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Climate Exposures and Child Undernutrition: Evidence from Indonesia

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Abstract

Global climate change has the potential to disrupt agricultural systems, undermine household socioeconomic status, and shape the prevalence and distribution of diseases. Each of these changes may influence children's nutritional status, which is sensitive to food availability, access, and utilization, and which may have lasting consequences for later-life health and socioeconomic outcomes. This paper contributes to the emerging literature on climate and child health by studying the effects of temperature and precipitation exposures on children's height and weight in Indonesia. Drawing on five rounds of the Indonesian Family Life Survey (IFLS) implemented between 1993 and 2015, we estimate fixed-effects regression models of height-for-age (HFA) and weight-for-height (WFH) among samples of children ages 24-59 months and 0-23 months, respectively. We test for heterogeneity in these effects across sub-populations expected to vary in their vulnerability. Results show that delays in monsoon onset are consistently associated with worse child health outcomes. Delays in monsoon onset during the prenatal period are associated with reduced child height among children age 2-4 years. The weight of young (<2 years) children is adversely affected by delays in the most recent monsoon season, and this relationship is particularly strong among residents of Java. Overall, our results underline the need for interventions that protect children's nutrition and underlying health against the effects of climate change.

Keywords

child nutrition; climate change; monsoon; stunting; wasting; Indonesia; rice production

1. Introduction

Climatic variability disrupts agricultural and socioeconomic systems throughout the world, and these impacts are expected to increase in the future as global climate change unfolds. Increases in temperature and atmospheric carbon dioxide, combined with greater variability in precipitation, are anticipated to affect the yields of many major crops—often, though not exclusively, in an adverse manner (Challinor et al. 2014; Lobell and Field 2007). Likewise,

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some households' ability to access food may be undermined by climate-induced shocks to labor productivity, income, and the prices of food or agricultural inputs (Bradbear and Friel 2013; Brown and Kshirsagar 2015). Individuals' ability to biologically utilize the food that is consumed may also be affected due to changes in disease transmission and physiological heat stress (Bandyopadhyay et al. 2012; de Casas et al. 1995; Mayer 2000; Pascual et al. 2006). These and related impacts are likely to be particularly pronounced in low-latitude developing countries, which are characterized by already-high temperatures alongside limited adaptive capacity and social protections (Knox et al. 2012; Lybbert and Sumner 2012).

The resulting changes in food security have many implications for the welfare of affected populations (Schmidhuber and Tubiello 2007), but are likely to have distinct consequences for the health and nutrition of children. Young children (e.g., below age five) are often most sensitive to nutritional deficits, and exposure to such conditions may result in sometimes-irreversible disadvantages to their cognitive development, health, and socioeconomic attainment over the life course (Alderman et al. 2006; Almond and Currie 2011; Bruckner et al. 2014; Martorell 1999). Adults may also suffer from such deficits but are beyond the critical developmental periods that make the impacts on children so costly (Hoddinott 2006; Hoddinott et al. 2013; Schwarzenberg et al. 2018). As such, it is important to understand how climatic changes may affect child undernutrition so that appropriate mitigation strategies can be designed and implemented (Alderman and Behrman 2006; Hoddinott et al. 2013).

The empirical record on the links between climate and nutrition has been limited to date (Phalkey et al. 2014). Only recently has a body of research on this issue emerged (Cooper et al. 2019; Grace et al. 2012, 2015; Kumar et al. 2016; Skoufias and Vinha 2012) to complement a broader literature on the impacts of other types of shocks (e.g., conflict, changes in income) on child health and development (Agadjanian and Prata 2003; Torche and Villarreal 2014). We advance this literature by using five rounds of panel data on child health across a 22-year period, by addressing the consequences of temperature and monsoon onset as well as total precipitation, and by going beyond average treatment effects to examine heterogeneity across age, gender, occupation, and location. Specifically, we focus on Indonesia, where changes in temperature and precipitation have been shown to affect a range of livelihood and demographic outcomes (Bohra-Mishra et al. 2014; Naylor et al., 2007; Skoufias et al. 2011; Sellers and Gray 2019; Thiede and Gray 2017). Pooling five rounds of data from the Indonesia Family Life Survey (IFLS, Strauss et al. 2016), we examine the consequences of temperature and precipitation variability for child height (stunting) and weight (wasting) among Indonesian children under age five. We also evaluate how the nutritional effects of climate change are distributed across major demographic groups to determine if particular sub-populations are more or less vulnerable than others. These analyses reveal that delays in monsoon onset have consistently negative effects on children's height and weight. In the context of prior research linking monsoon onset delays to declining in rice production (Naylor et al. 2007), our results highlight the nexus between climatic variability, agriculture, and child health.

2. Climatic variability and child nutrition

Climatic variability can affect children's nutritional status through multiple pathways, which are conceptually straightforward but in practice may interact and offset in a manner that precludes the development of *a priori* directional hypotheses. The proximate or immediate determinants of child undernutrition are inadequate dietary intake and disease, which are in turn affected by the availability of and access to food, child feeding and care practices, and sanitation and health (Black et al. 2008). These three sets of secondary causes are each potentially sensitive to climatic change and variability.

Food availability may be influenced by climate impacts on crop yields and area planted (Challinor et al. 2014; Lobell & Field 2007; Wheeler and von Braun 2013). Although the net impact of environmental changes on food availability globally is debated, certain regions of the world—particularly in the global tropics—are expected to experience climate-related reductions in crop yields and may therefore face declines in local and regional food availability. In parts of Africa and South Asia, for example, recent climatic changes have been shown to significantly reduce the yields of maize, wheat, and other staple crops—in some cases by more than 15 percent (Knox et al. 2012; Ray et al. 2019). While such reductions in agricultural productivity may produce subsistence crises at the local or regional level in cases of extreme drought, flooding, or similar disasters, it is perhaps more likely that such climate-induced perturbations will reduce households' ability to access food (Barrett 2010). That is, climate-induced disruptions to local and regional food systems may increase food prices, reduce household income, or otherwise impede households' ability to obtain the food that is available in local markets (Brown and Kshirsagar 2015; Mueller et al. 2014). The implication is that climatic variability may affect child malnutrition through changes in agricultural and food markets even in the absence of physical shortages of food.

Climate-induced changes in malnutrition may even occur in the absence of significant disruptions to agricultural systems, since changing environmental conditions can affect behavioral and biological food-utilization processes. For one, climate shocks may alter important childcare and feeding practices to the extent that they affect the health of caregivers or prompt coping strategies that re-allocate labor among household members (Maystadt et al. 2016; Moran et al. 2006; Mueller and Osgood 2009). For example, high temperatures have been shown to increase the prevalence of productivity-reducing diseases such as malaria and otherwise reduce adult health (Mueller and Gray 2018; Pascual et al. 2006), possibly decreasing affected adults' ability to properly care for children. Climate-induced changes in migration patterns may also affect childcare by changing household labor supply and altering roles among household members (Hunter et al. 2015; Mueller et al. 2014). For instance, in contexts with highly gendered divisions of labor, increased probability of out-migration by working-age males may raise the demand for on-farm labor among women and youth, thereby reducing available time for childcare. Such constraints to childcare may lead to sub-optimal feeding and care practices, increasing the risk of caloric and micronutrient deficits and malnutrition-inducing illnesses.

Additionally—and perhaps more importantly—changing temperatures and precipitation patterns may directly affect child health by altering disease transmission. Climate variability

has been linked to changes in the reproduction rate of disease vectors (e.g., mosquitos), drinking-water quality, and other determinants of childhood illnesses that have been shown to increase malnutrition (Rosinger 2018). Diarrheal diseases are known to have a particularly strong effect on children's nutritional status and to be affected by environmental conditions (Bandyopadhyay et al. 2012; Mayer 2000; Spears 2018), but vector-borne diseases (e.g., malaria, dengue) are also both sensitive to climate and determinants of malnutrition (Campbell et al. 2015; Pascual et al. 2006). Finally, changing temperature and precipitation patterns could also affect child nutritional directly such as through the physiological costs of extreme heat, including prenatally via the health of the mother (Andalón et al. 2016; Bakhtsiyarava et al. 2018; Basu et al. 2018; Deschênes et al. 2009; Grace et al. 2015; Molina and Saldarriaga 2017).

Environmental changes may affect child malnutrition through any of these pathways. However, it is difficult to predict the overall, net impact given the complicated and potentially non-linear effects of changing precipitation and temperature on agriculture and health. Prediction is also difficult since the mechanisms outlined above may operate in an offsetting manner. For instance, higher temperatures may be correlated with increasing crop yields until certain thresholds, after which further temperature increases reduce crop yields (Lobell et al. 2011). Moreover, rising temperatures may also lead to concurrent changes in disease patterns, which may either compound or offset temperature-induced changes in agriculture. The implication is that it is difficult to develop strong predictions about the direction of climate effects on child nutrition (Corwell and Inder 2015; Tiwari et al. 2017).

Previous studies have directly examined the consequences of environmental change for child nutritional status in Mongolia (Groppo and Kraehnert, 2016), Nepal (Shively et al. 2015), Bangladesh (Del Ninno et al. 2005), India (Kumar et al. 2016), Mexico (Skoufias and Vinha 2012), Ecuador (Rosales-Rueda 2018) and several countries in Sub-Saharan Africa (Hoddinott and Kinsey 2001; Davenport et al. 2017). A majority of studies have focused on the consequences of extreme events such as drought and flooding (Hoddinott and Kinsey 2001; Del Ninno et al. 2005; Rabassa et al. 2014; Groppo and Kraehnert, 2016; Kumar et al. 2016; Rosales-Rueda 2018). The results have consistently shown large negative effects on child nutritional status, supporting the relevance of the pathways described above. An extension of this approach examines the entire range of precipitation variability, including both wet and dry periods (Skoufias and Vinha 2012; Shively et al. 2015; Tiwari et al. 2017; Cooper et al. 2019), which in some settings reveals negative consequences from exposure to both extremes (Cooper et al. 2019). However, relatively few studies have investigated variability in temperature (Davenport et al. 2017), which is expected to be aspect of climate change that is most threatening to human health (Mora et al. 2017).

Our study builds most directly the approach used by Skoufias and Vinha (2012) and on a handful of studies that examined climatic effects on related outcomes in Indonesia. Skoufias and Vinhas used a nationally-representative household survey data from Mexico to examine the effects of climatic deviations from historical conditions on child height-for-age, and then extended this analysis to look for vulnerable populations. Their findings reveal that, in this predominantly dry and temperate context, wet and cold shocks have the strongest negative effects, but some populations also suffer from unusual heat. We extend this approach

through the use of longitudinal household data and through consideration of a third dimension of climate—the timing of the rainy season (Naylor et al. 2007). Specific to Indonesia, other studies using the IFLS data have revealed negative social consequences of rainfall deficits (for household expenditures and attained height; Skoufias et al. 2012; Maccini and Yang 2009), monsoon delays (for household expenditures: Sellers and Gray 2019), and temperature (for farm and non-farm household income; Thiede and Gray 2017). Naylor et al. (2002, 2007) and Caruso et al. (2016), using other data sources, also found negative consequences of monsoon delays and high temperatures for rice production. These studies do not directly examine child outcomes, but allow us to hypothesize that low rainfall, late monsoon onset and high temperature will adversely affect child health.

3. Research objectives

The main objective of this paper is to estimate the effects of temperature and precipitation variability on the linear growth and weight of Indonesian children. Indonesia is an appropriate and important setting for studying climate impacts on child nutrition. The country is home to more than 20 million children under age 5 and more than one third of them are stunted—among the highest rates in Asia and the Pacific (UNICEF 2019). Indonesia is also highly vulnerable to climate change and variability, with regular historical exposure to El Niño-related droughts (Naylor et al. 2002, 2007) and related wildfires (Field et al. 2016), as well as probable future exposure to deadly heatwaves (Mora et al. 2017).

By evaluating the empirical linkages (or lack thereof) between climatic changes and child nutrition, we aim to inform ongoing debates about how to promote food and nutritional security in a changing climate (Schmidhuber and Tubiello 2007; Sheffield and Landrigan 2011; Wheeler and Von Braun 2013). Toward our overall goal, we first estimate the overall effects of temperature and precipitation on height-for-age (HFA), a symptom of chronic malnutrition, among children ages 24-59 months in our sample. We examine the effects of mean temperature and two dimensions of precipitation variability—total rainfall and the timing of the monsoon season. Second, we study whether and how vulnerability to the nutritional impacts of climatic variability is distributed unequally across demographic groups, as has been shown in other cases of environmental influences on child health (Datar et al. 2013). We do so by estimating a series of models that allow the effects of our main climate variables to vary across child sex, household farm ownership, and two dimensions of place of residence. The third and fourth objectives of our study mirror the first two but focus on children's weight-for-height (WFH), which is a correlate of acute malnutrition that has important short- and long-term health and developmental consequences for children. The analysis of WFH focuses on children ages 0-23 months, who are expected to be most vulnerable to wasting (Alderman & Headey 2018).

3.1 Data

Our analyses draw on five waves of data from the Indonesian Family Life Survey (IFLS), which were respectively collected in 1993-4, 1997-8, 2000, 2007-8, and 2014-5. The IFLS is a uniquely rich longitudinal study of over 30,000 Indonesians. The sample was originally selected from over 300 enumeration areas (mean households per community = 22.5) and

designed to be representative of the population living in 13 of the 27 provinces in the country (accounting for 83 percent of the country's population; Strauss et al. 2009, 2016). For the purposes of the current analysis, the IFLS has the advantage of collecting anthropometric data on all individuals, including children, who were resident in the household at the time of the survey. The IFLS data also include information on a range of time-varying individual-, household-, and community-level control variables. Finally, because IFLS data were repeatedly collected from the same original communities over time, we are able to use a community fixed-effects analytical strategy (as described below) that fully accounts for potential contextual confounders of climate such as soils and topography.

We construct two separate analytic samples that respectively include children ages 0 to 23 months ($n = 4,812$) and 24 to 59 months ($n = 7,459$). Our analysis of HFA focuses on the latter since stunting (low HFA) tends to reflect the cumulative impact of nutritional deficits from conception to age two; and the WFH analysis focus on the younger sample since wasting (low WFH) reflects recent deficits and is most prevalent in early ages (Alderman & Headey 2018; Victoria et al. 2010). We exclude observations with biologically implausible anthropometric scores, defined as HFA z-scores with an absolute value above 6 and WFH z-scores greater than 5, and retain only observations in the 304 original IFLS enumeration areas (i.e., communities) for which the latitude and longitude are available via restricted access.

We link children to climate records using community geo-coordinates along with the date of anthropometric measurements and their date of birth, using a monthly time resolution. Note that the mean interview date was taken for individuals who were interviewed multiple times in a given IFLS wave and without clear records of the interview in which anthropometries were taken. Climate measures (see below) are based on daily precipitation and temperature records from NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al. 2011). MERRA is a reanalysis product that integrates both station and satellite data into a physically-consistent model that provides daily time series for a range of meteorological indicators from 1981 to the present at $0.5^\circ \times 0.66^\circ$ resolution. For the cells corresponding to each community in our analytic sample, we extract records from January 1, 1981 to December 31, 2014, and use these data to produce measures of mean temperature, mean precipitation rate, and mean monsoon onset delay for the childhood exposure periods of interest (described below). These data show significant time trends consistent with observed patterns of climate change: temperature is increasing by 0.01° degree per year, precipitation decreasing by 0.03 mm per day per year, and monsoon onset is being delayed by 0.08 days per year.

3.2 Measures and methods

Our analyses examine the effects of climate exposures on children's linear growth and weight, which we measure as height-for-age (FIFA) and weight-for-height (WFH). Both measures are expressed in terms of z-scores using international standards set by the World Health Organization (WHO). We treat the raw HFA and WFH z-scores as continuous variables and model these outcomes as linear functions of climatic conditions in cluster c during interval t , social and demographic control variables, and community and period fixed

effects. Analyses of WFH also include fixed effects for month-of-year (i.e., survey month, which varies within communities) to account for seasonal variation in this outcome. The inclusion of fixed effects for the location and period accounts for all time-stable characteristics of the community as well as time-varying characteristics of the national context that might confound the effects of climate. With the inclusion of these fixed effects, the regression coefficients are identified by within-community variation in climatic conditions that departs from the national climate trend (as well as the seasonal trend in the case of WFH). Because this variation is exogenous to households and individuals, it can be interpreted as a natural experiment (Nordkvelle et al. 2017). Building on previous analyses of child undernutrition in this context (De Silva and Sumarto 2018), we flexibility control for child age via a set of fixed effects for month of age. We also control for sex and sibship of the child and incorporate characteristics of the household head via controls for their age, educational attainment, farm ownership, and sex. We further control for household size, the number of household members under age five, and the rural or urban status of the child's community of residence. Standard errors are adjusted for clustering at the community level, accounting for multiple observations of the same community, household and child over time (Angeles et al. 2005). The sample is described in Table 1.

Our analyses focus on three climate variables of interest: mean temperature, mean precipitation rate, and mean monsoon onset delay. The first two variables represent the mean daily temperature (°C) and precipitation (mm/day) over the exposure periods of interest (see below). Monsoon onset delay is defined as the number of days after August 1 that pass until cumulative rainfall reaches 20 cm (Naylor et al. 2007; Skoufias et al. 2012). We attach this value to all months in a given monsoon year—defined to run from August through July—and then take the mean across the exposure period to define the mean monsoon onset delay.

We measure climate exposures in two ways according to the outcome of interest. When modeling HFA for children aged 24-59 months, we measure climate exposure for three biologically relevant periods of exposure: nine months prior to birth through the month before birth (the prenatal period), from the month of birth to the eleventh month of life (the first year of life) and from the twelfth to the twenty-third months of life (the second year of life). This approach captures the effects of both *in utero* and chronic exposure to adverse ecological conditions, which are expected to be determinants of stunting. In contrast, we measure climate exposure over the twelve months prior to the survey when modeling WFH, which is an indicator of acute malnutrition and thus typically more sensitive to recent food intake and health. We also tested a nonlinear specification by adding the square of each climate variable (Burke et al. 2015; Randell and Gray 2019), but in no case did it meaningfully improve the explanation.

4. Results

4.1 Height-for-age

The first part of our analysis examines the association between climatic exposures and children's height (HFA), which is inversely correlated with chronic malnutrition. For reference, note that the mean HFA across the analytic sample of children ages 24-59 months is $z = -1.798$ (Table 1), meaning that the average child in our sample is just over 0.2

standard deviations in height from being classified as stunted ($z < -2$). The implication is that the burden of chronic malnutrition is high across our sample, although the high degree of variability about this mean ($SD = 1.342$) suggests this pattern is far from uniform.

The first multivariate model (Model 1) examines the association between temperature, precipitation level, and monsoon onset and children's HFA across the sample, net of controls and fixed effects. Recall that all three dimensions of climate variability are disaggregated to differentiate between exposures during the prenatal period, year one of life, and year two of life. The results (Table 2) reveal that that delays in monsoon onset during the prenatal period lead to statistically significant declines in height, while temperature and precipitation levels are not independently associated with HFA. According to point estimates, each day of monsoon onset delay is associated with a decline in height of 0.003 standard deviations. These effects appear substantively meaningful in the context of the delays in precipitation that occurred during the study period. For example, a 48-day delay in monsoon onset—approximately 1 standard deviation greater than the average delay experienced by children in this analytic sample—would translate into a 0.114-point decline in HFA. Moreover, this finding is consistent with prior research linking delays in monsoon onset to diminished yields of rice, a staple crop central to food security in many parts of Indonesia (Naylor et al. 2007).

We next assess whether our estimates of average effects mask variation across sub-populations that may differ in vulnerability to climate, building on previous studies which have identified gender, economic activity (e.g., engagement in agriculture), and community context as key mediators of climatic effects (Skoufias and Vinha 2012; Davenport et al. 2017; Cooper et al. 2019). We do so by estimating a series of models that include interactions between the full set of climate variables and group identifiers (group-specific climate coefficients shown in Table 3). These four models respectively test for differences in climate effects by children's sex (Model 2), household farm ownership (Model 3), residence in a rural (or urban) community (Model 4), and residence in Java versus other parts of Indonesia (Model 5). We do not find statistically significant differences in the effects of prenatal monsoon onset delays and HFA between male and female children. For boys, delays in monsoon onset reduce HFA, with a marginal effect of -0.0038 . However, the net effect of monsoon timing is statistically non-significant for girls. Monsoon delay effects also differ in absolute strength and statistical significance across other sub-populations: monsoon delays reduce HFA among children in farm households ($\beta = -0.0046$) but not non-farm households (Model 3); in urban ($\beta = -0.0040$) but not rural households (Model 4); and in households that reside outside of Java ($\beta = -0.0045$) but not among residents of the island (Model 5). Overall, these results suggest that the negative effects of monsoon onset delays on HFA are concentrated within select subsets of the children in our sample, but in no case do we observe statistically positive effects of monsoon onset delays. Likewise, we do not observe statistically significant effects of temperature or precipitation levels among any of the sub-populations considered in these interaction models.

Finally, we tested the robustness of our results in three ways. First, we introduced controls for birth month to account for the potential long-run consequences of seasonal prenatal exposures. The coefficient on the prenatal monsoon exposure variable remained negative and

statistically significant in this additional model ($\beta = -0.0035$, $p = 0.013$). Second, we replaced survey fixed effects with controls for region-specific linear time trends. The coefficient on prenatal monsoon exposure remains negative but is no longer statistically significant at conventional thresholds ($\beta = -0.0021$, $p = 0.101$). Third, we estimated a similarly-specified “placebo” regression model that predicted the sex of the household head (0 = male, 1 = female), which we expected to be uncorrelated with climate exposures as defined here. The estimated coefficient on the prenatal monsoon variable was not statistically significant, as expected ($\beta = 0.0001$, $p = 0.804$; other results not shown).

4.2 Weight-for-height

The next set of analyses examines whether and how children’s weight (WFH)—an indicator of acute malnutrition—is affected by recent exposures to anomalous temperatures, precipitation levels, and monsoon onset. Summary statistics (Table 1) show that the average WFH across the analytic sample of children ages 0-23 months is $z = -0.276$, which is consistent with a relatively high prevalence of thinness (i.e., wasting). Our analysis of WFH begins with an overall model (Model 6) of average climate effects across the sample (Table 4). Recall that we model WFH as a function of climatic conditions over the 12 months prior to the survey because a child’s standardized weight is generally a function of their recent diet and health status—rather than chronic undernutrition and disease as in the case of HFA. Consistent with our models of HFA, we find that delays in monsoon onset are inversely associated with child health. According to point estimates, each day that the monsoon is delayed translates into a 0.007-point reduction in WFH. These marginal impacts may lead to large overall reductions in WFH in the event of the substantial delays in the monsoon that occurred during the study period. For example, a 44-day delay—1 standard deviation above the mean delay experienced by the children in this sample—would result in a 0.292-point decline in WFH. Such a decline would represent an approximately 106 percent change from the average WFH across the sample. As in the model of HFA, temperature and precipitation levels are not independently associated with WFH.

Our next set of analyses test for differences in climate effects on wasting across key sub-populations (Table 5). In parallel with the analysis of heterogeneous effects on HFA, we estimate a series of models of WFH that interact the three climate variables of interest with indicators of children’s sex (Model 7), household farm ownership, (Model 8) residence in a rural (or urban) community (Model 9), and residence in Java versus other parts of Indonesia (Model 10). These four models reveal that the adverse effects of monsoon delays are larger and more statistically significant for girls ($\beta = -0.0087$); children in households that do not own farms ($\beta = -0.0075$); rural households ($\beta = -0.0085$); and residents of Java ($\beta = -0.0133$), relative to boys, members of farm-owning households, urban households, and residents of sample provinces outside of Java. The estimated effect of monsoon onset is statistically non-significant or significant at only marginal levels ($p < 0.10$) among the latter four groups. However, we also note that the between-group difference in the magnitude of monsoon onset effects is only statistically significant for the Java-versus-other province comparison (interaction $\beta = -0.0119$, $p < 0.05$). As a result, these results are only suggestive of potential differences in vulnerability and not definitive.

Finally, we conduct three robustness checks on the overall model of WFH. First, we included an additional control for birth month to account for the residual influence of birth seasonality. The estimated effect of recent monsoon exposures remained negative and statistically significant ($\beta = -0.0067$, $p = 0.009$). Second, we replaced survey fixed effects with controls for region-specific linear time trends, which yields substantively similar estimates of monsoon delay effects ($\beta = -0.0072$, $p = 0.013$). Third, we estimate a “placebo” regression predicting the sex of the household head (0 = male, 1 = female). Our results reveal that recent monsoon exposures are not significantly associated with this outcome variable ($\beta = -0.0003$, $p = 0.632$; other results not shown), which increases confidence that our main results are not spurious.

5. Discussion and conclusions

This study evaluates the effects of climatic variability on indicators of chronic and acute child malnutrition in Indonesia. Our findings support two overall conclusions. First, levels of both chronic malnutrition (as indicated by low HFA) and acute malnutrition (as indicated by low WFH) are influenced to the timing of precipitation that children are exposed to during critical periods (Alderman and Headey 2018; Victoria et al. 2010). Delays in the monsoon season during the prenatal period are associated with diminished height among children ages 24-59 months, and the weight of children ages 0-23 months is similarly influenced by the timing of the most recent monsoon season. The estimated magnitude of both effects is substantively meaningful in the context of the delays in monsoon onset that have occurred in Indonesia during the study period. According to our point estimates, a monsoon onset delay on the order of one standard deviation above the sample mean will produce 0.114-point declines in HFA (6.3% of mean HFA) and 0.292-point declines in WFH (105.8% of mean WFH) among the respective groups of children in our sample. This difference in magnitudes is consistent with a process in which monsoon delays substantially undermine short-term nutritional status, and that this subsequently translates into smaller losses for long-term nutritional status once coping strategies and catch-up growth are accounted for.

In addition to the consistency and substantive significance of estimated monsoon onset effects across outcomes, our results also align with prior research on the effects of climatic variability on Indonesian agriculture. Specifically, Naylor et al. (2007) find that onset delays adversely affect rice output, estimating that a delay of 30 days led to average declines of between 6.5 and 11 percent across the main rice-growing regions of Java and Bali (Naylor et al. 2007). Other research by Naylor et al. (2002) show that delayed precipitation may also disrupt the timing (but not annual output) of corn production. In the context of these findings, the observed adverse effects of monsoon onset delay on both HFA and WFH can plausibly be interpreted as being driven by reductions in agricultural production and related disruptions to food and labor markets (Salafsky 1994).

Second, our results point to notable differences in the magnitude and statistical strength of estimated monsoon timing effects. Recent monsoon onset delays have a statistically stronger effect on WFH among residents of Java than other provinces. This finding is consistent with the above-cited evidence from Naylor et al. (2002, 2007), which suggest Java’s rice-oriented agricultural economy is particularly vulnerable to delays in the monsoon. The interaction

models that we estimate do not show statistically significant differences between the other groups of interest. However, estimates of group-specific monsoon effects reveal differences in the magnitude and statistical strength across other subsets of the sample. The net effects of monsoon onset delays on HFA are negative and statistically significant among children in farm households (but not non-farm households), urban (but not rural) residents, and in households that reside outside of Java (but not residents of the island). The analysis of WFH shows that monsoon timing effects are concentrated among girls, children in households that do not own farms, and rural residents. We caution against drawing strong conclusions about the distribution of vulnerability to climate variability based on these results. However, the lack of consistency across models suggests that the effects of monsoon onset delays on HFA and WFH may operate through different pathways and with distinct implications for sub-populations across our diverse sample.

Broadly, our findings demonstrate that children's health and nutritional status is sensitive to climatic variability and the second-order socioeconomic consequences of such changes. Our results, in conjunction with the emerging literature on climate and nutrition, should draw additional attention to this important but understudied consequence of climate change for both researchers and policymakers. Read in the context of research on Indonesian agriculture, our study suggests that delays in monsoon onset undermine children's nutrition via disruptions to agricultural production and related markets. This finding suggests that efforts to maintain crop yields and output in the face of increasingly adverse environmental conditions will need to be part of future climate protection strategies. Decision-makers must also give attention to the ways in which climate perturbations affect agricultural income and food prices, which may also influence food and nutritional security—including for populations far removed from agricultural production. Our findings are less consistent with possible biological mechanisms between climate and nutrition, but such processes (e.g., climate-related changes in disease transmission) may predominate in other contexts. Only by considering each of these pathways between climate and undernutrition, and tailoring interventions accordingly, can children's health be protected from the many possible consequences of environmental change.

References

- Agadjanian V, & Prata N (2003). Civil war and child health: regional and ethnic dimensions of child immunization and malnutrition in Angola. *Social Science & Medicine*, 56(12), 2515–2527. [PubMed: 12742614]
- Alderman H (2010). Safety nets can help address the risks to nutrition from increasing climate variability. *The Journal of Nutrition*, 140(1), 148S–152S. [PubMed: 19923387]
- Alderman H, & Behrman JR (2006). Reducing the incidence of low birth weight in low-income countries has substantial economic benefits. *The World Bank Research Observer*, 21(1), 25–48.
- Alderman H, & Headey D (2018). The timing of growth faltering has important implications for observational analyses of the underlying determinants of nutrition outcomes. *PloS one*, 13(4), e0195904. [PubMed: 29694431]
- Alderman H, Hoddinott J, & Kinsey B (2006). Long term consequences of early childhood malnutrition. *Oxford Economic Papers*, 58, 450–474.
- Almond D, & Currie J (2011). Killing me softly: The fetal origins hypothesis. *The Journal of Economic Perspectives*, 25(3), 153–172. [PubMed: 25152565]

- Andalón M, Azevedo JP, Rodríguez-Castelán C, Sanfelice V, & Valderrama-González D (2016). Weather shocks and health at birth in Colombia. *World Development*, 82, 69–82.
- Angeles G, Guilkey DK, & Mroz TA (2005). The impact of community-level variables on individual-level outcomes: theoretical results and applications. *Sociological Methods & Research*, 34(1), 76–121.
- Bakhtsiyarava M, Grace K, & Nawrotzki RJ (2018). Climate, birth weight, and agricultural livelihoods in Kenya and Mali. *American Journal of Public Health*, 108(S2), S144–S150. [PubMed: 29072943]
- Bandyopadhyay S, Kanji S, & Wang L (2012). The impact of rainfall and temperature variation on diarrheal prevalence in Sub-Saharan Africa. *Applied Geography*, 33, 63–72.
- Barrett CB (2010). Measuring food insecurity. *Science*, 327(5967), 825–828. [PubMed: 20150491]
- Basu R, Rau R, Pearson D, & Malig B (2018). Temperature and term low birth weight in California. *American Journal of Epidemiology*, 187(11), 2306–2314. [PubMed: 29901701]
- Black RE, Allen LH, Bhutta ZA, Caulfield LE, De Onis M, Ezzati M, ... & Maternal and Child Undernutrition Study Group. (2008). Maternal and child undernutrition: global and regional exposures and health consequences. *The Lancet*, 371(9608), 243–260.
- Bohra-Mishra P, Oppenheimer M, & Hsiang SM (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. *Proceedings of the National Academy of Sciences*, 777(27), 9780–9785.
- Bradbear C, & Friel S (2013). Integrating climate change, food prices and population health. *Food Policy*, 43, 56–66.
- Brown ME, & Kshirsagar V (2015). Weather and international price shocks on food prices in the developing world. *Global Environmental Change*, 35, 31–40.
- Bruckner TA, van den Berg GJ, Smith KR, & Catalano RA (2014). Ambient temperature during gestation and cold-related adult mortality in a Swedish cohort, 1915–2002. *Social Science & Medicine*, 119, 191–197. [PubMed: 24593929]
- Burke M, Hsiang SM, & Miguel E (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(1511), 235–239. [PubMed: 26503051]
- Campbell LP, Luther C, Moo-Llanes D, Ramsey JM, Danis-Lozano R, & Peterson AT (2015). Climate change influences on global distributions of dengue and chikungunya virus vectors. *Phil. Trans. R. Soc. B*, 370(1665), 20140135. [PubMed: 25688023]
- Caruso R, Petrarca L, & Ricciuti R (2016). Climate change, rice crops, and violence: Evidence from Indonesia. *Journal of Peace Research*, 53(1), 66–83..
- Challinor AJ, Watson J, Lobell DB, Howden SM, Smith DR, & Chhetri N (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, 4(4), 287.
- Cooper MW, Brown ME, Hochrainer-Stigler S, Pflug G, McCallum L, Fritz S, ... & Zvoleff A (2019). Mapping the effects of drought on child stunting. *Proceedings of the National Academy of Sciences*, 776(35), 17219–17224.
- Cornwell K, & Inder B (2015). Child health and rainfall in early life. *The Journal of Development Studies*, 57(7), 865–880.
- Datar A, Liu J, Linnemayr S, & Stecher C (2013). The impact of natural disasters on child health and investments in rural India. *Social Science & Medicine*, 76, 83–91. [PubMed: 23159307]
- Davenport F, Grace K, Funk C, & Shukla S (2017). Child health outcomes in sub-Saharan Africa: a comparison of changes in climate and socio-economic factors. *Global Environmental Change*, 46, 72–87.
- De Casas s., Curio SI, & Carcavallo RU. (1995). Climate change and vector-borne diseases distribution. *Social Science & Medicine*, 40(11), 1437–1440. [PubMed: 7667648]
- De Silva I, & Sumarto S (2018). Child Malnutrition in Indonesia: Can Education, Sanitation and Healthcare Augment the Role of Income? *Journal of International Development*, 30(5), 837–864.
- Del Ninno C, & Lundberg M (2005). Treading water: the long-term impact of the 1998 flood on nutrition in Bangladesh. *Economics & Human Biology*, 3(1), 67–96. [PubMed: 15722263]
- Deschênes O, Greenstone M, & Guryan J (2009). Climate change and birth weight. *American Economic Review*, 99(2), 211–17.

- Field RD, Van Der Werf GR, Fanin T, Fetzner EJ, Fuller R, Jethva H, ... & Worden HM (2016). Indonesian fire activity and smoke pollution in 2015 show persistent nonlinear sensitivity to El Niño-induced drought. *Proceedings of the National Academy of Sciences*, 113(33), 9204–9209.
- Grace K, Davenport F, Funk C, & Lerner AM (2012). Child malnutrition and climate in Sub-Saharan Africa: An analysis of recent trends in Kenya. *Applied Geography*, 35(1–2), 405–413.
- Grace K, Davenport F, Hanson H, Funk C, & Shukla S (2015). Linking climate change and health outcomes: examining the relationship between temperature, precipitation and birth weight in Africa. *Global Environmental Change*, 35, 125–137.
- Grosso V, & Kraehnert K (2016). Extreme weather events and child height: evidence from Mongolia. *World Development*, 86, 59–78.
- Hoddinott J, & Kinsey B (2001). Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics*, 63(4), 409–436.
- Hoddinott J (2006). Shocks and their consequences across and within households in rural Zimbabwe. *The Journal of Development Studies*, 42(2), 301–321.
- Hoddinott J, Alderman H, Behrman JR, Haddad L, & Horton S (2013). The economic rationale for investing in stunting reduction. *Maternal & Child Nutrition*, 9, 69–82. [PubMed: 24074319]
- Hunter LM, Luna JK, & Norton RM (2015). Environmental dimensions of migration. *Annual Review of Sociology*, 41, 377–397.
- Knox J, Hess T, Daccache A, & Wheeler T (2012). Climate change impacts on crop productivity in Africa and South Asia. *Environmental Research Letters*, 7(3), 034032.
- Kumar S, Molitor R, & Vollmer S (2016). Drought and early child health in rural India. *Population and Development Review*, 42(1), 53–68.
- Levy K, Woster AP, Goldstein RS, & Carlton EJ (2016). Untangling the impacts of climate change on waterborne diseases: a systematic review of relationships between diarrheal diseases and temperature, rainfall, flooding, and drought. *Environmental Science & Technology*, 50(10), 4905–4922. [PubMed: 27058059]
- Lobell DB, & Field CB (2007). Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, 2(1), 014002.
- Lobell DB, Bänziger M, Magorokosho C, & Vivek B (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature climate change*, 7(1), 42.
- Lybbert TJ, & Sumner DA (2012). Agricultural technologies for climate change in developing countries: Policy options for innovation and technology diffusion. *Food Policy*, 57(1), 114–123.
- Maccini S, & Yang D (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, 99(3), 1006–26.
- Mayer JD (2000). Geography, ecology and emerging infectious diseases. *Social Science & Medicine*, 50(7–8), 937–952. [PubMed: 10714918]
- Maystadt JF, Mueller V, & Sebastian A (2016). Environmental migration and labor markets in Nepal. *Journal of the Association of Environmental and Resource Economists*, 3(2), 417–452.
- Molina O, & Saldarriaga V (2017). The perils of climate change: In utero exposure to temperature variability and birth outcomes in the Andean region. *Economics & Human Biology*, 24, 111–124. [PubMed: 27984771]
- Mora C, Dousset B, Caldwell IR, Powell FE, Geronimo RC, Bielecki CR, ... & Lucas MP. (2017). Global risk of deadly heat. *Nature Climate Change*, 7(7), 501–506.
- Moran EF, Adams R, Bakoyéma B, Fiorini S, & Boucek B (2006). Human strategies for coping with El Niño related drought in Amazônia. *Climatic Change*, 77(3–4), 343–361.
- Mueller V, & Gray C (2018). Heat and adult health in China. *Population and Environment*, 1–26. [PubMed: 30349149]
- Mueller VA, & Osgood DE (2009). Long-term impacts of droughts on labour markets in developing countries: evidence from Brazil. *The Journal of Development Studies*, 45(10), 1651–1662.
- Mueller V, Gray C, & Kosec K (2014). Heat stress increases long-term human migration in rural Pakistan. *Nature climate change*, 4(3), 182.

- Naylor R, Falcon W, Wada N, & Rochberg D (2002). Using El Niño-Southern Oscillation climate data to improve food policy planning in Indonesia. *Bulletin of Indonesian Economic Studies*, 35(1), 75–91.
- Naylor RL, Battisti DS, Vimont DJ, Falcon WP, & Burke MB (2007). Assessing risks of climate variability and climate change for Indonesian rice agriculture. *Proceedings of the National Academy of Sciences*, 707(19), 7752–7757.
- Nordkvelle J, Rustad SA, & Salmivalli M (2017). Identifying the effect of climate variability on communal conflict through randomization. *Climatic Change*, 141(4), 627–639.
- Pascual M, Ahumada JA, Chaves LF, Rodo X, & Bouma M (2006). Malaria resurgence in the East African highlands: temperature trends revisited. *Proceedings of the National Academy of Sciences*, 103(15), 5829–5834.
- Phalkey RK, Aranda-Jan C, Marx S, Höfle B, & Sauerborn R (2015). Systematic review of current efforts to quantify the impacts of climate change on undernutrition. *Proceedings of the National Academy of Sciences*, 112(33), E4522–E4529.
- Rabassa M, Skoufias E, & Jacoby H (2014). Weather and Child Health in Rural Nigeria. *Journal of African Economies*, 23(4), 464–492.
- Rachmi CN, Agho KE, Li M, & Baur LA (2016). Stunting, underweight and overweight in children aged 2.0–4.9 years in Indonesia: prevalence trends and associated risk factors. *PloS one*, 11(5), e0154756. [PubMed: 27167973]
- Randell H, & Gray C (2019). Climate change and educational attainment in the global tropics. *Proceedings of the National Academy of Sciences*, 776(18), 8840–8845.
- Ray DK, West PC, Clark M, Gerber JS, Prishchepov AV, & Chatterjee S (2019). Climate change has likely already affected global food production. *PloS one*, 14(5).
- Rosales-Rueda M (2018). The impact of early life shocks on human capital formation: Evidence from El Nino floods in Ecuador. *Journal of Health Economics*, 62, 13–44. [PubMed: 30268992]
- Rosinger AY (2018). Household water insecurity after a historic flood: Diarrhea and dehydration in the Bolivian Amazon. *Social Science & Medicine*, 197, 192–202. [PubMed: 29253721]
- Salafsky N (1994). Drought in the rain forest: effects of the 1991 El Nino-Southern Oscillation event on a rural economy in West Kalimantan, Indonesia. *Climatic Change*, 27(4), 373–396.
- Schmidhuber J, & Tubiello FN (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences*, 104(50), 19703–19708.
- Schwarzenberg SJ, & Georgieff MK (2018). Advocacy for improving nutrition in the first 1000 days to support childhood development and adult health. *Pediatrics*, 141(2), e20173716. [PubMed: 29358479]
- Sellers S, & Gray C (2019). Climate shocks constrain human fertility in Indonesia. *World Development*, 117, 357–369. [PubMed: 31213734]
- Sheffield PE, & Landrigan PJ (2010). Global climate change and children's health: threats and strategies for prevention. *Environmental health perspectives*, 779(3), 291–298.
- Shively G, Sununtnasuk C, & Brown M (2015). Environmental variability and child growth in Nepal. *Health & Place*, 35, 37–51. [PubMed: 26183566]
- Skoufias E, & Vinha K (2012). Climate variability and child height in rural Mexico. *Economics & Human Biology*, 70(1), 54–73.
- Skoufias E, Katayama RS, & Essama-Nssah B (2012). Too little too late: welfare impacts of rainfall shocks in rural Indonesia. *Bulletin of Indonesian Economic Studies*, 48(3), 351–368.
- Spears D (2018). Exposure to open defecation can account for the Indian enigma of child height. *Journal of Development Economics*.
- Strauss J, Witoelar F, Sikoki B, & Wattie AM (2009). The fourth wave of the Indonesian Family Life Survey (IFLS4): overview and field report. RAND Corporation.
- Strauss J, Witoelar F, & Sikoki B (2016). The fifth wave of the Indonesia family life survey: overview and field report. RAND: Santa Monica, CA, USA.
- Thai TQ, & Falaris EM (2014). Child schooling, child health, and rainfall shocks: Evidence from rural Vietnam. *Journal of Development Studies*, 50(1), 1025–1037.

- Thiede BC, & Gray CL (2017). Heterogeneous climate effects on human migration in Indonesia. *Population and Environment*, 39(2), 173–195.
- Tiwari S, Jacoby HG, & Skoufias E (2017). Monsoon Babies: Rainfall Shocks and Child Nutrition in Nepal. *Economic Development and Cultural Change*, 65(2), 167–188.
- Torche F, & Villarreal A (2014). Prenatal exposure to violence and birth weight in Mexico: Selectivity, exposure, and behavioral responses. *American sociological review*, 79(5), 966–992. [PubMed: 25999601]
- UNICEF. (2019). *The State of the World's Children 2019*. UNICEF, New York
- Wheeler T, & Von Braun J (2013). Climate change impacts on global food security. *Science*, 347(6145), 508–513.

Table 1

Summary of variables

Variables	Age 0-23 months				Age 24-59 months			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Height-for-age (z-score)	-	-	-	-	-1.798	1.342	-5.960	5.050
Weight-for-height (z-score)	-0.276	1.552	-5.000	4.940	-	-	-	-
Temperature (°C)								
<i>Prenatal</i>	-	-	-	-	26.237	1.320	21.244	29.010
<i>Age 0 to 11 mo.</i>	-	-	-	-	26.242	1.292	21.258	28.848
<i>Age 12 to 23 mo.</i>	-	-	-	-	26.262	1.293	21.520	28.848
<i>12 mo. before survey</i>	26.188	1.248	21.498	28.770	-	-	-	-
Precipitation (mm/day)								
<i>Prenatal</i>	-	-	-	-	7.524	2.510	1.036	15.748
<i>Age 0 to 11 mo.</i>	-	-	-	-	7.451	2.187	2.255	17.039
<i>Age 12 to 23 mo.</i>	-	-	-	-	7.392	2.219	2.593	17.039
<i>12 mo. before survey</i>	7.185	2.090	2.255	14.289	-	-	-	-
Monsoon onset (days)								
<i>Prenatal</i>	-	-	-	-	24.622	23.213	1.000	118.000
<i>Age 0 to 11 mo.</i>	-	-	-	-	25.968	22.949	1.000	112.583
<i>Age 12 to 23 mo.</i>	-	-	-	-	28.882	25.276	1.000	118.000
<i>12 mo. before survey</i>	22.016	21.505	1.750	101.333	-	-	-	-
Sex = female	0.488	-	0	1	0.486	-	0	1
Age (months)	11.750	6.506	1	23	41.828	10.436	24	59
Household size	5.488	2.078	2	18	5.279	1.975	2	18
Number of children < 5 years	1.328	0.545	1	4	1.305	0.549	0	4
Head of household								
<i>Sex = female</i>	0.117	-	0	1	0.112	-	0	1
<i>Age (years)</i>	41.120	13.379	16	91	40.938	12.378	18	92
<i>Primary education = yes</i>	0.673	-	0	1	0.682	-	0	1
<i>Farm ownership = yes</i>	0.389	-	0	1	0.399	-	0	1
Rural community = yes	0.521	-	0	1	0.538	-	0	1
IFLS round								
<i>1993-4</i>	0.177	-	0	1	0.179	-	0	1
<i>1997-8</i>	0.152	-	0	1	0.170	-	0	1
<i>2000</i>	0.228	-	0	1	0.204	-	0	1
<i>2007-8</i>	0.214	-	0	1	0.225	-	0	1
<i>2014-5</i>	0.229	-	0	1	0.222	-	0	1
N		4,812				7,459		

Summary of age (months) shown for brevity. Regression models control for age using a series of age-in-month indicator variables.

Table 2

Estimates from regression models of child height-for-age (z-score)

Model 1			
Variables	β		SE
Temperature			
<i>Prenatal</i>	0.0088		0.0635
<i>Age 0 to 11 mo.</i>	-0.0137		0.0890
<i>Age 12 to 23 mo.</i>	0.0610		0.0835
Precipitation			
<i>Prenatal</i>	-0.0104		0.0114
<i>Age 0 to 11 mo.</i>	-0.0154		0.0185
<i>Age 12 to 23 mo.</i>	0.0159		0.0162
Monsoon onset			
<i>Prenatal</i>	-0.0033	**	0.0014
<i>Age 0 to 11 mo.</i>	0.0001		0.0015
<i>Age 12 to 23 mo.</i>	0.0006		0.0013
Sex = female	0.0194		0.0309
Household size	-0.0396	***	0.0118
Number of children < 5 years	-0.0157		0.0374
Head of household			
<i>Sex = female</i>	-0.0373		0.0504
<i>Age (years)</i>	0.0086	***	0.0016
<i>Primary education = yes</i>	0.1691	***	0.0409
<i>Farm ownership = yes</i>	-0.0394		0.0417
Rural community = yes	-0.0710		0.1029
IFLS round (ref = 1993-4)			
<i>1997-8</i>	0.1487	**	0.0632
<i>2000</i>	0.1386	[†]	0.0723
<i>2007-8</i>	0.4387	***	0.0752
<i>2014-5</i>	0.4535	***	0.0725
Age-in-month controls	Yes		
Community fixed effects	Yes		
Joint test, climate variables	1.22		
R ²	0.1820		
N	7,459		

p<0.01,**
p<0.05,[†]
p<0.10. Climate variables measured from age (-)9 months to 23 months. All standard errors are clustered at the community level. Constant not shown.

Table 3
Group-specific coefficient estimates from regression models of child height-for-age (z-score)

Variables	Model 2			Model 3			Model 4			Model 5		
	Male	Female	Farm = no	Farm = yes	Urban	Rural	Java	Other provinces	SE	SE	SE	SE
Temperature												
Prenatal	0.0361	-0.0164	0.0752	-0.0005	0.0715	0.0240	0.0873	0.0307	0.0795	-0.0019	0.0803	0.0935
Age 0 to 11 mo.	-0.0985	0.0651	0.1052	0.0725	0.1016	-0.1300	0.1121	0.0179	0.1124	-0.0329	0.0999	0.0144
Age 12 to 23 mo.	0.1247	-0.0135	0.0987	-0.0266	0.0926	0.1749	0.1058	0.0429	0.1063	0.0671	0.0953	0.0023
Precipitation												
Prenatal	-0.0105	-0.0114	0.0144	-0.0195	0.0136	0.0019	0.0154	-0.0166	0.0155	-0.0049	0.0143	0.1210
Age 0 to 11 mo.	-0.0193	-0.0133	0.0232	-0.0061	0.0223	-0.0295	0.0241	-0.0058	0.0252	-0.0251	0.0214	0.0243
Age 12 to 23 mo.	0.0101	0.0210	0.0199	0.0108	0.0197	0.0229	0.0209	0.0167	0.0226	0.0097	0.0199	0.0022
Monsoon onset												
Prenatal	-0.0038	-0.0029	0.0018	-0.0026	0.0016	-0.0046	0.0021	-0.0040	0.0018	-0.0028	0.0019	0.1199
Age 0 to 11 mo.	0.0021	-0.0020	0.0019	-0.0013	0.0017	0.0022	0.0021	0.0027	0.0020	-0.0021	0.0018	0.0240
Age 12 to 23 mo.	-0.0016	0.0030	0.0017	0.0008	0.0016	0.0009	0.0018	0.0003	0.0018	0.0010	0.0018	0.0021
Joint test, climate variables	1.24	1.12	0.88	1.98**	1.39	1.05	1.36	0.75				
Joint test, interaction terms		0.94		1.41		1.20						0.51
R ²		0.1831		0.1834		0.1833						0.1826
N		7,459		7,459		7,459						7,459

*** p<0.01,

** p<0.05,

† p<0.10. Climate variables measured from age (-)9 months to 23 months. All standard errors are clustered at the community level. Control variables and constant not shown.

Table 4

Estimates from regression models of child weight-for-height (z-score)

Model 6			
Variables	β		SE
Temperature	0.0322		0.2928
Precipitation	-0.0692		0.0420
Monsoon onset	-0.0066	**	0.0025
Sex = female	0.0623		0.0440
Household size	0.0001		0.0144
Number of children < 5 years	-0.0615		0.0512
Head of household			
<i>Sex = female</i>	0.0438		0.0753
<i>Age (years)</i>	0.0020		0.0022
<i>Primary education = yes</i>	-0.0557		0.0539
<i>Farm ownership = yes</i>	0.0090		0.0596
Rural community = yes	0.0400		0.1247
IFLS round (ref = 1993-4)			
1997-8	0.2215	$\dagger$	0.1259
2000	0.3371	***	0.1026
2007-8	0.3779	***	0.1139
2014-5	0.1556		0.1307
Age-in-month controls	Yes		
Community fixed effects	Yes		
Survey month fixed effects	Yes		
Joint test, climate variables	2.78	**	
R ²	0.1262		
N	4,812		

p<0.01,**
p<0.05, $\dagger$
p<0.10. Climate variables measured during the 12 months prior to the survey. All standard errors are clustered at the community level. Constant not shown.

Table 5

Group-specific coefficient estimates from regression models of child weight-for-height (z-score)

Variables	Model 7			Model 8			Model 9			Model 10						
	Male	Female	Farm = no	Farm = yes	Urban	Rural	Java	Other provinces								
	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE				
Temperature	0.0204	0.2961	0.0182	0.2926	0.0512	0.2853	0.0286	0.3034	-0.0118	0.2920	0.0676	0.2993	0.2080	0.3127	-0.2056	0.3529
Precipitation	-0.0547	0.0474	-0.0877	0.0455	-0.0726	0.0461	-0.0642	0.0486	-0.0872	0.0511	-0.0537	0.0481	-0.1237	0.0668	-0.0792	0.0507
Monsoon onset	-0.0049	0.0027	-0.0087	0.0032	-0.0075	0.0029	-0.0054	0.0032	-0.0053	0.0035	-0.0085	0.0032	-0.0133	0.0034	-0.0014	0.0034
Joint test, climate variables	1.30		3.03**		2.46†		1.40		1.38		2.51†		5.32***			0.96
Joint test, interaction terms		0.55			0.16					0.51				3.65**		
R ²		0.1265			0.1263					0.1265				0.1286		
N		4,812			4,812					4,812				4,812		

p<0.01,**
p<0.05,†
p<0.10.

Climate variables measured during the 12 months prior to the survey. All standard errors are clustered at the community level. Control variables and constant not shown.