Anticipatory Migration Responses to Rural Climate Shocks

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Special thanks to Brad Barham and Jens Engelmann. We are also grateful to Laura Schechter, Dan Phaneuf, Nick Parker, Jessica Zhu, Alexey Kalinin, Rachel Frattarola, Nick Hudson, Andrew Dillon, Jen Alix-Garcia, Peter Brummund, and Ali Akram for helping shape this research. All errors remain our own. This research was supported by training grant T32 HD007014 and core grant P2C HD047873, awarded to the Center for Demography and Ecology by the Eunice Kennedy Shriver National Institute of Child Health and Human Development, as well as the Science and Medicine Graduate Research Scholars Program.

Climate change is expected to increase the frequency, severity, and duration of climate shocks (Lesk, Rowhani, and Ramankutty, 2016), including extreme lows and highs in precipitation and high temperatures, affecting agricultural production.[1] The dark upper red layer in Figure 1 demonstrates the widespread increase in average annual temperatures in Mexico from 1980 to 2010.[2] The shifting climate distribution across the spectrum of low, medium, and high average temperature municipalities (left to right) is accompanied by an increased probability of climate-induced crop shocks.

[Insert Figure 1 Here]

Most of what we know about the impact of adverse climate events—that they increase morbidity and mortality, labor productivity and economic growth, as well as intensify conflict—is learned by studying behavioral responses after direct household exposure to climate change or disastrous shocks. Though observed levels of adaptation to climate shocks remain low (Carleton and Hsiang, 2016), poor households lessen adverse impacts by drawing down savings, smoothing and reducing consumption, relying on informal insurance networks, and diversifying their income-generating portfolio. Poor households in marginalized communities, especially those that rely on smallholder agricultural production, are particularly vulnerable to climate change. Their incomes are reliant on agriculture and adaptation options are limited for asset-poor households. One important mechanism of climate change adaptation for poor rural households is labor reallocation, often including migration.

Evidence that climate events result in migration is mixed. Studies in Ecuador and Mexico, show that—on average—climate shocks are followed by increases in migration (Gray and Bilsborrow, 2013; Jessoe, Manning,

[1] For a more detailed discussion of the relevant literature and other details, see Quiñones et al. (2022) available at https://tinyurl.com/yckbm9x7.

[2] Each rural municipality included in the MxFLS is presented in its own column, from the municipalities with the lowest average temperature on the left to the highest average temperature on the right. Annual average temperatures are presented in progressively darker hues from 1980 in light gray up to 2010 in dark red.

and Taylor, 2018). Multicountry studies in more than 100 countries—including Cameroon, Mexico, Thailand, and Vietnam—suggest that climate shocks reduce resources to finance migration journeys and depress outmigration (Cattaneo and Peri, 2015; Quiñones et al., 2021, especially when vulnerability is high but exposure or sensitivity to climate is less extreme (Riosmena et al. 2018).

A widely-held but rarely tested hypothesis embedded in many theories of migration (Bodvarsson et al. 2015) holds that individuals and households also migrate *ex ante*, in anticipation of future (climate) risks. The lack of research on anticipatory (*ex ante*) migration is due to the difficulty in empirically distinguishing between *ex ante* and *ex post* phenomena.[3] However, climate shocks are not transitory and are difficult to insure against locally, so it is essential to understand how households respond to the threat of future shocks based on previous and contemporaneous climate events.

Anticipatory migration can be defined in several ways; we focus on behavior that is plausibly a response to perceptions of increased risk to a household's agricultural outcomes. To examine anticipatory migration behavior, we leverage the idea that households evaluate the world and make decisions based on the behavior of fellow community members, we ask whether individuals adapt to the heat-induced crop losses of *neighboring households* by moving domestically or internationally. We are not asking whether people correctly anticipate future climate-induced crop shocks. Rather, we ask whether shocks that affect some community members have spillover effects on others—likely informing perceptions of increases in potential risks to households' agricultural productivity and income.

[3] Rosenzweig and Stark (1989), Rose (2001), and Dillon, Mueller, and Salau (2013) are notable exceptions.

I. Data and Measures

We integrate panel migration and socioeconomic data for rural households in Mexico from the 2002 and 2005 waves of the nationally-representative Mexican Family Life Survey (MxFLS) with longitudinal meteorological data for the municipalities where they reside from NASA's Agricultural Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) Climate Forcing Dataset for Agricultural Modeling. The MxFLS allows us to measure individual domestic and international migration from 2002 to 2005, as well as self-reported shocks to household crop production in rural Mexico from 1997 to 2005. The clustered sampling approach of the MxFLS—55 surveyed households per sampled community in 2002 with the vast majory reinterviewed in 2005—makes it possible to measure heat-induced crop-loss of *other* households in the same communities. This study focuses on the migration responses of roughly 3,000 individuals aged 15 and up from more than 1,200 households that own or use land, sampled from 45 rural communities (in distinct municipalities) that rely upon agriculture. To study anticipatory migration, we distinguish between households that directly experienced heat-induced crop loss and those that only witnessed it among other households in the community.[4]

Daily average temperature and precipitation data at 0.25° resolution for 1980-2005 (available through 2010) come from AgMERRA. AgMERRA data document daily extreme temperatures, which are crucial for modeling agricultural outcomes.[5] We integrate the climate data with the MxFLS at the municipality level (to serve as an instrument that refines our measure of self-reported crop loss) along with information on population, agriculture, and economic indicators from Mexico's 2000 Population Census and 2007 Agricultural Census. Retrospective international migration information from the Population Census was processed into a migration intensity index by the Mexican National Population Council, which we also use. Descriptive statistics on migration, catastrophic crop losses, heat waves, and covariates are available in the Appendix.

Domestic and International Migration: The MxFLS includes detailed modules on permanent migration (one year or more) and temporary migration (more than a month but less than a year) of individuals. In combination with detailed tracking information collected during the 2005 survey round for international migrants, we create multiple individual-level measures of international and domestic migration $(\mathbb{Y}_{it})$: (1) at any point between 2002 to 2005, (2) between 2002 to 2003, shortly after the exposure to the heat-induced crop losses measured between 2000-2002, and (3) between 2004 to 2005, a lagged or sustained migration relative to the exposure period. The 2002-2005 measures are the most comprehensive because some migration journeys cannot be categorized in the 2002-2003 or 2004-2005 windows due to

[4] More than 90 percent of the households surveyed in 2002 were reinterviewed in 2005. The vast majority of households that attrited are thought to be cases where all members relocated outside of the origin community but remain within Mexico.

[5] Monthly weather data is likely to understate the influence of weather nonlinearities, particularly the crossing of extreme thresholds, due to the smoothing (averaging) of daily information when aggregated to the monthly unit.

inadequate information.[6] We create two alternative measures of domestic migration between 2002 to 2005 given the lack of domestic migrant tracking information: a lower bound strictly based on reported journeys and respondent locations and an upper bound that incorporates attrited observations that may have migrated. Migration variables are binary, with a value of 1 indicating that the individual engaged in a type of migration during the specified time period ($\mathbb{Y}_{\mathrm{it}} \in \{0,1\}$). Rates of migration range from less than 1 percent for international migration in 2002-2003 and 2004-2005 each to 5 to 7 percent for domestic migration in 2002-2005 (lower and upper bounds, respectively).

Catastrophic Crop Losses: We use household reports of crop shocks to construct the community-level proportion of *other* households that experienced a catastrophic crop loss from 2000-2002 ($\mathbb{A}_{\mathrm{c02}} = \{0 \ldots 1\}$). Approximately 8.3 percent of households reported experiencing catastrophic crop losses from 2000-2002.

Heat Waves: To reflect the frequency and duration of extreme temperatures that cross important thresholds for agricultural production, we compute two measures of heat waves—continuous periods of extremely hot days—at the municipality level from 2000-2002: (1) The total number of harmful degree days (HDD) above 30 ℃ during the longest heat wave each year builds on agronomic evidence that accumulated heat exposure during a growing season is most influential in determining crop growth (Herrero and Johnson, 1980). Vegetation grows optimally when exposed to temperatures that are not too low or high; when crops are exposed to HDDs above (or below) critical thresholds, plants can no longer absorb appropriate levels of heat and nutrients, which stunts growth. The HDD measure captures exposure to unfavorable growing conditions. (2) The total number of days of extreme deviations during the longest heat wave each year (computed as a Z-score above 1 standard deviation relative to the historical average from 1980-1999)[7] represents temperature anomalies relative to municipalities' 20-year historical norms. It captures temperature deviations beyond previous climate shifts that may have been adapted to in the past. We sum the number of days for longest heat wave in 2000, 2001, and 2002 for each measure to characterize total

[6] The year to year variables account for the vast majority of domestic migration (71 to 95 percent), but reflect only a fraction of the international migration that is captured through the 2005 tracking exercise (18 percent). As a result, when drawing inferences about international migration we primarily rely on the 2002–2005 variable.

[7] A long time horizon, approaching a climate normal period of 30 years, is ideal for calculating a deviation from an expected value.

extreme heat exposure in each municipality ($\mathbb{T}_{m02} = \{0,1,2 \ldots\}$) and use these measures as instruments. Households experienced an average of 26.41 extreme heat deviation days and 17.51 HDDs during the longest annual heat waves over the 2000-2002 period.

II. Empirical Strategy

Observing the heat-induced crop damage of *other neighboring* households provides the basis for pursuing anticipatory responses to mitigate potential risks of similar future crop shocks. To examine *ex ante* migration responses, we specify a linear probability model in an instrumental variable framework (IV) to estimate the impact of observing but not experiencing heat-induced crop losses on migration decisions. We rely on IV to account for the endogeneity of experiencing catastrophic crop losses, mismeasurement of self-reported crop losses, including those for reasons other than extreme heat, by appealing to a heat waves instrument. The first-stage equation (1) that quantifies the relationship between extreme heat waves measured at the municipality level ($\mathbb{T}_{\mathrm{m02}}$) and the proportion of neighbors' crop shocks in a community ($\mathbb{A}_{\mathrm{c02}}$). The second-stage equation (2) characterizes the relationship between the extent of neighbors' crop shocks in a community ($\mathbb{A}_{\mathrm{c02}}$) and individual labor decisions ($\mathbb{Y}_{\mathrm{it}}$) as a function of extreme heat ($\mathbb{T}_{\mathrm{m02}}$). β in equation (2) represents the individual migration response to observing but not directly experiencing heat-induced crop losses during 2000-2002. It describes the effect of observing a 10 percentage point increase in the proportion of neighboring households experiencing heat-induced crop losses on migration decisions.[8]

(1)

$$\mathbb{A}_{c02} = \theta \mathbb{T}_{m02} + \boldsymbol{X}_{ihcm02}{}' \boldsymbol{\sigma} + \lambda_s + u_{ihcms02}\ ,$$

(2)

$$\mathbb{Y}_{ihcmst} = \beta \widetilde{\mathbb{A}}_{c02} + \boldsymbol{X}_{ihcm02}{}' \boldsymbol{\pi} + \lambda_s + v_{ihcmst}\ .$$

The identifying variation is the exogenous variation in extreme daily temperatures incorporated at the municipality level ($\mathbb{T}_{\mathrm{m02}}$). The intuition underlying the identification strategy is that plausibly exogenous variation in extreme daily temperatures at the municipality level, which result in household-level crop shocks in otherwise (conditionally)

[8] A 10 percentage point increase is essentially equivalent to a one standard deviation increase (0.103) and is easier to interpret than a 100 percentage point increase, which is the default for a regressor measured as a proportion.

similar communities and does not influence migration through other potential mechanisms,[9] facilitates a comparison of the migration decisions of individuals in households that do not suffer a direct shock.

State fixed effects (λ_s) account for state-level unobserved heterogeneity and ensure that the identifying variation is strictly sourced from deviations in daily extreme, high temperature realizations relative to average extreme heat realizations in each state. A threat to this empirical approach is why some households were not affected by the same heat shock that affected others in their communities. We condition on a vector of measures $(\boldsymbol{X}_{ihcm02})$ to help address potential differences in households, communities and municipalities. These include, but are not limited to, measures of (1) individual age, sex, education, (2) household size, previous migration, land size and type, (3) community infrastructure, and (4) municipality irrigation, crop area, economic diversity, marginalization, and migration intensity. Municipality-clustered errors are robust to heteroscedasticity.

[9] Subject to standard independence, relevance, exclusion, and monotonicity assumptions for IV models.

III. Results

In the first row of Table 1, in column (1) we observe a 0.8 percentage point increase in the probability of international migration from 2002-2003 and in column (4) a 2.6 percentage point increase in the probability of domestic migration associated when observing the catastrophic crop losses of others in 2000-2002.[10] The domestic migration coefficient represents a proportionately large impact relative to the mean: a nearly 87 percent increase in the probability of domestic migration. In contrast, in 2004-2005 we see a 1 percentage point decrease in the probability of international migration in column (2) and a statistically insignificant impact on domestic migration in column (5). While we do not observe an effect over the full 2002-2005 period for international migration in column (3), we do find a 3 to 4 percentage point increase in the probability of domestic migration in columns (6) and (7)—lower and upper bounds, respectively. This also represents a large proportional impact: a 60 to

[10] First-stage F-statistics range from 75 for extreme deviation days and 73 for HDDs, well above the heteroskedastic-robust rule-of-thumb of 23 (Montiel Olea and Pflueger, 2013), indicating that both instruments are strong. We interact the instruments to upweight instances where both the HDD and extreme deviation thresholds are crossed and find and F-statistic of 74. We rely on the total heat wave interaction as the preferred instrument to focus variation on cases where both agronomic (HDD) and behavioral expectations (deviations) thresholds are surpassed. Additional details regarding first stage results are available in the Appendix or see Quiñones et al. (2022) available at https://tinyurl.com/yckbm9x7.

66 percent increase in the probability of domestic migration.

Further below, we also observe the *ex post* migration impacts of experiencing catastrophic crop loss in the household, estimated in a similar manner but using the household's reports of own crop loss as opposed to neighbors. We generally find a similar pattern but, as expected, substantially larger *ex post* magnitudes. On average, *ex ante* migration accounts for approximately 30 percent of the total observed impact of heat-induced catastrophic crop losses on migration (*ex ante / ex ante + ex post*), which is a non-trivial share, with *ex post* migration accounting for the remaining 70 percent of the observed effect. This collection of estimates indicates that the vast majority of additional migration associated with the catastrophic crop losses of others took place during 2002-2003, but was not sustained in 2004-2005. From 2002 to 2005 we observe a similar pattern of results relative to those from 2002 to 2003, especially with respect to increases in domestic migration.

[Insert Table 1 Here]

Exploration of alternative explanations running from extreme heat to migration, based on the methods developed by Acharya, Blackwell, and Sen (2016), demonstrates that several potential alternative mechanisms do not shape the temperature-labor allocation relationship. For example, these include moderate crop losses within the household, reductions in productivity, or increased violence and crime.[11] The lack of residual correlation between heat waves and migration outcomes additionally suggests that the (conceptual) IV exogenous restriction may plausibly be satisfied. We also confirm that attrition of individuals between survey rounds does not drive result by estimating a similar relationship among individuals who are present in both survey rounds.

IV. Discussion

We find evidence of domestic migration that is plausibly a response to the perception of increased risks of future heat-induced reductions in crop-yield—*ex ante* migration. This *ex ante* migration adaptation is likely temporary, which may also constitute short-term or seasonal risk-mitigating behavior.

We interpret these findings as being indicative of *ex ante* or anticipatory adaptation to climate change associated with learning from others about crop losses and extreme heat. This study contributes to the literature by

[11] For a detailed presentation of these results and other robustness checks, see Quiñones et al. (2022) available at https://tinyurl.com/yckbm9x7.

demonstrating that individuals mitigate against the threat of future destabilizing climate events through domestic migration.

We illustrate that learning about the crop losses of others is a salient information channel in the context of climate change.[12] By focusing on *ex post* effects and responses, the literature emphasizes information that individuals and households directly learn from their own experiences and their reactions to recent stimuli. In contrast, this research demonstrates the importance of considering what individuals and households consider more broadly, *ex ante*, as well as how they may learn through information channels other than their own recent experiences. Our results suggest that individuals and households do adapt to climate risk prior to the onset of destabilizing events like climate-induced catastrophic crop losses, likely learning from and/or reacting to events affecting those around them. Indirect information channels about the probability of future climate-induced crop shocks are informative beyond what individuals and households learn from their own experiences.

These results have implications for migration (and other forms of) economic theorizing and modeling, which make implicit or explicit assumptions about *ex ante* behavior. We show evidence consistent with one type of *ex ante* behavior and other anticipatory may exist. Our research also has implications for the effective design and targeting of climate change mitigation and adaptation policies, which should serve the needs of households that experience climate-induced crop shocks and those who do not but may, nonetheless, respond. This is important for policy makers and researchers in their assessments of adaptation to climate change or lack thereof—so-called adaptation gaps (Carleton and Hsiang, 2016)—and what should be done moving forward. Finally, these findings have bearing on migration projections, which rarely incorporate *ex ante* migration associated with climate phenomena.

[12] This may be a result of learning about crop losses of neighbors, learning about changes in demand for labor in the community (general equilibrium changes explored by Jessoe, Manning, and Taylor, 2018), or a mix.

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FIGURE 1 — RISING ANNUAL TEMPERATURE IN MEXICO (1980-2010)

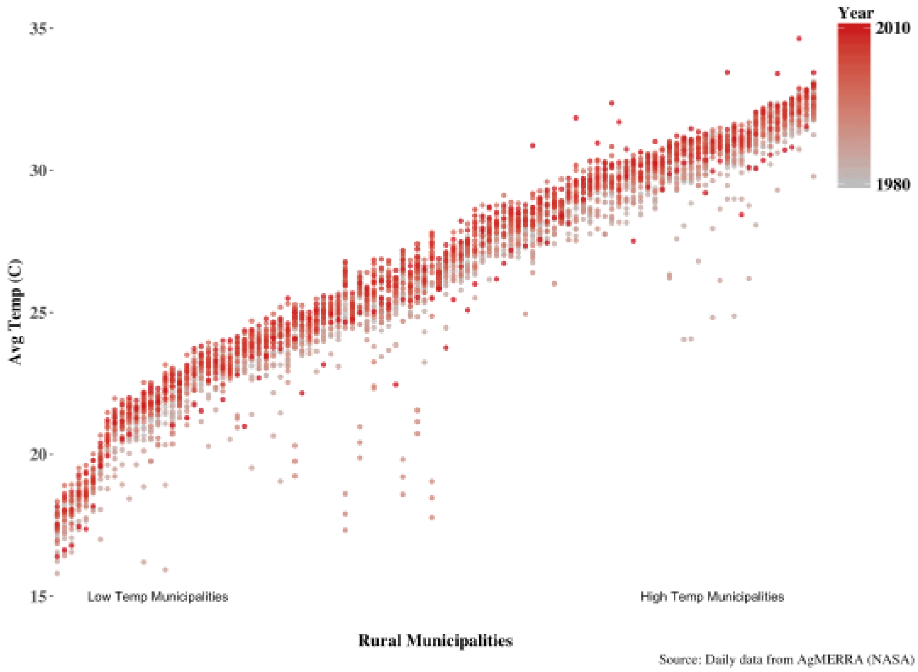

TABLE 1 — THE IMPACT OF HEAT-INDUCED CROP LOSSES ON INDIVIDUAL MIGRATION (SECOND STAGE)

	International migration			Domestic migration			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						Lower	*Upper*
	2002-2003	2004-2005	2002-2005	2002-2003	2004-2005	2002-2005	2002-2005
Panel A							
Ex ante	0.008***	-0.010**	0.010	0.026***	-0.010	0.031**	0.008***
migration	(0.002)	(0.005)	(0.011)	(0.007)	(0.012)	(0.012)	(0.002)
F-stat (MP)	74	74	74	74	74	74	74
N	2,908	2,908	2,908	2,908	2,908	2,908	2,908
Mean	0.003	0.006	0.04	0.03	0.02	0.05	0.06
Panel B							
Ex post	0.017***	-0.026***	0.032	0.051***	-0.310	0.052	0.076
migration	(0.005)	(0.011)	(0.028)	(0.019)	(0.030)	(0.033)	(0.047)
N	3,710	3,710	3,710	3,710	3,710	3,710	3,710
Mean	0.003	0.006	0.05	0.03	0.02	0.05	0.07

Notes: F-stat (MP): Montiel-Pflueger (2013). Robust standard errors are clustered at the municipality level in parentheses. Fixed effects for 12 states. Controlling for (i) Individual covariates: age, sex, marital or informal union, years of education, student or any employment stats; (ii) Household covariates: land size, ejido land, other land, household size, # of females, # of males, head age, head education, migration history, access to loan, piped water, toilet; (iii) Community covariates: % of agricultural employment, bus stop, hospital, secondary school, market; as well as, (iv) Municipality covariates: % of land irrigated, % of land maize, population, economic diversity, and migration intensity.

Source: Author calculations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Appendix for Anticipatory Migration Responses to Rural Climate Shocks

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Heat-induced Catastrophic Crop Losses: Table 2 demonstrates that extreme heat waves, represented as (1) total HDDs, (2) total extreme deviation days, and (3) total heat wave interaction from 2000-2002, have a positive, statistically significant effect on the proportion of neighboring households experiencing a crop shock in rural, agricultural. In column 1, we see that experiencing 10 additional consecutive HDDs increases the proportion of neighbors in a community suffering a crop shock by approximately 2.5 percentage points, which is roughly a 31 percent increase relative to the mean of 8.3 percent.[1] In column 2, we see that experiencing 10 more consecutive days of extreme heat deviation days increases the proportion by approximately 7 percentage points, which is roughly equivalent to an 87 percent increase. First-stage F-statistics ranging from 75 for extreme deviation days and 73 for HDDs, well above the heteroskedastic-robust rule-of-thumb of 23 (Montiel Olea and Pflueger, 2013), indicate that both instruments are strong. We interact the instruments to upweight instances where both the HDD and extreme deviation thresholds are crossed. We estimate a 5.2 percentage point increase in catastrophic crop losses with an F-statistic of 74. We rely on the total heat wave interaction as the preferred instrument to focus on variation from cases where both agronomic (HDD) and behavioral expectations (deviations) thresholds are surpassed.

[Insert Table 2 Here]

Descriptive Statistics:

[Insert Table 3 Here]

[Insert Table 4 Here]

[Insert Table 5 Here]

[1] For additional details regarding first stage results see Quiñones et al. (2022) available at https://tinyurl.com/yckbm9x7.

TABLE 2 — THE IMPACT OF HEAT WAVES ON CROP LOSSES (FIRST STAGE)

	Community proportion with crop loss		
	(1)	(2)	(3)
	HDDs	Deviation days	Interaction
Total HDDs	0.073***		
	(0.014)		
Total extreme deviation days		0.025***	
		(0.004)	
Total heat wave interaction			0.052***
			(0.006)
F-stat (MP)	73	75	74
N		2,908	
Mean		0.083	

Notes: F-stat (MP): Montiel-Pflueger (2013). Robust standard errors are clustered at the municipality level in parentheses. Fixed effects for 12 states. Controlling for (i) Individual covariates: age, sex, marital or informal union, years of education, student or any employment stats; (ii) Household covariates: land size, ejido land, other land, household size, # of females, # of males, head age, head education, migration history, access to loan, piped water, toilet; (iii) Community covariates: % of agricultural employment, bus stop, hospital, secondary school, market; as well as, (iv) Municipality covariates: % of land irrigated, % of land maize, population, economic diversity, and migration intensity.

Source: Author calculations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE 3 — DESCRIPTIVE STATISTICS: MIGRATION, CATASTROPHIC CROP LOSSES, AND HEAT WAVES (INDIVIDUAL LEVEL UNITS)

	(1)	(2)
	Mean	S.D.
Panel A: Individual Migration *(0/1)*		
International		
2002-2003	0.003	0.052
2004-2005	0.006	0.078
2002-2005	0.04	0.19
Domestic		
2002-2003	0.03	0.16
2004-2005	0.02	0.15
Lower 2002-2005	0.05	0.22
Upper 2002-2005	0.05	0.22
Panel B: Community Crop Losses		
Proportion with crop loss (0/1)	0.083	0.103
Panel C: Municipality Heat Waves		
Total HDDs	15.51	30.98
Total extreme deviation days	26.41	10.34
Number of individual level observations	2,908	

Notes: The *ex ante* analytical sample is comprised of 2,908 individual units, that span 1,161 households, over 45 rural communities and municipalities.

Source: Author calculations.

TABLE 4 — INDIVIDUAL AND HOUSEHOLD CHARACTERISTICS (INDIVIDUAL LEVEL UNITS)

	(1)	(2)
	Mean	S.D.
Panel D: Covariates		
Individual		
Age	40.96	18.89
Male (0/1)	0.48	0.50
Union (0/1)	0.62	0.49
Years of Education	4.83	3.93
Student (0/1)	0.08	0.27
Household		
Land (ha)	5.63	15.81
Land ejido (0/1)	0.73	0.44
Land private (0/1)	0.20	0.40
Land other (0/1)	0.11	0.31
Size	5.37	2.50
Number of adult females	0.75	0.88
Number of adult males	0.74	0.94
Head age	52.98	14.09
Head education	3.50	3.38
Previous migrant (0/1)	0.44	0.50
Loan	0.22	0.42
Piped water	0.83	0.38
Toilet	0.37	0.48
Number of individual level observations	2,908	

Notes: The *ex ante* analytical sample is comprised of 2,908 individual units, that span 1,161 households, over 45 rural communities and municipalities.

Source: Author calculations.

TABLE 5 — COMMUNITY AND MUNICIPALITY CHARACTERISTICS (INDIVIDUAL LEVEL UNITS)

	(1)	(2)
	Mean	S.D.
Community		
Agricultural Employment (0/1)	0.25	0.10
Bus Stop (0/1)	0.48	0.50
Hospital (0/1)	0.06	0.24
Secondary School (0/1)	0.21	0.41
Market (0/1)	0.13	0.33
Municipality		
% of Land Irrigated	35.29	37.49
% of Land with Maize	10.67	13.85
% of Land with Coffee	2.45	6.63
% of Land with Wheat	1.97	3.81
Population (10,000s)	5.98	11.54
Economic Diversity Index	0.68	0.22
Marginalization Index	-0.23	0.87
Migration Index	-0.01	0.91
Number of individual level observations	2,908	

Notes: The *ex ante* analytical sample is comprised of 2,908 individual units, that span 1,161 households, over 45 rural communities and municipalities.

Source: Author calculations.