Weather shocks, coping strategies and human capital investment: Evidence from Indonesia

*Andrew M. Simons and Brian C. Thiede**

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Abstract

This paper examines educational outcomes in response to weather-related shocks. We focus on how temperature and rainfall shocks affect schooling investments and outcomes among Indonesian children. Our study places attention on the link between moderate one-off shocks, vulnerability, and an outcome—education—with long-term development implications. We draw upon a combination of high-resolution weather data from NASA and four rounds of the Indonesian Family Life Survey (IFLS). We estimate regression models with random effects and event history models to estimate weather effects on household educational investments and school enrollment, respectively. We identify differences in the effect of weather shocks on school enrollment across correlates to vulnerability at the household and community levels. These include gender, wealth, and community setting.

Keywords: environmental shocks, human capital investment, vulnerability, education, gender effects, Indonesia

* Simons: Charles H. Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY 14850 (e-mail: ams727@cornell.edu); Thiede: Department of Sociology, Louisiana State University, Baton Rouge, LA 70803 (e-mail: bthiede@lsu.edu).

1. Introduction

Moments of rapid, unexpected, and exogenous change—or shocks—often pose significant challenges to the world's poorest households. These events also provide an opportunity to understand how and why households are adversely affected, as well as whether certain types of households are more or less vulnerable. The insights gained through research on shocks is therefore useful for developing informed expectations about vulnerability to longer-term climatic changes, and developing evidence-based resilience-building interventions.

Shocks come in many forms; environmental, economic, and disease are some of the most studied in the developing world (Asfaw & von Braun, 2004; Smith, Thomas, Frankenberg, Beegle, & Teruel, 2002; Thiede, 2014). Understanding how the poor are affected by, and respond to shocks is essential to governments, researchers, and policymakers working to protect the poor and enhance their ability to cope and thrive in challenging situations.

The manifestations of climate change—and expected future impacts—have spurred increased interest in understanding how individuals, households, and communities are affected by, and response to environmental change. This is not a new area of interest *per se* (see also Corbett, 1988; De Wall, 2004; Kinsey, Burger, & Gunning, 1998; Watts & Bohle, 1993), but the volume and sophistication of research on this topic has increased significantly in recent years. To date, scholars have been largely interested in the economic and demographic impacts of environmental change. Outcomes include poverty and expenditures (Dercon, Hoddinott, & Woldehanna, 2005; Little, Stone, Mogues, Castro, & Negatu, 2006), food consumption (Hoddinott, 2006; Hoddinott & Kinsey, 2001), and migration (Gray & Bilsborrow, 2013; Gray & Mueller, 2012). As well, the study of poverty traps—self-reinforcing mechanisms that cause poverty to persist (Azariadis & Stachurshi, 2005; Carter & Barrett, 2006)—shows that households often experience long term negative dynamics after falling below a threshold of asset poverty, often as a result of a shock. However, less research has examined whether and how household support for children's education is affected by the *immediate* impacts of, and responses to weather shocks.

The most analogous research examines the long-term effects of early exposure to shocks on human development and wellbeing over the *long run*. Typical studies focus on how *in utero* and/or early life shocks or relate to developmental outcomes much later in life. The fetal origins hypothesis originally proposed by Barker (1990) and more recently reviewed by Almond and Currie (2011) show how insults to fetal health *in utero* can cause large and far reaching effects much later in life (such as physical and cognitive development, income, and educational attainment). The early life shocks studies, many reviewed in Ferreira and Schady (2009), have examined topics as diverse as the long term consequences of childhood malnutrition (Alderman, Hoddinott, & Kinsey, 2006; Hoddinott & Kinsey, 2001), increases in adult earnings attributed to better early childhood nutrition (Hoddinott, Maluccio, Behrman, Flores, & Martorell, 2008), how forest fires affect child mortality (Frankenberg, McKee, & Thomas, 2005; Jayachandran, 2009), and how childhood environment affects economic and social indicators as far as sixty years into the future (Gould, Lavy, & Paserman, 2011).

Our present study is informed by these literatures, but also adds important differences. Like the poverty traps literature we are interested in the dynamics of a household's response to shocks, however we do not aim to define a threshold, nor prescribe policy for how to prevent households from falling below certain thresholds. Like the fetal origins hypothesis and early-life shocks literature, we examine how shocks affect households, but we focus on shorter-term outcomes, and smaller and moderate one-off shocks as opposed to major shocks like natural disasters or a financial crisis. Further, we narrow our focus and examine the link between moderate shocks and household decisions on educational investments and outcomes in Indonesia.

The paper is proceeds as follows. In section 2 we review how our study compares with related literature that examines shocks in the context of Indonesia, educational attainment, or both. Then we describe our data in section 3 and describe the construction of our outcome measures in section 4. We describe econometric methods in section 5 and report results in section 6. Finally we discuss and conclude (section 7).

2. Weather shocks, vulnerability, and child educational outcomes

This paper examines the effect of weather shocks on child educational outcomes, and examines potential between-group differences in these effects. Such differences would not only reflect inequality with respect to the distribution of pre-shock (*ex ante*) vulnerability to weather shocks, but also suggest that the long-term economic trajectory of children is likely to diverge according to group membership. That is, if a one-off weather shock leads to increased risk of school dropout in some group A, but not in some group B, we can expect the long-term prospects for upward social and economic mobility to differ between children in groups A and B. In this way, the interaction between weather shocks and unequally distributed vulnerability may produce new patterns of between-group stratification that persist across generations.

We examine this outcome in the Indonesian context. Due to the Indonesia's size and propensity to experience natural disasters—as well as the volume of high quality data—numerous studies have examined household coping strategies there. We review this literature and highlight additional contributions relevant to our study. We also examine the literature relating shocks and household's investments in children in other developing countries.

(a) Shocks, Indonesia, Education and Gender Bias

Numerous studies examine the effect of major shocks on investment in children's human capital in Indonesia. For example, Cameron and Worswick (2001) examine how income shocks due to El Niño, along with the financial crisis of the late 1990s, affected income and resultant investments in children's education among Indonesian households. Using the 1993 Indonesian Family Life Survey (IFLS), they find that among families exposed to negative income shocks, those with girls have a higher propensity to cut back on educational expenditures than do those with boys.

Thomas et al. (2004) examine the effects of the financial crisis of the late 1990s on education. They find that household spending on education declines, and most dramatically among the poorest households. Moreover, poor households attempted to protect education spending for older children at the expense of education spending on younger children. Another study examining how the financial crisis of the late 1990s affected investments in Indonesian children found somewhat contrary results. Levine and Ames (2003) use the nationally representative National Socio-Economic Survey (SUSENAS) and found that children were relatively unhurt by the crisis. They examine school enrollment, immunizations, and child mortality and find that while immunization rates fell in rural areas, children were not largely negatively affected in terms of school enrollment or mortality. Further, contrary to other studies, they found that girls were not harmed more than boys.

Finally, Gertler and colleagues examine the effect of a major shock on children's educational outcomes in Indonesia using parental death as a shock (rather than a major financial crisis) (Gertler, Levine, & Ames, 2004). Using 1994-96 SUSENAS data they find a large effect of parental death lowering children's enrollment rates, but little differential treatment based on gender.

(b) Shocks, Indonesia, and Long-Run Human Capital Accumulation

Another set of papers examines the long-term effects of shocks on human capital accumulation in Indonesia. Maccini and Yang (2009) find that among persons born between 1953-1974, rainfall shocks in early life affect adult health, education and socioeconomic status (measured in 2000). The estimated effects are much more pronounced in females than in males. For example, women who lived in an area with 20 percent more rainfall than usual in their birth year are 3.8 percentage points less likely to report poor health as an adult, 0.57 centimeters taller, completed 0.22 more grades of school, and live in households that scored 0.12 standard deviations higher on a constructed asset index. Maccini and Yang further argue that rainfall's effects on crop productivity, and therefore household income and food availability, is the channel that leads to these differences in adult outcomes. They also test whether rainfall shocks *in utero* impact adult outcomes, finding that rainfall in the year after birth accounts for all the results they observe rather than rainfall during pregnancy.

In a related but smaller study of 98 agricultural Indonesian villages, Yamauchi (2012) examines children aged 0-12 in 2010 and finds a relationship with birth weight and birth month, and suggests that between-month differences are caused by agricultural production seasonality. He further finds that an increased birth weight improves child growth outcomes such as height and weight z-scores, and that children with higher birth weight have fewer delays in starting school and fewer repeated grades.

(c) Shocks and Investment in Children in other Developing Countries

In addition to the Indonesian context, there are other important studies that have examined these issues in other developing countries. For example, Jensen (2000) examines changes to investment in children in response to income shocks in Cote d'Ivoire. He finds that critical investment in children (school enrollment, short term nutritional status, use of medical services) suffer dramatically when shocks deteriorate agricultural conditions. Jacoby and Skoufias (1997) examine how school attendance responds to seasonal fluctuations in the income of agrarian households in rural India. They find that seasonal fluctuations in school attendance are a form of self-insurance for households when negative shocks occur. Björkman-Nyqvist (2013) uses exogenous variation in rainfall in rural Uganda to estimate the causal effects of household income shocks on children's enrollment rates and educational performance. She finds negative deviations in rainfall from the long term mean have negative effects on female enrollment (especially for older girls). There is no effect on enrollment for boys or young girls. Additionally, negative income shocks negatively affect female student test scores, but not male student test scores.

Datar, Liu, Linnemayr and Stecher (2013) examine moderate one-off shocks in the Indian context. Similar to our study, they examine the effect of small and moderate shocks, but focus on health outcomes rather than educational outcomes. They find that exposure to a small or a moderate disaster in the preceding month increases the likelihood of diarrhea, fever, and acute respiratory illness in children by 9-18 percent. Exposure to a disaster in the past year reduces height-for-age and weight-for-age z-scores by 0.12–0.15 units, increases the likelihood of stunting and underweight by 7 percent, and reduces the likelihood of full age-appropriate immunization coverage by 18 percent. Further, they find that effects vary significantly by gender, age, and socioeconomic characteristics: growth outcomes are smaller among boys, infants, and families with more socioeconomic resources.

The aim of our paper is not to understand long-term human capital accumulation in Indonesia such as Maccini and Yang (2009) or Yamauchi (2012), but rather to understand the dynamics of how Indonesian families respond to moderate one-off shocks in the context of children's education. While there is an active and robust literature that examines household's responses to shocks in Indonesia, most papers focus only on major shocks such as financial crises (Levine & Ames, 2003; Thomas et al., 2004), major weather events caused by El Niño (Cameron & Worswick, 2001), or death of a parent (Gertler et al., 2004). As well, the growing literature on vulnerability to climate change has focused largely on short-term economic and demographic impacts—such as changes in expenditures, food consumption, nutrition, and migration—with little attention to short-run educational outcomes. Given the clear implications of education for the long-run life outcomes of affected youth, research on this topic is important. To the best of our knowledge, we present the first evidence of household's education-related responses to small and moderate shocks in Indonesia.

3. Data

Our analyses draw upon four panels of data from the Indonesian Family Life Survey (IFLS). The IFLS collected a comprehensive set of social and demographic data on over 30,000 individuals between 1993 and 2008. The sample of survey respondents was drawn from the population in 13 of Indonesia's 27 provinces and is representative of approximately 83 percent of the national population. The IFLS has a remarkably high rate of follow-up from one panel to the next. For example, 88 percent of eligible participants interviewed in IFLS1 were also interviewed in IFLS4 (Thomas et al. 2012). For our purposes, we use the four IFLS panels to construct a three-period dataset: period one spans from IFLS1 to IFLS2, period two from IFLS2 to IFLS3, and period three from IFLS3 to IFLS4. We will refer to the baseline of each period as the "period baseline" or t_0.

We examine educational investments in, and rates of school dropout and disruption among children aged 14 and under. Comparable data were not collected among youth or adults aged 15 and above. In order to link the period baseline covariates with inter-survey and end-of-period educational outcomes, we restrict our analytic sample to individuals who were observed during two consecutive surveys and were aged 14 or younger during at each end-of-period observation. In doing so, we exclude adolescents that reached age 15 during the inter-survey period.

We link observations from the IFLS to rainfall and temperature estimates for years 1983 through 2011, the longest period available for which data were available at the time they were aggregated. We use weather estimates produced by NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al., 2011). Geo-coordinates for IFLS observations are currently available only for the 304 communities in which the first round of the IFLS was fielded in 1993 and 1994. For the purposes of this study, we therefore drop observations outside of these communities.

The abovementioned restrictions are a potential source of bias in our results. The likelihood of such bias is equal to the extent that children in households that migrated from the original 304 communities, reached or exceeded 15 years of age, or dropped out of the study were disproportionately more or less likely to experience adverse educational outcomes. Our final analytic sample includes a total of 12,360 person-period observations; with variation in the population at risk of the three outcomes we model (see below).

4. Measures

We estimate the effect of weather shocks on three outcomes among children age 14 and under at the end of each inter-survey period: school dropout, school disruption, and educational investments. We define *school dropout* as children who were in school at the period baseline or entered school after the period baseline; but were not enrolled in school at the end of the period and had not graduated from the level of school they last attended (e.g., primary school). Children who did not continue their education due to said graduation were not identified as dropouts in this analysis, although this arguably represents an adverse outcome as well.

We identify children experiencing *school disruption* if they reported leaving but reentering school. The questions we use to identify children who experienced school disruption changed between IFLS3 and IFLS4. The precise reference period differs between the former two rounds and the latter; and the former only include data on school disruption among children still in school at the end of the period. We likely capture the average effect of these definitional changes by controlling for period fixed effects, but one should still interpret the results of this section with serious caution (and as provisional).

Finally, we estimate household *educational investments* in children using reported expenditures on education during the year prior to the end-of-period survey. We include the following categories of expenditures in this category: school registration, other scheduled fees, exam fees, books and writing supplies, uniforms, sports, transportation, housing and food, special courses, and other school-related expenses. These expenditures were reported for each child age 14 and younger at the time of the end-of-period survey. Expenditures are contingent upon enrollment in school. We set all expenditures for children not enrolled in school during the year in question as zero rupiah, the official Indonesian currency.

Our analyses focus on the effect of weather conditions on educational outcomes. We focus on *rainfall* and *temperature,* which we simultaneously control for in each model (Auffhammer, Hsiang, Schlenker, & Sobel, 2013). We present estimates from models that use three related but distinct measures. In the first, we simply include the mean temperature (°C) and mean annual rainfall (cm) over each inter-survey period. Our second measure identifies the average deviations in the temperature and rainfall in each community during the inter-survey period relative to long-term (1984-2011) trends for that given community. With respect to temperature, we calculate the average deviation of the annual average temperature among all years in the inter-survey period from the long-term (1984-2011) mean temperature for each community. For rainfall, we calculate the average deviation of annual rainfall among all years in the inter-survey period from the long-term mean annual rainfall for each community. The third measure is similar to the second, but expresses deviations from the long-term mean temperature and rainfall in terms of the standard deviations about the long-term means observed for each community. This measure has the advantage of accounting for long-term variability about the mean, but the interpretation is somewhat less clear than the simple deviations.

5. Methods

We use two analytic techniques to estimate the effect of weather conditions on educational outcomes. To examine school dropout and disruption, we estimate a series of discrete-time event-history models. These models demonstrate whether and how weather conditions affect the probability of each outcome, respectively, during each inter-survey period. For each of the specifications we describe below, we estimate the model a binary logit that takes the form:

$$\log\left(\frac{\pi_{it}}{1-\pi_{it}}\right) = \alpha_t + \alpha_r + \delta W_{ct} + \beta X_{it}$$

where π_{it} is the odds of dropout (disruption) for individual i in period t, α_t is the baseline likelihood of dropout (disruption) during period t, α_r is the baseline likelihood of dropout (disruption) in region r, W_{ct} is a vector of weather variables for community *c* during period t, X_{it} is a vector of control variables for individual i in the first year of period t, δ is a vector of parameters for weather effects, and β is a vector of parameters for the effect of control variables on the odds of dropout (disruption). Each model controls for a series of covariates expected to affect dropout (disruption), and includes region and period fixed effects. We adjust all standard errors (SEs) for clustering at the level of the 0.5°-by-0.5° areas for which weather conditions are measured.

To examine educational investments, we estimate linear regression models with random effects, which account for the complex error structure of our panel data. This takes the form:

$$y_{it} = \alpha_0 + \delta W_{ct} + \beta X_{it} + u_{it} + v_{it}$$

where y_{it} is the total household educational expenditures on child *i* during the last year of period t, α_0 is the intercept, W_{ct} is a vector of weather variables for community *c* during period t, X_{it} is a vector of control variables for individual i in the first year of period t, δ is a vector of parameters for weather effects, β is a vector of parameters for the effects of the control variables on educational expenditures, and u_{it} and v_{it} are error terms. Each model controls for a series of covariates expected to affect these expenditures, and includes region and period controls.

6. Results

We present our results as follows. In the first section of results, we describe the range of weather conditions that children were exposed to during the study period, and show bivariate associations between the three outcomes of interest and a set of social and demographic factors. In the subsequent three sections, we present estimates of the effect of weather shocks on school dropout, school disruption, and educational investments, respectively. For the sake of parsimony, we limit our discussion to arguably the most important results; but include a more comprehensive set of results in our tables for reference.

(a) Descriptive statistics

We begin by describing the range of weather conditions that children are exposed to during the study period (Table 1). On average, the mean temperature during the three inter-survey periods we consider is just over 27°C, but ranges from 21.3°C to 28.2°C. The average deviation of annual temperatures from the long-term mean within each inter-survey period and for each community ranges from -0.16°C to 0.20°C, or -0.22 to 0.24 in terms of each community's long-term standard deviation. The average annual rainfall during the inter-survey periods we consider is approximately 263cm in the average community, but again ranges greatly from 205.4cm to 485.3 cm. The average deviation in annual rainfall within each community and during each inter-survey period ranges from -54.4cm to 58.0cm, or -1.22 to 1.47 in terms of each community's long-term standard deviation.

(Table 1)

With respect to the outcomes of interest, we begin by examining rates of school dropout and disruption across a range of social and demographic variables expected to be associated with educational outcomes (Table 2). Here it is important to note that these outcomes are mutually exclusive. For example, if a child drops out of school during the inter-survey period, they are excluded from the population at risk of missing school during the inter-survey period (i.e., the denominator used when calculating the percent of children experiencing school disruption). Given potential selectivity into the at-risk population of these outcomes, the results should be interpreted with caution.

(Table 2)

Results yield only small differences in the incidence of school dropout between sexes, (0.2 percentage points), but male children are 1.3 percentage points more likely to experience school disruption during one of the three inter-survey periods. Both dropout and disruption vary according to the number of years of school that the child completed at period baseline (a strong correlate to age). Children with higher levels of education at baseline are, broadly, more likely to experience both dropout and disruption. However, children who have three or four years of education at period baseline are most likely to experience dropout in subsequent years (8.5 percent). Rates of dropout increase monotonically according to the number of other children in the household (i.e., sibship size), but showed little variation according to overall household size. School disruption incidence declines with both family size and sibship size.

Children from the poorest third of households are much more likely to experience dropout (6.6 percent) than their counterparts in the second and third wealth terciles (4.9 and 2.3 percent, respectively), but less likely to experience school disruption. This may reflect the abovementioned selectivity effects of how the populations at risk of both outcomes were defined. Finally, children living in rural communities are nearly 3 percentage points more likely to experience dropout, and slightly (0.5 percentage points) more likely to experience school disruption.

(Table 3)

Our descriptive analyses also reveal differences in educational expenditures across social and demographic groups. For example, the average household spends slightly more on the education of male (760.9 rupiah) than female (693.4 rupiah) children. Household expenditures in children also decline as household size and the number of the children in the household increase. On average, children from the wealthiest third of households receive double (1242.2 rupiah) the educational expenditures of children in the second wealth tercile (605.4 rupiah) and about four times children in the poorest tercile (335.0 rupiah). We also observe substantial differences in expenditures according to the child's educational history at baseline, with the highest expenditures among the least-educated (youngest) children. This difference likely reflects the start-up costs associated with school entrance (e.g., uniforms, entrance fees). Finally, the results show that rural households spend nearly 200 rupiah less per child (644.3 rupiah) than urban households (836.8 rupiah). Many of these between-group differences are small and statistically non-significant.

(b) School dropout

We begin our multivariate analyses by examining the effect of weather shocks on school dropout. Our first series of models (Table 4) includes three specifications, each with a different weather indicator as described earlier. The results indicate that inter-survey weather conditions have a significant effect on the probability of dropout, but these effects vary according to the measure used. Specification 1 shows that higher mean inter-survey temperatures and rainfall both increase the odds of dropout. However, in Specification 2, the average deviation of annual temperature during the inter-survey period from the long-term mean temperature is negatively associated with dropout odds; deviations in annual rainfall are positively associated with dropout odds. Considerable attention has been paid to the adverse effects of heat stress (Bohra-Mishra, Oppenheimer, & Hsiang, 2014; Mueller, Gray, & Kosec, 2014). Yet research has also shown that low temperatures often have adverse effects on agricultural production, a likely pathway through which weather affects livelihoods and thus educational outcomes. Indeed, research has shown that rice—Indonesia's primary agricultural product—is particularly vulnerable to low temperatures (Jena, Kim, Suh, Yang, & Kim, 2012).

The difference between Specifications 1 and 2 is marked. We ultimately favor Specification 2 because it is based on de-meaned weather indicators, which compare observed inter-survey weather conditions to long-term means observed within each community. As a result, use of these measures reduces the likelihood that our weather variables are capturing unobserved community-level effects. Our subsequent analyses of this outcome utilize only the weather variables used in Specification 2.

(Table 4)

The results in Table 4 indicate that, on average, temperature and wealth anomalies have a significant effect on school dropout. However, vulnerability to such shocks is rarely distributed evenly across exposed populations. We therefore estimate group-specific regression models of school dropout across wealth, gender, and rural (urban) sub-populations, and interpret differences in these estimates as evidence of heterogeneous vulnerability.

The results of these models (Table 5) reveal notable differences. For example, the effect of temperature deviations on school dropout is significant only among children from the poorest third of households; the positive effect of rainfall deviations is significant across all wealth groups. We also disaggregate our sample of children by sex. The effect of rainfall deviations is significant only among male children; and the effect of temperature deviations is non-significant (at the 0.05 level) among both male and female children. Finally, we estimate models for children in rural and urban communities separately and find that weather effects—both temperature and rainfall—are statistically significant in rural areas only. This finding is consistent with the expectation that weather shocks affect educational outcomes via their effect on agricultural production and agrarian economies.

(Table 5)

(c) School disruption

Next, we examine whether the probability of school disruption was affected by weather conditions. Here again it is worth noting that the population at risk of school disruption during a given inter-survey period excludes children who dropped out of school during that period. The population at risk of this outcome is therefore affected by selectivity into school dropout. This analysis also does not capture persons who experienced school disruption during one year in the inter-survey period and then dropped out at a later year, since these persons would be classified as dropouts.

(Table 6)

We start with a series of models estimated across the entire (i.e., aggregated) population, each of which uses a different weather variable (Table 6). Again, our estimated weather impacts vary markedly—albeit only in magnitude rather than statistical significance or direction—according to whether we estimate the effect of mean inter-period temperature and rainfall or the average deviation (both standardized and unstandardized) across the inter-survey period from a long-term mean. The estimated effect of the simple inter-period mean temperature (Specification 1) is much less (β=0.487) than the estimated effect of the average deviation during the inter-survey period from the long-term mean (Specification 2, β=3.319). The estimated effect of the standardized deviation from the long-term mean (Specification 3) is similar to the latter (β=3.540). The effects of rainfall on educational disruption vary less between Specifications 1 and 2, but increase notably in magnitude between Specifications 2 (β=0.014) and 3 (β=0.669).

(Table 7)

We also include results from the disaggregated models (Table 7), mainly for illustrative purposes. The estimates suggest that the effects of weather conditions on school disruption risk are less between the poorest third of households than the wealthiest two thirds. The results also indicate little to no difference in these effects between sexes or community setting (i.e., rural versus urban). We hypothesize that these unintuitive findings may reflect the estimation strategy used in these initial analyses.

(d) Educational investments

Next, we examine whether and how inter-survey weather conditions affect educational investments in children during the last year of the inter-survey period. We consider educational investments across all children in our analytic population, assuming that expenditures on education among dropouts were zero. The first series of models estimates the average effect of weather variables on educational expenditures across the entire population of children in our sample. We again consider three types of weather variables.

(Table 8)

In Specification 1, we estimate the effect of the mean temperature and annual rainfall during the inter-survey period on end-of-period investments. The results indicate non-significant effects (at the 0.05 level). However, the weather effects in Specifications 2 and 3 are statistically significant. The average deviation—both unstandardized and standardized—of annual weather conditions during the inter-survey period from the long-term mean for each community are positively associated with educational expenditures. These results are consistent with estimated weather effects on dropout risk: abnormally low temperatures and low rainfall are associated with diminished educational expenditures on children.

To assess potential between-group differences in vulnerability to weather shocks, we then estimate group-specific models within a set of different social and demographic groups. In step with our first series of estimates, we focus on the effects of the mean deviation of inter-survey weather conditions from the long-term community-specific means.

(Table 9)

When the sample of children is disaggregated by household wealth tercile, the effect of temperature anomalies is significant only among the poorest third of households. As in the main effects model, this effect is positive: lower-than-average temperatures are associated with decreased educational expenditures. The contrary holds true for rainfall effects: our estimates reveal non-significant effects (at the 0.05 level) among the poorest two-thirds of households, but statistically significant and positive effects among the wealthiest third of households.

We also compare the effects of weather anomalies on educational expenditures among male and female children, respectively. Estimates indicate that the effect of rainfall deviations are both statistically significant and of comparable magnitude among males and females. However, the effects of temperature are only significant (at the 0.05 level) among female children. This suggests that households are more likely to reduce expenditures among female children in response to temperature shocks than among male children.

Finally, we disaggregate children by whether their community of residence at period baseline is rural or urban. Temperature anomalies have significant effects on household educational expenditures on children in both rural and urban communities, but the effect of rainfall is significant only in urban communities. These results are contrary to the hypothesized agricultural mechanism linking weather conditions to educational outcomes, and merit further analysis.

7. Discussion and future research

In this paper, we have presented preliminary analyses of how children's educational outcomes are affected by weather shocks in the relatively short term. This line of inquiry stands in contrast to most previous research, which has focused on other demographic and economic outcomes in shock-affected contexts—or traced the long run, human development impacts of such shocks. Our estimates reveal significant weather effects on three educational outcomes and, importantly, differences between social and demographic groups. For example, differences between sexes and wealth groups are indicative of potential within-household gender inequalities and inter-household differences in vulnerability, respectively.

That said, the current analyses reveal at least two important steps for future research. For one, the unintuitive (and potentially problematic) estimates of weather effects on school disruption and educational investments reveal the pitfalls of not accounting for selectivity into certain "at risk" populations. This is undoubtedly an issue in the current paper, but is also pertinent to other quantitative research on the effects of, and responses to weather shocks and climate change. Many outcomes and responses in such context are sequential or multi-phasic—that is, outcome Y_n may be possible only if outcomes Y_{n-1} and Y_{n-2} have been realized. Estimates that do not account for such ordering are likely to produce biased and misleading results.

Second, attention to between-group differences is essential (as are refined measures of group membership). Much of the existing quantitative research on the effects of weather shocks has been framed in terms of vulnerability, but ultimately goes on the estimate average weather effects across affected populations. This approach is somewhat antithetical to the rich theoretical literature on vulnerability and its social construction, which suggests that it is an inherently unevenly distributed characteristic. Research attempting the understand vulnerability from a quantitative perspective should therefore examine substantively important group differences in the effects of, and responses to weather shocks.

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Tables

Table 1. Summary of weather variables

Variable	Mean	SD	Min	Max
Temperature, °C	27.29	1.60	21.28	28.23
Temperature deviation (mean), °C	-0.01	0.09	-0.16	0.20
Temperature standardized deviation (mean), °C	-0.01	0.10	-0.22	0.24
Rainfall, mm	263.81	59.52	205.42	485.40
Rainfall deviation (mean), mm	-3.31	20.95	-54.35	58.00
Rainfall standardized deviation (mean), mm	-0.11	0.59	-1.22	1.47

Table 2. Description of school dropout and disruption

Variable (*Category*)	% dropout	% disrupted
Sex		
Male	4.6	3.7
Female	4.8	2.4
Education completed (years)		
0 to 2	3.5	2.9
3 to 4	8.5	3.1
5+	6.4	4.7
Number of children in household		
1	4.1	3.9
2 to 3	4.4	3.0
4+	6.3	2.5
Household size		
1 to 3	5.0	3.9
4 to 6	4.6	3.0
7+	5.0	2.8
Household wealth tercile		
1st	6.6	2.6
2nd	4.9	3.1
3rd	2.3	3.6
Location		
Rural	5.9	3.3
Urban	3.1	2.7

Note: multivariate estimates also control for period and region of residence at period baseline

Table 3. Description of educational investments per observed child (1,000 rupiah)

Variable (*Category*)		Mean	SD
Sex			
	Male	760.9	8151.3
	Female	693.4	7043.7
Education completed (years)			
	0 to 2	1256.9	10300.0
	3 to 4	131.5	627.0
	5+	277.8	4383.5
Number of children in household			
	1	754.4	6374.3
	2 to 3	748.7	7799.6
	4+	709.7	8809.5
Household size			
	1 to 3	866.8	7570.4
	4 to 6	768.9	7962.3
	7+	561.9	6773.8
Household wealth tercile			
	1st	335.0	4561.1
	2nd	605.4	7192.0
	3rd	1242.2	10100.0
Location			
	Rural	644.3	7578.5
	Urban	836.8	7689.0

Note: multivariate estimates also control for period and region of residence at period baseline

Table 4. Regression estimates of weather effects on school dropout probability, select coefficients

Specification	Variable	β		Robust SE
1	Temperature (mean)	0.478	***	0.142
	Rainfall (mean)	0.011	**	0.004
2	Temperature (mean deviation)	-1.205	**	0.560
	Rainfall (mean deviation)	0.012	**	0.005
3	Temperature (mean deviation, standardized)	-0.733		0.563
	Rainfall (mean deviation, standardized)	0.515	***	0.162

***p<0.01, **p<0.05

Table 5. Regression estimates of weather effects on school dropout probability by subpopulation, select coefficients

Subpopulation	Variable	β		Robust SE
1st wealth tercile	Temperature (mean deviation)	-2.081	**	0.691
	Rainfall (mean deviation)	0.019	**	0.008
2nd wealth tercile	Temperature (mean deviation)	0.299		0.857
	Rainfall (mean deviation)	0.017	**	0.007
3trd wealth tercile	Temperature (mean deviation)	1.015		1.359
	Rainfall (mean deviation)	0.022	**	0.008
Sex = male	Temperature (mean deviation)	-1.241		0.795
	Rainfall (mean deviation)	0.016	***	0.006
Sex = female	Temperature (mean deviation)	-1.106	*	0.639
	Rainfall (mean deviation)	0.010		0.006
Rural	Temperature (mean deviation)	-2.119	***	0.638
	Rainfall (mean deviation)	0.015	**	0.006
Urban	Temperature (mean deviation)	0.768		0.920
	Rainfall (mean deviation)	0.009		0.007

***p<0.01, **p<0.05, *p<0.10

Table 6. Regression estimates of weather effects on school disruption probability, select coefficients

Specification	Variable	β		Robust SE
1	Temperature (mean)	0.487	**	0.194
	Rainfall (mean)	0.013	**	0.005
2	Temperature (mean deviation)	3.319	***	0.732
	Rainfall (mean deviation)	0.014	**	0.007
3	Temperature (mean deviation, standardized)	3.540	***	0.672
	Rainfall (mean deviation, standardized)	0.699	**	0.289

***p<0.01, **p<0.05

Table 7. Regression estimates of weather effects on school disruption probability by subpopulation, select coefficients

Subpopulation	Variable	β		Robust SE
1st wealth tercile	Temperature (mean deviation)	1.883		1.470
	Rainfall (mean deviation)	0.029		0.018
2nd wealth tercile	Temperature (mean deviation)	3.542	**	1.527
	Rainfall (mean deviation)	0.029	*	0.016
3trd wealth tercile	Temperature (mean deviation)	3.965	***	1.292
	Rainfall (mean deviation)	-0.005		0.011
Sex = male	Temperature (mean deviation)	3.077	***	1.001
	Rainfall (mean deviation)	0.016		0.011
Sex = female	Temperature (mean deviation)	3.647	***	0.934
	Rainfall (mean deviation)	0.013		0.008
Rural	Temperature (mean deviation)	3.271	***	1.039
	Rainfall (mean deviation)	0.022	**	0.011
Urban	Temperature (mean deviation)	3.245	***	1.192
	Rainfall (mean deviation)	-0.001		0.011

***p<0.01, **p<0.05, *p<0.10

Table 8. Regression estimates of weather effects on end-of-period educational investments per observed child (1,000 rupiah), select coefficients

Specification	Variable	β		SE
1	Temperature (mean)	-161.720		111.097
	Rainfall (mean)	2.780	*	1.431
2	Temperature (mean deviation)	1092.785	***	285.402
	Rainfall (mean deviation)	4.217	***	1.506
3	Temperature (mean deviation, standardized)	1690.154	***	265.339
	Rainfall (mean deviation, standardized)	285.216	***	56.179

***p<0.01, **p<0.05, *p<0.10

Table 9. Regression estimates of weather effects on end-of-period educational investments per observed child by subpopulation, select coefficients

Subpopulation	Variable	β		Robust SE
1st wealth tercile	Temperature (mean deviation)	965.4	***	271.4
	Rainfall (mean deviation)	2.640	*	1.463
2nd wealth tercile	Temperature (mean deviation)	870.6		724.9
	Rainfall (mean deviation)	4.587		3.794
3trd wealth tercile	Temperature (mean deviation)	853.5		681.6
	Rainfall (mean deviation)	13.492	***	4.043
Sex = male	Temperature (mean deviation)	768.1	*	412.8
	Rainfall (mean deviation)	4.979	**	2.181
Sex = female	Temperature (mean deviation)	1379.4	***	393.2
	Rainfall (mean deviation)	4.137	**	2.070
Rural	Temperature (mean deviation)	1089.2	***	408.1
	Rainfall (mean deviation)	1.061		2.041
Urban	Temperature (mean deviation)	1301.9	***	393.4
	Rainfall (mean deviation)	9.908	***	2.295

***p<0.01, **p<0.05, *p<0.10