The Child Education and Health Ethnic Inequality Consequences of Climate Shocks in Vietnam*

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Abstract

This paper provides a new explanation for ethnic disparities in education and health in Vietnam by studying the relationship between frequent, small-scale adverse rainfall shocks and child human capital. Exploiting plausibly random year-to-year variation in weather data that are linked to a longitudinal household- and individual-level dataset over the period 2008-2017, I find that excess rainfall during the annual typhoon season results in lower child subjective health status and school enrollment, with disproportionate effects on children of ethnic minorities. The negative lagged effects on education are concentrated in children at primary school start age, suggesting delaying children's school entry is a shock-coping strategy for poor ethnic minority households, albeit with potentially big negative long-run effect on their child lifetime earnings. Estimates suggest that rainfall shocks can explain approximately 28% of the observed ethnic gap in enrollment rates of children age 16-18 in the sample during the study period, and most is due to heterogeneous effects of rainfall shocks among ethnic groups, not differences in exposure to rainfall shocks.

Keywords: rainfall shocks, child human capital, ethnic disparities, developing countries, Vietnam

JEL Codes: I14, I24, J15, Q54

1 Introduction

It is well documented that climate and weather shocks affect various economic outcomes (Dell, Jones, and Olken 2014). A growing literature links climate change and associated weather events to worsening inequality. Global warming increased the per capita output gap between richest and poorest nations by roughly 25% over the period 1961-2010 (Diffenbaugh and Burke 2019). Other forms of (especially within-country) inequality, however, have received much less attention (Islam and Winkel 2017). Given that human capital formation is essential to boost labor productivity and foster long-run innovation and growth, and that child education and health have not only intrinsic value but also stimulate economic advance, understanding the relationship between climate and within-country human capital inequality is an important, under-researched question.

This paper provides new evidence on the relationship between weather shocks and ethnic disparities, particularly along health and education dimensions in Vietnam. The country comprises 54 different ethnic groups with one dominant (Kinh) ethnicity, making it an especially appropriate venue to study this question. Vietnam exhibits high vulnerability to climate risks (Eckstein, Künzel, Schäfer, and Winges 2020), but has also enjoyed favorable economic growth and improved living standards over the last two decades, although such progress has not been shared by ethnic minorities, who constituted only 14% of the population but 73% of the country's poor in 2016 (World Bank 2018). Ethnic disparities in education not only persist but have increased, with a particularly worrisome declining rate of enrollment in upper secondary schools among ethnic minorities especially since 2004 (Dang and Glewwe 2018). Similarly, minority children are disproportionately undernourished, with one in three suffering from stunting, and one in five underweight (Mbuya, Atwood, and Huynh 2019)–an alarming rate that is similar to that of many Sub-Saharan African countries. Earlier explanations for the observed ethnic inequality in the country include geographic disparities arising from the fact that minorities tend to live in less productive, rural areas with less access to markets and non-farm work opportunities, to public infrastructure, as well as differential returns to individual characteristics (Van de Walle and Gunewardena 2001), or differences in family background and endowment, especially parental education and household income (Trieu 2018; Arouri, Ben-Youssef, and C. Nguyen 2019; H. Nguyen 2019). Given the importance of weather shocks to human capital formation (Maccini and Yang 2009; Shah and Steinberg 2017; Tiwari, Jacoby, and Skoufias 2017), differential exposure to or capacity to manage weather risk could be an important understudied channel for perpetuating ethnic inequality intergenerationally.

Exploring the relationship between weather shocks and ethnic disparities in human capital can be challenging for several reasons. First, data constraints often confound causal inference. Previous work often compares those who were exposed to a shock with those who were not, which can fail to distinguish the effects of weather shocks on human capital outcomes from other underlying characteristics that are potentially correlated with the shock (Dell, Jones, and Olken 2014). If there is spatial sorting or selection such that ethnic majority households who choose to live in low-risk areas differ systematically from ethnic minorities who live in high-risk areas–which is often the case–then children exposed to shocks might have had different educational and health outcomes in comparison to other children even had the shock not occurred (Kousky 2016). Second, even with a panel dataset, attrition caused by mortality or out-migration associated with the shock could bias estimates. Third, the estimated impacts of rainfall shocks include not only the direct effects of adverse rainfall but also any actions taken in response (e.g., relief aid) by governments and other organizations, thus may understate the risks the shocks pose and the value of emergency relief.

I overcome these challenges by studying the impacts of frequent, small-scale rainfall shocks in rural Vietnam over the 2008-2017 period. By linking satellite-based weather data to a rich longitudinal dataset that covers individual members of approximately 2,000 households from three provinces in the Northern Central Coast and Northwestern Central Highlands regions, I can compare a given individual's health, and education under various rainfall conditions. In particular, I focus on extreme rainfall during the annual typhoon season (July to November), which overlaps with the summer-autumn and monsoon harvest of rice, the main staple crop. This approach controls for potential confounding factors by utilizing unpredictable and presumably random year-to-year local variation in rainfall realization during the typhoon season after controlling for individual and province-year fixed effects. The model includes both current year and previous year rainfall shocks, which allows me to separately examine the contemporaneous and lagged effects of rainfall shocks on human capital, a strategy similar to Shah and Steinberg (2017). The data set has low attrition, which is not significantly correlated with rainfall shocks. And although the rainfall shocks were significant enough to impact household and individual behaviors, they were not catastrophic enough to elicit emergency relief efforts by government or external donors, enabling estimation of impacts uncontaminated by endogenous efforts to cushion shocks' effects. As a further benefit, the longitudinal household data also allow me to directly examine potential mechanisms and remedies.

Two main findings emerge about the effects of adverse rainfall shocks on health and education of children. First, exposure to rainfall shocks in one year neither do not affect same year health status, the likelihood of getting an infectious disease, nor on-time grade progression conditional on being enrolled. The prior year's rainfall shocks, however, lower current year subjective health status but do not affect infectious disease incidence and grade progression once the child is enrolled in school. Both current-year and previous-year rainfall shocks negatively affect school enrollment.

Second, these results mask significant heterogeneity across ethnic groups. The impacts of rainfall shocks on school enrollment and perceived health are concentrated among children of minority groups. Specifically, while one unit increase in rainfall shocks last year lowers the probability of being in good health for Kinh children by roughly 10 percentage points this year, the effect for minority peers is 17 percentage points. Similarly, while previous year rainfall shocks virtually do not affect this year enrollment status of Kinh children, one unit increase in previous year shocks reduces the probability of being enrolled for children of minority group by about 9 percentage points (roughly 10% of the corresponding sample mean). In addition, last year adverse rainfall shocks result in lower likelihood of enrollment for ethnic minority children who are around the age of starting primary school (i.e., 6-9 years old) but virtually do not affect Kinh peers. Previous literature has documented different shock-coping strategies by poor households such as changing diet composition (Hou 2010), liquidating assets (Kazianga and Udry 2006), migrating (Gröger and Zylberberg 2016), and adjusting the timing of child marriage (Corno, Hildebrandt, and Voena 2020). This finding suggests another (imperfect) strategy with potentially big negative long-run effect: assuming rainfall shocks cause the child to complete one less year of schooling (i.e., the age at which schooling is finished does not change) and the rate of return to one year of schooling is 8%, then rainfall shocks-induced delayed school entry can result in a decrease of as much 8% in present discounted life-time earnings.

Finally, rainfall shocks appear an important contributor to ethnic disparities in upper-secondary education in Vietnam. Specifically, one additional month of extreme rainfall this year lowers school enrollment of minority students of upper-secondary school age (i.e., 16 to 18 years old) by roughly 8-9 percentage points, as compared to their Kinh peers who are virtually unaffected. This is consistent with the observed persistent and increased ethnic enrollment gap in upper-secondary education, which is almost completely driven by declining enrollment among ethnic minorities, as opposed to increasing enrollment among Kinh students (Dang and Glewwe 2018). Roughly 28% of the gap in upper-secondary education enrollment between ethnic majority and minority groups can be explained by rainfall shocks during the typhoon season over the study period.

Previous literature on the impacts of extreme weather events in general, and rainfall shocks in particular, on child human capital has focused on four main channels: elevated risk of infectious diseases, worsen household economic conditions, damages to healthcare and education facilities, as well as weakening aggregate local economy (labor wages) (e.g., Shah and Steinberg (2017), Tiwari, Jacoby, and Skoufias (2017), and Zimmermann (2020)). The null effects of both current and previous year rainfall shocks on infectious disease incidence suggests that it is not the disease environment associated with excess rainfall that worsens child health, as observed in other settings.[1] The healthcare and education supply channel likewise does not support the findings on perceived health and school enrollment. Additional analyses rule out the labor wage channel, and suggest a negative association between child health (education) and labor participation following rainfall shocks.

Most analyses in the ethnic disparity literature have focused on geographical factors such as access to public infrastructure, or social factors such as teacher quality, ethnicity and cultural bias (Redding 2019; DeJaeghere, Dao, Duong, and Luong 2021). There is especially a dearth of evidence from developing countries when it comes to the relationship between the physical environment, natural hazards, and ethnic disparities. Islam and Winkel (2017) propose three channels through which disadvantaged groups can be more affected: (i) higher exposure, (ii) higher susceptibility, and (iii) less ability to deal with and recover from climate shocks. These three together result in a vicious cycle of inequality and climate shocks. In this paper, I show that it is not the differences in exposure to rainfall shocks that could have driven more negative effects of rainfall shocks on children of minority groups. Several studies document that weather-induced agricultural productivity shocks have disproportionately affected children of less educated households and marginalized socioeconomic groups, for example, through decreased spending on education and increased child labor in India (Nordman, Sharma, and Sunder forthcoming). In this setting, however, despite no significant ethnic difference exists in the estimated

[1] For example, Tiwari, Jacoby, and Skoufias (2017) estimate that monsoon rainfall in Nepal negatively affects child weight for height through altering disease environment, but such impact is relatively small compared to the positive income effect, which results in a net positive effect.

lagged effects on household spending and diet composition, the differential lagged effects of rainfall shocks on child health and enrollment status by ethnicity are significant, suggesting that mechanisms other than parental investments could have driven these results.[2]

The remainder of the paper proceeds as follows. Section 2 describes the data, including construction of the rainfall shocks variable with summary statistics, and presents the empirical strategy. Section 3 discusses the effects of rainfall shocks on child human capital, placebo test and robustness checks of the main results. Section 4 provides heterogeneous analysis along the ethnic group dimension, as well as links rainfall shocks with ethnic disparities in school enrollment rates at upper-secondary education. Section 5 discusses potential pathways underlying the results. Section 6 notes important caveats to the analysis and concludes the paper.

2 Data, Background and Empirical Strategy

2.1 Household and Individual-level Data

The main dataset is drawn from the Thailand-Vietnam Socio-Economic Panel (TVSEP) household database, collected by Leibniz Universität Hannover in collaboration with other local universities (Grote, Thomsen, Waibel, and Kis-Katos 2019).[3] The Vietnamese data covers 110 communes of two provinces in the Northern Central Coast region (Ha Tinh and Thua Thien Hue) and one province in the Northwestern Central Highlands region (Dak Lak) (Figure 1).

[FIGURE 1 AROUND HERE]

[2]If anything, ethnic minority households actually significantly increased health and education expenditures following rainfall shocks of the same year, as opposed to a decreased spending as observed among Kinh households.

[3]Data are available for research purposes from the Thailand-Vietnam Socioeconomic Panel Survey Database Manager. Details are available at https://www.tvsep.de/data_access.html

Although these provinces represent diverse agro-ecological and climate conditions, infrastructure, as well as development potential, they share some common characteristics: being influenced by the Annamite Range, and heavy rain can lead to local submergence of crops and houses. The survey is representative of the rural population in Central Vietnam and areas with similar conditions (Hardeweg, Klasen, and Waibel 2013). All surveys were conducted during the summer with the reference period between May and April of the preceding year.[4] I use four rounds of this panel (2008, 2010, 2013, 2017) to construct a unique individual identification based on household identifiers and individual characteristics including age, gender, and relationship with the household head, and successfully track 3,938 individuals who were 0-18 years old in 2008 to the 2010 survey wave, of which 3,743 individuals were observed again in the 2013 wave, and 2,877 in the 2017 wave.[5]

The focus of this paper is to estimate the impacts of rainfall shocks on health and education of children. Health outcomes include an indicator for good subjective health status, which is coded 1 if the answer to the survey question "How healthy is [the member]?" is "healthy", and 0 if the answer is either "can manage" or "sick", as well as an indicator of whether the child has suffered from any serious infectious disease during the 12-month reference period.[6] As for education outcome, I focus on the extensive margin where an individual is considered enrolled if she was attending or completed school in the school year during the reference period. I also construct a measure of conditional on-time grade progression, which is a binary variable indicating whether a child is in the correct grade for their age, relative to the previous wave of survey. Specifically, the variable is coded 1 if age minus grade is at most 6 for an individual's first observation in the panel when

[4] Timing of the survey, school year, agricultural production is depicted in Appendix Figure D1.

[5] It appears that although the attrition rate at the individual level is high in more recent waves of the survey, most of the individuals that exit the sample in these waves are not part of the analysis, e.g., they are young adults who might have left for higher education or employment in other regions. An analysis of individual-level, household-level characteristics, and exposure to the rainfall shocks in Appendix A shows little evidence of non-random exit.

[6] These infectious diseases include, for example, bronchitis, dengue hemorrhagic fever, diarrhea, gastroenteritis of presumed infectious origin, encephalitis, hepatitis B, influenza, measles, rubella, pertussis, pneumonia, and tuberculosis.

she reaches 6 years old.[7] That is, if an 8-year-old is in second or third grade in 2008, she is considered on-track, but if she is in first grade, she is not. The variable in the later waves is determined based on the grade progression between waves of survey. Using the same example above and assuming the child is in second grade in 2008, she is considered off-track if being enrolled in third grade in 2010, and on-track again if in sixth grade in 2013.

One particular concern about the construction of education outcomes is that the analysis data are not of consecutive years and thus changes in educational outcomes could be misattributed over time. For example, non-enrollment in a given year may be a result of drop-out in a previous year, and not because of some specific shock.[8] This concern is mitigated with two additional survey questions that help determine whether and when a student has dropped out of school, as well as whether they have graduated. Specifically, the answer to the survey question "How old was [the member] when he/she left school?," determines when a child has dropped out of school, and the answer to "What was [the member]'s highest educational attainment?" helps verify whether a student has graduated, which together with data from other years can help determine their graduation year. In defining the final analysis sample, I apply two restrictions. First, if a child is reported to leave school more than two years prior to the current survey, she is no longer in the sample analysis in the current and subsequent surveys. Second, if a child is reported to have attained grade 12 as her highest educational level and left school before the current survey, she is considered already graduated and therefore not part of the

[7]One might suggest constructing on-time grade progression using child's starting school age. However, it might be problematic because the school year often starts at the beginning of August, whereas the survey is conducted in the Summer. Since age is rounded down, there are cases in which 6-year-old children have yet to be enrolled in school (i.e., yet to start the first grade). For these cases, enrollment status and grade level are both coded 0. The above method could help avoid this problem. In addition, it is noteworthy that children in disadvantaged areas or under special circumstances can start the first grade at age 7 or even later.

[8]Children in the sample tend to drop out of school as soon as they reach 12 years old. Of the 297 children who reported to have left school by 2008, 38% left when they were 12-14 years old, 41% left when they were 16 years old, and approximately 8% left when they were 17-18 years old. Among children age 12 who were not enrolled in year 2008, the share of getting back to school in the subsequent year (2010) is approximately 30%. The share drops to 3-10% for children age 13 and beyond.

analysis sample even if she is still in the school-age range.[9] Together, the two restrictions remove 440 observations from the final analysis sample. This source of measurement error, however, becomes more concerning for on-track measure, for which I do not have additional information to infer the exact year during which there was a delay in schooling. Therefore, findings on the on-track outcome should be interpreted with caution.

In addition, to examine the potential mechanisms, household-level information, including agricultural production, income, and consumption, is linked to each child and survey wave. Total income of a household includes net profits from agricultural production (crops and livestock), income from natural resource extraction, self-employment, wage employment (off-farm labor earnings), remittances and government transfers, income from renting out land, as well as interest earned on savings accounts. Household consumption expenditure includes food consumption, nonfood consumption, as well as spending on education and healthcare.

[TABLE 1 AROUND HERE]

Table 1 provides descriptive statistics of the study sample in 2008–the first wave of the analysis dataset. First, an average household in the sample is less well-off compared to an average nationally representative household (per capita total income US$ 1,470 vs. US$ 2,294 in PPP 2005 term), reflecting the sample selection targeting rural, disadvantaged areas in the country.[10] Second, the main income source of an average sample household is agricultural income, accounting for more than 47.4% of total income on average, and varying across regions with an average low of 22.9% in Hue and an average high of 62.6% in Dak Lak. Staples and vegetables are the main agricultural products for the North Central Coast provinces, accounting for more than 79% of crop income, and rice alone accounts for more than 24.5% and 54.3% of total agricultural income for an average household in Ha Tinh and Hue, respectively. In contrast, perennial industrial crops such

[9] For an illustration of these two restrictions, see Appendix A.

[10] Data for the average nationally representative household are from the Vietnam Household Living Standard Survey (VHLSS) 2008 (General Statistics Office of Vietnam n.d.).

as coffee and peppers are predominantly cultivated in Dak Lak, contributing to more than 89.1% of crop income and 77.2% of income from agriculture.

Consumption patterns of the sample households follow that of a typical poor household. Approximately 50.2% of total consumption are spent on food, 39.7% on nonfood (including personal care, clothing, electricity, water, transportation, and communication, as well as social purposes such as celebrations and funerals, recreation, and entertainment). Spending on education and healthcare accounts for only 9.5% of total household consumption.

The low out-of-pocket spending on education and healthcare may not necessarily reflect low investment in human capital, given that government subsidies and contributions from other organizations are not included. In addition, curative and preventative health care are considered a priority by the government, with more than 30% of the total healthcare dollars on preventive medicine, leading to high return even with low spending (Cheng 2014). As for education, most of primary and lower-secondary schools are public, which are financed by both government subsidies and other sources (Dang and Glewwe 2018). Households are often responsible for inputs such as stationery, uniforms, and other informal fees including contribution to school facilities. Children of poor households, ethnic minority, and in disadvantaged areas may also have their tuition waived and receive financial aid, free meals, and rice allowance from the government (McAleavy, Tran, and Fitzpatrick 2018).[11] These are reflected in the higher-than-average enrollment rate of children aged 7-18 in the study sample compared to VHLSS sample (80.2%).

Although the study sample has high school enrollment rate, it is considered relatively poorly when it comes to grade progression. Defining a child as being in the correct grade for her/his age if age minus grade is at most six, only 56.1% of children aged 7-18 years are considered on track, compared to approximately 74.7% in the VHLSS sample. It is

[11] Although TVSEP do not have details on tuition exemption and reduction, VHLSS 2008 data show that on average, more than 45% of school-aged children in rural areas of Ha Tinh receive tuition exemption or reduction, and the corresponding numbers for Hue and Dak Lak are 49% and 71%, respectively, compared to less than 42% for the national average.

worth mentioning that even though children should normally start compulsory primary education at the age of six, the above comparison might be misleading given that children in disadvantaged areas, ethnic minorities or poor households may start school at age seven or even later. The gap is indeed closer when defining being on track as age minus grade is at most seven, although there still seems to be substantial difference in this variable between the two groups of children, with 86.0% of nationally representative children aged 7-18 being in correct grade in contrast to only 78.4% of those in the study sample.

Vietnam has enjoyed favorable growth with improved living standards and declining poverty rate for both ethnic majority and minority groups, but the existing ethnic inequalities persist along many dimensions (World Bank 2018). In 2014, the human capital index is 0.75 for the ethnic majority–which is on par with many high-income countries, while that for the ethnic minority groups is only 0.62 (World Bank 2020a).[12] The minority groups are overwhelmingly living in rural mountainous communes. Although majority and minority children have similar enrollment rates at lower education levels, their educational paths diverge after lower secondary school, with a 30-percentage-point gap in enrollment rates in upper secondary school. Ethnic minority students less likely progress on time through school (Le and Inoue 2019). Besides other documented channels such as family background and school quality differences, existing literature also indicate that it is unlikely discrimination against ethnic minority students that drive ethnic educational disparities (World Bank 2018).

Consistent with the national ethnic inequality, there are stark differences between Kinh and ethnic minority children (and their households) in the sample. Minority households' heads have on average lower educational attainment. Minorities also have much

[12]The human capital index is constructed based on three components: (i) Survival from birth to school age, measured using under-5 mortality rates, (ii) Expected years of learning-adjusted school, combining information on the quantity and quality of education, and (iii) Health, as measured by adult survival rates (fraction of 15-year-olds who survive until age 60), and the rate of stunting for children under age 5 (World Bank 2020b).

lower level of income, consumption, savings and less access to credit. School-aged children of ethnic minorities are less likely enrolled in school, and if they are, less likely to be on-track compared to their Kinh peers.

2.2 Rainfall Data and Construction of Rainfall Shocks

I use daily accumulated rainfall data retrieved from the NASA "Integrated Multi-satellitE Retrievals for the Global Precipitation Measurement" (IMERG) Version 06 Final Run to determine rainfall shocks during the typhoon season (July to November). IMERG is a satellite-gauge product and available as gridded data of 0.1×0.1 degree resolution (roughly 10 km x 10 km at the equator) (Huffman et al. 2019). The dataset is available for daily rainfall since June 2000. I use data for 21 years from 2000 to 2020 in this paper.

I calculate monthly rainfall for each grid point by summing up daily rainfall of the corresponding month. The grid-level rainfall dataset is spatially merged with the household- and individual-level dataset using the geographical location of the commune where each child resided during the reference period of the survey. Specifically, I calculate the rainfall of each commune using inverse distance weighting, where the weight is the inverse of the square root of a grid point's distance from the geographic centroid of each commune and assign that level of rainfall to the commune for each month. The 110 household communes are distributed over 74 grid-cells (Ha Tinh: 23, Hue: 21, and Dak Lak: 30). The number of communes per grid-cell varies from a minimum of 1 to a maximum of 4.[13] By matching the household and weather data, I can assign to each commune the monthly rainfall time series.

Although satellite-based data are a powerful resource, (potential) errors could bias causal inference, which have been largely overlooked by social scientists.[14] To ensure that

[13] An average commune is very small, with a geographical area of approximately 42 km^2, i.e., 6×7 km. The largest commune is Ea H'leo (340 km^2, Dak Lak Province) and the smallest commune is Phu Hai (3 km^2, Hue). As a result, there is not much difference when using geographic centroid or other measures of distance to convert grid-level data to administrative-level data.

[14] Auffhammer, Hsiang, Schlenker, and Sobel (2013) show that although different weather data sets pro-

there are no significant biases associated with these data, I compare the satellite-based rainfall data and ground-based rainfall data collected by the local government, which is available from 2002 to 2019 only for the city of Hue within the study sample.[15] Appendix Figure D2 shows that indeed there is some difference in the total rainfall level between the two data sources. However, there appears no significant difference in the trend of rainfall across years for each month, and the two measures of rainfall are highly correlated. The pairwise correlation coefficients between ground-based rainfall and satellite-based rainfall of each month are 0.9199 (July), 0.9643 (August), 0.9417 (September), 0.9383 (October), and 0.9509 (November). Therefore, I measure the excess rainfall for each month as the deviation of the observed precipitation in that month m of commune s from the long-term mean divided by the historical monthly standard deviation (Standardized Precipitation Index–SPI):

$$\mathrm{SPI_{msy}} = (\mathrm{R_{msy}} - \overline{\mathrm{R_{ms}}})/\sigma_{\mathrm{ms}}$$

where R_{msy} is the observed rainfall for a given month m in year y at commune s, $\overline{R_{ms}}$ is the long-term mean of rainfall for month m at commune s, and σ_{ms} is the corresponding standard deviation. The index helps determine the level of excess relative to the climatological norm for the location.[16] At the commune level s, I then compute the exposure to the rainfall shocks as the sum of SPI during typhoon season before the survey time of wave w (i.e., between July of the year $w-1$ and November of $w-1$) when observed rainfall exceeded historical levels for that month by at least one standard deviation:

vide similar mean value of variables across space, they often do not reach a consensus on the deviations from that mean. Jain (2020) discusses common types of systematic error in mapping land cover such as non-random mis-classification, saturation effects, atmospheric effects and suggests that it is important to thoroughly examine the validation results of any satellite data product to understand other potential sources of bias.

[15]Data can be downloaded from the General Statistics Office of Vietnam (gso.gov.vn)

[16]Ideally one needs at least 20-30 years of monthly values with 50-60 years or more being optimal and preferred (World Meteorological Organization 2012). Due to the data availability, I use the mean rainfall of the 20-year period since 2000 as the long-term mean. The use of "future" rainfall to construct long-term mean and exposure to extreme events in the past is also common in other papers exploring rainfall shocks (e.g., Björkman-Nyqvist 2013). Distribution of SPI by month is available in Appendix Figure D3.

$$\text{Current year rainfall shocks:} \quad R_{sw} \quad = \sum_{m=Jul(w-1)}^{Nov(w-1)} SPI_{ms} * \mathbb{I}\{SPI_{ms} > 1\}$$

$$\text{Previous year rainfall shocks:} \quad R_{sw-1} = \sum_{m=Jul(w-2)}^{Nov(w-2)} SPI_{ms} * \mathbb{I}\{SPI_{ms} > 1\}$$

where $\mathbb{I}\{.\}$ denotes an indicator function.

In each wave of the survey, households are asked whether they have strategies to prevent or mitigate the negative impacts of potential risks on household income and assets. Among the sample households, for such risks as flooding on agricultural land, unusually heavy rainfall, and typhoon, in 2008, only about 28.5% reported to be prepared for future risk prevention or mitigation (flood: 14.0%, excess rainfall 5.0%, storm 18.5%) and this number does not change significantly across waves of surveys (23.1% in 2017). Those preventive strategies include, for example, income diversification by crops, livestock, or other sources of income (18.8% of the households), migration (8.4%), investment in physical and human capital (20.4%). The attitude towards climate risk varies across regions, with the preparedness ranging from less than 1% of households in Dak Lak to more than 40% in Ha Tinh and Hue, the two coastal provinces highly prone to natural disasters. If adverse rainfall shocks of this year are correlated with adverse rainfall shocks of next year, it is difficult to tell the extent to which the analysis picks up the effects of shocks in a single year or multiple years. Even though the two Northern Central Coast provinces are more likely to experience heavy rainfall due to their geographic locations, during the typhoon season, the precipitation patterns and rainfall shocks do not repeat themselves in a consistent way at the local level. As shown in Appendix Figure D4, the spatial distribution of extreme precipitation changes over this season in a rather unpredictable way. Results from a test for the serial correlation in rainfall suggest no significant evidence of serial correlation across years in each commune (Appendix Table D1).

[TABLE 2 AROUND HERE]

Table 2 presents exposures rainfall shocks during the annual typhoon season by calendar year for children in the sample. The rainfall shocks during the typhoon season in calendar years 2006 and 2007, respectively, correspond to the previous year and current year rainfall shocks of the survey wave 2008. During the 2008 survey reference period, all children in the sample experienced at least one month of extreme rainfall. In contrast, approximately 40% of the children in the sample did not experience any extreme rainfall within one year before the study waves 2010 and 2013. In 2017, approximately 30% of children experienced at least one month of excess rainfall during the typhoon season within 12 months before the survey. Importantly, about 21% of the sample children are observed with three months of extreme rainfall in the last year of the study period (Panel A). There are no systematic differences in the exposure to current year rainfall shocks by ethnic groups. Compared with ethnicity children in the same province, Kinh children experienced slightly less current year rainfall shocks in waves 2008 and 2012 but more current year shocks in waves 2010 and 2017, although these differences are not statistically significant at conventional levels. In contrast, Kinh children experienced more previous year rainfall shocks in all survey waves except 2017 relative to same-province children of minorities, although only the difference in the survey wave 2013 is significant at conventional levels (Panel C, conditional difference).

2.3 Empirical Strategy

This section describes the econometric models for children's health and education. Because current and previous year rainfall shocks might affect current year children's outcomes to different extents and there appears to be no serial correlation in rainfall shocks across years in each commune, to capture the contemporaneous and lagged impacts of rainfall shocks, I follow Shah and Steinberg (2017) and estimate the following equation using a linear probability model:

$$y_{ispw} = \beta_c R_{sw} + \beta_l R_{sw-1} + X'_{iw}\gamma + W'_{sw}\eta + \theta_i + \theta_{pw} \ + \ \varepsilon_{ispw} \tag{1}$$

where y_{ispw} is an outcome for child i in commune s of province p surveyed in wave w, which is 2008-2010-2013-2017. The terms R_{sw} and R_{sw-1} are rainfall shock exposures as constructed in Section 2.2 for commune s. X_{iw} is a vector of time-varying individual-level characteristics of individual i including age dummy and number of siblings $\leq$ 15 years old. W_{sw} is a vector of current and previous year total rainfall outside of the typhoon season. The vector θ_i is individual fixed effects, which absorb all observed and unobserved individual-specific time-invariant determinants of the outcomes, disentangling the shock from many other possible sources of omitted variable bias. The vector θ_{pw} represents province-and-wave-specific fixed effects, which account for changes in wages, prices, and living conditions over time in each province, and ε_{ispw} is the error term. Analysis is restricted to those of school age, from 7 to 18 years old at the time of the survey.

Although rainfall shocks have frequently affected these areas, one might expect the events to have been associated with strong typhoons or other natural disasters and therefore attracted government and international relief aid, which could mitigate adverse effects. Thus, the estimated impacts include not only the effects of adverse rainfall but also any actions taken in response by the government and other organizations, and the analysis does not (cannot) disentangle them. In other words, to the extent that rainfall shocks within child-commune-wave cells are uncorrelated with unobserved factors affecting child health and education, the β_c and β_l parameter estimates represent the contemporaneous and lagged net causal effects of the full translation of all current and previous year rainfall shocks-induced differences in individual and household conditions, some of which may have worked against the direct effects of adverse rainfall itself. I find no evidence of increase in public transfers to the households following the shocks, however. In contrast, there was a decrease in crop yields (particularly of rice) as well as an increase in the amount of remittances from relatives and friends in the same year the shocks happened, which suggests that the shocks were not catastrophic enough to elicit public relief aid but still negatively affected household economic conditions, inducing some informal assistance (Appendix Tables D2 and D4).

A few further issues are worth noting. The first issue is with respect to the interpretation of the coefficients β_c and β_l. Because the measure of rainfall shocks is constructed as the sum of monthly SPI exceeding one across months over the typhoon season, β_c and β_l could be interpreted as the effects of one unit increase in the rainfall shock measure with the understanding that this one unit increase is equivalent to some increase in severity of the rainfall shock (i.e., an increase in the severity of SPI deviation in one or more months). Such interpretation might be an overlook if, for example, one month with SPI of 2.2 has different effects compared to two months with SPI of 1.1 each. In Appendix B, I provide evidence that the estimates obtained from Equation 1 and its variant which controls for SPIs for each month in the season separately are comparable in magnitude, which reassures this interpretation.

Second, given the nature of the rainfall shock variable, i.e., the source of variation is at the commune level, it is likely that the error terms are correlated within commune groups over time. Therefore, I cluster standard errors at this source of variation–the commune level, which is the preferred measure based on which statistical inferences are discussed in the paper. In addition, because district is the lowest level of local administration at which reports on disasters-related damage records and the need for recovery funds must be prepared to help rebuild and/or update healthcare and schooling facilities, and in part support affected households financially, and because I am testing multiple hypotheses, I also report standard errors clustered at the district level as well as Romano-Wolf step-down adjusted p-values as robustness check for the set of main results (Romano and Wolf 2005a; Romano and Wolf 2005b).[17]

[17] The Romano-Wolf approach controls for the family-wise error rate while allowing for dependence among p-values by bootstrap re-sampling. I implement this procedure using Stata command "rwolf" developed by Clarke, Romano, and Wolf (2020), with 1000 bootstrap replications.

Third, it might be of concern to control for other time-varying observables at the household and/or village/commune level. Although the inclusion can help absorb residual variation and thus produce more precise estimates, if those variables are endogenous to the rainfall shocks then over-controlling would be problematic. Several candidates include, for example, household size and village characteristics. Household size could change because of shock-induced migration. There could also be ex-post reinvestment or improvements in village/commune infrastructure (road, public water supply, internet) in response to the shocks. I provide a robustness check that controls for household-level time-varying characteristics in Appendix B.

Another key problem with panel data analysis is attrition bias. Individuals and households present in the first round may drop out in later rounds because of mortality, or out-migration after the events, which has been shown to be an effective coping strategy to aggregate shocks or adverse climatic conditions (Gröger and Zylberberg 2016). The estimates could be biased if the people who leave the survey have characteristics correlated with the outcome variables. Prospective attrition bias seems minor at worst, however. Results reported in Appendix A suggest that those who exited the sample are mostly young adults and are not part of the main analysis. Importantly, there is no significant correlation between rainfall shocks and attrition: individuals (and households) who stay and who exit experience similar level of rainfall shocks in the past. If girls and minority children are more likely to exit the longitudinal sample, and if the effects are found to be stronger for girls and for ethnic minorities as documented in other settings, estimates from the longitudinal panel would be biased toward zero, that is, the estimates would be lower bound of the true effects. Nevertheless, the main empirical sample has relatively stable gender composition, ethnicity composition, and age distribution over time.

3 The Effects of Rainfall Shocks on Child Human Capital

This section reports the effects of rainfall shocks on children's health and education, using the sample of all individuals who appeared in at least two waves of the survey (unbalanced sample).

[TABLE 3 AROUND HERE]

Table 3 reports the main results obtained from estimating Equation 1. Column 1 shows that there is strong evidence of previous year rainfall shocks on current year health status. One unit increase in previous year rainfall shocks lowers the probability of being healthy this year by approximately 11 percentage points, or 0.2 standard deviations and the impact is statistically significant at the 1% level. I do not find evidence that supports the possibility of disease outbreak following extremely high rainfall (Column 2). Given that this year shocks neither worsen this year health status nor increase the risk of suffering from serious infectious disease, one possible explanation could be the relatively better access to health care systems.

With respect to educational outcomes, one unit increase in this year and last year rainfall shocks appears to lower the probability of being enrolled in school this year by roughly 1.4 and 1.7 percentage points, respectively, or 6% of a standard deviation (Column 3). The contemporaneous and lagged effects on enrollment are statistically significant at conventional levels when clustering standard errors at the commune and district levels. These effects, however, are insignificant at the conventional levels when errors are adjusted for multiple hypothesis testing. Conditional on being enrolled in school, on-time grade progression is not affected by rainfall shocks (Column 4).

Placebo Test and Robustness Checks I perform a series of robustness checks in Appendix B. To summarize, the results are robust to different specifications (with the inclusion of household-level time-varying characteristics, and lower-than-long-term-mean rainfall shocks), to different measures of shocks (number of months with excess rainfall, separate controls for SPI of months with excess rainfall), and samples (balanced sample of children, with and without sampling weights). I also conduct a placebo test where (unpredictable) future shocks are used as main independent variables of interest, which further confirms that the results are not driven by confounding factors or omitted variable bias.

4 Differential Effects by Ethnic Group

The analysis thus far focuses on the average effects of adverse rainfall shocks. It can mask significant heterogeneity in effects across groups, given stark differences in background between Kinh and minority children. This section explores whether ethnic minority children suffer more in response to rainfall shocks, and whether rainfall shocks can serve as an explanation for the observed increased ethnic disparity in enrollment rates in upper-secondary education in Vietnam over the past decade.

To answer the first question, I estimate the following equation:

$$\begin{aligned} y_{ispw} &= \delta_c R_{sw} + \psi_c R_{sw} \mathbb{I}\left\{\text{Ethnicity}_i = \text{Minorities}\right\} \\ &+ \delta_l R_{sw-1} + \psi_l R_{sw-1} \mathbb{I}\left\{\text{Ethnicity}_i = \text{Minorities}\right\} \\ &+ X'_{iw}\gamma + W'_{sw}\eta + \theta_i + \theta_{pw} + \varepsilon_{ispw} \end{aligned} \tag{2}$$

where ψ_c and ψ_l, respectively, denote the differential effects of current and previous year rainfall shocks on minority children relative to their peers of Kinh ethnic group, whereas δ_c and δ_l are the current and previous year effects, respectively, on Kinh children. Other terms are the same as in Equation 1. The total effects of current year and previous year rainfall shocks on minorities would be $\delta_c + \psi_c$, and $\delta_l + \psi_l$, respectively.

[TABLE 4 AROUND HERE]

Table 4 presents the effects on Kinh children ($\hat{\delta}_c, \hat{\delta}_l$) as well as the differential effects of rainfall shocks on minority groups ($\hat{\psi}_c, \hat{\psi}_l$) estimated from Equation 2. I do not observe any heterogeneous effects on the probability of getting an infectious disease, as well as being on-track conditional on school enrollment (Columns 2 and 4). However, there are large differential effects on health and school enrollment status. Specifically, while one unit increase in last year rainfall shocks lowers the probability of being in good health this year for Kinh children by roughly 10 percentage points, the effect for minority peers is nearly 17 percentage points (Column 1). Similarly, while previous year rainfall shock virtually do not affect this year enrollment status of Kinh children, the same shock reduces the probability of being enrolled for children of minority group by more than 8 percentage points, amounting to roughly 10% of the corresponding sample mean (Column 3). The differential lagged effects in health and enrollment status are statistically significant at the 1% level when clustering errors at the commune and district levels, and the inference is also robust to multiple hypothesis testing with the Romano-Wolf approach. There is also differential contemporaneous effect of current year shock on health across the two groups where minorities are more negatively affected, although the difference is not robust to multiple hypothesis testing. There is a significant effect of current rainfall shocks on Kinh student enrollment, but the effect is not statistically different from that on minority students.

That the differences in health and enrollment effects are not only statistically but also economically significant suggests rainfall shocks can potentially explain the persistent gap in health, and especially the increasing gap in upper-secondary education enrollment between ethnic minority and majority groups in Vietnam over the last decade (Dang and Glewwe 2018). To explore this, it is necessary to examine the effects along both age and ethnicity dimensions. I estimate the following equation:

$$
\begin{aligned}
y_{ispw} = \beta_c R_{sw} + \beta_l R_{sw-1} + \sum_{a=7, a\neq 15}^{18} \phi_{ca} R_{sw} \mathbb{I}\left\{\text{Age}_i = a\right\} + \sum_{a=7, a\neq 15}^{18} \phi_{la} R_{sw-1} \mathbb{I}\left\{\text{Age}_i = a\right\} \\
+\psi_c R_{sw} \mathbb{I}\left\{\text{Ethnicity}_i = \text{Minorities}\right\} + \psi_l R_{sw-1} \mathbb{I}\left\{\text{Ethnicity}_i = \text{Minorities}\right\} \\
+ \sum_{a=7, a\neq 15}^{18} \alpha_{ca} R_{sw} \mathbb{I}\left\{\text{Age}_i = a\right\} \mathbb{I}\left\{\text{Ethnicity}_i = \text{Minorities}\right\} \\
+ \sum_{a=7, a\neq 15}^{18} \alpha_{la} R_{sw-1} \mathbb{I}\left\{\text{Age}_i = a\right\} \mathbb{I}\left\{\text{Ethnicity}_i = \text{Minorities}\right\} \\
+X'_{iw}\gamma \ + W'_{sw}\eta + \theta_i + \delta_{pw} + \varepsilon_{ispw}
\end{aligned}
\tag{3}
$$

where β_c and β_l, respectively, represent the current and previous year effects of rainfall shocks on Kinh children aged 15. The terms ϕ_c and ϕ_l, respectively, denote the differential effects of current and previous year rainfall shocks on Kinh children of other ages relative to a Kinh child of 15 years old. The effects of current and previous year shocks on an average minority child relative to an average Kinh child are ψ_c and ψ_l, respectively. Finally, the terms α_c and α_l represent the the age-specific ethnic minority-specific differential effects of rainfall shocks. Other terms are the same as in Equation 1. With this equation, the total effect of current year rainfall shocks on 16-year old Kinh children can be computed as $\beta_c + \phi_{c16}$, whereas the contemporaneous effect on the same-age minority children is $\beta_c + \phi_{c16} + \psi_c + \alpha_{c16}$.

[FIGURE 2 AROUND HERE]

Figure 2 plots the point estimates and 95% confidence interval of the total effects of current and previous year rainfall shocks on subjective health (Panel A) and enrollment (Panel B) of Kinh and minority children by age, which are obtained from estimating Equation 3. Three main findings emerge. First, there is no strong evidence of statistically differential effects on perceived health status by age, although older children tend to be somewhat more affected by previous year rainfall shocks.

Second, last year adverse rainfall shocks result in lower likelihood of enrollment for children who are around the age of starting primary school and this effect is entirely driven by children of ethnic minorities. This finding suggests that poor households respond to rainfall shocks by delaying school entry of children to formal primary education, which is consistent with the government policy that allows children of poor households, ethnic minorities, and of disadvantaged areas to start the first grade late but no later than three years after the 6 year old threshold, that is, children can start grade 1 as long as they are 7 to 9 years old.[18]

Third, while there are no significantly differential effects of current year shocks on enrollment of younger children across ethnicity groups, the heterogeneous effects are especially pronounced among 15-18 years old students. Specifically, older Kinh majority students are virtually not affected, whereas minority students are approximately 8-10 percentage points less likely to be enrolled in school following a same-year shock.

The fact that ethnic minority households choose to delay their young children's school entry, and to drop out their older children from school can have potentially large effects. Specifically, delaying children's entry to school can adversely affect their life-time earnings. Assuming rainfall shocks cause the child to complete one less year of schooling (i.e., the age at which schooling is finished does not change) and the rate of return to one year of schooling is 8%–a rate considered relatively low compared to the private rates of return to education in East Asia and Pacific and many other developing countries (Patrinos and Psacharopoulos 2020), then delaying school enrollment can lead to an 8% decrease in the present discounted value of life-time earnings. Alternatively, if the child can finish the same number of years of schooling but complete one year later, delaying school enrollment will push back life-cycle earnings by one year and so also reduces the value of life cycle earnings by the level of interest rate that is used as a discount rate. These findings also suggest the important role of physical environment and natural hazards in

[18] This is mentioned in Article 40 Circular 41/2010/TT-BGDDT, and most recently in Article 33 Circular 28/2020/TT-BGDDT by the Vietnam Ministry of Education and Training.

the observed perpetuating ethnic disparities intergenerationally.

The estimates in Figure 2 allow me to compute the fraction of the enrollment gap in upper-secondary education between ethnic groups that is driven by a combination of the heterogeneous effects of rainfall shocks by ethnic groups and ethnic differences in exposure to rainfall shocks. Note that children age 16-18 of the two groups have been exposed to rainfall shocks to roughly similar extent, and if anything, Kinh children are somewhat exposed to more shocks and thus the contribution of rainfall shocks mostly comes from the differential effects of rainfall shocks by ethnic groups. My estimates suggest that for these children, total exposure to excess rainfall during the typhoon season over the study period lowers minorities' enrollment rate by roughly 7.3 percentage points (-8.94 percentage points per additional unit x 0.82 units of excess rainfall). The comparable effect for Kinh peers is 0.9 percentage points (0.8 percentage points per additional unit x 1.13 units of excess rainfall). This means that small-scale, frequent current year rainfall shocks alone widen the enrollment gap by approximately 8.23 percentage points, or approximately 28% of the 29.3 percentage point enrollment gap in the sample by 2017.[19]

5 Potential Mechanisms

The analysis so far has yielded two main results. First, positive monthly rainfall shocks that are at least a standard deviation above normal lead to reduced reported health and enrollment among 7-to 18-year-old children. Second, the effects are heterogeneous by ethnicity. This section aims to explore mechanisms that could have driven these results.

[19]In fact, the evolution of the enrollment rate gap of children age 16-18 in the sample is very similar to the national gap in upper-secondary education enrollment rates reported by Dang and Glewwe (2018). Specifically, the ethnic enrollment rate gaps in 2008 and in 2017 for the sampling children are 14.7 and 29.3 percentage points, respectively, and the increased gap is driven mostly by declining enrollment rate of minority children as opposed to increasing enrollment rate of Kinh children.

5.1 Mechanisms: The Lagged and Contemporaneous Effects

Figure 3 illustrates the multiple pathways via which exposure to rainfall shocks can directly or indirectly affect the health and education of children, according to previous empirical literature. These mechanisms can be grouped into four main categories: disease environment, household economic conditions (spending on health and education), aggregate shock on local economy, and education and healthcare supply.[20] In what follows, I focus on household economic conditions, spending on education and healthcare, and child labor. For a complete discussion on relevant empirical literature and why disease environment, education and healthcare supply, as well as aggregate shock on local economy are unlikely the drivers of the main results, see Appendix C.

[FIGURE 3 AROUND HERE]

Excess rainfall might cause income loss, hurting household financial liquidity and/or wealth. In developing countries where rural household income heavily relies on agricultural production, extreme rainfall could damage crops. The reduction in income and/or increase in expenditure to cover damages (e.g., reconstruction of damaged housing and other property, health expenses), as well as defensive investments in loss abatement (e.g., sandbags to defend against flooding, pesticides against increased pests), in combination with incomplete insurance and credit markets, might lead to reduction in household discretionary spending on goods and services for children such as food, healthcare and education. At the same time, children might be pushed to participate in alternative income generating activities to help households compensate for lost income (Beegle, Dehejia, and Gatti 2006), or participate in uncompensated domestic work while adults increase their employment outside of households.

[20] Excess rainfall might also affect human capital through the general equilibrium effects in crop markets, i.e., adverse rainfall in some locations change prices in other locations. The study provinces, however, are modest producers of rice and other staple foods (Dak Lak is the only province considered a large producer of cash crops). Given that most non-perennial crop agricultural production is concentrated in Red River and Mekong Delta provinces, any changes in crop yields and associated food prices in the study provinces should not affect general equilibrium prices much.

Recall that rainfall shocks are constructed over the typhoon season, which overlaps with the harvest season of summer-autumn and monsoon rice (GRiSP 2013), as well as other main crops cultivated by households in the study sample (See Appendix Figure D1 for the timing of agricultural production and the typhoon season). Among these crops, rice, maize, and beans are most likely affected by heavy rainfall during ripening phase because when fields are inundated, they could either be bent or have completely fallen. Heavy rainfall could also potentially lead to delays in drying, incomplete or ineffective drying, which reduces grain quality and results in losses. As shown in Appendix Table D2, rainfall shocks in one year affect rice yield of the same year, but do not affect agricultural yields next year. Rainfall shocks do not affect yields of other annual crops (e.g., cotton), as well as perennial crops (e.g., coffee and pepper). Specifically, exposure to one unit increase in rainfall shocks reduces rice yield by nearly 10% on average (and could be up to 20%).

The reduction in crop yields as a consequence of rainfall shocks appear to translate to a decrease in household diet composition and spending on education. These shock-induced changes, however, are not statistically insignificant at conventional levels (Appendix Table D3).

The fact that rainfall shocks significantly affect agricultural production, but do not affect household consumption and spending that much suggests rural households might have employed different strategies to deal with income loss. A common informal risk sharing strategy is private transfers (Gröger and Zylberberg 2016). As shown in Appendix Table D4, there was an increase in remittances from relatives and friends following a shock. There is no evidence of an increase in government transfers, however, which further suggests that small-scale, frequent rainfall shocks did negatively affect household economic conditions, but the effect was not catastrophic enough to attract relief aid from the government.

Another strategy is income diversification. Households might to choose to engage (their children) in other economic activities that are less dependent on climate. Consistent with the evidence on shock-induced agricultural production disruption, households reduce their own demand for child labor in farming activities in response to this year rainfall shocks. There is some suggestive evidence of an increase in child labor in non-farm activities following rainfall shocks this year, although the effect is not significant at conventional levels. Children exposed to rainfall shocks last year are more likely to be engaged in child labor this year, and most is driven by an increase in engagement in household non-farm occasional work (Table 5, Panel A). Households' decision to reallocate child labor from farming to non-farm activities is consistent with growing evidence on intersectoral labor reallocation as an adaptation strategy to manage agricultural productivity shocks due to climate change (Colmer 2021). In addition, the increase in child labor and the non-decrease in household adult labor (Appendix Table D5) also suggest the prevalence of child labor is for survival reasons, especially in the presence of credit constraints (Basu and Van 1998; Ranjan 2001).

[TABLE 5 AROUND HERE]

While these analyses are not sufficient to draw a causal relationship between shock-induced change in economic conditions and child human capital outcomes, piecing these findings together, it appears that the decrease in child farm labor and enrollment this year might have been driven by agricultural production disruption caused by same-year rainfall shocks. The increase in child labor might have worsened perceived health and decreased school enrollment following last year shocks.

5.2 Mechanisms: The Differential Effects by Ethnicity

The heterogeneous impacts of rainfall shocks by ethnicity might be because minority groups are more exposed to correlated income shocks that interact with the primary weather shock to exacerbate the effects (Almond, Currie, and Duque 2018). Islam and

Winkel (2017) propose three channels through which disadvantaged groups can be more affected: (i) they are more likely exposed, (ii) they are more susceptible, and (iii) they have less ability to deal with and recover from climate shocks. These channels together result in a vicious cycle of inequality and climate shocks, and the shocks end up worsening inequality. In what follows, I will examine these pathways in detail when data allow.

First, there is no evidence that supports the exposure channel. Table 2 shows that minorities were more exposed to current year shocks on average in 2008, but that was not the case in other years. In fact, ethnic minority children were less exposed to previous year shocks during the study period. Cumulatively, the exposure to rainfall shocks was less among minority children compared to Kinh majority children for the main analysis sample.

Second, I examine whether households of ethnic minority have less ability to deal with and recover from climate shocks. Specifically, I test whether there is any difference in the effect of rainfall shocks on remittances, diet composition, spending on education and health across households of different ethnicity groups by estimating a variant of Equation 2 where the unit of analysis is household-year. Results in Appendix Table D7 suggest that households of minority groups received a somewhat larger amount of private remittances relative to Kinh majority households after a shock this year, which is consistent with minority households having a greater need following the shock. Minority households had a less diverse diet, spent more on education and healthcare as a consequence of current-year rainfall shocks. As for previous year shocks, however, there is no significant differential effects along the ethnicity dimension on these outcomes. Neither do I observe a differential effect of current and previous year shocks on public remittances. The fact that diet composition of ethnic minority households is more negatively affected by this year shock could play a role in explaining the differential contemporaneous health effects between the two groups.

Despite no significant ethnic difference exists in the estimated lagged effects on household spending and diet composition, the differential lagged effects of rainfall shocks on child health and enrollment by ethnicity are significant, both statistically and economically. These findings seem to suggest that mechanisms other than parental investments channel, where households of marginalized groups are more negatively affected by adverse weather shocks and thus invested less in their children as found in other settings (for example, Nordman, Sharma, and Sunder forthcoming), could have driven the differential lagged effects of rainfall shocks by ethnicity.[21]

Although I do not find any differential effects of rainfall shocks on child labor across groups (Table 5, Panel B), it is worth noting that the measure of child labor in this paper is at the extensive margin. Minorities are more likely to live in more rural areas with limited labor market opportunities. It might have been that children of minority groups had to work a lot more hours relative to their Kinh peers in response to rainfall shocks, which could affect their health and education. Unfortunately, I cannot capture such an effect because of data limitation.

With that caveat in mind, minority children being more susceptible to rainfall shocks appears to be the only remaining channel. Children of minority groups might be more affected because they have poorer health to begin with. Minority children might also find it harder to continue school after an adverse shock because their parents are not able to help them with schoolwork. For many minority students, language becomes a barrier to study when they do not have enough learning time with teachers and peers at school, which likely is the only place where they get exposed to the Vietnamese language. The current dataset, however, does not allow me to have a conclusive answer.

[21] The current year shock-induced decrease in spending on education among Kinh households seems to be consistent with the finding on lower enrollment of Kinh children. This could be explained by the fact that a current rainfall shock causes a student to not be enrolled and so the family no longer has to pay school fees, etc. for that student. The finding on lower enrollment without a corresponding decrease in spending on education following a previous year shock for minority children is surprising. In a sense, however, this result is consistent with the descriptive evidence on preventive/mitigation strategies reported by households in the sample, with investment in human capital being a major strategy (Section 2.2). Given that household economic conditions are worsened because of the rainfall shocks, minority households might have reallocated resources among their children, so that those who remained in school would have the best resources possible to keep up with their peers.

6 Conclusions

Understanding whether and to what extent weather shocks induce changes in household economic conditions that affect children's human capital outcomes is an important question and of heightened policy relevance, given that extreme weather events are expected to increase in both frequency and intensity in most parts of the world, and given that most of the vulnerable population in the developing world have limited access to aggregate-shock coping mechanisms.

In this paper, I estimate the contemporaneous and lagged effects of adverse rainfall shocks on child health and education in rural Vietnam. The evidence presented highlights that even small-scale, but frequent rainfall shocks affect household economic conditions, and their children along multiple dimensions, and the effects may not be immediate. Poor households respond to the shocks by delaying children's entry to primary school with potentially big negative effects on their life-time earnings, and having their children engaged in different economic activities. These suggest that prevention strategies and policies that have the potential to improve capabilities to cope with adverse shocks that affect poor households with school-aged children, should receive more emphasis.

Importantly, even within the sample of rural households in Vietnam, rainfall shocks can explain a substantial part in the observed enrollment gaps, especially in upper-secondary education, between Kinh children and their ethnic minority peers. This is not driven by different exposures to excess rainfall, but by differential effects of rainfall shocks across groups. As suggested by Islam and Winkel (2017), this can be because ethnic minorities are more susceptible but less able to cope with these shocks. Examinations of commonly-studied economic channels such as parental investments, however, do not support the heterogeneous effects by ethnicity, which leaves an open question for future research.

References

Alderman, K., L. R. Turner, and S. Tong (2012). "Floods and human health: a systematic review". *Environment International* 47, pp. 37–47.

Almond, D., J. Currie, and V. Duque (2018). "Childhood circumstances and adult outcomes: Act II". *Journal of Economic Literature* 56.4, pp. 1360–1446.

Arouri, M., A. Ben-Youssef, and C. Nguyen (2019). "Ethnic and racial disparities in children's education: Comparative evidence from Ethiopia, India, Peru and Viet Nam". *Children and Youth Services Review* 100, pp. 503–514.

Auffhammer, M., S. M. Hsiang, W. Schlenker, and A. Sobel (2013). "Using weather data and climate model output in economic analyses of climate change". *Review of Environmental Economics and Policy* 7.2, pp. 181–198.

Basu, K. and P. H. Van (1998). "The economics of child labor". *American Economic Review*, pp. 412–427.

Beegle, K., R. H. Dehejia, and R. Gatti (2006). "Child labor and agricultural shocks". *Journal of Development Economics* 81.1, pp. 80–96.

Björkman-Nyqvist, M. (2013). "Income shocks and gender gaps in education: Evidence from Uganda". *Journal of Development Economics* 105, pp. 237–253.

Cheng, T. M. (2014). "Vietnam's health care system emphasizes prevention and pursues universal coverage". *Health Affairs* 33.11, pp. 2057–63.

Clarke, D., J. Romano, and M. Wolf (2020). "The Romano–Wolf multiple-hypothesis correction in Stata". *Stata Journal* 20.4, pp. 812–843.

Colmer, J. (2021). "Temperature, labor reallocation, and industrial production: Evidence from India". *American Economic Journal: Applied Economics* 13.4, pp. 101–24.

Corno, L., N. Hildebrandt, and A. Voena (2020). "Age of marriage, weather shocks, and the direction of marriage payments". *Econometrica* 88.3, pp. 879–915.

Dang, H. A. and P. W. Glewwe (2018). "Well Begun, But Aiming Higher: A Review of Vietnam's Education Trends in the Past 20 Years and Emerging Challenges". *Journal of Development Studies* 54.7, pp. 1171–1195.

DeJaeghere, J., V. Dao, B.-H. Duong, and P. Luong (2021). *Inequalities in Learning in Vietnam: Teachers Beliefs about and Classroom Practices for Ethnic Minorities*. Tech. rep.

Dell, M., B. F. Jones, and B. A. Olken (2014). "What do we learn from the weather? The new climate-economy literature". *Journal of Economic Literature* 52.3, pp. 740–98.

Diffenbaugh, N. S. and M. Burke (2019). "Global warming has increased global economic inequality". *Proceedings of the National Academy of Sciences* 116.20, pp. 9808–9813.

Ding, W., S. F. Lehrer, J. N. Rosenquist, and J. Audrain-McGovern (2009). "The impact of poor health on academic performance: New evidence using genetic markers". *Journal of Health Economics* 28.3, pp. 578–97.

Eckstein, D., V. Künzel, L. Schäfer, and M. Winges (2020). *Global Climate Risk Index 2020: who suffers most from extreme weather events? Weather-related loss events in 2018 and 1999–2018.* Report.

Fletcher, J. M. and S. F. Lehrer (2011). "Genetic lotteries within families". *Journal of Health Economics* 30.4, pp. 647–659.

General Statistics Office of Vietnam (n.d.). *Vietnam Household Living Standard Surveys*. Dataset.

GRiSP (2013). *Rice Almanac*. 4th edition. Los Baños (Philippines): International Rice Research Institute, p. 283.

Gröger, A. and Y. Zylberberg (2016). "Internal Labor Migration as a Shock Coping Strategy: Evidence from a Typhoon". *American Economic Journal: Applied Economics* 8.2, pp. 123–153.

Grote, U., S. Thomsen, H. Waibel, and K. Kis-Katos (2019). *Thailand-Vietnam Socio Economic Panel 2008, 2010, 2013, 2017*. Dataset.

Hales, S., S. Edwards, and R. Kovats (2003). “Impacts on health of climate extremes”. *Climate change and human health: Risks and responses*. Ed. by A. J. McMichael et al. Geneva: World Health Organization. Chap. 5, pp. 79–102.

Hardeweg, B., S. Klasen, and H. Waibel (2013). “Establishing a database for vulnerability assessment.” *Vulnerability to Poverty: Theory, Measurement and Determinants, with Case Studies from Thailand and Vietnam*. Ed. by S. Klasen and H. Waibel. London: Palgrave Macmillan, pp. 50–79.

Hou, X. (2010). “Can drought increase total calorie availability? The impact of drought on food consumption and the mitigating effects of a conditional cash transfer program”. *Economic Development and Cultural Change* 58.4, pp. 713–737.

Huffman, G. et al. (2019). *GPM IMERG Final Precipitation L3 1 day 0.1 degree x 0.1 degree V06, Edited by Andrey Savtchenko, Greenbelt, MD, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: January 19, 2020, 10.5067/GPM/IMERGDF/DAY/06*. Dataset.

Islam, N. and J. Winkel (2017). *Climate change and social inequality*. DESA Working Paper No. 152. United Nations Department of Economic and Social Affairs.

Jain, M. (2020). “The Benefits and Pitfalls of Using Satellite Data for Causal Inference”. *Review of Environmental Economics and Policy* 14.1, pp. 157–169.

Kazianga, H. and C. Udry (2006). “Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso”. *Journal of Development Economics* 79.2, pp. 413–446.

Kirchberger, M. (2017). “Natural disasters and labor markets”. *Journal of Development Economics* 125, pp. 40–58.

Kousky, C. (2016). “Impacts of Natural Disasters on Children”. *Future of Children* 26.1, pp. 73–92.

Le, T. Q. A. and K. Inoue (2019). *To close Vietnam's human capital development gap, look to ethnic minorities*.

Maccini, S. and D. Yang (2009). "Under the weather: Health, schooling, and economic consequences of early-life rainfall". *American Economic Review* 99.3, pp. 1006–26.

Mbuya, N. V., S. J. Atwood, and P. N. Huynh (2019). *Persistent Malnutrition in Ethnic Minority Communities of Vietnam: Issues and Options for Policy and Interventions*. World Bank Publications.

McAleavy, T., T. H. Tran, and R. Fitzpatrick (2018). *Promising practice: government schools in Vietnam*. Tech. rep. Education Development Trust.

Nguyen, H. (2019). "Ethnic gaps in child education outcomes in Vietnam: an investigation using Young Lives data". *Education Economics* 27.1, pp. 93–111.

Nordman, C. J., S. Sharma, and N. Sunder (forthcoming). "Here Comes the Rain Again: Productivity Shocks, Educational Investments and Child Work". *Economic Development and Cultural Change*.

Patrinos, H. A. and G. Psacharopoulos (2020). "Chapter 4 - Returns to education in developing countries". *The Economics of Education (Second Edition)*. Ed. by S. Bradley and C. Green. Second Edition. Elsevier, pp. 53–64.

Ranjan, P. (2001). "Credit constraints and the phenomenon of child labor". *Journal of Development Economics* 64.1, pp. 81–102.

Redding, C. (2019). "A teacher like me: A review of the effect of student–teacher racial/ethnic matching on teacher perceptions of students and student academic and behavioral outcomes". *Review of Educational Research* 89.4, pp. 499–535.

Romano, J. and M. Wolf (2005a). "Exact and approximate stepdown methods for multiple hypothesis testing". *Journal of the American Statistical Association* 100.469, pp. 94–108.

— (2005b). "Stepwise multiple testing as formalized data snooping". *Econometrica* 73.4, pp. 1237–1282.

Saulnier, D. D., K. Brolin Ribacke, and J. von Schreeb (2017). "No Calm After the Storm: A Systematic Review of Human Health Following Flood and Storm Disasters". *Prehospital and Disaster Medicine* 32.5, pp. 568–579.

Shah, M. and B. M. Steinberg (2017). “Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital”. *Journal of Political Economy* 125.2, pp. 527–561.

Thomas, D., E. Frankenberg, and J. P. Smith (2001). “Lost but not forgotten: Attrition and follow-up in the Indonesia Family Life Survey”. *Journal of Human Resources*, pp. 556–592.

Tiwari, S., H. G. Jacoby, and E. Skoufias (2017). “Monsoon babies: Rainfall shocks and child nutrition in Nepal”. *Economic Development and Cultural Change* 65.2, pp. 167–188.

Trieu, Q. T. (2018). *Ethnic Disparities in Education in Vietnam*. Dissertation.

Van de Walle, D. and D. Gunewardena (2001). “Sources of ethnic inequality in Viet Nam”. *Journal of Development Economics* 65.1, pp. 177–207.

World Bank (2018). *Climbing the Ladder: Poverty Reduction and Shared Prosperity in Vietnam*. World Bank.

— (2020a). *Insights from Disaggregating the Human Capital Index*. Tech. rep. World Bank Group.

— (2020b). *The Human Capital Index 2020 Update : Human Capital in the Time of COVID-19*. Tech. rep. World Bank Group.

World Meteorological Organization (2012). *Standardized Precipitation Index User Guide*.

Zimmermann, L. (2020). “Remember when it rained–Schooling responses to shocks in India”. *World Development* 126, p. 104705.

Tables

Table 1: Characteristics of the Study Sample, 2008

		Province			Ethnic Group	
	(1)	(2)	(3)	(4)	(5)	(6)
	ALL	HaTinh	Hue	Daklak	Kinh	Minorities
Household head						
Gender (1=Male)	0.836	0.829	0.827	0.851	0.832	0.851
Age	48.950	52.362	49.393	45.224	50.490	42.920
Years of schooling	7.484	8.463	6.702	7.086	7.781	5.967
Household characteristics						
Number of nucleus members	4.361	3.875	4.489	4.711	4.165	5.130
Share of male aged 16-59	0.269	0.250	0.259	0.298	0.269	0.271
Share of female aged 16-59	0.293	0.295	0.278	0.307	0.293	0.295
Income and consumption						
Total income	1479	1469	963	1978	1650	809
Income from crops and livestock	702	620	220	1240	757	486
Income from resource extraction	51	39	92	24	54	39
Income from wage	201	184	207	213	221	125
Income from self-employment	225	164	232	277	274	29
Income from remittances	167	259	100	141	205	19
Total consumption	1259	1209	1192	1369	1371	820
Food consumption	633	581	629	687	669	491
Nonfood consumption	500	470	474	552	557	275
Spending on education/healthcare	121	153	82	126	139	50
Savings and borrowing						
Savings	73	83	51	85	84	31
Outstanding loan	540	557	356	697	607	276
Formal	364	384	265	438	416	159
Observations	2148	713	699	736	1711	437
Children aged 7-18						
Enrolled in school	0.864	0.895	0.835	0.867	0.884	0.804
On-track (A)	0.561	0.691	0.459	0.558	0.607	0.420
On-track (B)	0.784	0.865	0.732	0.771	0.827	0.653
Observations	3003	813	1009	1181	2257	746

Notes: The sample includes individuals aged 7-18 in 2008 and their households. All monetary variables are expressed in 2005 US$ (PPP) per capita, where household size is the number of household members who stayed at least 180 days during the reference period. On-track A (B) is coded 1 if age minus grade is at most six (seven). Sources: Household and individual data are from TVSEP 2008.

Table 2: Exposure to Adverse Rainfall Shocks during the Annual Typhoon Season

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
			Survey		Survey			Survey			
Calendar Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Panel A: Distribution by number of months with rainfall shocks (%)											
0	34		35	40		35	40	39	61	75	70
1	66	55	65	60	7	17	60	30	39	25	4
2		42		1	93	33		31			5
3		2				15					21
Panel B: Mean shock intensity experienced by ethnicity											
Kinh	1.207	2.453	1.138	1.303	3.901	1.803	0.906	1.437	0.675	0.571	1.684
Observations	2134	2134	1965	1965	1443	1443	1443	1016	1016	1016	1016
Minority	0.645	3.007	0.747	1.550	4.131	1.134	1.056	1.015	1.397	0.000	0.025
Observations	702	702	686	686	661	661	661	405	405	405	405
Panel C: Difference in shock intensity experienced by ethnicity (Kinh - Minorities)											
Unconditional	0.562	-0.554	0.391	-0.247	-0.230	0.670	-0.149	0.423	-0.722	0.571	1.658
	(0.035)	(0.028)	(0.037)	(0.052)	(0.034)	(0.060)	(0.038)	(0.072)	(0.065)	(0.024)	(0.068)
Conditional	0.043	-0.195	0.093	0.185	-0.079	0.211	-0.032	-0.114	-0.002	0.000	0.080
	(0.058)	(0.136)	(0.064)	(0.114)	(0.111)	(0.102)	(0.028)	(0.070)	(0.039)	(0.000)	(0.049)
Observations	2836	2836	2651	2651	2104	2104	2104	1421	1421	1421	1421

Notes: This table presents the exposure to adverse rainfall shocks during the typhoon season by calendar year. The 2007 typhoon-season rainfall shocks are considered current rainfall shocks of the survey wave 2008, the 2006 typhoon-season rainfall shocks are considered previous rainfall shocks of the survey wave 2008. Panel A shows the share of children in the study sample by the number of months with rainfall shocks they experienced each year. A month is considered having a rainfall shock if the observed rainfall exceeded historical levels for that month by at least one standard deviation. Panel B shows the mean intensity of rainfall shocks (measured as sum of monthly SPI exceeding one during the typhoon season) experienced by the sample of Kinh children and the sample of ethnic minority children. Panel C shows the difference in mean intensity of rainfall shocks by ethnicity. Unconditional difference is obtained from regressions of rainfall shocks on an indicator of Kinh ethnicity, with robust standard errors in parentheses. Conditional difference is obtained from regressions of rainfall shocks on an indicator of Kinh ethnicity, controlling for province fixed effects, with standard errors clustered at the commune level in parentheses. Analysis sample is defined in the main text. Sources: Household and individual data are from TVSEP 2008-17. Rainfall data are from IMERG.

Table 3: The Effects of Rainfall Shocks on Child Health and Education

	(1) Health	(2) Disease	(3) Enrolled	(4) Ontrack
Current year shocks	-0.008	0.004	-0.014	0.023
	(0.021)	(0.008)	(0.007)	(0.022)
	[0.023]	[0.006]	[0.008]	[0.021]
	{0.886}	{0.886}	{0.558}	{0.597}
Previous year shocks	-0.113	0.011	-0.017	0.007
	(0.022)	(0.010)	(0.010)	(0.017)
	[0.021]	[0.010]	[0.007]	[0.018]
	{0.001}	{0.544}	{0.374}	{0.749}
N	9012	9012	9012	8234
R^2	0.152	0.010	0.116	0.139
Sample Mean	0.585	0.045	0.914	0.809
Sample SD	0.493	0.208	0.281	0.393

Notes: Results are obtained from estimating Equation 1. Each column is from a separate regression. The unit of analysis is child-year, corresponding to 4,017 individuals. Rainfall shocks are defined as in the main text. Sample includes individuals who appeared in at least two waves of the survey. Analysis is restricted to age range 7-18. All regressions include individual age (indicators), number of siblings less than 15 years old, total rainfall during months outside the typhoon season, province-specific wave fixed effects, and individual fixed effects. Standard errors clustered at the commune and district level are in parentheses and brackets, respectively. Romano-Wolf adjusted p-values for multiple hypothesis testing are in braces. Sources: Individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Table 4: The Differential Effects of Adverse Rainfall Shocks by Ethnic Group

	(1) Health	(2) Disease	(3) Enrolled	(4) Ontrack
Current year shocks	0.006	0.003	-0.015	0.030
	(0.022)	(0.009)	(0.008)	(0.021)
	[0.021]	[0.007]	[0.008]	[0.022]
	{0.962}	{0.962}	{0.395}	{0.395}
Current year shocks × Minority	-0.038	0.004	-0.002	-0.022
	(0.016)	(0.006)	(0.009)	(0.014)
	[0.012]	[0.004]	[0.007]	[0.012]
	{0.192}	{0.885}	{0.896}	{0.448}
Previous year shocks	-0.099	0.011	-0.010	0.012
	(0.022)	(0.010)	(0.012)	(0.017)
	[0.020]	[0.010]	[0.013]	[0.018]
	{0.005}	{0.759}	{0.759}	{0.759}
Previous year shocks × Minority	-0.069	-0.009	-0.084	-0.013
	(0.024)	(0.006)	(0.018)	(0.021)
	[0.025]	[0.006]	[0.029]	[0.016]
	{0.023}	{0.560}	{0.003}	{0.598}
N	9012	9012	9012	8234
R^2	0.156	0.010	0.133	0.140
Sample mean for Kinh	0.615	0.043	0.943	0.832
Sample mean for Minority	0.506	0.051	0.837	0.739

Notes: Results are obtained from estimating Equation 2. Each column is from a separate regression. Other notes are similar to Table 3. Standard errors clustered at the commune and district level are in parentheses and brackets, respectively. Romano-Wolf adjusted p-values for multiple hypothesis testing are in braces. Sources: Individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

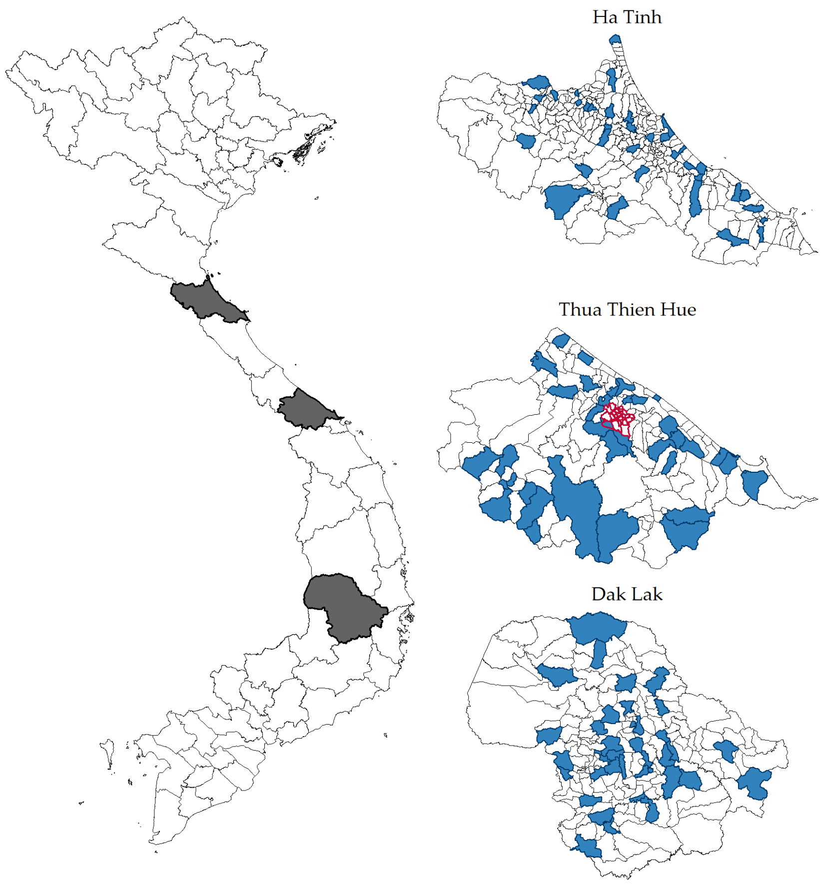
Table 5: The Effects of Rainfall Shocks on Child Health, Education, and Labor

	Human Capital		Child Labor			
	(1)	(2)	(3)	(4)	(5)	(6)
	Health	Enrolled	AllLabor	HHFarm	HHNFarm	WageEmp
			Panel A: Average Effects			
Current year shocks	-0.007	-0.014	0.008	-0.028	0.032	-0.004
	(0.021)	(0.007)	(0.032)	(0.009)	(0.030)	(0.006)
	[0.024]	[0.008]	[0.041]	[0.011]	[0.041]	[0.006]
	{0.960}	{0.676}	{0.960}	{0.372}	{0.436}	{0.960}
Previous year shocks	-0.113	-0.017	0.106	0.006	0.083	0.009
	(0.022)	(0.010)	(0.031)	(0.008)	(0.028)	(0.006)
	[0.021]	[0.007]	[0.035]	[0.008]	[0.036]	[0.006]
	{0.012}	{0.216}	{0.012}	{0.486}	{0.012}	{0.337}
Sample mean	0.585	0.913	0.251	0.081	0.117	0.036
Sample SD	0.493	0.281	0.433	0.273	0.322	0.185
			Panel B: Differential Effects			
Current year shocks × Minority	-0.038	-0.002	0.005	-0.040	0.038	-0.010
	(0.016)	(0.009)	(0.015)	(0.007)	(0.016)	(0.006)
	[0.012]	[0.007]	[0.015]	[0.009]	[0.015]	[0.009]
	{0.261}	{0.960}	{0.960}	{0.011}	{0.050}	{0.489}
Previous year shocks × Minority	-0.069	-0.084	-0.004	0.009	-0.009	-0.000
	(0.024)	(0.018)	(0.019)	(0.008)	(0.013)	(0.007)
	[0.025]	[0.029]	[0.016]	[0.006]	[0.012]	[0.009]
	{0.037}	{0.003}	{0.982}	{0.864}	{0.874}	{0.982}
N	9012	9012	9012	9012	9012	9012
R^2	0.157	0.134	0.122	0.117	0.183	0.086
Sample mean for Kinh	0.615	0.942	0.226	0.064	0.101	0.033
Sample mean for Minority	0.505	0.836	0.316	0.127	0.161	0.042

Notes: Panel A presents results estimated from Equation 1. Panel B presents estimates of coefficients on the interacted rainfall shock and minority indicator variable from Equation 2. Each panel-column is from a separate regression. Child labor is an extensive margin measure, taking the value of 1 if a child's most or second-most time-consuming activities is in the corresponding category and 0 otherwise. The three categories of child labor include household farming (HHFarm), non-farm activities (HHNFarm), and non-household wage work (WageEmp). These outcomes are not mutually exclusive, that is, a child can be engaged in different activities, depending on their time constraints. Other notes are similar to Table 3. Standard errors clustered at the commune and district level are in parentheses and brackets, respectively. Romano-Wolf adjusted p-values for multiple hypothesis testing are in braces. Sources: Individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

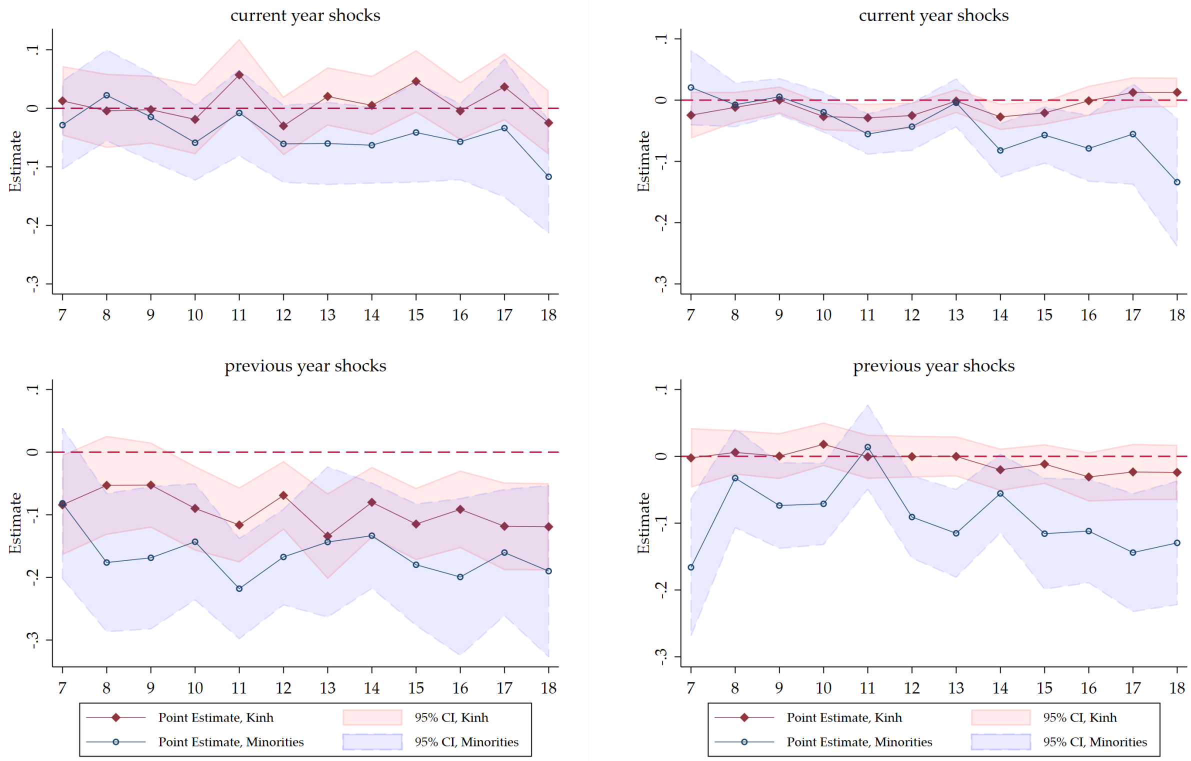
Figures

Figure 1: Study Sample



Notes: Grey areas indicate three study provinces. Blue areas indicate the communes covered in the study sample. Hue City is the area with red-colored boundary.

Figure 2: The Effects of Adverse Rainfall Shocks on Child Health and School Enrollment, by Age and Ethnic Group

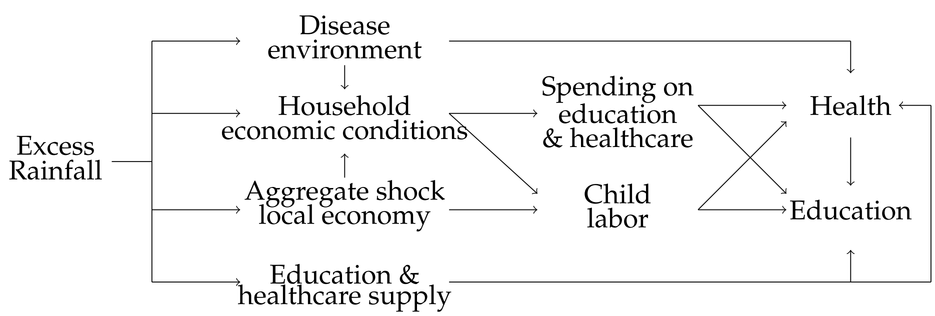


(a) Health Status

(b) School Enrollment Status

Notes: This figure plots the point estimate and lower/upper 95% confidence interval of the total effects of current and previous year rainfall shocks on school enrollment status for different ages of Kinh and ethnic minorities obtained from estimating Equation 3. The ethnicity-differential enrollment effects of current year shocks for children age 16-18, and of previous year shocks for children age 7-9 are robust to multiple hypothesis testing using Romano-Wolf approach. Rainfall shocks are defined as in the main text. Sample includes individuals who appeared in at least two waves of the survey. Analysis is restricted to age range 7-18. Regression includes individual age dummies, interactions of age with current and previous rainfall shocks, indicator of ethnic minority, interactions of minority indicator with current and previous rainfall shocks, interactions of age-minority with current and previous rainfall shocks, number of siblings less than 15 years old, total rainfall outside the typhoon season of current and previous years, province-specific wave fixed effects, and individual fixed effects. Sources: Household and individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Figure 3: Potential Pathways



Supplemental Materials

A Data and Attrition **S2**

Data and Sample S2

Constructing Education Variables S2

Attrition Analysis S5

B Placebo Test and Robustness Checks **S7**

B.1 Placebo Test S7

B.2 Robustness Checks S7

C Potential Mechanisms **S11**

Disease environment S11

Education and healthcare supply S12

Aggregate shock on local economy S12

D Additional Tables and Figures **S14**

A Data and Attrition

Data and Sample The household and individual dataset is constructed from the Thailand-Vietnam Socioeconomic Panel (TVSEP). The Vietnamese survey has been conducted in 2007, 2008, 2010, 2011, 2013, 2016, and 2017. In this paper, I use data from the 2008, 2010, 2013, and 2017 waves.

The survey is designed as a rooftop survey, that is, it does not track individuals or split-off households. To construct a longitudinal dataset of individuals over time, I create a unique identification for each individual, which is based on their gender and age. In cases a household has two individuals of the same age and of the same gender, I then consider their relationship with the household head, and the highest grade completed. I drop 298 observations that are unable to distinguish based on observable characteristics (e.g., twins), which accounts for 0.7% of the total sample.

Table A1 shows the number of households and their individuals in the TVSEP sample, as well as in the final sample that is used in the main analysis. As for the total Vietnamese sample, TVSEP has a relatively low attrition rate at the household level, which is 11.7% over the period 2008-2017 or 1.2% annually. The low attrition rate is on par with other high-quality household longitudinal data sets such as the Indonesia Family Life Survey (Thomas, Frankenberg, and Smith 2001). Tracking a group of individuals aged 0-18 years in 2008 over time, most of the attrition at the individual level during the 2008-2013 period was caused by households exiting the survey sample. In 2017, however, attrition was mainly due to individuals exiting the remaining households, which is expected given the higher possibility of split-off households over time when individuals are now in adulthood.

Constructing Education Variables One particular concern about the construction of education outcomes is that the analysis data are not of consecutive years and thus changes

Table A1: Sample Size

	2008	2010	2013	2017
TVSEP Vietnamese sample				
Number of households	2,148	2,107	2,010	1,898
Number of individuals	10,744	11,109	11,295	8,511
Sample of individuals 0-18 years old in 2008				
Number of households	1,711	1,680	1,607	1,384
Number of individuals	4,003	3,938	3,743	2,877
Loss of individuals compared to 2008	-	65	260	1,126
Of which:				
Loss by households exiting the survey	-	61	216	361
Loss by individuals exiting the remaining households	-	4	44	765
Of which, individuals older than 18 years	-	1	21	618
Sample of children in the main empirical analysis				
Number of households	1,446	1,434	1,230	891
Number of individuals	2,960	2,749	2,224	1,519
Share of male individuals	0.504	0.503	0.513	0.505
Share of Kinh individuals	0.750	0.735	0.674	0.697
Mean age	13.109	13.187	13.192	13.399
Median age	13	14	13	14

Notes: Sample of children in the main empirical analysis includes children who were 7-18 years old at the time of any wave of the survey and appeared in at least two waves of survey.

in educational outcomes could be misattributed over time. For example, non-enrollment in a given year may be a result of drop-out in a previous year, and not because of some specific shock. This concern is mitigated with two additional survey questions that help determine whether and when a student has dropped out of school, as well as whether they have graduated. Specifically, the answer to the survey question "How old was [the member] when he/she left school?," determines when a child has dropped out of school, and the answer to "What was [the member]'s highest educational attainment?" helps verify whether a student has graduated, which together with data from other years can help determine their graduation year. In defining the final analysis sample, I apply two restrictions. First, if a child is reported to leave school more than two years prior to the current survey, she is no longer in the sample analysis in the current and subsequent surveys. Second, if a child is reported to have attained grade 12 as her highest educational level and left school before the current survey, she is considered already graduated and therefore not part of the analysis sample even if she is still in the school-age range. Together, the two restrictions remove 440 observations from the final analysis sample. This source of measurement error, however, becomes more concerning for on-track measure, for which I do not have additional information to infer the exact year during which there was a delay in schooling. Therefore, findings on the on-track outcome should be interpreted with caution.

Table A2 illustrates how enrollment and on-track variables are constructed. The first individual (ID 1) is observed in four survey waves. The child was enrolled in school in 2008 and 2013, when they were 7 and 12 years old, respectively. In these two years, the enrollment variable is coded 1. In 2010, because this child was not enrolled and did not report to leave school, the enrollment variable takes value 0. In the 2017 survey, the child reported to have left school when they were 13 years old and their highest educational attainment was grade 6. As a result, their 2017 observation is not considered part of the analysis. Turning to the on-track measure, the student was considered on track in 2008 because age minus grade is at most 6, but this student was not on-track in 2013 because they progressed to the next four grades over the course of five years.

The second individual (ID 2) is also observed in four survey waves. The student was enrolled in 2008-2010-2013 and considered on-track in these years. In 2017, however, they were not enrolled in school and reported to have left school when they were 15. For this student, I assume that the non-enrollment when they were 16 could have been attributed to shocks that happened between the age of 14-16 (e.g., current and last year rainfall shocks). As a result, the enrollment variable in the survey wave 2017 is coded 0 and their 2017 observation is still considered part of the analysis.

The third individual is first observed when they were 13 years old. Because of the non-consecutive year structure of the panel data, their 2017 observation is automatically

Table A2: Variable Construction

ID	Year	Age	Grade If Enrolled	Highest Attainment	Age Left School	Enrollment	On-track	Sample
1	2008	7	1	.	.	1	1	Yes
1	2010	9	.	.	.	0	.	Yes
1	2013	12	5	.	.	1	0	Yes
1	2017	16	.	6	13	.	.	No
2	2008	7	1	.	.	1	1	Yes
2	2010	9	3	.	.	1	1	Yes
2	2013	12	6	.	.	1	1	Yes
2	2017	16	.	9	15	0	.	Yes
3	2008	13	8	.	.	1	1	Yes
3	2010	15	10	.	.	1	1	Yes
3	2013	18	.	12	17	.	.	No
3	2017	22	.	12	17	.	.	No

dropped from the analysis. Since the student reported to leave school when they were 17 years old, and already completed 12 years of education, the student was considered graduated and their 2013 observation when they were 18 years old is not part of the analysis.

Attrition Analysis Table A3 presents the attrition analysis for the sample of individuals aged 0-18 years in 2008. I compare former-wave observable characteristics of individuals and their households in each two-wave panel. Results from pairwise t-tests and the F-test of overall significance suggest that attrition appears to be random until the survey wave 2013. In 2017, individual age, gender, and ethnicity are important determinants of the attrition. However, there is no evidence of significant correlation between attrition and the measure of rainfall shocks.

Based on this group, I then restrict the sample of main empirical analysis to children who were 7-18 years old at the time of each survey wave and were surveyed at least twice over the study period. The gender and ethnicity composition of the analysis sample remains relatively stable over time, with approximately 50% being boys, and 30% being ethnic minorities. So does the age distribution (See Table A1).

Table A3: Attrition Analysis

	Panel 2008-10			Panel 2010-13			Panel 2013-17		
	Stay	Exit	p-val	Stay	Exit	p-val	Stay	Exit	p-val
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Individual characteristics									
Individual age	12.064	11.667	0.665	14.103	13.306	0.170	16.038	19.064	0.000
Individual gender (1=Male)	0.278	0.333	0.481	0.275	0.329	0.278	0.313	0.203	0.000
Ethnicity (1=Kinh)	0.758	0.879	0.108	0.759	0.741	0.705	0.729	0.533	0.000
Household characteristics									
Head is male	0.866	0.818	0.427	0.860	0.835	0.521	0.864	0.825	0.037
Head's main occupation is farmer	0.682	0.515	0.042	0.671	0.647	0.650	0.647	0.679	0.199
Share of members aged 16-59	0.581	0.619	0.296	0.616	0.578	0.155	0.650	0.712	0.000
Share of children aged 0-5	0.096	0.120	0.326	0.068	0.082	0.283	0.056	0.042	
Exposure to shocks									
Current year shocks	2.585	2.444	0.282	1.307	1.475	0.225	0.950	0.995	0.278
Previous year shocks	1.080	0.940	0.309	1.012	1.129	0.194	1.602	1.576	0.706
p-val for F-test of shocks			0.185			0.339			0.517
p-val for F-test of characteristics & shocks			0.175			0.688			0.000
Household income and consumption									
Total income	1369	1041	0.400	1443	1290	0.512	1649	1697	0.771
Income from agriculture	706	338	0.224	416	292	0.150	501	419	0.154
Total consumption	1156	1625	0.002	1193	1166	0.780	1421	1301	0.036

Notes This table shows the mean of the former-year characteristics of children (and their households) who are observed (Stay) and not observed (Exit) in the latter year of each panel. Children include those who were 0-18 years old in 2008. Columns (3), (6), and (9) present the p-value obtained from the student's t-test of equality of means in the corresponding two columns Stay vs. Exit in each panel. Rainfall shocks are defined as in the main text. All monetary variables are expressed in 2005 US$ (PPP) per capita, i.e., normalized by the number of members who stay in the household for at least 180 days during the reference period. Sources: Household and individual data are from TVSEP 2008-17. Rainfall data are from IMERG.

B Placebo Test and Robustness Checks

B.1 Placebo Test

I perform a placebo test that uses the same sample of children but future rainfall shocks as treatment variables. Previous (current) year rainfall shocks are defined using the typhoon season of one year (two years) after the reference period. Because there is no serial correlation in rainfall shocks over time at the local level, future rainfall shocks should not affect current year child outcomes. If the effects of rainfall shocks on child outcomes documented in Table 3 are confounded with omitted variables or trend, this exercise would yield estimates of rainfall shock coefficients of the same sign and similar magnitude to those obtained in the corresponding analysis using the correct rainfall shocks. Table B1 shows that the estimated coefficients on rainfall shocks are smaller in magnitude and statistically insignificant. Underlying trends or omitted variables therefore cannot account for the strong relationship between rainfall shocks and perceived health and education enrollment reported in Table 3, further validating the identification strategy.

B.2 Robustness Checks

I present additional checks to confirm that the results are robust to different specifications, measures of rainfall shocks, and samples. The key coefficients are shown in Table B2.

First, I explore the robustness of the results with alternative specification in which time-varying household-level characteristics are also controlled. The inclusion of such variables could help absorb residual variation and produce more precise estimates but could also be problematic if these variables themselves are considered outcome variables. I re-estimate Equation 1 with the inclusion of time-varying household-level controls. Specifically, these variables include whether the household head is male, whether the household head's main occupation is farmer, household size (number of members),

Table B1: The Effects of Placebo Adverse Rainfall Shocks on Children

	(1) Health	(2) Disease	(3) Enrolled	(4) Ontrack
Current year shocks	0.020	0.003	-0.003	-0.014
	(0.026)	(0.010)	(0.008)	(0.019)
	[0.027]	[0.010]	[0.008]	[0.016]
Previous year shocks	-0.034	0.003	0.012	-0.025
	(0.028)	(0.010)	(0.012)	(0.019)
	[0.027]	[0.010]	[0.014]	[0.016]
N	9012	9012	9012	8234
R^2	0.146	0.009	0.115	0.138
Sample Mean	0.585	0.045	0.914	0.809
Sample SD	0.493	0.208	0.281	0.393

Notes: Same as Table 3, except that previous (current) year rainfall shocks are defined as the sum of standard precipitation index for months with observed rainfall exceeded historical monthly levels by at least one standard deviation during the typhoon season of one (two) year(s) after the reference period. Standard errors clustered at commune and at district level are in parentheses and brackets, respectively. Sources: Individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

the share of children less than 6 years old, the share of 16–59-year-old male members, and the share of 16-59-year-old female members. The results are almost identical to those obtained from the base specification.

Second, the main analysis considers only higher-than-long-term-average rainfall and argues that these shocks can negatively affect the ripening/harvesting phase of main crops. As the typhoon season spans from July to November, it might cover other stages of production, where lower-than-long-term-average rainfall can potentially negatively affect crop yields as well. I construct this type of rainfall shocks using a similar approach as in Section 2.2, except that rainfall is considered negative if it is at least one standard deviation lower than the long-term mean. I then re-estimate Equation 1 with the inclusion of two types of rainfall shocks: lower-than-long-term-average and higher-than-long-term-average. The main coefficients of interests are similar to the baseline results.

Table B2: Robustness Checks:
The Effects of Previous Year Adverse Rainfall Shocks on Children

	(1) Health		(2) Enrolled	
Base specification	-0.113	(0.022)	-0.017	(0.010)
Standard errors clusted at the district level	-0.113	(0.021)	-0.017	(0.007)
Control for household characteristics	-0.112	(0.022)	-0.017	(0.010)
Control for negative shocks	-0.111	(0.022)	-0.015	(0.011)
Use balanced panel instead of unbalanced panel	-0.103	(0.023)	-0.014	(0.009)
Add weights	-0.098	(0.022)	-0.016	(0.010)
Drop DakLak province	-0.090	(0.027)	-0.018	(0.014)
Shock is defined as the number of months with SPI> 1	-0.157	(0.027)	-0.015	(0.011)
Shock is defined as SPI for each month separately where SPI> 1	-0.331	(0.072)	-0.045	(0.038)

Notes: Standard errors clustered at the commune level are in parentheses, unless noted otherwise. Sources: Individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Third, Dak Lak appears to be different from other two provinces in the Central Vietnam in terms of weather patterns, and agricultural production. Given that the average rainfall is generally lower in Dak Lak with relatively little variation over time, positive SPIs could be obtained even though the deviation from the long-term mean is relatively small, making the rainfall shocks constructed based on one-month SPI misleading (World Meteorological Organization 2012). I redo Equation 1 while removing this province. Again, children exposed to more rainfall shocks during the typhoon season last year are less likely to be healthy and enrolled in school.

Fourth, I test the robustness of the results by using a different measure of rainfall shocks—the number of months with SPI exceeding one. Although this measure is easy to interpret, it is not without disadvantage: we cannot take into account the intensity of the shock. Specifically, a month of moderate above-average rainfall with SPI of 1.1 is treated similarly as a month with more intense shock SPI of 2.0 (or above). While the average effects on health and enrollment are of similar sign, they are less precisely estimated.

Fifth, one might worry that the original measure of rainfall shocks cannot capture the potentially different effects of two scenarios, for example, a rainfall shock of 3.3 could mean there was extreme rainfall (SPI of 3.3) in one month or more moderate above-normal rainfall (SPI of 1.1) in three months. To test if this is the case, I define shock as SPI of each month with excess rainfall during the season. Because each year has at most three months with SPI>1 during the typhoon season, I proxy for shock by three separate variables: SPI of the first month (conditional on being greater than 1), SPI of the second month (conditional on being greater than 1), and SPI of the third month (conditional on being greater than 1) and estimate a variant of Equation 1:

$$y_{ispw} = \sum_{j=1,2,3} \beta_{cj} R_{sw,j} + \sum_{j=1,2,3} \beta_{lj} R_{sw-1,j} + X'_{iw}\gamma + W'_{sw}\eta + \theta_i + \theta_{pw} + \varepsilon_{ispw} \tag{S1}$$

where $R_{sw,j}$ denotes the value of SPI of the jth month with excess rainfall ($SPI > 1$) during the season. By estimating Equation S1, we can estimate the potentially differential effects of, for example, three months with sum SPI 3.3 and a month with SPI 1.1. The coefficients on $R_{sw,1}$, $R_{sw,2}$, $R_{sw,3}$ obtained from this regression, however, are similar and I cannot reject the null hypothesis that they are equal.

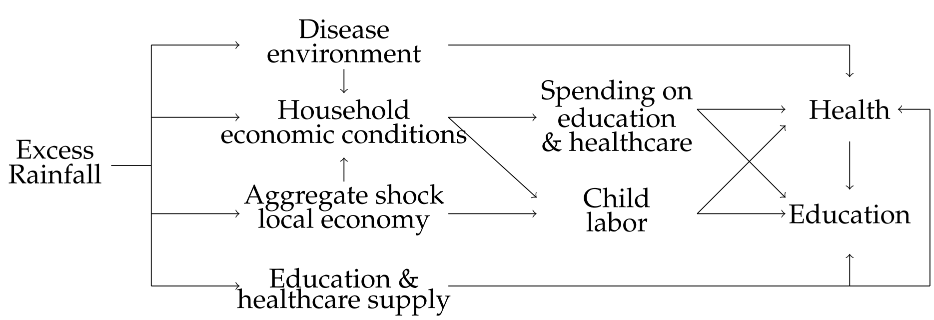
I then calculate the cumulative effect of current year rainfall shocks by computing a sum of $\beta_{c1}, \beta_{c2}, \beta_{c3}$ and conduct hypothesis testing with the null hypothesis being $\beta_{c1} + \beta_{c2} + \beta_{c3} = 0$. Similarly, I test the null hypothesis of cumulative previous year shocks. As shown in the last row of Table B2, the results remain qualitatively similar. It should be noted that we cannot directly compare the point estimates obtained from this exercise with the base specification because the measure of shock is constructed differently. To proceed, let us revisit the example above: suppose last year shock has $SPI = 3.3$, and we are interested in knowing the potentially differential effects of two scenarios: (i) one month with $SPI = 3.3$, and (ii) three months with $SPI = 1.1$. According to the base specification, the total effect of previous year shocks on perceived health status is $3.3 \times (-0.110) = -0.333$. According to this exercise, the corresponding total effect of previous year shocks is $1.1 \times (-0.317) = -0.349$. These two effects are similar in magnitude.

The results reported so far do not employ sampling weights and are from the analysis of the sample of children who were surveyed at least twice. The results are robust to using weights, and to the balanced panel of individuals who appear in all four waves of the survey.

C Potential Mechanisms

The following Figure illustrates the multiple pathways via which exposure to rainfall shocks can directly or indirectly affect the health and education of children. These mechanisms can be categorized into four groups: disease environment, household economic conditions (spending on health and education), aggregate shock on local economy, and education and healthcare supply. This section explains relevant empirical literature and why disease environment, education and healthcare supply, as well as aggregate shock on local economy are unlikely the mechanisms.

Potential Pathways



Disease environment Above-average rainfall can harm children's health through immediate changes in the disease environment, including that of vector-borne, water-related diseases, and enteric illnesses, particularly for vulnerable populations (Hales, Edwards, and Kovats 2003). If heavy precipitation is associated with flooding and tropical cyclones, the health effects could be more severe, including increased mortality rates. Although most physical health problems occur within four weeks of these weather events (Saulnier, Brolin Ribacke, and Schreeb 2017), anxiety could last up to two years after, thereby worsening their health (Alderman, Turner, and Tong 2012). The resulting poor physical and especially mental health could in turn lower their education performance (Ding, Lehrer, Rosenquist, and Audrain-McGovern 2009; Fletcher and Lehrer 2011).

The null effects on infectious disease incidence presented in Section 3 however imply that it is unlikely the disease environment that could drive the results. In addition, that rainfall shocks do not affect grade progression once students are enrolled in school also rules out the mental health channel.

Education and healthcare supply Another mechanism is through the effects of heavy rainfall on education and healthcare supply. Heavy rainfall associated with typhoons and strong winds could destroy or damage health care facilities and schools, which might result in higher search and transportation costs, increasing the marginal cost of education and health investments. If this is the case, then we should have also observed contemporaneous effects on health. It is hard to think that any damages to health care facilities caused by rainfall shocks one year only affect student health next year but not the same year. Thus, healthcare supply is unlikely the mechanism.

As for educational outcomes, we observe a decline in school enrollment following a same-year shock, but such an effect is most prevalent among older minority children. We also observe a decline in school enrollment following a previous year shock and such an effect is driven by minority children. These seem to be consistent with education facilities in remote areas for minority children more likely being damaged by rainfall shocks. However, if education supply was the driver, we should have also observed a comparable contemporaneous negative effects on enrollment among younger minority children.

Aggregate shock on local economy Excess rainfall can cause an aggregate shock to the local economy, dampening demand for labor and decreasing both employment and wages. On one hand, this might decrease child labor participation and improve child education by lowering the opportunity cost of children's time in school. It is also possible that following an aggregate adverse shock, labor reallocation in the local market could potentially improve marginal product of labor and thus positively affect local wage (Kirchberger 2017). In that case, parents would face trade-offs between investing in children's education and increasing child labor for productive work (Shah and Steinberg 2017). The increase in child labor could interrupt their studies and adversely affect their health.

To test this mechanism, I examine the effects of adverse rainfall shocks on local wages at the district and commune level. Using information from off-farm employment module in the TVSEP dataset, district and commune wages are constructed as the median and mean hourly wages that workers receive from their main occupation in the district and commune, respectively. As shown in Appendix Table D6, there is no evidence that supports the local wages mechanism.

D Additional Tables and Figures

Table D1: Test for Serial Correlation in Rainfall Shocks

Dependent variable is current year rainfall shocks

	(1)	(2)	(3)	(4)
Previous year shocks	0.047	0.068	0.037	0.039
	(0.031)	(0.057)	(0.054)	(0.053)
	[0.049]	[0.061]	[0.066]	[0.066]
R^2	0.965	0.906	0.878	0.882
Province-wave FE	Yes	Yes	Yes	Yes
Observations	2090	440	9452	7170

Notes: Each cell is from a separate regression. The unit of analysis is commune-year in Columns (1)-(2), and individual-year in Columns (3)-(4). The sample is the 2000-2019 period for Column (1), the study period for Column (2), the unblanced sample of children during the study period for Column (3), and the balanced sample of children during the study period for Column (4). In Column (1), shocks are defined as the sum of rainfall deviation from the long-term median monthly rainfall level for July-November. In Columns (2)-(4) current (previous) year rainfall shocks are defined as the number of months with observed rainfall exceeded historical monthly levels by at least one standard deviation during July-November of (one year prior to) the reference period. Standard errors clustered at commune and at district level are in parentheses and brackets, respectively. Sources: Rainfall data are from IMERG.

Table D2: Rainfall Shocks and Crop Yields

	Rice		Annual Crops		Perennial Crops	
	(1)	(2)	(3)	(4)	(5)	(6)
Current year shocks	-0.023	-0.023	0.052	0.050	-0.040	-0.041
	(0.008)	(0.008)	(0.104)	(0.105)	(0.033)	(0.033)
	[0.007]	[0.008]	[0.105]	[0.103]	[0.045]	[0.045]
Previous year shocks	0.010	0.010	-0.000	-0.002	-0.037	-0.037
	(0.009)	(0.009)	(0.092)	(0.092)	(0.035)	(0.035)
	[0.009]	[0.010]	[0.104]	[0.104]	[0.039]	[0.039]
N	4895	4895	4895	4895	4895	4895
R^2	0.092	0.094	0.034	0.036	0.012	0.013
Sample Mean	0.269	0.269	0.710	0.710	0.228	0.228
HH Controls	No	Yes	No	Yes	No	Yes
Province-wave FE	Yes	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column is from a separate regression. The unit of analysis is household-year. Rainfall shocks are defined as in the main text. Sample includes 1,705 households with children in the analysis sample. Crop yields are measured as total volume of production (kilograms) divided by total area of cultivation (squared meters). Household controls include head gender, whether head's main occupation is farmer, household size, share of children less than 6 years old, share of 16-59-year-old male members, share of 16-59-year-old female members. All regressions also control for total rainfall outside of the typhoon season. Standard errors clustered at commune and at district level are in parentheses and brackets, respectively. Sources: Household data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Table D3: Rainfall Shocks and Household Diet and Spending

	Diet Composition		Spending on Education		Spending on Healthcare	
	(1)	(2)	(3)	(4)	(5)	(6)
Current year shocks	-0.095	-0.096	-9.437	-9.682	0.972	1.083
	(0.069)	(0.068)	(9.015)	(9.071)	(9.401)	(9.927)
	[0.092]	[0.091]	[9.351]	[9.186]	[9.067]	[9.419]
Previous year shocks	0.112	0.110	12.521	9.414	1.226	-0.383
	(0.100)	(0.100)	(9.592)	(9.741)	(8.349)	(8.279)
	[0.127]	[0.127]	[8.986]	[9.043]	[9.682]	[9.564]
N	4895	4895	4895	4895	4895	4895
R^2	0.335	0.337	0.174	0.201	0.022	0.028
Sample Mean	5	5	118	118	58	58
HH Controls	No	Yes	No	Yes	No	Yes
Province-wave FE	Yes	Yes	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column is from a separate regression. The unit of analysis is household-year. Diet composition is a count number of six food categories that households have consumed during the reference period, including poutry, egg, beef, fish, vegetables, and fruits. Education and health spending are expressed in per capita term, in PPP$2005. Other notes are similar to Table D2. Standard errors clustered at commune and at district level are in parentheses and brackets, respectively. Sources: Household data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Table D4: Rainfall Shocks and Transfers

	Public Transfers		Private Remittances	
	(1)	(2)	(3)	(4)
Current year shocks	6.634	7.515	47.713	50.590
	(10.520)	(10.560)	(23.406)	(22.237)
	[9.421]	[9.476]	[19.201]	[17.171]
Previous year shocks	13.671	13.749	112.944	107.284
	(11.516)	(11.453)	(31.737)	(29.983)
	[10.755]	[10.672]	[31.245]	[29.934]
N	4895	4895	4895	4895
R^2	0.004	0.007	0.047	0.090
Sample Mean	66	66	204	204
HH Controls	No	Yes	No	Yes
Province-wave FE	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	Yes	Yes

Notes: Each column is from a separate regression. The unit of analysis is household-year. Public transfers include all-purposed transfers from the government and other organizations. Private remittances include transfers from relatives and friends. Other notes are similar to Table D2. Standard errors clustered at commune and at district level are in parentheses and brackets, respectively. Sources: Household data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Table D5: Rainfall Shocks and Outcomes of Household Adults

	Health Outcomes		Labor Outcomes	
	(1)	(2)	(3)	(4)
	Health	Disease	All Actitivites	Economic Activities
Current year shocks	-0.016	0.007	0.005	0.005
	(0.014)	(0.009)	(0.005)	(0.006)
	[0.014]	[0.010]	[0.005]	[0.006]
Previous year shocks	-0.025	0.005	-0.007	-0.005
	(0.014)	(0.009)	(0.009)	(0.009)
	[0.016]	[0.009]	[0.008]	[0.009]
N	16357	16357	16357	16357
R^2	0.116	0.072	0.153	0.124
Sample Mean	0.282	0.097	0.910	0.882
Sample SD	0.450	0.296	0.287	0.323

Notes: Each column is from a separate regression. Rainfall shocks are defined as in the main text. Sample includes individuals who appeared in at least two waves of the survey. Analysis is restricted to 7821 individuals in the age range 20-59. All regressions include individual age, household controls (head gender, whether head's main occupation is farmer, household size, share of children less than 6 years old, share of 16-59-year-old male members, share of 16-59-year-old female members), total rainfall outside the typhoon season, province-specific wave fixed effects, and individual fixed effects. Standard errors clustered at commune and at district level are in parentheses and brackets, respectively. Sources: Individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Table D6: Rainfall Shocks and Local Wages

	Local		Agriculture		Industry		Service	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median wage								
Current year shocks	-0.016	-0.025	0.017	-0.018	-0.027	-0.034	0.170	0.119
	(0.032)	(0.043)	(0.041)	(0.045)	(0.068)	(0.061)	(0.139)	(0.168)
Previous year shocks	-0.012	-0.018	0.097	0.092	0.016	0.058	-0.164	-0.235
	(0.047)	(0.050)	(0.081)	(0.089)	(0.057)	(0.063)	(0.131)	(0.222)
R^2	0.529	0.631	0.693	0.771	0.570	0.714	0.464	0.458
Sample Mean	1.4947	1.4947	1.438	1.438	1.634	1.634	1.444	1.444
Mean wage								
Current year shocks	-0.006	0.000	0.037	0.032	-0.003	-0.022	0.210	0.211
	(0.036)	(0.058)	(0.046)	(0.068)	(0.077)	(0.079)	(0.136)	(0.166)
Previous year shocks	0.124	0.113	0.253	0.250	0.052	0.106	-0.171	-0.214
	(0.096)	(0.091)	(0.183)	(0.180)	(0.105)	(0.116)	(0.137)	(0.222)
R^2	0.329	0.403	0.580	0.637	0.555	0.676	0.382	0.397
Sample Mean	1.5749	1.5749	1.483	1.483	1.692	1.692	1.583	1.583
Province-wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commune FE	No	Yes						
District FE			No	Yes	No	Yes	No	Yes
Observations	428	428	113	113	122	122	116	116

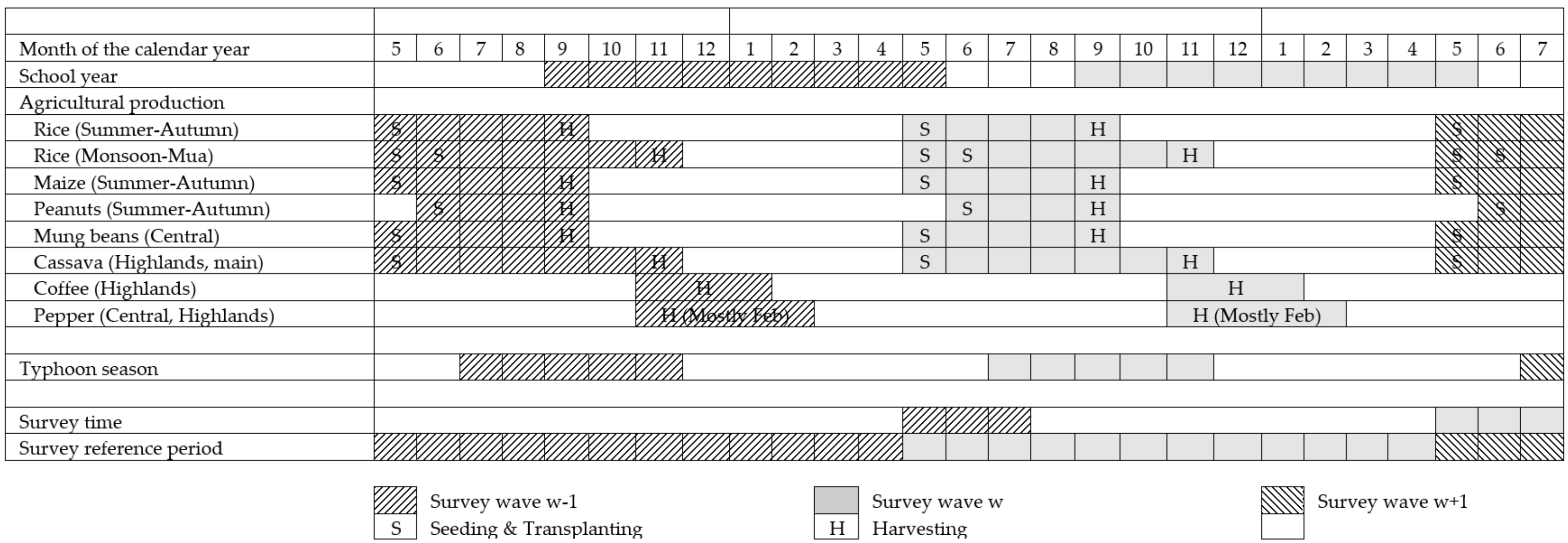
Notes: The unit of analysis is commune-year in Columns (1)-(2), and district-year in Columns (3)-(8). Rainfall shocks are defined in the main text. In Columns (1) and (2), dependent variable is constructed as median (mean) hourly wages that all workers receive from their main job in the same village or commune, regardless of the industry in which they were working. In Columns (3) and (4), dependent variable is constructed as median (mean) hourly wages that all workers receive from their main job in the same district, in agricultural sector. In Columns (5) and (6), dependent variable is constructed as median (mean) hourly wages that all workers receive from their main job in the same district, in industrial sector. Standard errors are clustered at commune level for the first two columns, and at district level for the remaining. Sources: Household and individual data are from TVSEP 2008-17. Rainfall data are from IMERG.

Table D7: Mechanisms: Rainfall Shocks and Household Outcomes by Ethnicity

	(1) Public Remittances	(2) Private Remittances	(3) Diet Composition	(4) Spending Education	(5) Spending Healthcare
Current year shocks	6.253	39.599	-0.034	-24.036	-4.840
	(10.884)	(24.617)	(0.068)	(9.328)	(10.805)
	[12.298]	[20.298]	[0.083]	[9.022]	[11.133]
Current year shocks × Minority	1.942	24.059	-0.171	43.719	17.509
	(7.521)	(10.946)	(0.047)	(5.888)	(8.362)
	[14.087]	[13.005]	[0.034]	[8.511]	[9.572]
Previous year shocks	13.036	107.907	0.145	3.247	-2.518
	(11.848)	(32.323)	(0.095)	(9.034)	(8.438)
	[10.923]	[30.879]	[0.113]	[8.621]	[10.005]
Previous year shocks × Minority	10.984	4.452	0.098	13.726	6.872
	(9.911)	(25.053)	(0.097)	(9.758)	(7.226)
	[9.044]	[25.345]	[0.092]	[9.600]	[6.888]
N	4895	4895	4895	4895	4895
R^2	0.004	0.047	0.339	0.188	0.024
Sample mean for Kinh	66.531	252.440	4.981	138.740	66.666
Sample mean for Minority	63.805	45.217	4.075	47.491	31.566

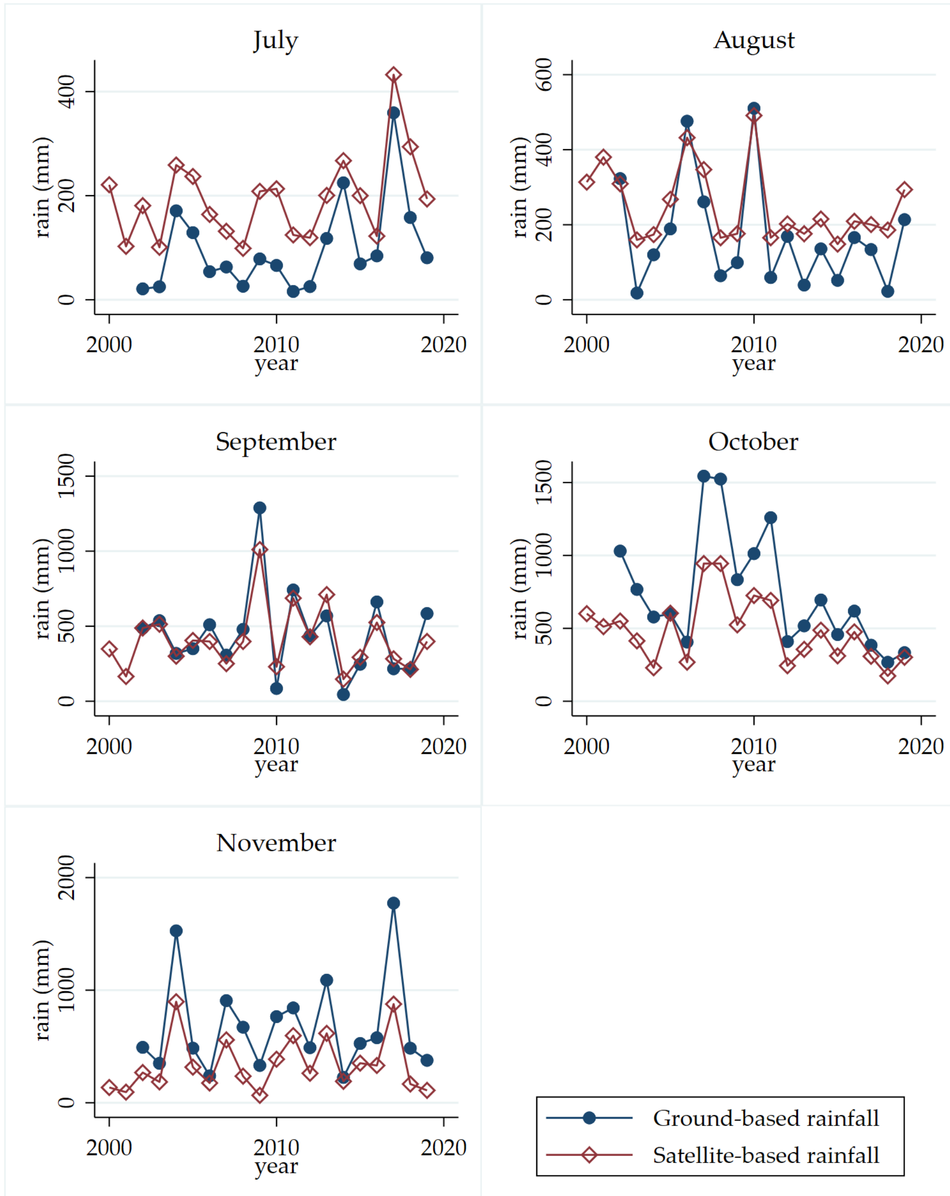
Notes: Each column is from a separate regression. Rainfall shocks are defined as in the main text. Standard errors clustered at commune and at district level are in parentheses and brackets, respectively. Sources: Individual data are from TVSEP 2008-2017. Rainfall data are from IMERG.

Figure D1: Timing of School Year, Agricultural Production, Rainfall Shocks



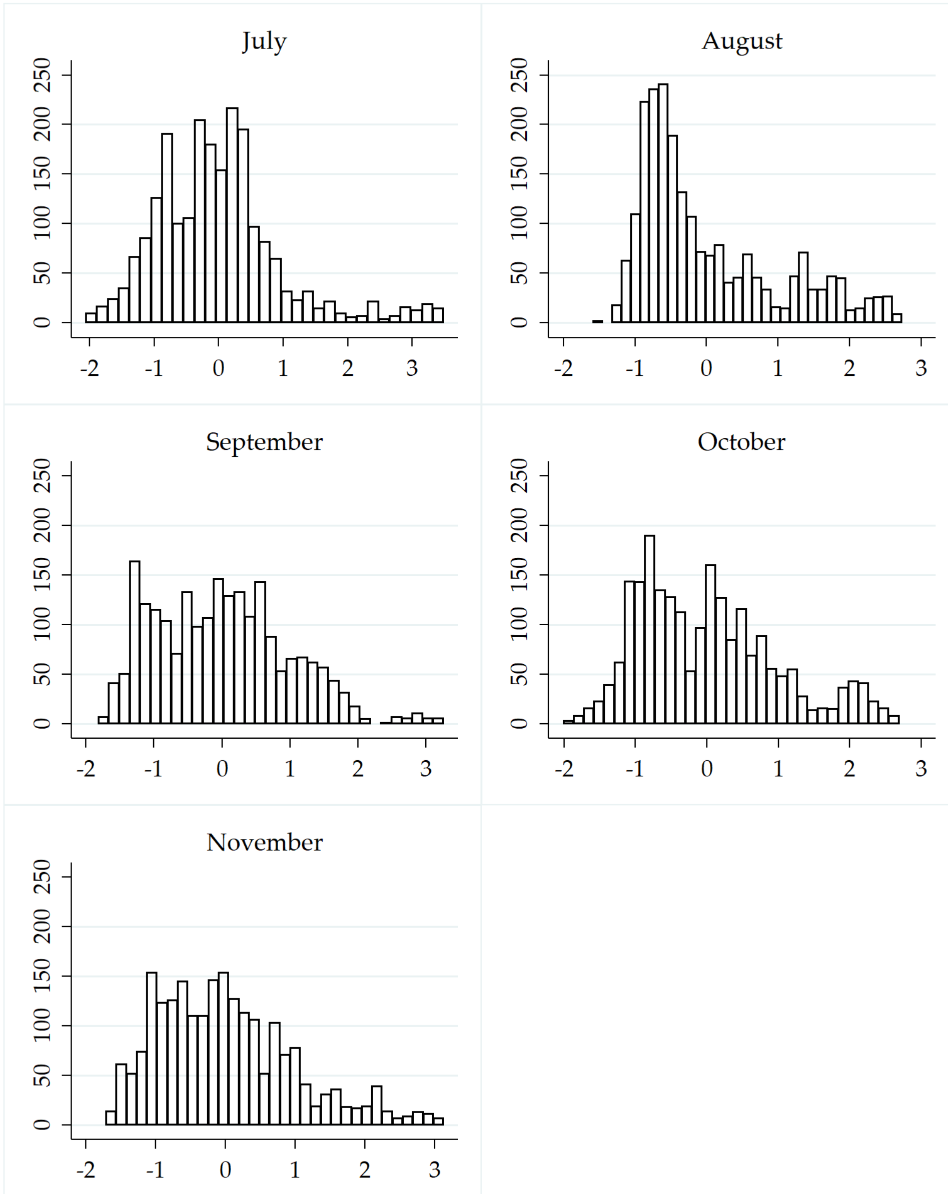
Notes: This figure shows the timing of school year, common crop production cycles, the definition of extreme rainfall variables with respect to the survey reference period and to the months of the calendar year. Current year rainfall shocks are defined during the typhoon season (July to November) of the reference period w. Previous year rainfall shocks are defined during the typhoon season (July to November) of the year w-1.

Figure D2: Ground-based Rainfall vs. Satellite-based Rainfall



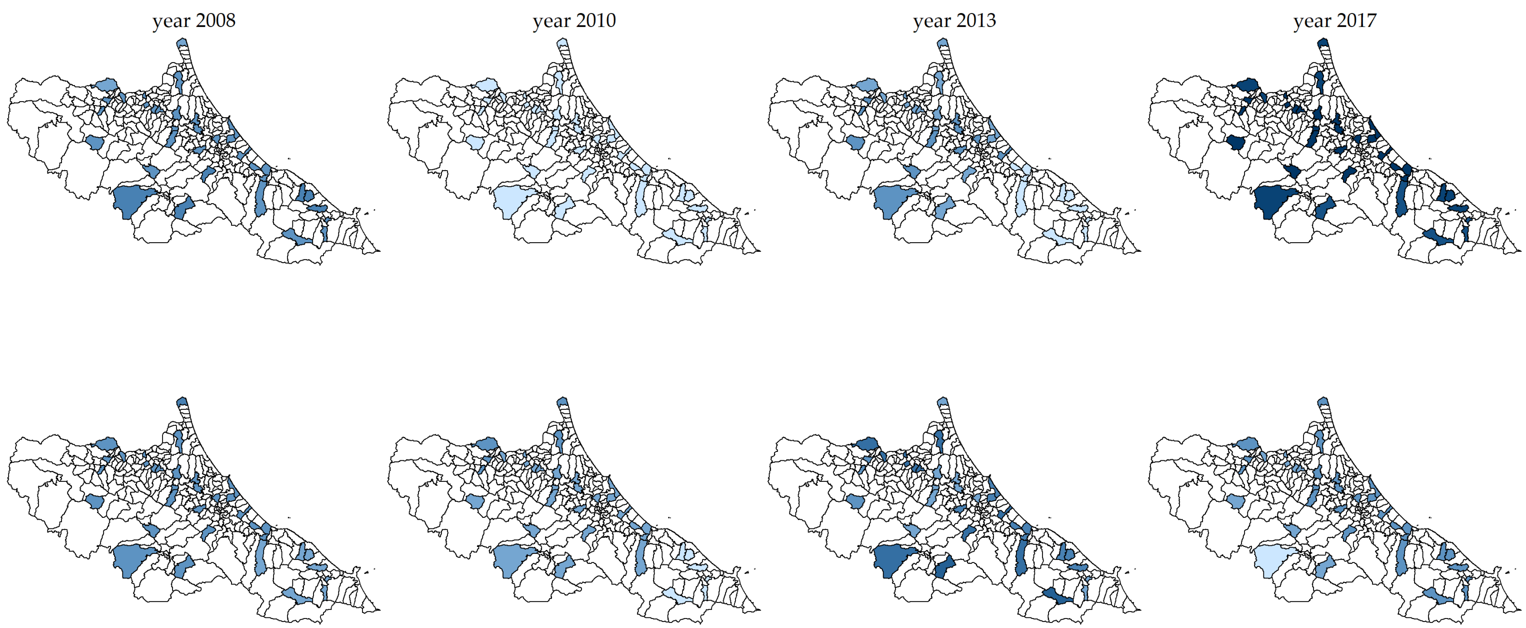
Monthly rainfall data for Hue City. The pairwise correlation coefficients between ground-based rainfall and satellite-based rainfall in July, August, September, October, and November are 0.9199, 0.9643, 0.9417, 0.9383, and 0.9509, respectively. Sources: Ground-based rainfall data are from the official website of the General Statistics Office of Vietnam and available for the 2002-2019 period (Accessed July 2021). Satellite-based rainfall data are from IMERG and available for the 2000-2019 period.

Figure D3: Distribution of Standardized Precipitation Index (SPI) by Month



Notes: This figure shows the distribution of standardized precipitation index by month. Standardized precipitation index of commune s in month m in year y is calculated as $SPI_{msy} = (R_{msy} - \overline{R_{ms}})/\sigma_{ms}$ where R_{msy} is the observed rainfall for a given month m in year y at commune s, $\overline{R_{ms}}$ is the long-term mean for month m at commune s, and σ_{ms} is the corresponding standard deviation. The index helps determine the level of excess relative to the climatological norm for the location. Rainfall data are from IMERG and available for the 2000-2019 period.

Figure D4: Spatial Distribution of Rainfall Shocks in Ha Tinh



Notes: First row denotes current year rainfall shocks, and second row denotes previous year rainfall shocks of the corresponding year. Current (previous) year rainfall shocks are defined as the sum of standard precipitation index for months with observed rainfall exceeded historical monthly levels by at least one standard deviation during the typhoon season of (one year prior to) the reference period. Darker color indicates more shocks. White color indicates no data. Sources: Rainfall data are from IMERG.