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by James Manley

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By James Manley[1]

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[1] Professor of Economics, Towson University, 8000 York Road, Towson, MD 21252. Phone (410) 704-2146. jmanley@towson.edu. No competing financial interests exist.

Abstract

Combining information on household characteristics with data from nearby weather stations, we investigate the effect of fluctuations in temperature and rainfall on the incidence of diarrheal disease among Peruvian children under age 5 in the high altitude sierra region. Considering jointly the role of precipitation and temperature we find that a larger temperature gap, from a higher minimum and/ or lower maximum, means less risk for children. Also we see protective effects of rain in the current month and negative effects of rain in the prior month. Effects are heightened during the rainy season and marginal effects are higher as rainfall amounts rise. Access to indoor drinking water and sanitation seem not to make much difference.

Introduction

The human costs of climate change are likely to be high, and one place in particular danger is Perú. As one paper puts it, "By the end of the 21st century… the tropical Andes may experience a massive warming on the order of 4.5–5 °C. Predicted changes in precipitation include an increase in precipitation during the wet season and a decrease during the dry season, which would effectively enhance the seasonal hydrological cycle in the tropical Andes." (Vuille et al. 2008). This massive warming and amplified variance of precipitation swings could have profound human impacts: climate change "will without a doubt affect future access to clean drinking water as well as to water for sanitation, irrigation and agriculture, mining operations, and hydropower production in the tropical Andes" (Vuille 2013). In an area that is already poor, consequences could be catastrophic.

Climate change is anticipated to raise the average temperature, to create large, problematic rainfall anomalies and to increase the frequency of weather and climate extremes (IPCC 2007, Correa et al. 2016). Rising temperatures will continue to melt glaciers (Vuille et al. 2008), and associated hydrological changes will affect the quantity and quality of water available in Perú, greatly affecting the human population both directly via impairing access to water from drinking, washing, and sanitation, and also as water tables change, affecting agriculture and shifting patterns of economic activity (Mark et al. 2010). Such flooding and droughts can have direct effects such as injury, communicable disease, and exposure to pollutants, but also longer term effects such as malnutrition and mental health disorders (McMichael et al. 2006, Del Ninno & Lundberg 2005).

This paper's outcome of interest is diarrheal disease. A number of studies have documented the relationship between variation in temperature and/ or rainfall on the one hand and on diarrhea on the other. Even small temperature and precipitation changes can have measurable impacts on diarrhea and malnutrition (Haines et al. 2006). Chou et al. (2010) linked both maximum temperatures and the number of days with heavy rainfall to the incidence of diarrheal disease in Taiwan. Bandyopadhyay et al. (2012) link variations in precipitation and temperature to the regional prevalence of diarrhea in sub-Saharan Africa. Singh et al. (2001)

document something similar on several Pacific islands. Carlton et al. (2013) tracked rainfall but not temperatures in Ecuador, finding that heavy rainfall events following dry periods led to increased diarrhea incidence. More recently Horn et al. (2018) in Mozambique link increased rainfall to an increase in the incidence of diarrhea by about 0.6% - 2%. In Costa Rica Ureña-Castro et al. (2019) find that hospitalizations for diarrhea peak two months after rainfall events. Wang et al. (2018) link rainfall and temperature to hospitalizations for acute diarrhea in Hong Kong, with higher temperatures decreasing hospital admissions for diarrhea. Overall, "the delayed effect of precipitation on both rotavirus and norovirus remains unclear" (Wang et al. 2018).

In Perú, diarrhea is a major factor in child development, with the cumulative effect on child growth being larger than even malaria (Lee et al. 2012). Worldwide, "Studies have consistently shown that diarrhoea is the single most important infectious disease determinant of stunting of linear growth" (Black et al. 2013). Growth is an indicator of a child's underlying health status, and children showing lower levels of physical development for their age are often delayed in their mental development as well (Hoddinott & Kinsey 2001). Suboptimal growth increases the risk of cognitive, motor, and educational problems as well as of death from infectious diseases in childhood (Black et al. 2013). Children with below average height have also thereby a permanently reduced mental capacity, decreased productivity, and about a 10% expected reduction in lifetime earning potential (Alderman, Hoddinott, & Kinsey 2006).

Diarrhea tied to exposure to poor sanitation (and thereby to pathogens affecting the ability to digest food and retain water properly) has been linked to decreased physical height and/or growth (Merchant et al. 2003). Children in Africa are taller than their counterparts in India even though the latter children live in households with higher income (and thus most likely with better food), which one study attributes in part to sanitation conditions (Spears 2013). A large scale review concludes that a 1% increase in sanitation coverage is associated with a decrease of about 0.05-0.1% in diarrhea prevalence, but improved water source access is not statistically linked to improved child health (Headey and Palloni 2019).

In several studies, Checkley et al. (2000, 2003, 2004) look at the effect of temperature variability on the incidence of diarrhea in one suburb of Lima (coastal Perú) from 1995-1998. They found that during the 1987-88 El Niño episode, when mean temperatures in Lima went up by up to 5º C, the number of hospital admissions for diarrhea increased dramatically, even doubling, with the most dramatic effects during the winter months (Checkley et al. 2000). A second study tracked 224 children for 35 months from 1995-98, linking diarrhea to height deficits in children up to 24 months and finding that children contracting diarrhea in their first six months of life may be permanently limited in their growth (Checkley et al. 2003). Children living in areas with poor access to water are about 1 cm shorter when they are just 24 months old, and they have over 50% more episodes of diarrhea than children with better water access (Checkley et al. 2004).

Few studies have looked at both temperature and rainfall (in spite of the fact that Auffhammer et al. (2013) contend that failure to do so creates econometric problems) and only Carlton et al. (2013) had a sample larger than a few hundred children. No study we have seen has incorporated climate, weather, economic, and environmental variables into one analysis investigating child welfare, though writers such as Grace et al. (2015) look at birthweight in a similar way. Finally, no study has looked at the impacts of the environment on health in the interior of Perú. (Barron et al. 2018 look at the role of cold in exacerbating maternal anemia in affecting fetal wellbeing in utero in the sierra of Perú.)

By combining precise, accurate measurements of precipitation and temperatures with measures of child health and development as well as of economic welfare, we observe the human impacts of recent weather variation. If we understand the effects of short-term changes, we will know better what to expect as larger climatic changes occur.

Data

Household Data

The Demographic and Health Surveys (Measure DHS) have gathered data from 2004-2007 in Perú, including geo-references. Since exposure in early childhood is the most damaging, we chose data covering children from birth until 5 years old.

The survey is done annually, but it is neither a panel nor is it a consistently repeated cross section. Up to 39 households are grouped in a given year and the geo-reference for a given "group" is shifted in a random direction by up to 2.5 km in urban areas or up to 10 km in rural areas. Thus, we grouped all observations within 5 km in urban areas and within 20 km in rural areas. Since each group refers to data collected in a single year, we compiled groups into "sites" to identify areas visited repeatedly by the DHS survey teams in the years from 2004-2007. 42 urban sites had been sampled in each of the five years. To examine rural areas also, we looked for areas that were the most sampled during the period, choosing the 40 sites sampled in three or more years.

Weather data

We matched the locations of active weather stations as reported on the Perúvian government website http://senamhi.gob.pe/ (SENAMHI, the Servicio Nacional de Meteorología e Hydrología del Perú) to the DHS data collection sites, choosing 35 stations to maximize overlap. From each station we acquired monthly observations from the five year period on each of the four variables: median, minimum, and maximum temperatures. (Not all variables contain all observations.) Each monthly temperature variable is the mean of daily data, so the "maximum temperature" for a given month is actually the mean of the maximum temperatures from each day of the month. We took rainfall data from the US Government's Tropical Rainfall Measuring Mission, interpolated to the match the locations of the weather stations.

Perú consists of three regions: the coast, the jungle, and the mountainous sierra region. We focus on the sierra region because both the coast and the jungle interior are constantly quite warm. For example, at the weather station Campo de Marte, located in Lima, over 5 years, the lowest mean monthly minimum temperature measured was 17.1º C, while highest monthly mean maximum was 21.2º. Over the same period, at Tarapoto in the interior, the minimum was 21.8º and the maximum 32.8º. Similarly, rainfall varies considerably from 0.2 mm in rain-shadowed, coastal Trujillo to over 500 mm at San Gaban, near the Bolivian border. So, we chose to focus on the more heterogeneous temperatures and variable precipitation in the Sierra region.

The Sierra region contains about 11.7 million people, about 38% of the country's population (INEI 2014). Figure 1 shows the locations of the 18 weather stations used in this study, which are marked with an S. In the Sierra the mean minimum temperature is 4.7° and the mean maximum was 19.1°C. The mean (median) altitude of data in the Sierra region is about 3235 (3314) meters, while the altitude of data in the other regions combined is 372 (154) meters (data not shown).

We merge the information about weather and climate, on the one hand, with household data, including economic and health. This dataset has as one child as an observation and it includes the minimum and maximum temperature in the month in which the child's health data was recorded, as well as the month previous. From the DHS we also included an indicator for whether the household has a toilet (indoor or outdoor); the child's age in months; and finally an indicator for indoor access to water.

Sample Statistics are found in Table 1.

Methods

To investigate the relationship between diarrheal disease and weather, we have run a variety of investigatory regressions using a variety of measures of temperature and precipitation, including high, low, and median temperatures from a given month as well as from the previous month. Again, as noted above by Auffhammer et al. (2013), econometrically speaking it is important to include both temperature and precipitation in some form in each regression. We tried using precipitation in the current month as well the previous month, and included each temperature variable on its own as well as with each precipitation variable. In the end the variables that proved to matter the most were two differences: the current month's temperature spread between maximum and minimum, and the difference between precipitation in the current month and the previous month.

Unfortunately the maximum, median and maximum temperatures are highly correlated ($\rho \approx 0.9$) so we cannot include more than one in any regression. Therefore to investigate the relationship between temperatures and health we consider a variety of specifications, including each of these on its own as well as in a few combinations, such as the difference between the maximum and minimum temperature.

Precipitation can have variable effects. Flooding caused by excess rainfall can spread fecal material into potable supplies, while low rainfall may force the use of contaminated water (Molina 2009, Githeko et al. 2000, Carlton et al. 2013). Thus, access to clean water and modern sanitation are likely to help. Indeed, Checkley et al. (2004) affirm that they are particularly important in Lima, Perú.

Higher temperatures can increase food spoilage rates and dry up water sources, concentrating contamination. Also warmth can facilitate the reproduction and increase survival rates for both the pathogens themselves and vectors such as flies. On the other hand, low temperatures should inhibit reproduction of the various organisms that cause the illness.

Our first investigation considers the nonparametric relationship between diarrhea and our two preferred climate variables: current month temperature differentials (i.e. max vs. minimum temperatures within the month) and the change in precipitation (i.e. precipitation in the past month minus precipitation in the current month). Next, we include these two explanatory variables together.

Next we include a vector of household characteristics. Characteristics such as access to indoor water and improved sanitation are expected to cut the incidence of diarrhea. Wealth quintile and electricity are also expected to be protective while a dirt floor might be both a proxy for poverty and an independent vector through which diarrheal disease is transferred. Conditional on these characteristics, it is not clear whether a household being in a rural area might be protective (as a reduced population density might mean reduced exposure to pathogens) or negative (as amenities such as water treatment are unavailable). Finally, altitude is included in all regressions as well.

Thus, the regressions we estimate take the form

$$\mathrm{Diar}_{im} = \beta \mathrm{climate}_{\mathrm{m}} + \gamma \mathrm{h}_i + \delta_{\mathrm{s}} + \varepsilon_{\mathrm{i}}$$

where Diar is a dummy variable indicating whether the child had diarrhea in the past two weeks. The vector climate represents the two variables described above. Household variables, denoted by h, include access to electricity, wealth quintile, rural status, dirt floor in home, indoor water, and type of toilet. δ_s indicates the weather station, to correct for any idiosyncratic errors in the local area, while ε indicates an error term at the child (i) and month (m) level.

All regressions were carried out with both OLS and the logit specifications. For ease of interpreting the marginal effect, we report OLS coefficients, but in all cases the signs were identical and the p-values of the logit coefficient are similar.

Results

We first consider the nonparametric relationships. As shown in Figures 2 and 3, both climate variables show negative relationships overall, with the temperature differential showing a very clear relationship while the effect of precipitation is less obvious. We now consider each separately.

The data show that a larger temperature gap, from a higher minimum and/ or lower maximum, means less risk for children. When the differential between high and low temperatures is greater, that means children are less likely to come down with diarrheal illness. The association between colder nights and decreasing pathogen activity is intuitive, particularly in the higher altitudes where freezing temperatures are possible. At the same time, our preferred measure of temperature difference suggests a protective effect of higher temperatures. Noting that in our sample (Table 1) maximum temperatures vary from 9° to 28° (with the mean and median both around 19.5°) we suggest that simple thermal comfort may be the protective mechanism. In other words, temperature differentials are positively associated with overall warmer temperatures and with lower rates of diarrhea. Note that we did evaluate each temperature on its own first and found that the difference had a higher F-statistic than either the minimum or the maximum on its own.

A similar finding holds for rainfall: more precipitation in the preceding month is associated with diarrhea, while less precipitation in the current month is also so associated. One way to think of this is that perhaps rainfall keeps children indoors in the short term but after the rain is over children go outside and are exposed to pathogens. Thus neither constant rainfall nor constant dry weather increase diarrheal illness. Figure 3 shows the nonparametric relationship between the change in precipitation and diarrhea, which shows relatively consistent marginal effects. When we considered current month precipitation and past month precipitation separately, the past month's precipitation is much more significant than that of the current month. Overall, based on our need to include both variables and within that based on the separate F tests we chose to keep these two variables together for all remaining specifications.

Moving on to parametric regressions, we see that the coefficients are comparable in size throughout Table 2. In our most parsimonious specification, shown in column 1 of Table 2, we see that both variables on their own are negative and statistically significant. In column 2 we see that adding the household characteristics decreases the effect of the temperature differential by about 15% and the change in precipitation drops by about 6%. The sign is constant and the variables are always significant at the 5% level. Looking at the impact of the other covariates we see that while the child's age and the altitude are always significant, the same cannot be said of the household infrastructure. Neither toilet access nor indoor water access appreciably affect illness rates.

In columns 3-4 we include monthly average temperatures and rainfall amounts from the past 30 years. We find that these baseline temperatures and precipitation amounts are not themselves significant but they do affect the statistical significance of the temperature differential. However, the sign is consistent and the size of the temperature coefficient is larger than other specifications. Conversely the size of the precipitation coefficient has decreased a bit but the sign and significance continue to be strong.

In Table 3 we try breaking the sample into different groups. The first two columns show the effects of limiting the sample to children ages 2 and below. Although the statistical significance comes and goes, the coefficients have not changed much; it is difficult to disentangle the effects of working with a smaller sample from the actual effect of looking at different age groups.

Columns 3-4 compare the rainy season (October – April) against the rest of the year, and this difference is striking. Compared to the baseline regression in column 2 of table 2, impacts during the dry season have subsided considerably, with temperature differentials almost 90% less impactful and rainfall having about a 30% diminished marginal effect. On the other hand, during the rainy season, the importance of temperature rises to nearly three times its baseline level. Precipitation also increases in importance by about 30%.

Column 5 limits the sample to months with at least 10 mm of rainfall, and column 6 considers only months with at least 20 mm of rain. The results in these two columns are similar to those in the rainy season column: as the amount of rainfall increases, the marginal effects of temperature differentials jump, while the effects of additional rainfall climb more slowly. Specifically, as we go from a typical month to a month with at least 10 mm of precipitation, the effects of temperature increase by almost 90%. With at least 20 mm of precipitation, the effect nearly doubles to about 170%.

Discussion

The results show that the temperatures and precipitation have a small but significant effect on children's health. In particular, a higher temperature differential in a given month (i.e. lower minimum and higher maximum temperatures) is protective. Also we see protective effects of rain in the current month and negative effects of rain in the prior month. This is consistent with rain in the previous month increasing disease incidence while less rain in the current month does the same.

Overall the effects are not large: under the most bullish scenario (which occurs in the rainy season and/ or in months when 20 mm of rain has fallen) the effect of temperature differentials is an increase or decrease in diarrheal incidence of about one half of 1%, or about 5 children per 1000. The effect of rainfall in a given month accounts for at most about one tenth of 1%, about one child per thousand. In the simplest specification, the two variables on their own have a F statistic of 7.67, a number that is below most standards for a weak instrument. R-squared statistics for all regressions are below 4%.

Finally, a brief word about what seems not to matter. We separately tried a large number of additional factors, including rural vs. urban, dirt floors, and electricity, but nothing proved significant. We tried separately including freezing temperatures, but beyond their effect on minimum temperatures, no effect was noted. And we were unable to restrain ourselves from including indoor water and sanitation access, but as you can see in tables 2 and 3, it never contributed, reifying the findings of Pickering et al. (2019) that interventions need to be substantial to achieve a sustained impact on diarrhea.

Conclusion

Water shortages in Perú are likely to exacerbate the impacts of climatic change, and the situation looks increasingly "dire" (Bury et al. 2013). Anticipating future effects requires using precisely matched household and weather data and considering a broad variety of variables. The good news is that clarifying the linkages, most crucially at the local and seasonal levels, lays the groundwork for potential policy solutions (Altizer et al. 2013).

In the high altitude environs of central, sierra Perú, where temperatures rarely drop below freezing and never get as high as 30°C, we have identified weather conditions that affect the prevalence of diarrhea. Remembering the econometric imperative to always consider precipitation and temperature jointly, we determine that the best specification includes the difference between minimum and maximum temperatures as well as the difference between the current month's precipitation and that from the previous month.

Higher maximum and lower minimum temperatures are protective, likely for opposite reasons: minimum temperatures chill the environment, reducing bacterial activity, while maximum temperatures (which again in this data are only between 9° and 28°) may only provide thermal comfort. Meanwhile precipitation in the past month increases the prevalence of diarrhea while precipitation in the current month is protective. This is in line with previous by Carlton et al. (2013) that rainfall after dry periods increases diarrhea while continuous precipitation decreases incidence following wet periods, and with Ureña-Castro et al. (2019) that cases bad enough to warrant hospitalization are tied to precipitation two months prior.

Perhaps not surprisingly impacts are much stronger during the rainy season and in months when some rain has already fallen. Effects seem slightly larger and are more statistically significant for older children, but point estimates of impacts are not much different between the two. Unfortunately also in line with Carlton et al. (2013) sanitation does not make much difference, though unlike the present study they find that treating drinking water can help.

Links between the physical environment and health are always complicated. As climate change raises temperatures across this threshold, the incidence of diarrhea is likely to increase, so it behooves us to improve child safety through all means available to us.

Works Cited

Alderman, Harold, John Hoddinott, and Bill Kinsey. 2006. "Long Term Consequences of Early Childhood Malnutrition." *Oxford Economic Papers* 58:450–74.

Altizer, S., Ostfeld, R. S., Johnson, P. T., Kutz, S., & Harvell, C. D. 2013. "Climate change and infectious diseases: From evidence to a predictive framework." *Science*, 341(6145), 514-519.

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, 7(2), 181-198.

Bandyopadhyay, Sushenjit, Shireen Kanji, and Limin Wang. 2012. "The impact of rainfall and temperature variation on diarrheal prevalence in Sub-Saharan Africa." *Applied Geography* 33: 63-72.

Barron, M., Heft-Neal, S., & Perez, T. (2018). Long-term effects of weather during gestation on education and labor outcomes: Evidence from Perú (No. 134).

Black, Robert E., Cesar G. Victora, Susan P. Walker, Zulfiqar A. Bhutta, Parul Christian, Mercedes De Onis, Majid Ezzati et al. 2013. "Maternal and child undernutrition and overweight in low-income and middle-income countries." *The Lancet* 382, no. 9890: 427-451.

Bury, J., Mark, B. G., Carey, M., Young, K. R., McKenzie, J. M., Baraer, M., ... & Polk, M. H. 2013. "New geographies of water and climate change in Perú: Coupled natural and social transformations in the Santa River watershed." Annals of the Association of American Geographers, 103(2), 363-374.

Carlton, E.J., Eisenberg, J.N., Goldstick, J., Cevallos, W., Trostle, J. and Levy, K., 2013. Heavy rainfall events and diarrhea incidence: the role of social and environmental factors. *American journal of epidemiology*, p.kwt279.

Checkley, W., Epstein, L. D., Gilman, R. H., Figueroa, D., Cama, R. I., Patz, J. A., & Black, R. E. 2000. Effects of *El Niño* and ambient temperature on hospital admissions for diarrhoeal diseases in Perúvian children. *The Lancet*,*355*(9202), 442-450.

Checkley, W., Epstein, L. D., Gilman, R. H., Cabrera, L., & Black, R. E. 2003. Effects of acute diarrhea on linear growth in Perúvian children. *American Journal of Epidemiology*, *157*(2), 166-175.

Checkley, W., Gilman, R. H., Black, R. E., Epstein, L. D., Cabrera, L., Sterling, C. R., & Moulton, L. H. 2004. Effect of water and sanitation on childhood health in a poor Perúvian peri-urban community. *The Lancet*,*363*(9403), 112-118.

Chou, Wei-Chun, Jiunn-Lin Wu, Yu-Chun Wang, Hsin Huang, Fung-Chang Sung, and Chun-Yu Chuang. 2010. “Modeling the impact of climate variability on diarrhea-associated diseases in Taiwan (1996-2007).” *Science of the Total Environment* 409: 43-51.

Correa, S. W., Mello, C. R., Chou, S. C., Curi, N., & Norton, L. D. (2016). Soil erosion risk associated with climate change at Mantaro River basin, Perúvian Andes. *Catena*, *147*, 110-124.

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.

Grace, K., F. Davenport, H. Hanson, C. Funk, and S. Shukla. 2015. "Linking climate change and health outcomes: Examining the relationship between temperature, precipitation and birth weight in Africa." *Global Environmental Change* 35: 125-137.

Headey, D., & Palloni, G. (2019). Water, sanitation, and child health: evidence from subnational panel data in 59 countries. Demography, 56(2), 729-752.

Hoddinott, John, and Bill Kinsey. 2001. “Child Growth in Time of Drought.” *Oxford Bulletin of Economics and Statistics* 63(4): 409 - 436.

Horn, L., Hajat, A., Sheppard, L., Quinn, C., Colborn, J., Zermoglio, M., ... & Ebi, K. 2018. Association between precipitation and diarrheal disease in Mozambique. International journal of environmental research and public health, 15(4), 709.

Haines, A., R. S. Kovats, D. Campbell-Lendrum, and C. Corvalan. 2006. “Climate Change and Human Health: Impacts, Vulnerability and Public Health.” *Public Health* 120: 585-596.

INEI (Instituto Nacional de Estadística e Informática, ed.) (2014). “Perú: Población estimada al 30 de junio y tasa de crecimiento de las ciudades capitales, por departamento, 2014” Available online as of July 2019 at
https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1157/libro.pdf

IPCC, 2007: Chapter 13 Executive Summary. In: Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge, UK.

Lee, G., Yori, P., Olortegui, M. P., Pan, W., Caulfield, L., Gilman, R. H., ... & Kosek, M. (2012). Comparative effects of vivax malaria, fever and diarrhoea on child growth. *International journal of epidemiology*, *41*(2), 531-539.

Mark, B. G., Bury, J., McKenzie, J. M., French, A., & Baraer, M. (2010). Climate change and tropical Andean glacier recession: evaluating hydrologic changes and livelihood vulnerability in the Cordillera Blanca, Perú. *Annals of the Association of American Geographers*, *100*(4), 794-805

McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: present and future risks. *The Lancet*, *367*(9513), 859-869.

Merchant, AT, C Jones, A Kiure, R Kupka, G Fitzmaurice, MG Herrera, and WW Fawzi. 2003. “Water and Sanitation Associated with Improved Growth.” *European Journal of Clinical Nutrition* 57: 1562-1568.

Pickering, A. J., Null, C., Winch, P. J., Mangwadu, G., Arnold, B. F., Prendergast, A. J., ... & Stewart, C. P. (2019). The WASH Benefits and SHINE trials: interpretation of WASH intervention effects on linear growth and diarrhoea. The Lancet Global Health, 7(8), e1139-e1146.

Singh, Reena B. K., Simon Hales, Neil de Wet, Rishi Raj, Mark Hearnden, and Phil Weinstein. 2001. “The Influence of Climate Variation and Change on Diarrheal Disease in the Pacific Islands.” *Environmental Health Perspectives* 109(2): 155-159.

Spears, Dean. 2013. “How Much International Variation in Child Height can Sanitation Explain?” *World Bank Policy Research Working Paper 6351.* 55pp.

Ureña-Castro, K., Ávila, S., Gutierrez, M., Naumova, E. N., Ulloa-Gutierrez, R., & Mora-Guevara, A. (2019). Seasonality of Rotavirus Hospitalizations at Costa Rica’s National Children’s Hospital in 2010–2015. International journal of environmental research and public health, 16(13), 2321.

Vuille, M., Francou, B., Wagnon, P., Juen, I., Kaser, G., Mark, B. G., & Bradley, R. S. 2008. Climate change and tropical Andean glaciers: Past, present and future. *Earth-Science Reviews*, *89*(3), 79-96.

Vuille, M. 2013. “Climate Change and Water Resources in the Tropical Andes.” Inter-American Development Bank Environmental Safeguards Unit Technical Note IDB-TN-515. 35pp.

Wang, P., Goggins, W. B., & Chan, E. Y. 2018. A time-series study of the association of rainfall, relative humidity and ambient temperature with hospitalizations for rotavirus and norovirus infection among children in Hong Kong. Science of The Total Environment, 643, 414-422.

Table 1. Sample Statistics

	Mean	SD	Min	Max
Max Temp Current Month	19.35	3.83	9.4	33.2
Min Temp Current Month	4.46	4.73	-10.8	21.3
Max - Min Current Month	14.89	4.03	5.1	27.9
Precip Current Month (mm)	62.92	57.37	0	274.5
Precip Diff Current - Last Month (mm)	-10.34	49.28	-255.3	204.5
Altitude	3340	624.7	420	4723
Age (months)	29.86	17.18	0	59
Had diarrhea in past two weeks	0.16		0	1
No toilet (1/0)	0.31		0	1
Indoor plumbing (1/0)	0.62		0	1
1 = rural 0 = urban	0.72		0	1
Electricity (1/0)	0.59		0	1
Dirt floor (1/0)	0.72		0	1

Table 2. Covariate Analysis

	(1) Had diarrhea in past two weeks	(2) Had diarrhea in past two weeks	(3) Had diarrhea in past two weeks	(4) Had diarrhea in past two weeks
Max - Min temp current mth	-0.00765***	-0.00654***	-0.00941*	-0.00751
	(0.00219)	(0.00217)	(0.00514)	(0.00549)
Precip: current - last mth (mm)	-0.000394**	-0.000371**	-0.000375**	-0.000361**
	(0.000175)	(0.000173)	(0.000179)	(0.000176)
No toilet access = 1		0.00828	0.00735	0.00741
		(0.0143)	(0.0143)	(0.0143)
Age (months)		0.00342**	0.00343**	0.00344**
		(0.00144)	(0.00144)	(0.00144)
Age squared / 100		-0.0107***	-0.0108***	-0.0108***
		(0.00234)	(0.00234)	(0.00234)
Indoor water		-0.00901	-0.00983	-0.00988
		(0.0135)	(0.0136)	(0.0136)
Altitude in 100's of meters		-0.0403***	-0.0389***	-0.0384***
		(0.0132)	(0.0133)	(0.0133)
Min temp, historical avg			0.000218	
			(0.00644)	
Precipitation, historical avg			-0.000230	-0.000293
			(0.000227)	(0.000250)
Monthly high - low, hist avg				-0.00351
				(0.00730)
Constant	0.266***	0.413***	0.462***	0.489***
	(0.0330)	(0.0568)	(0.111)	(0.0891)
Observations	3292	3292	3292	3292
R^2	0.005	0.034	0.035	0.035

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Subgroup Analysis

	(1) 24 mos or under	(2) Over 24 mos	(3) Dry season	(4) Rainy season	(5) Min 10 mm rain	(6) Min 20 mm rain
Max - Min temp current mth	-0.00540	-0.00647***	-0.000813	-0.0204*	-0.0123***	-0.0177***
	(0.00391)	(0.00245)	(0.00496)	(0.0107)	(0.00352)	(0.00461)
Precip: current - last mth (mm)	-0.000352	-0.000376*	-0.000265	-0.000494*	-0.000369*	-0.000436*
	(0.000315)	(0.000193)	(0.000291)	(0.000297)	(0.000195)	(0.000224)
No toilet access = 1	-0.00952	0.0228	0.00895	0.000261	0.0124	0.000330
	(0.0256)	(0.0161)	(0.0168)	(0.0277)	(0.0185)	(0.0216)
Age (months)	0.0236***	-0.0139**	0.00370**	0.00287	0.00333*	0.00338
	(0.00629)	(0.00642)	(0.00171)	(0.00265)	(0.00183)	(0.00210)
Age squared / 100	-0.0671***	0.0123	-0.0112***	-0.0102**	-0.0102***	-0.0104***
	(0.0251)	(0.00758)	(0.00277)	(0.00428)	(0.00296)	(0.00339)
Indoor water	-0.00756	-0.00587	-0.00744	-0.0217	-0.00592	-0.00754
	(0.0242)	(0.0154)	(0.0163)	(0.0249)	(0.0172)	(0.0200)
Altitude in 100's of meters	-0.0601**	-0.0260*	-0.0456***	-0.00757	-0.0195	-0.0411**
	(0.0233)	(0.0151)	(0.0152)	(0.0322)	(0.0162)	(0.0209)
Constant	0.353***	0.641***	0.330***	0.494***	0.406***	0.545***
	(0.102)	(0.142)	(0.0954)	(0.183)	(0.0741)	(0.0968)
Observations	1360	1932	2161	1131	2171	1651
R^2	0.028	0.023	0.034	0.030	0.030	0.036

The dependent variable in all regressions is the incidence of diarrhea in the past two weeks. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1. Locations sampled

(S = weather station)

Figure 2. Temperature differentials & diarrhea rates

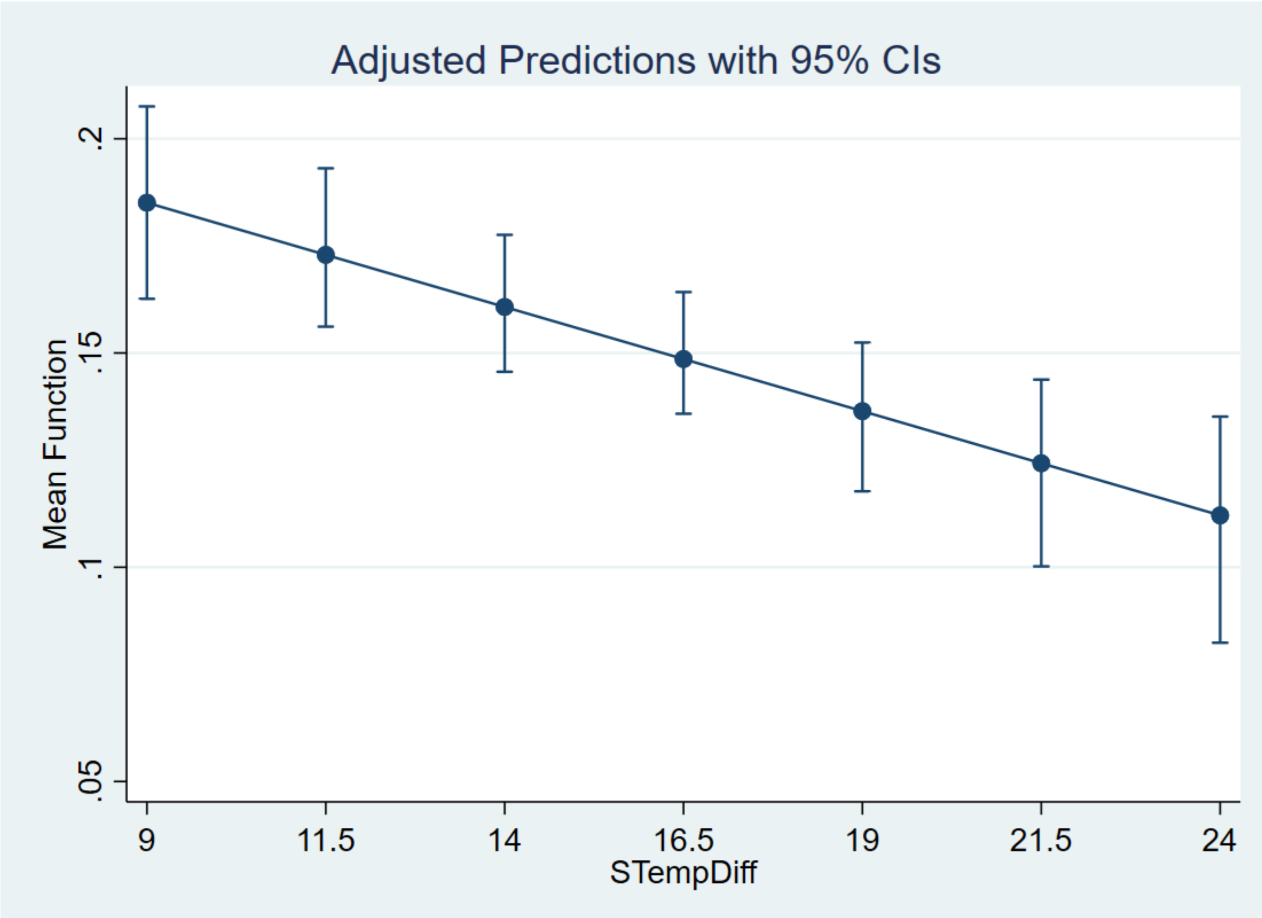

Figure 3. Change in precipitation & diarrhea rates