

Heat Exposure and Youth Migration in Central America and the Caribbean[†]

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Emerging evidence demonstrates migration may be used by individuals in the southern hemisphere to adapt to environmental changes. Few studies measure the environmental drivers of migration in the Latin America and Caribbean region as a whole. Furthermore, while it is well-documented that the liquidity-constrained often move temporarily or over short distances in response to a localized, negative shock (Fussell, Hunter, and Gray 2014), the permanent migration impact of prolonged or repeated exposure to changes in the environment is poorly understood. First, ambiguities about risk caused by gradual environmental degradation may result in minimal behavioral change (Lee et al. 2015). Second, low-income households may not be able to afford transportation between locations or have sufficient social capital to secure employment in urban areas (Bryan, Chowdhury, and Mobarak 2014). These features challenge the forced migration rhetoric, instead offering a scenario in which populations are trapped in place (Black et al. 2011).

We build upon recent work in the region using a similar triple difference-in-difference quasi-experimental design and dataset to test whether repeated and/or prolonged heat exposure affect inter-province migration (Baez et al. 2017). We previously illustrated that youth are more likely to move in response to hurricanes and droughts. Exposure to temperature extremes

may render greater consequences on the mobility of individuals than natural disasters. Social protection programs often target populations affected by natural disasters reducing their vulnerability, but individuals rarely receive social assistance due to being exposed to a heat wave. In addition, widespread disasters can compromise employment opportunities and inflate transportation costs; both reducing net migration benefits.

The growth literature has pointed to numerous examples in which environmental migration contributes to urbanization (Henderson, Storeygard, and Deichmann 2017) without growth (Poelhekke 2011). We therefore additionally predict how gradual changes in temperature influence the skill set of who migrates and their location choice. We further confirm using two separate datasets whether the observed mobility patterns correspond to changes in income levels, by examining the GDP losses at the district and national levels. The former may be indicative of local vulnerability, while national vulnerability from prolonged heat exposure can narrow the set of employment opportunities at destinations reducing the desirability of environmental migration.

I. Data

Migration.—Migration data are taken from censuses conducted in the following countries (Minnesota Population Center 2015): Costa Rica (2000, 2011), Dominican Republic (2002, 2010), El Salvador (1992, 2007), Haiti (1982, 2003), Mexico (2000, 2010), Nicaragua (1995, 2005), and Panama (2000, 2010). The information allows for measurement of individual inter-province migration over the five years prior to the census. We create three migration variables based on the province destination of each individual, whether the person migrated across provinces, whether the person migrated

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across provinces to the national capital, and whether the person migrated across provinces to a provincial capital. Individual age, gender, education, and province origin are used to formulate the explanatory variables included in the regressions.¹

Climate.—Daily temperature are extracted from the Global Land Data Assimilation System Version 2 (1983–2010) (Rodell and Beaudoin NASA/GSFC/HSL 2015).² We focus on heat exposure over the migration period.³ To formulate a standardized measure of heat exposure, we perform the following steps. First, we create a binary indicator for whether the daily minimum temperature is in the ninetieth percentile of the province distribution.⁴ Second, we create variables reflecting the number of days that the daily minimum temperature exceeds the ninetieth percentile over moving five-year averages, starting with 1983 and ending with 2010. Third, we use the distribution (24 points) of the number of “extremely hot” days over periods of five years to construct the means and standard deviations of each province distribution of heat.

Next, we use the above data to create a heat exposure z -score to facilitate the interpretation of results: the number of days exceeding the ninetieth percentile (over the five-year migration period in the census follow-up round), and the means and standard deviations of each origin province distribution of heat. Areas with heat exposure values of zero or below in the follow-up round are considered “unaffected” for the purpose of the experiment. The z -score val-

ues less than zero are replaced by the value zero. “affected” areas are defined by provinces having positive z -score values, allowing heat exposure to vary in intensity by maintaining the continuous z -score values.⁵

Precipitation data are taken from the Climate Research Unit’s Time Series of the University of East Anglia (1983–2010). Five-year average precipitation and precipitation squared variables are created to reduce bias from unobserved, correlated weather characteristics in regressions (Auffhammer et al. 2013). All temperature and precipitation variables are then merged by the origin province and survey year of each individual in the censuses.

Gross Domestic Product.—To examine whether heat-induced income fluctuations drive migration patterns, we use two sources of GDP data adjusted using the purchasing power parity rates in 2011 international dollars. The first source comes from statistical models produced by the World Bank to predict province-level GDP.⁶ One shortcoming of the detailed data is its limited spatial (e.g., Costa Rica, El Salvador, Nicaragua, and Panama) and temporal (2000, 2005, 2010) availability. We therefore also exploit the World Development Indicators (WDI) database which concentrates on the national GDP for all seven countries over the time frame of our censuses (1987–2010).

II. Identification

We evaluate the effect of repeated and prolonged heat exposure on inter-province migration by building on the triple difference-in-difference (DID) design in Baez et al. (2017). Double DID models are commonly used to identify the impact of shocks on outcomes in the absence of panel data, comparing outcomes before and after exposure in affected and unaffected provinces. One drawback of the double DID approach is it assumes there are no other micro-level shocks in affected areas at the time of exposure. Using the same data, Baez et al. (2017) exploit an additional dimension, timing of birth, for identification decomposing

¹ Summary statistics of the explanatory variables included in the empirical model can be found in the online Appendix.

² We use this dataset over others that measure surface temperature as it offers daily (rather than monthly) values at a fine scale. It should be noted the data come from a surface hydrology model that takes temperature as an input from the Princeton Global Meteorological Forcing Dataset.

³ Typically, the literature focuses on contemporaneous (or lagged) exposure during the year of move. We create a five-year measure of exposure, since censuses ask whether the individual is located in a different province than he/she resided in five years prior to the interview.

⁴ We use minimum (rather than average or maximum) temperature values as a conservative measure of heat. Transforming temperature into percentile indicators standardizes the definition of extreme heat by accounting for local frames of reference. Migration responses to extreme heat have been shown to be robust to the use of percentile and average temperature measures in other settings (Mueller, Gray, and Kosec 2014).

⁵ A figure illustrating the distribution of the heat exposure variable is provided in the online Appendix.

⁶ For further details, refer to the online Appendix.

the sample by high-mobility (ages 15–25, 26–35) and low-mobility (ages 36–45, 46–55, and 56–65) groups. This additional dimension circumvents the bias caused by time variant shocks by further drawing comparisons of the changes in outcomes by heat exposure across age groups.

A linear probability model is used to quantify the effects of heat exposure on the migration of men and women:

$$\begin{aligned}
 (1) \quad M_{ijkat} = & \beta_1(\text{Temp}_k \times \mathbf{Age}_a \times \text{After}) \\
 & + \beta_2(\text{Temp}_k \times \mathbf{Age}_a) \\
 & + \beta_3(\text{Temp}_k \times \text{After}) \\
 & + \beta_4(\mathbf{Age}_a \times \text{After}) + \theta \mathbf{X}_{ijkt} \\
 & + \alpha_j + \delta_t + \gamma_a + \epsilon_{ijkat},
 \end{aligned}$$

where M_{ijkat} is a binary variable for whether individual i at destination province j from origin province k in age group a at time t migrated in the last five years; \mathbf{Age}_a is a vector of 10-year age indicators (15–25, 26–35, 36–45, 46–55, 56–65 omitted); After_t signifies the follow-up census for the country; \mathbf{X}_{ijkt} is a vector of pre-shock variables (indicators for being male and having completed primary school, and five-year average precipitation and precipitation squared at origin). Location, generational and temporal factors that influence migration patterns are controlled for by including origin α_j , age γ_a , and year δ_t fixed effects.⁷ Standard errors are clustered by origin province and birth year.

Identification rests on the following assumptions. First, our methodology assumes disasters would affect the migration status of an individual in the 15–35 age range significantly more than individuals outside of that age range (36–65). Difference-in-difference regression results which compare the change in the mobility patterns across age groups confirm that younger men and women are more likely to move and the migration patterns of young men and women are

more likely affected in the follow-up censuses (online Appendix). Second, we assume differences across birth cohorts in migration rates would be similar across “affected” and “non-affected” districts in the absence of the shock. We validate that the changes in the baseline characteristic averages across age groups and exposure categories are statistically insignificant (online Appendix).

III. Results

Table 1 provides the parameter estimates and standard errors from model (1) using the three migration outcomes disaggregated by the gender of the individual. We only observe a positive and statistically significant effect on the migration of women to a provincial capital. The tendency of women to migrate in response to temperature variability is consistent with recent evidence in South America (Thiede, Gray, and Mueller 2016). Women may be used to diversify risk, if the opportunity cost of having an absent young male member of the household exceeds that of a young female member. Alternatively, income losses caused by fluctuations in temperature may affect the demand for goods and services provided by female-dominated industries (e.g., seamstresses).

Table 2 presents the migration impacts of heat exposure among the unskilled (has not completed a primary education).⁸ A 1 standard deviation increase in heat exposure more than doubles (quadruples) the probability of a young (ages 15–25), unskilled woman migrating to a provincial (national) capital. Restricting the focus to the unskilled also introduces a positive and significant effect on the provincial capital migration of women ages 26–35, and a positive and significant effect on the provincial capital migration of young men.

The GDP regressions qualitatively suggest that the observed migration patterns do not coincide with any broad economic losses (online Appendix). Young women may be used by households to obtain auxiliary income to smooth consumption. Consequently, they travel to provincial and national capitals because these areas

⁷Controlling for pull factors through the inclusion of destination province fixed effects does not change inferences on the parameters of interest. We focus on the abbreviated empirical model given concerns over the potential for biased estimates generated from the endogeneity of location decisions.

⁸There are no significant impacts on the skilled sample (online Appendix).

TABLE 1—IMPACT OF HEAT EXPOSURE ON MIGRATION

Sample: Destination:	Women			Men		
	Any	National capital	Provincial capital	Any	National capital	Provincial capital
Temp × after × age 15–25	−0.00011 (0.0058)	−0.00106 (0.00110)	0.00300 (0.00178)	−0.00018 (0.00562)	0.00012 (0.00081)	0.00161 (0.00168)
Temp × after × age 26–35	0.00282 (0.00654)	0.00027 (0.00107)	0.00169 (0.00188)	0.00053 (0.00704)	−0.00003 (0.00099)	0.00062 (0.00190)
Temp × after × age 36–45	0.00193 (0.00546)	0.00026 (0.00009)	0.00864 (0.00187)	0.00008 (0.00615)	0.00040 (0.00083)	0.00001 (0.00183)
Temp × after × age 46–55	0.00284 (0.00590)	0.00061 (0.00109)	0.00069 (0.00222)	−0.00074 (0.00649)	0.00046 (0.00093)	−0.00088 (0.00214)
Constant	−0.00502 (0.01321)	−0.01988 (0.00342)	−0.02864 (0.00468)	−0.01062 (0.01421)	−0.01573 (0.00253)	−0.02328 (0.00440)
Mean temp	0.751	0.752	0.749	0.737	0.738	0.735
Mean control migration rate	0.023	0.001	0.008	0.024	0.001	0.008
R ²	0.073	0.242	0.113	0.061	0.259	0.098
Observations	8,599,759	8,283,727	8,310,807	7,883,317	7,589,007	7,618,804

Notes: Temp represents the standardized number of excessive heat days experienced over a five-year period. Origin-province by birth year clustered standard errors in parentheses.

TABLE 2—HEAT-INDUCED MIGRATION PATTERNS OF THE UNSKILLED, WITHOUT PRIMARY EDUCATION

Sample: Destination:	Women			Men		
	Any	National capital	Provincial capital	Any	National capital	Provincial capital
Temp × after × age 15–25	0.00571 (0.00550)	0.00443 (0.00185)	0.00760 (0.00201)	0.00201 (0.00447)	0.00111 (0.00082)	0.00212 (0.01263)
Temp × after × age 26–35	0.00637 (0.00533)	0.00109 (0.00096)	0.00271 (0.00141)	0.00010 (0.00491)	0.00082 (0.00069)	0.00012 (0.00121)
Temp × after × age 36–45	0.00354 (0.00455)	0.00160 (0.00098)	0.00190 (0.00143)	−0.00136 (0.00452)	0.00120 (0.00058)	0.00003 (0.00106)
Temp × after × age 46–55	0.00256 (0.00463)	0.00115 (0.00084)	0.00062 (0.00142)	−0.00027 (0.00444)	0.00025 (0.00058)	−0.00104 (0.00118)
Constant	0.06011 (0.01502)	0.01794 (0.00703)	0.00935 (0.00849)	0.01811 (0.01392)	0.00583 (0.00347)	−0.00985 (0.00570)
Mean temp	0.782	0.784	0.782	0.737	0.739	0.737
Mean control migration rate	0.020	0.001	0.005	0.019	0.001	0.005
R ²	0.117	0.324	0.212	0.080	0.318	0.145
Observations	2,688,088	2,612,545	2,619,639	2,246,249	2,184,378	2,191,324

Notes: Temp represents the standardized number of excessive heat days experienced over a five-year period. Origin-province by birth year clustered standard errors in parentheses.

are at least perceived to offer a greater range of employment opportunities given their skills.

young women⁹ and 1,578 young men. The total effect is smaller than that observed under

IV. Discussion

Our results imply that a 1 standard deviation increase in heat would affect the lives of 7,314

⁹This calculation comes from multiplying the total number of unskilled workers (2,619,639), the percentage of individuals aged 15–25 (0.35), and the coefficient in Table 2 (0.008).

droughts (41,559 people) or hurricanes (13,931 people), but could increase with climate change. In all instances, we are likely to omit a significant fraction of short-distance moves due to data limitations. What is most disconcerting is that youth are more likely to wind up in urban centers when exposed to heat than the common disasters experienced in the region. Additional research is warranted over the welfare implications of these choices in the long term and the interventions available to minimize distress migration.

REFERENCES

- Auffhammer, Maximilian, Solomon M. Hsiang, Wolfram Schlenker, and Adam Sobel.** 2013. "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change." *Review of Environmental Economics and Policy* 7 (2): 181–98.
- Baez, Javier, German Caruso, Valerie Mueller, and Chiyu Niu.** 2017. "Droughts Augment Youth Migration in Northern Latin America and the Caribbean." *Climatic Change* 140 (30): 423–35.
- Black, Richard, Stephen R. G. Bennett, Sandy M. Thomas, and John R. Beddington.** 2011. "Climate Change: Migration as Adaption." *Nature* 478: 447–49.
- Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak.** 2014. "Under-Investment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh." *Econometrica* 82 (5): 1671–1748.
- Fussell, Elizabeth, Lori M. Hunter, and Clark L. Gray.** 2014. "Measuring the Environmental Dimensions of Human Migration: The Demographer's Toolkit." *Global Environmental Change* 28: 182–91.
- Henderson, J. Vernon, Adam Storeygard, and Uwe Deichmann.** 2017. "Has Climate Change Driven Urbanization in Africa?" *Journal of Development Economics* 124: 60–82.
- Lee, Tien Ming, Ezra M. Markowitz, Peter D. Howe, Chia-Ying Ko, and Anthony A. Leiserowitz.** 2015. "Predictors of Public Climate Change Awareness and Risk Perception around the World." *Nature Climate Change* 5: 1014–20.
- Minnesota Population Center.** 2015. "Integrated Public Use Microdata Series, International: Version 6.4." University of Minnesota (accessed June 15, 2015).
- Mueller, V., C. Gray, and K. Kosec.** 2014. "Heat Stress Increases Long-Term Human Migration in Rural Pakistan." *Nature Climate Change* 4: 182–85.
- Poelhekke, Steven.** 2011. "Urban Growth and Uninsured Rural Risk: Booming Towns in Burst Times." *Journal of Development Economics* 96 (2): 461–75.
- Rodell, Matthew, and Hiroko Kato Beaudoin.** 2015. "GLDAS Noah Land Surface Model L4 monthly 0.25 x 0.25 degree Version 2.0." Goddard Earth Sciences Data and Information Services Center, Greenbelt, MD. https://disc.sci.gsfc.nasa.gov/uui/datasets/GLDAS_NOAH025_3H_2.0/summary#citation (accessed August 2016).
- Thiede, Brian, Clark Gray, and Valerie Mueller.** 2016. "Climate Variability and Inter-provincial Migration in South America, 1970–2011." *Global Environmental Change* 41: 228–40.