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IFPRI Discussion Paper 01007

July 2010

Migratory Responses to Agricultural Risk in Northern Nigeria

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PARTNERS AND CONTRIBUTORS

IFPRI gratefully acknowledges the generous unrestricted funding from Australia, Canada, China, Denmark, Finland, France, Germany, India, Ireland, Italy, Japan, the Netherlands, Norway, the Philippines, South Africa, Sweden, Switzerland, the United Kingdom, the United States, and the World Bank.

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ABSTRACT

We investigate the extent in which northern Nigerian households engage in internal migration to insure against ex ante and ex post agricultural risk due to weather-related variability and shocks. We use data on the migration patterns of individuals over a 20-year period and temperature degree-days to identify agricultural risk. Controlling for ex ante and ex post risk, we find that households with higher ex ante risk are more likely to send migrants. Households facing hot shocks before the migrant's move tend to keep their male migrants in closer proximity. These findings suggest that households use migration as a risk management strategy in response to both ex ante and ex post risk, but that migration responses are gender-specific. These findings have implications not only for understanding the insurance motives of households, but also potential policy responses tied to climatic warming.

Keywords: migration, risk, temperature degree days, Nigeria

ACKNOWLEDGMENTS

Many thanks to Practical Sampling International for assistance in collecting these data, especially Taofeeq Akinremi, Moses Shola, and Tokbish Yohannah. Christopher Udry generously provided public access to these data, and the International Food Policy Research Institute financially supported the 2008 survey and tracking exercises. Additional thanks go to Esteban Quiñones for his excellent research assistance in the field and preparation of the data, and to Jose Funes for his creation of the climate and distance data. All errors remain the responsibility of the authors.

1. INTRODUCTION

One of the primary sources of agricultural income risk is production uncertainty caused by weather-related events. A lack of formal institutions to reduce household vulnerability to agricultural income risk in developing countries poses limitations to their short- and long-term growth. Households deplete their productive assets to subsist during transitory shocks (Rosenzweig and Wolpin 1993; Fafchamps, Udry, and Czukas 1998; Kazianga and Udry 2006; Quisumbing 2008), and invest in low-risk, low-return investments to mitigate risk over time (Eswaran and Kotwal 1990; Rosenzweig and Binswanger 1993; Zimmerman and Carter 2003). Further, the complex process of climate change magnifies the uncertainty of income, by increasing rainfall variance, the incidence of natural disasters, and temperature fluctuations, among others (IPCC 2007). Households may use differing strategies to mitigate these risks. When financing the relocation of a household member within a country is more affordable than other alternatives, migration offers poor households a potential risk management strategy. Moreover, households can target destinations where income risk is least correlated with risk at home (Rosenzweig and Stark 1989). Understanding the effectiveness of migration as a risk management strategy and its limitations can shed light on the private capacity to adapt to risk and inform the design of policies to improve its use, especially in response to weather-related shocks.

In this paper, we investigate the extent Nigerian households engage in internal migration to insure against ex ante and ex post agricultural risk.[1] We differentiate migration strategies by the gender of the migrant, since evidence of marriage migration (Watts 1984) and female rural-urban migration in Nigeria (Mberu 2005) exists despite cultural constraints prohibiting women from living alone in a different community or seeking opportunities elsewhere without the approval of their husbands. We also measure income variability through temperature (growing degree-days) rather than rainfall variance as done in earlier work (Rosenzweig and Stark 1989; Paxson 1992; Jayachandran 2006). Temperature extremes alter the optimal growing conditions of a plant, resulting in reduced yields and agricultural income (Hatfield et al. 2008). Measurement of temperature through growing degree-days considers the optimal growing conditions of the plant, recently applied for this reason to evaluate the climate change impacts on U.S. farmland values (Schlenker, Hanemann, and Fisher 2006). The consequences of temperature are arguably more severe, since it is difficult to control without major investments.

We combine the temperature data with a unique household survey performed in 2008 in northern Nigeria, which collected information on individuals (including their destinations) that permanently migrated out of villages originally sampled in 1988 (Udry 1990, 1994). Most households have at least one migrant highlighting the relevance of this issue in the region. We exploit information on permanent moves out of the initial 1988 households to investigate long-term insurance motives behind migration. While the duration of the panel is unique, the survey itself does pose limitations in the analysis. Two hundred households spanning four villages were surveyed initially in 1988. Therefore, the analysis is not nationally representative and subject to the standard empirical issues associated with small sample sizes. We apply the wild bootstrap method to calculate the appropriate standard errors in samples with small cluster sizes (Cameron, Gelbach, and Miller 2008). The dataset provides a rich amount of information to study weather-related risk and migration among rural agricultural populations.

We find that households in northern Nigeria use migration to deal with ex ante and ex post risk. To construct proxies of ex ante and ex post risk, we use the distribution of degree-days interacted with landholdings. To measure ex ante risk, we use the coefficient of variation of this distribution over the 25-year period 1983-2008, which includes the five years prior to the initial household survey conducted in 1988. This measures the expected risk a household faces over time. Weather variability increases

[1] The motives behind internal migration within Nigeria are relatively understudied despite its relative importance and scale (Fadayomi 1998; Adewale 2005; Mberu 2005; de Haas 2006). Few studies examine the role of migration in mitigating the vulnerability of households to risk in Africa (de Haan, Brock, and Coulibaly 2002; Gubert 2002; and Azam and Gubert 2006 are exceptions). Focusing on motives to remit, Osili (2007) finds empirical evidence of altruistic and investment motives from international Nigerian migrants, although she does not explicitly test for the insurance motive.

agricultural income risk and the ability of households to insure using alternative mechanisms can mitigate risk as measured through the interaction with inherited wealth (Rosenzweig and Stark 1989). Our measures of ex post risk are constructed as shock variables using the lagged standard deviation of the distribution five years prior to the year the migrant moved. When we control for both ex ante and ex post risk, households facing greater ex ante risk have a greater probability of having at least one migrant. We also find that the impact of ex post risk on the probability of a household's having a migrant depends on the period of time assessed.

We further explore how the type of ex post risk affects migration decisions, by estimating the relationship between the distances traveled by migrants and risk. We find that the distances of male migrants are the most responsive to ex ante and ex post risk in northern Nigeria. Male migrants travel longer distances in response to ex ante risk. Distances are shortened in response to ex post risk. Households facing hot shocks before the migrant's move tend to keep their male migrants close. While the results contrast the evidence from marriage migration (Rosenzweig and Stark 1989), they remain consistent with Halliday (2006), who shows earthquakes in El Salvador keep male migrants at home to assist in the household's recovery. Such a migration response elicits the limitations of migration as a coping strategy, particularly in the wake of global climate change. A 20-percent reduction in the growing period is predicted to occur by 2050 in the Sahel (Thornton et al. 2006 as cited by Boko et al. 2007), which motivates understanding private capacities to adapt and their limitations to ameliorate the expected damages from climate change through policy.

The next section of this paper reviews the literature on migration and risk, which provides the theoretical framework from which we derive our econometric specifications in the third section. The fourth section presents the data and its descriptive statistics. The fifth section presents our results, and the last section concludes.

2. MIGRATION AND RISK

A rich literature focuses on the use of migration to overcome the perils caused by risk, capital market imperfections, and liquidity constraints (Rosenzweig and Stark 1989; Stark 1991; Azam and Gubert 2006; Giles 2006; Halliday 2006). Increased agricultural income variance can induce households to spatially disaggregate risk by increasing the number of migrants per household with the expectation that if income sources are diversified spatially then idiosyncratic shocks are insurable. If covariate risk is uninsurable due to credit market imperfections, then a household may use migration to mitigate risk ex ante by preemptively allocating labor optimally across space, reducing their income vulnerability. The migrant provides some form of assistance (for example, via sending remittances, or by relaxing resource constraints via his departure) to facilitate the household's ability to smooth consumption when facing a transitory shock. Furthermore, households can also adjust the distance traveled by migrants to reduce the correlation between origin and destination income shocks (Rosenzweig and Stark 1989).

The benefit of using ex ante migration to mitigate risk depends on the conditions of the labor market and the composition of the household. In general, households facing labor constraints may not engage in these spatial contractual arrangements, unless as an ex post migration strategy to cope with the sudden income loss of shocks and productive opportunities. Halliday (2006) finds that agricultural shocks motivate migration ex post whereas earthquakes reduce migration in El Salvador. The empirical evidence supports the tendency for households to retain labor for recovery (rather than due to the inability to finance migration) following a major earthquake. The Halliday findings suggest there are also limitations in using migration as an ex post coping strategy, particularly when the shock is severe.

While previous studies focus on ex ante and ex post risk management strategies distinctly, it is possible that households use a combination of the two. Rose (2001) shows that households in India adjust their off-farm labor supply in response to ex ante and ex post risk. In her theoretical model, households reduce risk ex ante by increasing off-farm, less risky labor (the portfolio effect) and consume less leisure to avoid income loss (the precautionary effect). Both of these effects generate a positive labor response to ex ante risk. She further describes why household labor supply response may be affected ex post. Households increase their labor supply off of the farm ex post to smooth income (income effect). There is also the substitution effect, where households substitute away risky own farm production and labor activities for leisure. She shows that under certain conditions, the substitution effect reinforces the income effect, rendering a positive labor supply response to risk ex post. In this paper, we build upon Rose (2001) to consider the role of migrant labor in household's risk management strategies.

A final consideration is the trade-offs households face when utilizing female and male migrant labor as part of their risk management strategy. Rosenzweig and Stark (1989) demonstrate in earlier work that the trade-offs favored sending women away for marriage in India. In other settings, societal norms and limited employment options can discourage female mobility (Davis and Winters 2001). Regarding the latter, households may be hesitant to send female migrants abroad if the level of uncertainty of the return to migration is high or if they have access to alternative coping mechanisms. Davis and Winters (2001) find networks dominated by females affect the probability of female migrants traveling to a specific location. One possible interpretation of this effect is that improving employment information flows reduces the level of uncertainty of the migration benefits. Since the trade-offs a household faces in sending migrant labor will depend on the gender of the migrant, we further evaluate how migrant's gender influences risk management practices.

3. ECONOMETRIC SPECIFICATION

The literature on how households respond to both ex ante and ex post shocks motivates our econometric specifications. Two specifications are employed to examine how migration is used to mitigate agricultural risk. We use these models to test the hypotheses of whether there are statistically significant effects of climate-induced risk on migration behavior and the distances migrants travel. We also disaggregate the decision to migrate and distances traveled by gender to estimate whether there are gender-differentiated effects of agricultural risk. To identify sources of ex ante and ex post risk, we are careful in the construction of our shock variables that are constructed from temperature degree-days described below.

The first specification investigates the household decision to send a migrant. We estimate a linear probability model (LPM) to measure the determinants of the household having at least one migrant M_h since 1988, the first round of our data, such that

$$M_{h,2008} = \beta X_{h,1988} + \delta Z_{h,1988} + \varepsilon_{h,v,2008}, \tag{1}$$

where the vector X refers to premigration household characteristics, such as household size, education of household head, landholdings, and household assets. We include premigration household variables to reflect factors that influence households' decisions to send migrants that are uncorrelated with climate fluctuations. The vector Z includes variables that proxy for fluctuations in agricultural profit. We differentiate between ex ante and ex post agricultural risk. We proxy for ex ante agricultural risk by using degree-days over the period 1983 to 2008, which we discuss in further detail below. In the specification, we also assume an additive error term, which is independent of the household variables,

$$\varepsilon_{h,v} = \tau_v + v_{h,v}.$$

Unobserved characteristics at the village level, such as differences in social norms or labor market conditions, are accounted for in the village dummy variables. By using the LPM, we are not forced to impose any arbitrary restrictions on the error term. The LPM produces accurate predictions of the probability for values of variables close to the sample mean (Wooldridge 2002).

In our second specification, we investigate how households allocate members across space to diversify risk conditional on their decision to send a member to migrate. We therefore estimate the following ordinary least squares (OLS) regression:

$$D_{i,h,v,2008} = \alpha W_{i,2008} + \beta X_{h,1988} + \delta Z_{h,1988} + \varepsilon_{h,v,2008,} \tag{2}$$

where D is the distance migrated; W is a vector of individual characteristics, such as gender and age; X is a vector of household characteristics, similar to the previous specification. The vector Z includes climate variables that characterizes ex ante and ex post agricultural risk. Some of these variables will vary from specification (1) as they exploit variation in the timing of the migrant's decision to move. We also control for village-level unobserved characteristics by including village dummy variables.

Measures of Ex Ante and Ex Post Risk

In both models (1) and (2), we draw on previous work that uses climate variability, specifically precipitation, to measure agricultural income variability (Rosenzweig and Stark 1989; Rosenzweig and Binswanger 1993; Rosenzweig and Wolpin 1993; Fafchamps, Udry, and Czukas 1998; Kochar 1999; Rose 2001; Jayachandran 2006; Kazianga and Udry 2006; Mueller and Osgood 2009). Our measures of risk vary from the literature in four ways.

First, we use temperature degree-days to proxy agricultural income variability. Schlenker, Hanemann, and Fisher (2006) first used temperature degree-days to evaluate the impact of climate change on U.S. farmland values. They argue temperature expressed in degree-days is the most relevant measure for plant growth. Degree-days account for the nonlinear relationship between plant growth and climate.

Specifically, it documents the number of days in a given agricultural cycle where temperature exceeds the minimum growing requirements.

Second, we use the coefficient of variation of degree-days in each household's local government area (LGA) interacted with household landholdings to measure ex ante risk.[2] We use the coefficient of variation (Rose 2001) rather than the variance of climate (Rosenzweig and Stark 1989) to avoid sensitivity to scaling. The coefficient of variation is similar in measurement as it divides the standard deviation by the mean of the historical distribution of climate. We interact household's landholdings with the coefficient of variation of temperature degree-days to account for one's ability to mitigate increases in agricultural income risk through inherited wealth (Rosenzweig and Stark 1989).

Third, we include measures for both ex ante and ex post risk following Rose (2001). Most studies focus on the latter. Since we have a relatively long time series of daily temperature data and data on migration behavior over 20 years, we are able to create distinguishable ex ante and ex post risk variables. As we will explain next, ex post risk variables in equation (2) will depend on the timing of the migrant's move adding more variation than possible in specification (1).

Fourth, we differentiate between the effects of ex post risk by type (hot and cool), and frequency (sudden versus cumulative shocks) on distances migrants travel. In the determinants of migration analysis (1), we include variables measuring the standard deviation of temperature degree-days over the five-year period prior to migration (interacted with landholdings). This captures fluctuations in the frequency of degree-days over shorter time periods that may differ from household expectations. When evaluating the impact of risk on distances traveled, we are able to exploit the variation in years when migrants moved to capture different aspects of risk. Our first measure of ex post risk is the number of standard deviations from the mean one year prior to the move. Our second measure distinguishes hot (cool) periods by differentiating the number of standard deviations above (below) the mean one year prior to the move. Our third and fourth measures attempt to examine the impact of cumulative shocks on distances traveled. Specifically, the third measure is the number of times the standard deviation was above or below one standard deviation from the mean five years prior to the move. The fourth measure distinguishes cumulative hot (cool) shocks by measuring the number of times the standard deviation was above (below) one standard deviation from the mean five years prior to the move. All four measures of ex post risk used in the distance regressions are interacted with household landholdings. By constructing alternative measures of ex post risk, our results provide some evidence as to which types of unexpected events households may respond to using migration.

Bootstrapping Clustered Standard Errors

A key econometric issue that we address in all regression specifications is the correction of the standard errors for within group dependence. Heteroskedastic-robust standard errors are commonly calculated following White (1980). In our regression specifications, we present heteroskedastic robust standard errors clustered at the village level to correct for within village correlations due to the sample design. However, a large literature illustrates that cluster robust standard errors might be downward biased if the number of clusters in the sample is small, as in our sample (Moulton 1986, 1990; Angrist and Lavy 2002; Bertrand, Duflo, and Mullainathan 2004; Donald and Lang 2007). This is because inference is based on the asymptotic assumption that the number of clusters tends to infinity. Cameron, Gelbach, and Miller (2008) illustrate that wild bootstrap methods perform particularly well in estimating standard estimates with small numbers of clusters.[3] Following their approach, we first estimate in the original sample the standard errors, coefficient estimates, and residuals imposing the null hypothesis. We then resample with replacement from the original sample residual vectors, $\hat{u}_V^* = \hat{u}_V$ with probability .5 and $\hat{u}_V^* = -\hat{u}_V$ with

[2] In the regression, we also include landholdings by type of elevation. In particular, we include the possession of high quality land, *Fadama*. *Fadama* land is at low altitudes and is considered of greater quality because it retains water.

[3] The wild bootstrap was developed by Wu (1986), Liu (1988), and Mammen (1993).

probability .5, to construct a pseudo-sample of $\{(\hat{y}_1^*, X_1),...,(\hat{y}_V^*, X_V)\}$ where the subscript V is the number of village clusters and $\hat{y}_V^* = X_V^{'}\hat{\beta} + \hat{u}_V^*$. In our analysis, we present the p values for the Wald test, for the risk parameters of interest in brackets, which result from imposing the null hypothesis that the coefficient estimates are equal to zero. This provides additional econometric evidence that, despite our small sample size, coefficient estimates for the agricultural risk variables are statistically meaningful.

4. DATA

We use three sources of data: a tracking survey in 2008, an initial household survey from 1988-1989, and climate data. The tracking survey collected detailed information on all household members that originally participated in the 1988-1989 Northern Nigeria Household Survey.[4] The tracking questionnaire records for each individual in the original household survey, whether they were still resident in the household and if not, where they were currently living, why they moved out of the household, and in what year the move occurred. For the purpose of our study, a *migrant* is any member who moved to another village since 1988. Of the original 200 households interviewed, 31 households, or 15.5 percent, were not able to be reinterviewed for information about their 2008 household characteristics. We matched individual migrants with the roster data from the 1988-1989 survey by name, age, their relationship to the household head in 1988, and gender. We merge the data from the tracking survey to the data collected in 1988 to create a dataset of households that includes variables on initial 1988 household and individual endowments to explain migration decisions since 1988. We also compute the distance between each individual migrant's origin and destination local government area (LGA), the smallest spatial unit of analysis these data permit, to also observe what determines the spatial allocation of migrants.[5]

Daily temperature data (1983-2008) are extrapolated from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center to construct the number of degree-days per growing season per year by LGA (Ritchie and NeSmith 1991).[6] We merge the household survey data with the daily temperature data to specifically construct the measures of risk we describe above.

Descriptive Statistics

Table 1 presents summary statistics of households in our sample by migration status. Long-term migration is prevalent in most of the originally surveyed households, where 78 percent of these households have at least one migrant. We perform t-tests for the differences in variable means across samples using village-clustered standard errors. The tests indicate that migrant households tend to be larger, have a lower (greater) share of boys (girls), and a greater proportion of heads with at least a primary education. There are no discernible differences by migration status in risk exposure as measured by the coefficient of variation or standard deviation of degree-days interacted with landholdings.

We next compare household characteristics by the gender of migrants in Table 2. We categorize households into households without migrants, households with only female migrants, households with only male migrants, and households with both female and male migrants. We do not find any statistically significant differences between households with no migrants and those with only male migrants. One explanation for this is that there are too few households with only male migrants. Interestingly, households with female migrants, columns 2 and 4 in Table 2, tend to have a lower share of boys, which, at the time of the 2008 survey, would be men of prime working age. Moreover, these households tend to have a greater proportion of household heads with a primary education. Households with female migrants only, column 2 in Table 2, tend to have a lower share of men and greater share of women in the household than non-migrant households. They also have fewer male household heads. Households with both female and male are larger, had a greater share of girls in 1988, and have a greater proportion of household heads with a secondary education. These figures confirm that there are different migration

[4] These data were originally collected by Christopher Udry in 1988/89 in association with Amadou Bello University in Kaduna State, Nigeria.

[5] Since we are only able to calculate distances between origin and destination LGAs, migrants that move to villages within the same LGA are assigned a value of zero for the distance traveled.

[6] The data were extrapolated from the following site URL: http://power.larc.nasa.gov.

practices in our sample, and the motivations for male and female migration may differ. There are no differences by gender in the household's exposure to risk as measured by our degree-day variables.

Table 1. Descriptive statistics of households, by migration status

	Non-migrant households	Migrant households	Difference in means
	Mean	Mean	T statistic
Household size (1988)	6.90	9.53	-9.12***
Adults (1988)	3.06	4.16	-10.80***
Share of men in household (1988)	0.14	0.13	0.27
Share of women in household (1988)	0.05	0.08	-1.08
Share of boys in household (1988)	0.48	0.39	2.84***
Share of girls in household (1988)	0.33	0.40	-2.90*
Male household head (1988)	0.93	0.90	0.70
Household head has primary education (1988)	0.24	0.44	-2.98**
Household head has secondary education (1988)	0.15	0.15	0.01
Fadama land (hectares) (1988)	0.40	0.42	-0.19
Livestock value (1988)	1,546	1,813	-0.27
Household capital value (1988)	815	1,248	-1.00
Coefficient of variation of degree-days*land	1.06	0.78	1.32
Standard deviation of degree-days (1983-1987)*land	576	542	0.38
Standard deviation of degree-days (1988-1992)*land	431	406	0.36
Standard deviation of degree-days (1993-1997)*land	319	300	0.37
Standard deviation of degree-days (1998-2002)*land	339	317	0.41
Standard deviation of degree-days (2003-2008)*land	1,896	1,449	1.25
Households	41	144	

Source: Authors calculations from 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: T-tests use village-clustered standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2. Descriptive statistics of households, by gender of migrants

	(1) None Mean	(2) Females Mean	(3) Males Mean	(4) Both Mean	(1)-(2) Difference in means T-statistic	(1)-(3) Difference in means T-statistic	(1)-(4) Difference in means T-statistic
Household size (1988)	6.90	8.16	6.89	13.22	-1.96	0.01	-14.52***
Adults (1988)	3.06	3.54	3.23	5.67	-1.50	-0.35	-15.18***
Share of men in household (1988)	0.14	0.08	0.22	0.15	2.56*	-1.56	-0.32
Share of women in household (1988)	0.05	0.08	0.05	0.08	-0.79	-0.03	-19.39***
Share of boys in household (1988)	0.48	0.36	0.48	0.38	4.55**	0.04	2.38*
Share of girls in household (1988)	0.33	0.48	0.25	0.38	-3.42**	1.18	-1.35
Male household head (1988)	0.93	0.81	0.96	1.00	3.57**	-1.58	-1.71
Household head has primary education (1988)	0.24	0.41	0.36	0.52	-2.67*	-0.74	-3.69**
Household head has secondary education (1988)	0.15	0.07	0.11	0.28	1.84	0.44	-3.32**
Fadama land (hectares) (1988)	0.40	0.35	0.68	0.37	0.35	-1.62	0.17
Livestock value (1988)	1,546	1,842	810	2,380	-0.25	0.95	-0.76
Household capital value (1988)	815	945	986	1,869	-0.48	-1.36	-1.30
Coefficient of variation of degree-days* land	1.06	0.64	0.68	1.04	1.73	0.80	0.05
Standard deviation of degree-days (1983-1987)* land	576	490	502	644	0.69	0.42	-1.39
Standard deviation of degree-days (1988-1992)* land	431	368	377	483	0.67	0.41	-1.48
Standard deviation of degree-days (1993-1997)* land	319	272	278	357	0.68	0.41	-1.43
Standard deviation of degree-days (1998-2002)* land	339	286	294	378	0.72	0.43	-1.28
Standard deviation of degree-days (2003-2008)* land	1,896	1,218	1,284	1,901	1.61	0.76	-0.01
Households	41	70	28	46			

Source: Authors calculations from 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: T-tests use village-clustered standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We describe the characteristics of the individual migrants in our sample by gender in Table 3. We observe that male migrants are sent longer distances than female migrants. Differences in vulnerability to ex ante risk, as measured by the coefficient of variation interacted with landholdings during the entire time series, do not appear statistically significant. However, there is slight evidence that male migrants come from households facing greater ex post risk. Although the migration decision does not appear correlated with risk, it is possible that households spatially allocate male migrants further away so that their incomes do not correlate with the shock from their origin communities.

Table 3. Descriptive statistics of distances traveled and shocks, by migrant's gender

	Females		Males		Difference in means
	Mean	Standard Deviation	Mean	Standard Deviation	T statistic
Distance migrated (km)	24.01	46.73	157.70	204.64	-4.28**
Age (1988)	11.41	10.02	12.64	10.38	-0.78
Coefficient of variation of degree-days*land	1.07	1.75	1.26	2.13	-0.74
Lagged SD in origin	0.29	0.60	-0.12	1.03	2.68*
Lagged SD in origin*land	1.36	5.34	-1.17	10.60	1.41
Lagged SD above mean in origin	0.41	0.29	0.35	0.34	1.01
Lagged SD above mean in origin*land	2.20	3.24	1.99	3.85	0.41
Lagged SD below mean in origin	0.13	0.42	0.47	0.78	-3.73**
Lagged SD below mean in origin*land	0.84	3.78	3.15	9.21	-1.82
Times over 5 years 1 SD above/below mean in origin	0.68	0.94	0.97	1.23	-1.23
Times over 5 years 1 SD above/below mean in origin*land	3.36	7.36	7.00	19.10	-1.80
Times over 5 years 1 SD above mean in origin	0.16	0.36	0.14	0.35	0.38
Times over 5 years 1 SD above mean in origin*land	0.59	1.81	0.88	3.14	-0.54
Times over 5 years 1 SD below mean in origin	0.52	0.79	0.83	1.16	-1.44
Times over 5 years 1 SD*land below mean in origin	2.77	6.88	6.12	18.54	-1.55
Individuals	154		58		

Source: Authors calculations from 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: T-tests use village-clustered standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Attrition

Before estimating the econometric specifications, we conduct an investigation of the determinants of household attrition from the 1988 data. As described above, 15.5 percent of households interviewed in 1988 were not able to be tracked. We estimate a linear probability model (LPM) with village indicators in Table 4, controlling for household head characteristics, household composition, and household assets in column 1. In columns 2 and 3, we include our measures of agricultural risk, the coefficient of variation of temperature degree-days, and the standard deviation of temperature degree-days. Column 4 includes both variables with the other household covariates and village indicators.

In column 1, we find that the number of women, and wealth in the form of value of livestock and the *fadama*, or low-elevation, landholdings affect attrition. The result on *fadama* land is somewhat surprising, given that these lands are more valuable to farmers because they retain water over longer periods of time. *Fadama* landholdings provide greater stability of yields than *gona*, or higher-elevation, landholdings. Each additional hectare of *fadama* land held increased the probability of household attrition by 5.5 percent. Our results suggest that wealthier households may be more likely to attrite, however, as we will show that the parameters on the wealth variables are not statistically robust across attrition model specifications.

Adding the degree-day variables independently, in columns 2 and 3 of Table 4, has no statistically significant effect on the likelihood of attrition. The effect on the number of women of prime working age in the sample remains robust across the specifications, suggesting that an additional woman in the household decreases attrition by 4 percent. When both degree-day variables are included jointly in the attrition specification in column 4, both variables affect the likelihood of attrition. This is not surprising, as our hypothesis posits that increased shocks raise migration rates of individuals, but shocks could also increase the mobility of households. This finding suggests that our results likely underestimate the effect of temperature-related shocks on migration, as our tracking study was not able to find those households who migrated as a unit.

Table 4. Attrition

	(1)	(2)	(3)	(4)
	No temperature variables	Coefficient of Variation (CV)	Temperature shocks	CV and shocks
Total assets value(in 1,000 naira)	-0.002	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)
Total value of livestock (in 1,000 naira)	0.010***	0.009**	0.009**	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Total number of livestock in TLU	0.000	-0.002	-0.002	-0.002
	(0.011)	(0.011)	(0.011)	(0.011)
Age of household head	-0.001	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Number of men	-0.042	-0.048***	-0.048***	-0.046***
	(0.037)	(0.017)	(0.017)	(0.017)
Number of women	-0.054***	-0.044***	-0.044***	-0.044***
	(0.006)	(0.008)	(0.008)	(0.008)
Number of household dependents	0.004	0.005	0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.008)
Gona land size in hectares	-0.006	-0.011	-0.011	0.000
	(0.005)	(0.011)	(0.011)	(0.016)
Fadama land size in hectares	0.055***	0.038	0.038	0.049*
	(0.019)	(0.026)	(0.026)	(0.028)
Coefficient of variation		0.024		4.600*
		(0.029)		(2.649)
Temperature shocks			0.000	-0.002*
			(0.000)	(0.001)
Number of observations	196	190	190	190
Adjusted R2	0.068	0.041	0.041	0.040

Source: Authors calculations from 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. All household variables are from the 1988 data. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: *** p < 0.01, ** p < 0.05, * p < 0.10.

5. RESULTS

Migration and Risk

We present the results from the migration regression in Table 5 using the following dependent variables: the household has at least one migrant (column 1), the household has at least one male migrant (column 2), and the household has at least one female migrant (column 3). In column 1, we observe that households with a greater share of boys in 1988 tend to have fewer migrants, which is primarily driven by the fact that most of the migration activity is females moving out of the household. Primary education of the household head has a positive effect on migration, and the opposite is true for the household's head completion of a secondary education. Lastly, ex ante risk has a negative effect in the pooled specification, but we see in our gender disaggregated analysis that ex ante risk is positively associated with male migration.[7]

We further compare the effects of having at least one male migrant versus one female migrant in columns 2 and 3 of Table 5. We find that most coefficients are statistically insignificant in the male regression, potentially due to the limited number of households in our sample with at least one male migrant. Interestingly, the estimate of ex ante risk on migration corroborates previous work on off-farm labor participation (Rose 2001) that suggest that increased ex ante risk increases the likelihood of male migration. Household size, share of girls in the household, and whether the household head completed a primary education are positive and significant determinants of having at least one female migrant. There is evidence that households facing risk are less inclined to send female migrants elsewhere (p-value = 0.13 for the coefficient of variation parameter according to the t-test, and p-value = 0.19 according to the Wald test using the wild bootstrapped standard errors), which may be driving the ex ante risk effect in column 1. Note that this is opposite to the Rosenzweig and Stark (1989) result, which finds that the number of female migrants is positively correlated with ex ante risk. There are a few possible explanations for this effect. First, this specification does not control for ex post risk, so it may be that households evaluate both ex ante and ex post risk before allocating migrants. In our specifications below, we introduce controls for both ex ante and ex post risk in the specification. Second, because marriage migration may be the primary motivation for women, low-income or labor-constrained households facing riskier distributions may retain their women for labor on the farm or within the household. Third, women in households who face risk may tend to marry within their village if expanding the household is the preferred mechanism of risk pooling rather than diversifying the spatial allocation of household members (Townsend 1994). Lastly, it is also possible that households facing greater ex ante risk are less likely to finance the move of migrants. For female migrants, the household may need to accumulate savings for a dowry. For male migrants, the household may need to mobilize resources to finance the transit and set-up costs at the destination.

To evaluate whether income constraints may be driving the effect on the ex ante risk parameter, we reestimate the migration specification for the pooled sample, differentiating the effect by wealth status in column 4 of Table 5. We create a low-income dummy variable, in which low-income households include those that have total household capital values less than or equal to the 25th percentile of the sample. We find that the effect of risk on migration is more pronounced among low-income households; however, the overall effect remains negative and not robust to tests using the wild bootstrapped standard errors, suggesting that the financial constraints may not be driving the negative effect.[8] This suggests that ex ante risk pooling by marriage within the village or retaining household labor may be preferred due to incomplete labor markets rather than credit constraints.

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[7] We have also estimated a probit version of the model that assumes the errors are distributed normally. We obtain a negative and significant effect on the ex ante risk parameter. The coefficient is -0.13 and is significant at the one percent critical level.

[8] It is possible that households who are risk-averse may be more or less inclined to send migrants that could also bias our risk parameter. We control for risk-aversion to the extent that it is correlated with wealth.

Table 5. Migration and ex ante risk

	(1) Has migrant	(2) Has male migrant	(3) Has female migrant	(4) Has migrant
Household size	0.010	0.017	0.024**	0.010
	(0.010)	(0.011)	(0.007)	(0.011)
Share of boys in household	-0.215**	-0.266	-0.112	-0.224**
	(0.064)	(0.178)	(0.064)	(0.062)
Share of girls in household	0.099	-0.290	0.495*	0.103
	(0.121)	(0.150)	(0.183)	(0.124)
Male household head	0.007	0.242	-0.040	0.019
	(0.163)	(0.126)	(0.280)	(0.173)
Household head has primary education	0.156*	-0.067	0.158*	0.150*
	(0.052)	(0.163)	(0.064)	(0.048)
Household head has secondary education	-0.196*	0.034	-0.098	-0.197*
	(0.075)	(0.102)	(0.085)	(0.080)
Fadama land	0.010	-0.001	-0.046	0.014
	(0.019)	(0.022)	(0.023)	(0.018)
Livestock value	7.54e-06	1.37e-06	1.61e-05	6.67e-06
	(7.69e-06)	(7.30e-06)	(8.35e-06)	(8.07e-06)
Household capital value	2.05e-06	3.31e-06	-1.24e-06	2.49e-06
	(3.02e-06)	(1.96e-06)	(5.43e-06)	(2.15e-06)
Coefficient of variation of degree-days*land	-0.036**	0.012	-0.019	-0.029*
	(0.007)	(0.009)	(0.009)	(0.012)
	[0.055]	[0.311]	[0.185]	[0.301]
Coefficient of variation of degree-days*land*low-income dummy				-0.053*
				(0.021)
				[0.441]
Low-income dummy				0.069
				(0.062)
Constant	0.752***	0.347*	0.271	0.731**
	(0.119)	(0.143)	(0.239)	(0.138)
F-test: CV and CV*low income = 0				134.76***
Number of observations	185	185	185	185
R-squared	0.117	0.140	0.224	0.123

Source: Authors calculations from 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. All household variables are from the 1988 data. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: Village-clustered standard errors are in parentheses. P value of the wild bootstrapped standard errors, testing the null hypothesis that the coefficient is zero, is in brackets. Village indicators are included in the regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Households in Nigeria may use migration to respond to ex post risk. When households face severe shocks, they may be less inclined to send members elsewhere, due to their need to retain labor (Halliday 2006). Alternatively, shocks may induce migration to pool risk and spatially diversify income. One of the challenges in identifying the presence of an ex post risk management strategy is that our dataset consists of a cross-section of households' migration outcomes. Therefore, it is difficult to develop a counterfactual shock for nonmigrant households. To account for the possibility of migration as an ex post risk management strategy, we first test the hypothesis that the timing of the migration does not affect the relationship between ex ante risk and migration.

Table 6 provides regression results for having at least one migrant move at various time periods. The results show that timing of migration matters. The parameters on the ex ante risk variable are positive both in columns 1 and 4, and significantly different (according to the Chow tests) than the parameter in the pooled version of the model (column 1, Table 6). We further attempt to capture specific shocks and the household's ex post response to risk in the model explicitly by including the standard deviation of temperature degree-days over the five-year period of migration. The results in columns 5 and 8 are consistent with the previous specification, indicating that ex ante risk is positively associated with migration behavior. Ex ante and ex post risk measures in columns 5 and 8 significantly affect the time-specific migration behavior according to F statistics testing their parameters joint significance, and the Wald statistics testing the parameters individual significance in column 8. Specifically, we find that previous shocks positively (negatively) affected migration in the first (fifth) period. The fact that there is a negative effect of the parameter in the fifth period is not surprising, considering that northern Nigeria experienced a record drought in the 1980s (Blench and Dendo 2004). We would expect that shocks of more intense magnitude may induce households to retain labor following Halliday (2006), but that less severe shocks may induce households to spatially disaggregate risk. Our results provide support that households respond to both ex ante and ex post risk by sending household members elsewhere, and that controlling for ex post risk generates estimates consistent with previous studies.

Spatial Allocation of Household Members and Risk

Upon deciding to send a household member elsewhere, the household is then faced with the decision of how far to send migrants in order to diversify risk. We next compare whether households base their decision of where to locate individuals according to ex ante risk in columns 1 and 3 of Table 7. The results are consistent with the earlier migration specification, where we see a negative effect on the coefficient of variation parameter in the pooled and female regressions and a positive effect on the parameter in the male regressions. However, for the case of distances, not one of these three parameters is statistically significant from zero.[9]

As in the migration specification, the negative coefficient on the ex ante risk parameter may be driven by the omission of a control for ex post risk. We next include the number of standard deviations above/below the mean one year prior to the migrant's move to examine the impact of ex post risk in the distance regression. Columns 4 through 6 in Table 7 present the results from those regressions. As in the migration specification (1), the coefficient of variation parameter changes from negative to positive in the pooled and male regressions when we control for a measure of ex post risk. However, according to the F statistics testing joint significance and the t and Wald statistics testing the individual significance of the ex ante and ex post parameters, we cannot reject that these parameters are statistically equal to zero at the 10-percent critical level.

[9] Due to data limitations, we are only able to compute distances between the origin and destination LGAs. Since many migrants move within an LGA, a large fraction of our sample has values of zero for the dependent variable. The measurement error is somewhat small in our case because the origin LGAs are small: Giwa and Soba are 2,066 and 2,234 square kilometers, respectively (National Bureau of Statistics GeoDatabase). Moreover, the estimates from the distance regression using our sample of female migrants will more likely suffer from such measurement error as a larger fraction of them (59.74 percent) make within LGA moves than male migrants (18.97 percent). To observe how sensitive our results are to the measurement error, we reestimate the regressions excluding those migrants that move within their LGA. We find that the estimates on the coefficient of variation parameters in the female and male regressions are within the order of magnitude of those reported in Table 8. In particular, the parameters are -0.17 (p-value = 0.95) and 5.48 (p-value = 0.81), in the female and male distance regressions, respectively.

Table 6. Timing of migration and risk

	(1) At least 1 moves 88-92	(2) At least 1 moves 93-97	(3) At least 1 moves 98-02	(4) At least 1 moves 03-08	(5) At least 1 moves 88-92	(6) At least 1 moves 93-97	(7) At least 1 moves 98-02	(8) At least 1 moves 03-08
CV of degree-days*land	0.037**	-0.021	-0.030	0.012	0.026	0.017	-0.074	0.215
	(0.009)	(0.015)	(0.024)	(0.011)	(0.0474)	(0.040)	(0.068)	(0.095)
	[0.053]	[0.337]	[0.435]	[0.277]	[0.665]	[0.665]	[0.435]	[0.053]
SD (1988-1992)*land					4.03e-05			
					(0.000167)			
					[0.819]			
SD (1993-1997)*land						-1.87e-04		
						(1.96e-04)		
						[0.919]		
SD (1998-2002)*land							2.02e-04	
							(3.03e-04)	
							[0.985]	
SD (2003-2008)*land								-1.20e-04
								(6.17e-05)
								[0.055]
F-test: CV pooled= CV(1, 2, 3, or 4)	13.44**	3.57	2.70	7.99*				
F-test: CV and SD=0					9.36*	1.07	1.05	33.05***
Households with at least one migrant	52	61	81	43	52	61	81	43
Households	185	185	185	185	185	185	185	185
R-squared	0.094	0.116	0.088	0.101	0.095	0.119	0.092	0.102

Source: Data are from the 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. All household variables are from the 1988 data. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: Village-clustered standard errors are in parentheses. P value of the wild bootstrapped standard errors, testing the null hypothesis that the coefficient is zero, is in brackets. CV refers to coefficient of variation of temperature degree-days, and SD refers to the standard deviation of temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7. Distances traveled and risk

	(1) Pooled	(2) Females	(3) Males	(4) Pooled	(5) Females	(6) Males
Female	-133.3**			-132.2**		
	(34.25)			(33.81)		
Age	-0.154	-0.009	-3.326	-0.176	-0.008	-3.724
	(0.866)	(1.037)	(4.174)	(0.834)	(1.045)	(4.568)
Age squared	-0.008	0.007	0.006	-0.008	0.007	0.008
	(0.020)	(0.016)	(0.097)	(0.020)	(0.016)	(0.110)
Household size	-1.234	-0.022	-5.512	-1.206	-0.012	-4.392
	(2.925)	(0.960)	(6.184)	(2.962)	(0.966)	(6.302)
Share of boys in household	5.698	42.66	-71.96	4.152	42.84	-79.46
	(57.66)	(19.80)	(187.8)	(60.57)	(20.34)	(196.4)
Share of girls in household	12.24	-31.61**	72.22	11.41	-31.66**	79.24
	(37.85)	(8.443)	(152.6)	(38.15)	(8.459)	(146.3)
Male household head	-37.47	-44.14***	-82.13	-38.34	-44.23***	-80.59
	(40.47)	(5.367)	(60.40)	(39.77)	(5.220)	(84.94)
Household head has primary education	3.051	-10.44	81.96	2.452	-10.33	74.99
	(10.80)	(14.19)	(50.56)	(9.327)	(14.12)	(50.41)
Household head has secondary education	42.61	14.05	64.83	44.32	13.70	72.34
	(23.23)	(10.87)	(158.9)	(25.77)	(10.99)	(156.6)
Fadama land	-10.35	-0.276	-25.18	-11.29	-0.401	-27.28
	(12.17)	(6.287)	(33.31)	(13.16)	(6.357)	(31.10)
Livestock value	0.003	0.002	0.010	0.003	0.002	0.010
	(0.003)	(0.002)	(0.013)	(0.003)	(0.002)	(0.013)
Household capital value in 1,000 naira units	0.543	0.298	0.816	0.552	0.294	0.799
	(0.306)	(0.481)	(1.50)	(0.322)	(0.487)	(1.36)
Coefficient of variation of degree-days*land	-0.239	-0.216	5.758	0.108	-0.381	1.560
	(5.796)	(1.414)	(25.15)	(6.371)	(1.461)	(21.96)
	[0.849]	[0.927]	[0.613]	[0.917]	[0.829]	[0.881]
Lagged SD in origin*land				-0.557	0.115	-2.179
				(1.136)	(0.231)	(1.850)
				[0.811]	[0.819]	[0.285]
Constant	202.3*	64.15**	318.9	203.2*	64.25**	312.7
	(69.44)	(13.71)	(144.2)	(70.35)	(13.90)	(134.6)
F-test: CV and SD=0				0.72	0.14	1.03
Observations	212	154	58	212	154	58
R-squared	0.279	0.135	0.217	0.280	0.135	0.225

Source: Data are from the 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. All household variables are from the 1988 data. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.

Notes: Village indicators are included in the regression. Village-clustered standard errors are in parentheses. P value of the wild bootstrapped standard errors, testing the null hypothesis that the coefficient is zero, is in brackets. CV refers to coefficient of variation of temperature degree-days, and SD refers to the standard deviation of temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

It is possible that the parameters on the ex post variables are not statistically different from zero because hot and cool shocks have opposing effects on the spatial allocation of household members. This phenomenon has the potential to attenuate the effect our shock parameter has on distance. We differentiate ex post risk by hot and cool in the next set of specifications (Table 8). The estimates in columns 1 through 3 indicate that the magnitude of the effects of hot shocks is greater than the magnitude of cool shocks. Ex post risk is only significant in the pooled and male distance regressions according to the F tests of joint significance at the 10-percent critical level and the Wald test for individual significance in the pooled distance regression.

Table 8. Distances traveled and ex post risk associated with hot and cool shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Females	Males	Pooled	Females	Males
Coefficient of variation	3.797	-3.987	8.156	4.104	-3.576	21.69
	(2.087)	(5.693)	(17.98)	(2.526)	(7.592)	(16.99)
	[0.161]	[0.581]	[0.781]	[0.161]	[0.683]	[0.407]
Lagged SD above mean in origin*land	-2.811	2.179	-7.939	-2.558	0.928	-3.347
	(1.563)	(2.790)	(3.916)	(2.362)	(3.009)	(5.602)
	[0.055]	[0.429]	[0.163]	[0.333]	[0.685]	[0.689]
Lagged SD below mean in origin*land	-0.362	0.516	-0.381	-0.539	0.195	-0.832
	(2.009)	(0.608)	(2.878)	(2.339)	(0.874)	(3.957)
	[0.849]	[0.313]	[0.823]	[0.849]	[0.819]	[0.689]
Lagged SD above mean in origin*land*low-income dummy				-3.140	6.290	-45.84
				(7.779)	(8.750)	(33.46)
				[0.507]	[0.565]	[0.055]
Lagged SD below mean in origin*land low-income Dummy				0.880	1.529*	-0.851
				(2.128)	(0.615)	(6.478)
				[0.687]	[0.465]	[0.641]
Low-income dummy				12.29	-21.36	151.7
				(30.59)	(13.70)	(130.7)
				[0.657]	[0.055]	[0.283]
F test joint significance of hot and cool shocks	8.80*	0.36	8.70*			
F test joint significance of hot shocks				109.91***	0.26	20.29**
F test joint significance of cool shocks				0.17	4.11	0.7
Observations	212	154	58	212	154	58
R-squared	0.281	0.138	0.232	0.283	0.165	0.290

Source: Data are from the 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. All household variables are from the 1988 data. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: Village-clustered standard errors are in parentheses. P value of the wild bootstrapped standard errors, testing the null hypothesis that the coefficient is zero, is in brackets. CV refers to coefficient of variation of temperature degree-days, and SD refers to the standard deviation of temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Next, in columns 4 through 6 of Table 8, we differentiate the impact of hot and cool shocks by wealth to evaluate whether financing costs may prohibit households from sending migrants further away. We find that hot shocks continue to be the important factor in the decision of how far to send a migrant (in the pooled and male distances regressions). The effect remains negative, meaning that households that face greater risk associated with hot shocks tend to retain labor irrespective of the wealth status of household. The inability to finance the move of migrants is not driving the entirety of the result. This suggests that additional constraints, such as incomplete labor markets, which inhibit hiring labor substitutes, or access to networks to reduce costs associated with the uncertainty of migrant employment, may factor into the decision of where to allocate household members.

Distance Traveled and Frequency of Disasters

Our final consideration is that the cumulative realization of shocks may also bear an effect on where to place migrants spatially. To capture the cumulative effects of shocks, we include the number of times during the five years prior to the migrant's move that the standard deviation of degree-days was one standard deviation above or below the mean level of degree-days. We also create variables that differentiate the number of times households experienced cool and hot shocks five years prior to the migrant's move. The results from these regressions are in Table 9. From columns 1-3, we find that households facing frequent shocks tend to keep migrants closer; however, the effect is only statistically significant at the 5-percent level in the pooled regression and not robust to Wald test using the wild bootstrapped standard errors. Next, we find in the pooled regression similar negative effects on the impact of cumulative hot and cool shocks on distances traveled. Interestingly, the coefficient of variation is negative but not significant according to the t-test or F test of joint significance at the 10-percent critical level, but significant at the 10-percent critical level according to the Wald test. Upon distinguishing the distances traveled by gender, we do not observe any effects on the distances females travel, but we do witness more pronounced and significant effects of frequent shocks on the distances male migrants travel. In particular, cumulative hot shocks have a pronounced negative and significant (at the 10-percent critical level according to t and Wald tests) effect on distances traveled by males. Moreover, the sign on the ex ante risk parameter has become negative and jointly significant according to the F test. We further check whether multicollinearity between the coefficient of variation in degree-days and the hot shock variable may be affecting the precision of the estimate on the coefficient of variation, which our sample may be particularly sensitive to since it is small. We find that the correlation between these two variables is rather low and negative (-0.13). Furthermore, we cannot reject that the partial correlation coefficient is statistically equivalent to zero (p-value = 0.35). Thus, while households facing hot shocks prior to the migrant's move tend to keep male migrants close by, the number of hot shocks households face also matters. In particular, households facing frequent hot shocks tend to increase the proximity of the migrant to the original community.

Table 9. Distances traveled and frequency of shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Females	Males	Pooled	Females	Males
Coefficient of variation in degree-days	0.245 (5.649) [0.917]	-0.191 (1.440) [0.927]	6.508 (24.38) [0.952]	-0.293 (5.771) [0.955]	-0.180 (1.450) [0.927]	-3.416 (20.52) [0.839]
Times over 5 years SD above/below mean in origin*land	-0.756** (0.204) [0.163]	-0.265 (0.394) [0.951]	-0.518 (0.814) [0.865]			
Times over 5 years 1 SD above mean in origin*land				-2.142 (1.212) [0.055]	1.188 (0.699) [0.457]	-7.700** (1.933) [0.055]
Times over 5 years 1 SD below mean in origin*land				-0.839* (0.280) [0.055]	-0.382 (0.386) [0.543]	-0.968 (0.569) [0.865]
F test joint significance of hot/cool shock				6.67*	2.39	121.69***
F test joint significance of CV and hot shock				4.31	2.66	30.83***
Observations	212	154	58	212	154	58
R-squared	0.282	0.136	0.218	0.283	0.138	0.223

Source: Data are from the 1988 Northern Nigeria survey (Udry 1991) and the 2008 tracking survey conducted by the authors. All household variables are from the 1988 data. Degree-days are calculated from daily temperature data (1983–2008) from the Surface Meteorology and Solar Energy (SSE-release 6.0) product developed by the Atmospheric Sciences Data Center at the NASA Langley Research Center.
Notes: Village-clustered standard errors are in parentheses. P value of the wild bootstrapped standard errors, testing the null hypothesis that the coefficient is zero, is in brackets. CV refers to coefficient of variation of temperature degree-days, and SD refers to the standard deviation of temperature. *** p < 0.01, ** p < 0.05, * p < 0.1.

6. CONCLUSION

Our findings are broadly consistent with important precursors in the literature (Rosenzweig and Stark 1989; Halliday 2006) and suggest important policy implications. First, households with higher ex ante risk are more likely to send migrants. This is broadly consistent with Rosenzweig and Stark (1989) when we control in our specifications for both ex ante and ex post risk. These results use an alternative set of climate variables, temperature degree-days, rather than rainfall. Second, our results show that households use migration to mitigate risk in northern Nigeria. Households facing greater ex post risk keep members, particularly, males close by, in response to hot shocks. Further investigation into why households tend to keep male members close by is warranted. Robustness checks suggest that income constraints cannot entirely explain this tendency. Since male migrants are, on average, of prime working age, labor shortages or constraints on agricultural inputs may restrict the mobility of migrants. Future work evaluating whether such risk management strategies are welfare-enhancing and the role of social norms and agricultural input constraints on mobility may offer insight into what mechanisms can facilitate private adaptation to risk.

These results have implications for current debates surrounding global climate change and the adaptability of households to climatic variation. Global climate change will affect the efficacy of existing risk management strategies. The viability of migration as an ex ante risk management strategy will depend on how warming affects the correlation of incomes across space. If warming increases the correlation of income variability between origin and destination locations, migration will be a less reliable strategy to deal with ex ante. If warming is widespread, it is possible that households may choose to retain labor to maintain their own level of productivity. Even by retaining labor close by, severe cases of warming may result in famine or overall displacement without additional resources to buffer households (for example, if retention of labor is not entirely driven by productivity but also by strong social norms). Understanding how climate affects migration decisions and household risk management strategies can inform the targeting of resources and public services necessary to respond to the policy challenges from climate change.

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