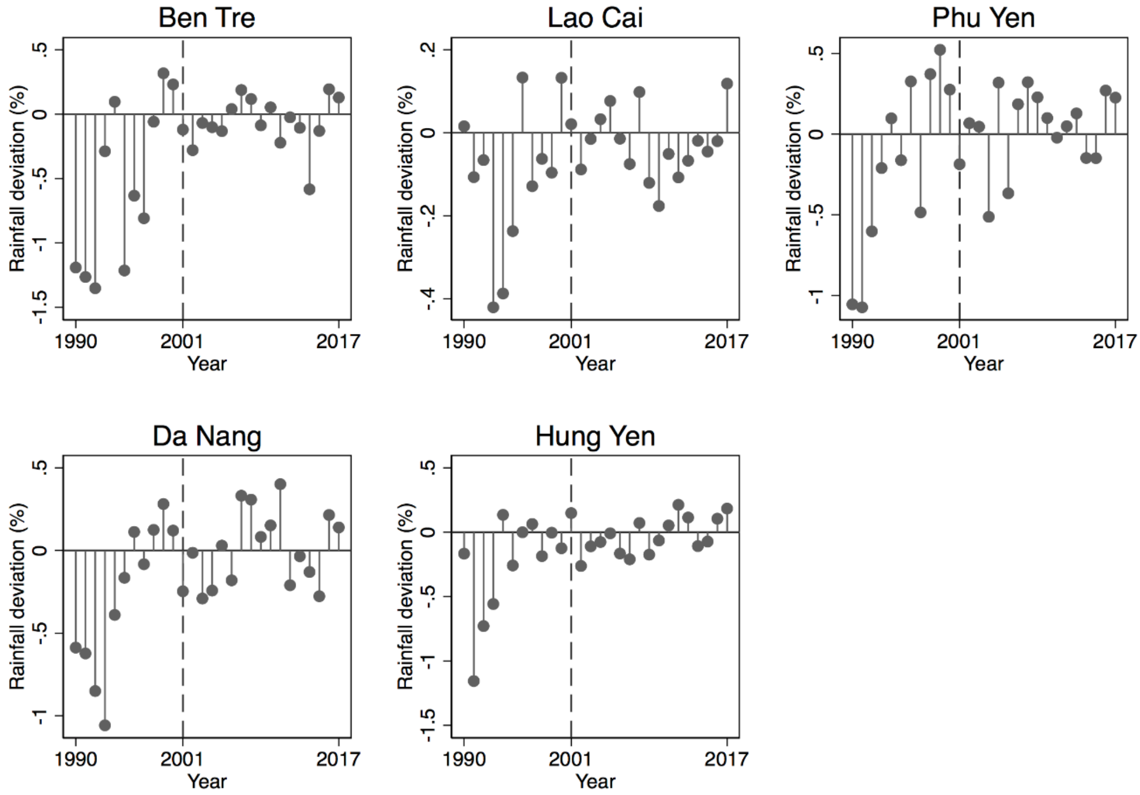
[13] We suppress year *t* below because the children in our sample were born in the same year (2001).
[14] For example, if a child was born in September 2001, the historical mean refers to the average September rainfall for the years 1900–2017.
[15] For this reason, we rely on monthly variations in rainfall deviations from the historical norm, instead of constructing a variable based on the Standardized Precipitation Index or counting the number of months with ‘abnormal rainfall’.

Figure 2: Rainfall Deviation from the Historical Average in the Young Lives Provinces by Birth Month in 2001



Notes: The figure shows the (log) deviations from the historical average in each province. Rainfall deviation = Log(actual rainfall) – log(historical average rainfall). For example, rainfall deviation 1 year after birth = 0.3, meaning that rainfall in that period is 30% higher than the historical average.
Source: Authors' creation based on Young Lives data.

Figure 3: Rainfall Deviation from the Historical Average in the Young Lives Provinces for the Study Period



Notes: The figure uses a sample of three Young Lives provinces in which information on rainfall is available. Interpretation: Rainfall deviation = Log(actual rainfall) – log(historical average rainfall). For example, rainfall deviation 1 year after birth = 0.3, meaning that rainfall in that period is 30% higher than the historical average.
Source: Authors' creation based on Young Lives data.

Regression Specification

Like many other studies, we assume that the intensity of the rainfall was a random event creating exogenous shocks to the households. We use the following two strategies, depending on the availability of cognitive outcomes.

The first strategy looks for an association between the extent of abnormal rainfalls and measures of cognitive development of preschool-aged children, specified as:

(2)
$$Y_{i,c,m} = \alpha_0 + \alpha_1 \Delta Rain\_utero_{i,j,m} + \alpha_2 X_i + \delta_m + \emptyset_c + \varepsilon_{i,c,m}$$

Cognitive skill in the dependent variable (*Y*) takes the score from either the PPVT or CDA. We then use this same strategy to examine alternative measures of child development, such as levels of reading and writing. The coefficient of our interests is α_1, which indicates whether prenatal rain exposure affects current cognitive skills for the affected child *i*. α_1 is identified through cross-sectional and temporal variations in rainfall deviations, which should not correlate with any unobserved determinants of child cognitive performance in later life, $\varepsilon_{i,c,m}$.

It is important to highlight that the identification of prenatal weather effects relies on different aspects of cognitive indicators at different ages in the life cycle of the same children by exploiting the panel feature of the dataset. We also include birth month (*m*) and cluster (c) fixed effects in the estimation. A vector of a child and his/her family characteristics is included in *X* (a dummy for the gender, parental age, total educational attainment of the parents, and number of children in the household). The second strategy is similar to the above formulation, but the cognitive outcome is related to test scores in school, permitting us to control for school fixed effects:

$$Y_{i,c,m}=\alpha_0+\alpha_1\Delta Rain\_utero_{i,j,m}+\alpha_2 X_i+\delta_m+\emptyset_c+\omega_s+\varepsilon_{i,c,m} \tag{3}$$

where *Y* represents cognitive performance, measured by test scores in Vietnamese (or English) and mathematics, of child *i* born in cluster *c* at ages 10 and 15.

Most importantly, this specification includes school fixed effects, ω_s that absorb school and teacher quality (Glewwe, Krutikova, and Rolleston, 2017). The advantage of introducing school fixed effects is that it controls for both observed and unobserved school quality, which may have a tangible influence on a child's learning environment. To our knowledge, this is the first study to include school fixed effects in estimating prenatal rainfall shocks on current cognitive and school performance. As shown below, school fixed effects are key to understanding how prenatal exposure to rainfall shocks translates into children's cognitive development.

Table 1 shows the summary statistics of variables used in this analysis. Panel A shows the children's cognitive outcomes, while Panel B shows the parental characteristics.

Table 1A: Descriptive Statistics – Child Development Outcomes

Survey (age of a child)	Age	Outcomes	Description	Mean	Std. Dev.
Young Lives Children Survey					
YL Children Survey, Round 2 in 2006	5	PPVT	Peabody Picture Vocabulary Test (0–204)	35.4	18.2
YL Children, Round 2	5	CDA	Cognitive Development Assessment – Quantity Test (0–15)	9.6	2.6
YL Children Survey, Round 3 in 2009	8	Reading	0 = Having difficulty in reading (Can't read, read letters, read words); 1 = No difficulties (Read sentences)	0.9	0.3
YL Children, Round 3	8	Writing	0 = Having difficulty in writing (Can't write or with some difficulties); 1 = No difficulties	0.9	0.3
YL Children, Round 3	8	PPVT	Peabody Picture Vocabulary Test (0–204)	90.4	27.9
YL Children Survey, Round 4 in 2013	12	PPVT	Peabody Picture Vocabulary Test (0–76)	57.7	8.9
YL Children, Round 4	12	Vietnamese	0–30 point scale	14.3	5.1
YL Children, Round 4	12	Mathematics	0–34 point scale	15.5	5.4
YL Children Survey, Round 5 in 2016	15	PPVT	Peabody Picture Vocabulary Test (0–76)	58.3	9.7
YL Children, Round 5	15	Vietnamese	0–31 point scale	14.0	6.6
YL Children, Round 5	15	Mathematics	0–26 point scale	14.1	5.1
Young Lives School Survey					
YL School Survey in 2011	10	Vietnamese	0–10 point scale	7.7	1.6
YL School Survey, 2011	10	Mathematics	0–10 point scale	7.7	1.8
YL School Survey, 2011	10	Academic ability	Class teacher's evaluation of a child's academic ability (0 – very low, low, medium; 1 – high, very high)	0.5	0.5

YL School Survey, 2011	10	Motivation	Class teacher's evaluation of a child's motivation to succeed at school (0 – very low, low, medium; 1 – high, very high)	0.6	0.5
YL School Survey, 2011	10	Participation	Class teacher's evaluation of a child's participation in class (0 – very low, low, medium; 1 – high, very high)	0.7	0.5
YL School Survey, 2016	15	English	0–40 point scale	25.2	7.2
YL School Survey, 2016	15	Mathematics	0–40 point scale	21.4	7.2

CDA = Cognitive Development Assessment, PPVT = Peabody Picture Vocabulary Test, YL = Young Lives.
Source: Authors' creation based on Young Lives data.

Table 1B: Descriptive Statistics – Child and Parental Characteristics in the Young Lives Survey

Variable	Description	Mean	Std. Dev.
Gender	Gender, girl = 1, boy = 0	0.5	0.5
Paternal age	Age of father (in years)	37.4	7.9
Maternal age	Age of mother (in years)	34.6	7.7
Paternal education	Education of father (in years)	6.5	4.0
Maternal education	Education of mother (in years)	5.9	4.0
Number of children	Number of children in households	1.1	1.0
Minorities	Non-Kinh ethnicity (dummy)	0.2	0.4
Rural	Living in rural areas (dummy)	0.7	0.4

Std. Dev. = standard deviation.
Notes: Child and parent characteristics are derived from round 1 of the Young Lives survey. Part A, the Peabody Picture Vocabulary Test, and the Cognitive Development Assessment are shown in the raw scores in this table. They are standardised when used as cognitive outcomes in regressions.
Source: Authors' creation based on Young Lives data.

4. Results

We begin with the children's survey results for prenatal rainfall exposure on children's cognitive skills, recorded when children were aged 5, 8, 12, and 15. In the Vietnamese education system, children begin school at age 6. Each column in Table 2 is a separate regression that includes each month of the pregnancy (a 9-month period) as well as conception and a month before the pregnancy. All regressions include children's and parental characteristics (dummies for the gender, parental age, number of years of parental educational attainment, and number of children in the household, as well as indicators for ethnic minorities, and for living in a rural area), together with a set of cluster and birth month fixed effects. Both of the PPVT and CDA (columns 1 and 2 in Table 2) cognitive measures are only available in the 2006 Young Lives children survey (thus only covering children aged 5); and only the PPVT is available for the subsequent surveys. We display the results in such a way that one can track the cognitive development of the same children at different ages from age 5, following prenatal exposure to rainfall. To preserve consistency across the cognitive measures, we have standardised the outcome measures.[16]

The main results indicate that above-average rainfall in the first two trimesters (i.e. the first 6 months) is associated with higher cognitive scores at age 5. For instance, a 10% increase in rainfall from historical norms in the second month of pregnancy leads to a 1 standard deviation increase in the PPVT and CDA, on average (columns 1 and 2). Similarly positive or even stronger impacts are observed throughout the second trimester (i.e. up to the fifth month of pregnancy), and extending into the last trimester (column 1). This trend is clearly seen in column 2 using CDA, which shows a positive and statistically significant effect of rainfall in the fifth month of pregnancy. After that period, however, the effects taper off.

[16] The raw PPVT scores vary in each survey (see Table 1, Panel A).

Table 2: Rainfall Deviation in Prenatal and Cognitive Skills in Preschool-Aged Children (Age 5, 8, 12, and 15)

	Age 5		**Age 8**	**Age 12**	**Age 15**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Cognitive outcome	PPVT	CDA	PPVT	PPVT	PPVT
1 month prior	0.005	–0.004	0.012	0.045	–0.046
	(0.054)	(0.053)	(0.051)	(0.054)	(0.054)
Pregnancy month 0	0.074*	0.013	0.087**	0.016	–0.006
	(0.043)	(0.040)	(0.043)	(0.045)	(0.045)
Pregnancy month 1	0.104**	0.042	0.076*	–0.040	–0.010
	(0.048)	(0.041)	(0.042)	(0.044)	(0.045)
Pregnancy month 2	0.089**	0.101***	0.050	0.047	0.008
	(0.042)	(0.037)	(0.046)	(0.040)	(0.038)
Pregnancy month 3	0.146***	0.052	0.071*	0.018	–0.023
	(0.046)	(0.038)	(0.042)	(0.037)	(0.048)
Pregnancy month 4	0.097**	0.057	0.096**	0.042	–0.046
	(0.042)	(0.035)	(0.044)	(0.040)	(0.039)
Pregnancy month 5	0.134***	0.111***	0.080*	–0.008	0.037
	(0.047)	(0.040)	(0.044)	(0.040)	(0.039)
Pregnancy month 6	0.084*	0.024	0.062	0.020	–0.047
	(0.045)	(0.033)	(0.045)	(0.038)	(0.040)
Pregnancy month 7	0.102*	0.024	0.045	0.047	0.000
	(0.052)	(0.043)	(0.051)	(0.042)	(0.043)
Pregnancy month 8	0.022	0.006	0.022	0.030	–0.003
	(0.047)	(0.035)	(0.045)	(0.043)	(0.050)
Pregnancy month 9	0.085**	0.006	–0.009	–0.032	–0.039
	(0.043)	(0.034)	(0.041)	(0.038)	(0.039)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes
Birth month fixed effects	Yes	Yes	Yes	Yes	Yes
Cluster fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,209	1,302	1,236	1,241	1,277

PPVT = Peabody Picture Vocabulary Test, CDA = Cognitive Development Assessment.
Notes: The sample is restricted to the young cohort. Each column is a separate regression with dummies for the month of birth, geographical clusters (total number of sentinel site), gender, school, the education of father and mother, and the number of children in the household. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.
Source: Authors' creation based on Young Lives data.

Similar results are obtained when using CDA as an alternative cognitive outcome. This is consistent with several studies showing a positive association between income and positive rainfall shocks, leading to better nutritional intakes for pregnant mothers (Rosales-Rueda, 2018). This results in better cognitive development for children. These results conform to the medical literature emphasising that the gestational environment during early pregnancy can impact fetal brain structure, thus affecting the cognitive development of affected children.

Similar results continue to hold at age 8 (column 3): prenatal exposure to plentiful rainfall in utero is associated with better cognitive performance. Again, this is more evident in the first two trimesters, and there are no statistically significant effects in the last trimester. However, as we move to track cognitive development at ages 12 and 15, the results show that after age 8, these positive effects are completely absent. This suggests that the benefits of positive rainfall exposure in utero seen at an early age (ages 5 and 8) are not automatically preserved in the cognitive development process. It should be noted that rainfall in Viet Nam in the birth year of the Young Lives children (2001) was not categorised as extreme weather relative to the historical average (Figure 2). This could attenuate the positive effects on cognitive development in more sustained way, compared to other extreme events used in other studies.

As a placebo check, we also included the month before pregnancy, which was shown to be statistically insignificant (columns 1 and 2). This confirms that rainfall variations in the period before conception do not affect the results. In fact, all regressions performed including those a month before pregnancy were statistically insignificant (Table 2). This validates the hypothesis that income shocks outside the pregnancy period do not impact children’s cognitive outcomes in their later life. Our finding is consistent with that of Carrillo (2019), who examines exposure to rainfall shocks in months 10–12, 13–15, and 16–18 before birth and finds little evidence of any impact.

Table 3 shows the results for reading and writing skills at the age of 8, and mathematics and Vietnamese for ages 12 and 15. These cognitive measures are available for all of the children since they were administered by designated staff from the Young Lives project. Again, to achieve consistency across different ages, we used the standardised version of variables, but the results remain the same using the raw score as the cognitive outcome. Column 1 shows that prenatal rainfall exposure led to better outcomes in writing at age 8, an effect more pronounced when exposure occurred in the first two trimesters. However, as we move to another cognitive measure (reading in column 2) at ages 12 and 15, such effects become fragmentary, making it difficult to generalise the previously obtained results.

Table 3: Effect of Rainfall Deviation on Prenatal and Cognitive Development (Ages 8, 12, and 15)

	Age 8		**Age 12**		**Age 15**	
Cognitive outcome	Writing	Reading	Mathematics	Vietnamese	Mathematics	Vietnamese
1 month prior	–0.009	0.002	0.027	0.064	–0.491*	–0.058
	(0.021)	(0.021)	(0.331)	(0.311)	(0.283)	(0.366)
Pregnancy month 0	0.003	0.002	0.377	0.174	0.232	0.054
	(0.015)	(0.015)	(0.229)	(0.238)	(0.222)	(0.278)
Pregnancy month 1	0.005	0.010	–0.033	0.155	0.140	–0.355
	(0.018)	(0.017)	(0.255)	(0.248)	(0.224)	(0.294)
Pregnancy month 2	0.021*	0.017	0.131	0.124	0.023	–0.010
	(0.012)	(0.013)	(0.221)	(0.211)	(0.193)	(0.266)
Pregnancy month 3	–0.019	–0.003	0.344	0.255	0.095	0.154
	(0.013)	(0.014)	(0.242)	(0.223)	(0.216)	(0.288)
Pregnancy month 4	0.024*	0.013	0.041	0.110	0.238	0.562**
	(0.013)	(0.013)	(0.238)	(0.229)	(0.219)	(0.284)
Pregnancy month 5	0.021	0.016	0.403*	–0.068	–0.002	–0.123
	(0.015)	(0.014)	(0.229)	(0.228)	(0.216)	(0.270)
Pregnancy month 6	0.024**	0.017	0.031	–0.098	–0.094	0.102
	(0.012)	(0.013)	(0.237)	(0.226)	(0.210)	(0.285)
Pregnancy month 7	0.008	0.015	0.142	0.269	0.057	–0.440
	(0.014)	(0.015)	(0.287)	(0.271)	(0.248)	(0.323)
Pregnancy month 8	0.012	–0.002	0.012	0.231	0.227	–0.286
	(0.013)	(0.015)	(0.248)	(0.242)	(0.231)	(0.303)
Pregnancy month 9	–0.014	–0.002	0.091	0.049	–0.134	–0.780***
	(0.013)	(0.013)	(0.224)	(0.231)	(0.217)	(0.264)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Birth month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,313	1,322	1,214	1,214	1,245	1,242

Notes: The sample is restricted to the young cohort. Each column is a separate regression with dummies for month of birth, geographical clusters (total number of sentinel sites), gender, school, class, the age and education of father and mother, and the number of children in the household.
Source: Authors' creation based on Young Lives data.

Table 4 shows the cognitive development results of children sampled in the 2011 school survey. Using the school survey reduces the sample size to 750. It is also important to acknowledge that the students sampled in the school survey were randomly selected, making the analysis less prone to selection bias in the school survey. The benefit of using the school survey is that school quality can be included

(Glewwe, Huang, and Part, 2017). In this survey, the positive effects of rainfall observed earlier also lose statistical significance: no single variable displays a positive effect of plentiful rainfall during pregnancy. This finding remains consistent, even accounting for the school fixed effects in columns 3 and 4.

Table 4: Effect of Rainfall Deviation on Prenatal and Cognitive Skills – The 2011 School Survey (Age 10)

Age 10	**School fixed effects – No**		**School fixed effects – Yes**	
Test scores	Vietnamese	Mathematics	Vietnamese	Mathematics
1 month prior	0.075	0.082	0.021	0.041
	(0.120)	(0.135)	(0.132)	(0.143)
Pregnancy month 0	0.050	0.064	0.058	0.018
	(0.132)	(0.146)	(0.135)	(0.148)
Pregnancy month 1	0.054	0.041	0.085	–0.020
	(0.121)	(0.141)	(0.132)	(0.154)
Pregnancy month 2	0.071	0.116	0.090	0.057
	(0.107)	(0.122)	(0.112)	(0.129)
Pregnancy month 3	0.072	0.012	0.108	–0.064
	(0.120)	(0.131)	(0.122)	(0.137)
Pregnancy month 4	0.182	0.120	0.195	–0.002
	(0.123)	(0.143)	(0.134)	(0.160)
Pregnancy month 5	0.086	0.096	0.110	–0.005
	(0.133)	(0.153)	(0.137)	(0.159)
Pregnancy month 6	0.098	0.076	0.105	–0.025
	(0.126)	(0.145)	(0.134)	(0.154)
Pregnancy month 7	0.063	0.097	0.099	0.024
	(0.114)	(0.126)	(0.118)	(0.135)
Pregnancy month 8	0.040	0.045	0.049	–0.115
	(0.109)	(0.119)	(0.116)	(0.127)
Pregnancy month 9	–0.009	0.060	0.035	0.054
	(0.070)	(0.082)	(0.073)	(0.085)
Child and parent characteristics	Yes	Yes	Yes	Yes
Birth month fixed effects	Yes	Yes	Yes	Yes
Cluster fixed effects	Yes	Yes	Yes	Yes
Observations	750	750	750	750

Notes: The sample is restricted to the young cohort. Each column is a separate regression with dummies for month of birth, geographical clusters (total number of sentinel sites), gender, school, class, the age and education of father and mother, and the number of children in the household.
Source: Authors' creation based on Young Lives data.

In Table 5, we use the sample of children from the 2016 school survey. The sample size is smaller because some of the children sampled in the 2011 survey dropped out of school. Again, positive effects of rainfall in utero are completely absent in this sample, both with (column 3 and 4) and without the school fixed effects (column 1 and 2).

Table 5: Effect of Rainfall Deviation on Prenatal and Cognitive Skills – The 2016 School Survey (Age 15)

Age 15	**School fixed effects – No**		**School fixed effects – Yes**	
Test scores	English	Mathematics	English	Mathematics
1 month prior	0.179	0.188	–0.049	–0.116
	(0.430)	(0.372)	(0.554)	(0.491)
Pregnancy month 0	0.361	0.104	0.280	0.042
	(0.328)	(0.330)	(0.672)	(0.698)
Pregnancy month 1	–0.120	0.200	–0.292	–0.400
	(0.493)	(0.465)	(0.742)	(0.580)
Pregnancy month 2	–0.121	0.050	–0.191	–0.136
	(0.324)	(0.319)	(0.471)	(0.469)
Pregnancy month 3	–0.080	0.346	0.023	0.075
	(0.377)	(0.335)	(0.612)	(0.501)
Pregnancy month 4	0.097	0.184	0.159	–0.243
	(0.413)	(0.400)	(0.581)	(0.590)
Pregnancy month 5	–0.244	0.128	–0.317	–0.106
	(0.385)	(0.335)	(0.560)	(0.474)
Pregnancy month 6	–0.133	–0.187	–0.065	–0.633
	(0.395)	(0.383)	(0.544)	(0.498)
Pregnancy month 7	–0.046	0.206	0.005	0.009
	(0.342)	(0.303)	(0.539)	(0.509)
Pregnancy month 8	–0.039	0.059	–0.023	–0.450
	(0.320)	(0.326)	(0.456)	(0.410)
Pregnancy month 9	–0.286	0.104	–0.204	0.126
	(0.256)	(0.237)	(0.472)	(0.475)
Child and parent characteristics	Yes	Yes	Yes	Yes
Birth month fixed effects	Yes	Yes	Yes	Yes
Cluster fixed effects	Yes	Yes	Yes	Yes
Observations	195	195	169	170

Notes: The sample is restricted to the young cohort. Each column is a separate regression with dummies for month of birth, geographical clusters (total number of sentinel sites), gender, school, class, the age and education of father and mother, and the number of children in the household.
Source: Authors' creation based on Young Lives data.

Table 6 uses a similar analytical structure, but focuses on student behaviours assessed by teachers, as reported in the 2011 school survey. These variables –

academic ability, motivation, and participation – replace cognitive outcomes. While not perfect, they can be a proxy for non-cognitive development. Once we control for school quality, some months of rainfall are associated with a lower score for academic ability as assessed by the teachers. However, a lack of consistency prevents us from making any concrete observations from this exercise.

Table 6: Effect of Rainfall Deviation on Prenatal and Student Behaviour – The 2011 School Survey

Age 10	**School fixed effects – No**			**School fixed effects – Yes**		
	Ability	Motivation	Participation	Ability	Motivation	Participation
1 month prior	–0.050	–0.049	–0.059	–0.049	–0.032	–0.054
	(0.071)	(0.073)	(0.070)	(0.084)	(0.080)	(0.072)
Pregnancy month 0	–0.121	–0.104	–0.069	–0.100	–0.079	–0.074
	(0.078)	(0.078)	(0.075)	(0.085)	(0.083)	(0.076)
Pregnancy month 1	–0.114	–0.029	–0.012	–0.129	–0.010	0.002
	(0.073)	(0.077)	(0.071)	(0.087)	(0.082)	(0.069)
Pregnancy month 2	–0.083	–0.014	–0.034	–0.093	0.002	–0.005
	(0.065)	(0.067)	(0.061)	(0.071)	(0.069)	(0.061)
Pregnancy month 3	–0.098	–0.034	–0.018	–0.133*	–0.020	–0.007
	(0.070)	(0.073)	(0.064)	(0.077)	(0.077)	(0.065)
Pregnancy month 4	–0.079	0.021	–0.027	–0.100	0.034	–0.013
	(0.075)	(0.077)	(0.071)	(0.086)	(0.082)	(0.072)
Pregnancy month 5	–0.093	–0.027	–0.063	–0.103	–0.011	–0.040
	(0.080)	(0.081)	(0.075)	(0.088)	(0.084)	(0.075)
Pregnancy month 6	–0.103	–0.014	–0.050	–0.137	–0.007	–0.044
	(0.075)	(0.077)	(0.073)	(0.085)	(0.081)	(0.072)
Pregnancy month 7	–0.080	–0.048	–0.049	–0.092	–0.028	–0.035
	(0.067)	(0.069)	(0.061)	(0.074)	(0.073)	(0.062)
Pregnancy month 8	–0.088	–0.025	–0.046	–0.133*	–0.030	–0.057
	(0.063)	(0.064)	(0.061)	(0.070)	(0.067)	(0.063)
Pregnancy month 9	–0.054	–0.007	–0.029	–0.051	0.005	–0.010
	(0.043)	(0.045)	(0.042)	(0.046)	(0.046)	(0.042)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Birth month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
School fixed effects	No	No	Yes	Yes	Yes	Yes
Observations	750	750	745	750	750	745

Notes: The sample is restricted to the young cohort. Each column is a separate regression with dummies for month of birth, geographical clusters (total number of sentinel sites), gender, school, class, the age and education of father and mother, and the number of children in the household.
Source: Authors' creation based on Young Lives data.

Mechanism

What is driving the positive effects of prenatal exposure to plentiful rainfalls on young children? One channel highlighted in the literature is that the positive association between income and rainfall leads to better nutritional intakes for the mothers during their pregnancies (Shah and Steinberg, 2017).[17] We show this possible channel in two ways. First, we demonstrate an association between rainfalls in utero and the health status (weight and height) of children at birth and age 1. Second, we demonstrate a positive relationship between crops (i.e. rice) and rainfall shocks at the province level. This indicates an indirect relationship between income and rainfall.

First, we replace cognition with the following health outcomes: weight at birth (column 1), and height and weight at age 1 (Table 7), both taken from the first round of the children's survey. Consistent with several other studies (e.g. Maccini and Yang, 2009), plentiful rainfalls during pregnancy are generally associated with better health outcomes at birth. In particular, as the medical studies suggest, the first two trimesters are a critical window for the child's health at birth (at months 1 and 3). It is puzzling to observe a negative estimated coefficient at month 0. However, it should be noted that birth weight is retrospective data and not actually measured, meaning that the mother has been asked to recall child's birth weight. This may partly explain the spotty results in column 1. When considering other health measures (i.e. height and weight) at age 1, the results overwhelmingly support the positive association between good rainfalls in utero and subsequent health outcomes.

[17] Other studies also support this association. For example, Tiwari, Jacoby, and Skoufias (2017) find that an increase in rainfall from historical norms during the most recent monsoon led to a 0.13 standard deviation increase in the weight and height of children aged 0–60 months.

Table 7: Effect of Rainfall Deviation on Prenatal and Child Health

	At Birth	Age 1	
	Weight (kg)	Height (metre)	Weight (kg)
1 month prior	0.009	0.238***	0.013***
	(0.035)	(0.066)	(0.002)
Pregnancy month 0	–0.062**	0.260***	0.018***
	(0.025)	(0.055)	(0.002)
Pregnancy month 1	0.061**	0.257***	0.015***
	(0.028)	(0.053)	(0.002)
Pregnancy month 2	0.022	0.352***	0.017***
	(0.020)	(0.048)	(0.001)
Pregnancy month 3	0.052**	0.296***	0.016***
	(0.025)	(0.052)	(0.002)
Pregnancy month 4	0.029	0.288***	0.020***
	(0.023)	(0.054)	(0.002)
Pregnancy month 5	0.037	0.267***	0.018***
	(0.025)	(0.057)	(0.002)
Pregnancy month 6	0.035	0.263***	0.018***
	(0.024)	(0.053)	(0.002)
Pregnancy month 7	0.032	0.154**	0.013***
	(0.029)	(0.074)	(0.002)
Pregnancy month 8	–0.028	0.137**	0.013***
	(0.023)	(0.054)	(0.001)
Pregnancy month 9	0.048**	0.052	0.004***
	(0.023)	(0.050)	(0.001)
Child and parent characteristics	Yes	Yes	Yes
Birth month fixed effects	Yes	Yes	Yes
Cluster fixed effects	Yes	Yes	Yes
Observations	1,141	1,373	1,373

kg = kilogramme.

Notes: The sample is restricted to the young cohort. Each column is a separate regression with dummies for month of birth, geographical clusters (total number of sentinel sites), gender, school, class, the age and education of father and mother, and the number of children in the household.

Source: Authors' creation based on Young Lives data.

Second, we look at the association between crop yields and rainfall variables. We collected crop yield data for 1995–2016 from the annual Statistical Yearbook of Vietnam (crop yield is defined as the production of rice per one area unit of harvested land during the agricultural year in a given province, and the measure takes harvested rice production divided by harvested area).[18] The results indicate a positive association between good rainfall and rice yields in Viet Nam (Table 8). Overall, while not directly estimating the effects, we have shown the mechanism at play in the beneficial effects of good rainfalls in utero. This could be driving subsequent positive outcomes through health effects on cognitive development.

Table 8: Rainfall Deviation and Crop (Rice) Yield in Provinces for the Period 1995–2016

Sample	All provinces	YL provinces
Dependent var.: log (crop yield)	(1)	(2)
log (rain deviations)	0.455*	0.390***
	(0.228)	(0.061)
Constant	–2.821	–2.430***
	(1.714)	(0.475)
Observations	1,081	105
R-squared	0.917	0.809

YL = Young Lives.
Source: Statistical Yearbook of Vietnam, 1995–2016.

5. Conclusion

It is widely acknowledged that a gradual increase in temperature and unpredictable patterns of precipitation, along with frequent climatic shocks, all have enduring effects across sectors, regions, and different income groups, and particularly on the livelihoods of rural dwellers who rely substantially on agricultural incomes. In particular, outcomes resulting from prenatal exposure to rainfall shocks on the transitional years of schooling has been much understudied and is relevant for public policy. In this context, this chapter provides evidence for how prenatal exposure to rainfall shocks can shape cognitive development, by tracking the same children exposed to prenatal rainfalls in Viet Nam, using data from the Young Lives survey.

[18] Available from the General Statistics Office of Viet Nam.

The main findings can be summarised as follows. First, exposure to plentiful rainfall while in utero is associated with better cognitive development at ages 5 and 8. This positive association is only observed when the rainfall shocks occur in the first two trimesters but not in the last trimester. This finding is driven the positive association between incomes and abnormally high rainfalls, resulting in better nutritional intakes for pregnant mothers and better health outcomes for the children. The second main finding, however, indicates that these positive effects are not sustained after the age of 8, contrary to existing evidence in the literature. Our data show that the observed benefits of plentiful rainfall in early life on cognition at ages 5 and 8 disappear after age 10. This does not change when cognitive measures from the school surveys are used and the school fixed effect is accounted for. At the same time, since rainfall in the birth year (2001) in Viet Nam did not constitute extreme weather, any rainfall effects may be transitory, compared to other extreme cases such as the 1997–1998 El Niño (Rosales-Rueda, 2018).

So far, the Government of Viet Nam has not yet established the necessary national climate-change adaptation strategies to ameliorate these impacts. This chapter's findings can be used to inform policy to strengthen school resources by improving school quality to provide a sustained pathway for cognitive development in human capital development in the developing world.

Building on this research, several future areas of study are possible. First, by collecting data for the same individuals in early adulthood, it may be possible to link exposure to prenatal rainfall shocks to their performance in the labour market. In this way, future research can shed light on how human capital development shaped by early life income shocks can translate into labour market outcomes. Second, the case study of Viet Nam can be extended to examine the experience of children in other weather shock-prone countries.

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