Human Migratory Responses to Climate Variability in South America

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I. Introduction and research objectives

While the demographic effects of catastrophic events in the developing world often draw public attention, human migration is also consistently linked to less visible changes in climate such as increased temperature (Gray & Mueller, 2012; Marchiori, Maystadt, & Schumacher, 2012; Bohra-Mishra, Oppenheimer, & Hsiang, 2014; Mueller, Gray, & Kosec, 2014). Yet existing studies been narrow in geographic scope, leaving the extent to which findings are generalizable across populations an open question. Application of diverse methodologies across studies generates added concerns about the comparability of metrics. Our study addresses these limitations by quantifying human migration responses to climate variability using multiple rounds of census microdata from seven South American countries, and applying a common methodology and uniform definitions of migration and climate.

Climate anomalies have been linked to short-term welfare losses in many developing countries (Paxson 1992; Jalan & Ravallion, 1999; Dercon, 2004; Kazianga & Udry, 2006). Individuals with limited resources commonly mitigate such income risks through labor diversification, which often involves geographic mobility (Kochar, 1999; Rose, 2001; Jayachandran, 2006; Dillon, Mueller, & Sheu, 2010). However, precise estimates of climate effects on migration are sensitive to how variability is conceptualized and measured. Here, we focus on two aspects of climate variability that have received little attention to date. First, we consider gradual changes in climatic conditions, to which individuals may adapt via migration. Second, we also examine the effect of repeated or prolonged exposure to extremes. This avenue is of particular interest from a development standpoint concerned with understanding how to design resilience-enhancing social protection programs (Barrett & Constas, 2014).

South America represents an appropriate region for investigating the influence of climatic variation on population distribution. First, agriculture remains a major source of livelihood across the continent, particularly among vulnerable low-skilled workers and poor households (Vergara et al. 2014). Second, the historical precedence of internal and international migration in the region (Cerrutti & Parrado, 2015) suggests that relocation is a likely adaptation response to climate change. Third, conditions for adaptation are heterogeneous across the continent, as evidenced by variation in overall levels of development, inequality, and the existence of social protection programs. Such diversity provides a unique environment for cross-national comparisons of how macroeconomic factors mediate adaptation to climate variability (Dell et al., 2012; Dell et al., 2014).

II. Data

We use two secondary data sources for our analysis. First, we extracted multiple rounds of census data from IPUMS International to create a person-period dataset that includes an indicator of migration status, individual characteristics (age, education, and sex), and location on census day and five years prior. We restrict our sample to seven countries that collected information on persons’ five-year migration status and their location of residence five years prior to the census at the first-order subnational level or below. We also limit our sample to adults

Second, we extracted monthly rainfall and temperature data from the Climate Research Unit’s Time Series (CRUTS). We constructed two sets of variables to measure exposure to climate variability at the province level: (1) temperature and rainfall averages over the 5- and 10-year periods prior to the census year, normalized to all other 5- and 10-year country-specific periods, respectively; and (2) the number of monthly z-scores (normalized to the full history) exceeding 2 standard deviations (a) above and (b) below the mean during the 5- and 10-year period prior to the census. By merging the province-year climate dataset to the person-period dataset we can measure how exposure to climate variability affects the likelihood of inter-province migration.

Comparing results using different frames of reference allows for an explicit test of whether slow changes in climate affect mobility decisions. Contrasting findings produced from measures of changes in multi-year averages to cumulative exposure to extremes allows us to further assess whether migration is driven by gradual variations in climate or repeated or prolonged exposure to shocks in the medium run.

III. Empirical Strategy

We estimate a series of logistic regression models applied to our person-period dataset to measure individual migration responses to climate variability at a continental scale. We control for individual pre-migration characteristics (age, gender, and educational attainment) and climate variability implicit in vector $X_{it}$, as well as $\alpha_p$ origin province and $\alpha_t$ survey-year fixed effects, stratified by country:

$$\log \left( \frac{\pi_{mit}}{\pi_{nit}} \right) = \alpha_t + \alpha_p + \beta X_{it}. \quad (1)$$

Since our dependent variable is binary, we assume a logit specification for the model, where $\pi_{mit}$ signifies the odds of moving and $\pi_{nit}$ the odds of not moving for individual $i$ in year $t$. We cluster standard errors at the origin province-by-survey year level to allow for correlation in unobserved residential and time-specific factors that influence migration outcomes.

Our first set of analyses focuses on period climate averages. Here we estimate two versions of equation (1) that respectively use the five- and ten-year average climate measures. To assess whether slow or rapid changes in climate put individuals at greater risk of moving, we explicitly test whether the estimated coefficients on these variables differ across the two specifications for each country. To determine whether migration is a more accessible adaptation option among particular subpopulations in each country, we also perform the tests on samples stratified by individual gender, age, and sex. Finally, we conduct tests for cross-national differences in climate effects on migration. Our second pair of analyses proceed in identical manner, but examine our second pair of climate variability measures: those that focus on

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1 The location of previous residence varies by country in definition, despite similarity in geographic scale: province (Argentina, Chile, Ecuador), department (Colombia, Uruguay), state (Bolivia, Brazil). We herein refer to all previous locations as provinces despite distinctions in terminology.

2 We define these 5- and 10-year periods, respectively, as the 60- and 120-month period prior to the month that the census day occurred in.
repeated or prolonged exposure to shocks over the five- and ten-year periods prior to each census.

IV. Preliminary results

Our preliminary analyses have focused on estimating the effect of each of the four sets of climate variables we constructed (descriptive statistics available upon request). The four specifications (A-D) in Table 1 each correspond with one set of measures. A number of general points emerge from these preliminary results. Exposure to repeated or prolonged shocks (measured on a monthly scale) has more consistent effects on migration across the continent than exposure to deviations in five- or ten-year average conditions. As well, non-trivial differences between the five- and ten-year averages suggest that the length of time over which persons are exposed to climate anomalies is important. As a whole, these preliminary findings highlight the heterogeneity of climate effects across the continent, which we suggest reflect substantive rather than methodological differences given our harmonized approach to measurement and analysis.

V. References


### Table 1: Results of logistic regression predicting 5-year migration status, 5-year standardized climate variables

<table>
<thead>
<tr>
<th>Model</th>
<th>Variable</th>
<th>Argentina</th>
<th>Bolivia</th>
<th>Brazil</th>
<th>Chile</th>
<th>Colombia</th>
<th>Ecuador</th>
<th>Uruguay</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Specification A</strong></td>
<td>Temperature, 5y (standardized)</td>
<td>1.097</td>
<td>1.061</td>
<td>1.097 **</td>
<td>1.158 ***</td>
<td>0.947</td>
<td>1.123 **</td>
<td>1.059</td>
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<tr>
<td></td>
<td>Rainfall, 5y (standardized)</td>
<td>1.073</td>
<td>1.021</td>
<td>1.009</td>
<td>1.008</td>
<td>0.902</td>
<td>0.964</td>
<td>1.096</td>
</tr>
<tr>
<td></td>
<td>Joint test</td>
<td>***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Specification B</strong></td>
<td>Temperature, 10y (standardized)</td>
<td>1.434 ***</td>
<td>1.099 +</td>
<td>1.057</td>
<td>1.026</td>
<td>0.941</td>
<td>1.125 **</td>
<td>1.058</td>
</tr>
<tr>
<td></td>
<td>Rainfall, 10y (standardized)</td>
<td>1.157</td>
<td>0.980</td>
<td>1.046</td>
<td>1.009</td>
<td>0.867</td>
<td>1.076 **</td>
<td>1.127</td>
</tr>
<tr>
<td></td>
<td>Joint test</td>
<td>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Specification C</strong></td>
<td>Monthly pos. temp. shock, 5y count</td>
<td>1.159 ***</td>
<td>1.035</td>
<td>1.001</td>
<td>0.994</td>
<td>0.972</td>
<td>1.012</td>
<td>0.850</td>
</tr>
<tr>
<td></td>
<td>Monthly neg. temp. shock, 5y count</td>
<td>1.182 ***</td>
<td>0.979</td>
<td>1.110 ***</td>
<td>1.201 ***</td>
<td>1.006</td>
<td>1.027</td>
<td>1.056</td>
</tr>
<tr>
<td></td>
<td>Monthly pos. rain. shock, 5y count</td>
<td>1.181 ***</td>
<td>1.036 **</td>
<td>1.019</td>
<td>1.026 **</td>
<td>0.993</td>
<td>0.974 **</td>
<td>0.973</td>
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<tr>
<td></td>
<td>Monthly neg. rain. shock, 5y count</td>
<td>1.070</td>
<td>0.745 ***</td>
<td>1.133 **</td>
<td>(none)</td>
<td>0.824</td>
<td>0.971</td>
<td>(none)</td>
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<tr>
<td></td>
<td>Joint test</td>
<td>*** ***</td>
<td>** ***</td>
<td>***</td>
<td>** ***</td>
<td>+</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Specification D</strong></td>
<td>Monthly pos. temp. shock, 10y count</td>
<td>1.154 ***</td>
<td>1.026 ***</td>
<td>1.003</td>
<td>1.005</td>
<td>0.977</td>
<td>1.022 ***</td>
<td>0.960</td>
</tr>
<tr>
<td></td>
<td>Monthly neg. temp. shock, 10y count</td>
<td>1.096 **</td>
<td>0.990</td>
<td>1.086 ***</td>
<td>0.991</td>
<td>0.959 +</td>
<td>1.036 +</td>
<td>0.964</td>
</tr>
<tr>
<td></td>
<td>Monthly pos. rain. shock, 10y count</td>
<td>1.092 ***</td>
<td>1.018 ***</td>
<td>0.993</td>
<td>1.063 ***</td>
<td>0.872 **</td>
<td>0.983 ***</td>
<td>0.962 +</td>
</tr>
<tr>
<td></td>
<td>Monthly neg. rain. shock, 10y count</td>
<td>0.826</td>
<td>0.832 ***</td>
<td>1.032</td>
<td>0.719 ***</td>
<td>0.928</td>
<td>1.013</td>
<td>(none)</td>
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<tr>
<td></td>
<td>Joint test</td>
<td>***</td>
<td>** ***</td>
<td>+++ ***</td>
<td>*** ***</td>
<td>+</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p<0.10  **p<0.05  ***p<0.01* All coefficients represent odds ratios. Models include controls for age, sex, and educational attainment. Models include year and province-of-origin (or equivalent) fixed effects. Standard errors clustered at the year-province (or equivalent) level.

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