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Do Social Protection Programs Foster Short-term and Long-term Migration Adaptation Strategies?

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Abstract

We examine how migration is influenced by temperature and precipitation variability, and the extent to which the receipt of a cash transfer affects the use of migration as an adaptation strategy. Climate data is merged with georeferenced panel data (2010–2014) on individual migration collected from the Zambian Child Grant Program (CGP) sites. We use the person-year dataset to identify the direct and heterogeneous causal effects of the CGP on mobility. Having access to cash transfers doubles the rate of male, short-distance moves during cool periods irrespective of wealth. Receipt of cash transfers (among wealthier households) during extreme heat causes an additional retention of males. Cash transfers positively spur long-distance migration under normal climate conditions in the long term. They also facilitate short-distance responses to climate, but not long-distance responses that might be demanded by future climate change.

I. INTRODUCTION

There is a growing consensus that rapid- and slow-onset climatic events drive mobility patterns across the developing world (Henry *et al.*, 2004; Feng *et al.*, 2010; Gray and Mueller, 2012; Bohra-Mishra *et al.*, 2014; Mueller *et al.*, 2014; Robalino *et al.*, 2014; Thiede *et al.*, 2016). The narrative which characterizes climate migrants as victims is changing with new data sources and quantitative approaches to study this phenomenon (Fussell *et al.*, 2014). In fact, recent studies have shown that migration can be used to manage risk, particularly for the asset poor who reside in countries lacking formal insurance or credit institutions (Stark and Lucas, 1988; Bryan *et al.*, 2014; De Weerdt and Hirvonen, 2016). In some cases, these strategies have generated long-term improvements to household welfare through access to auxiliary income channels (Beegle *et al.*, 2011; Bryan *et al.*, 2014).

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However, they have also been shown to bear deleterious consequences for the labor markets of hosting economies (Strobl and Valfort, 2015; Maystadt *et al.*, 2016).

With increased certainty in the increasing frequency of climate extremes (IPCC, 2013), the dialogue has begun to shift away from raising awareness of the climate-induced migration phenomenon toward identifying policy interventions to reduce the imminent vulnerability of sending populations. The nature of the policy interventions proposed varies quite drastically, rendering quite distinct implications for the international community. Some advocate for the promotion of insurance programs to make agriculture resilient (Ceballos and Robles, 2014). Others endorse opening borders and relaxing visa requirements to welcome and foster immigration (Clemens, 2010).

We posit governments may already be influencing mobility patterns inadvertently through their existing policies. Knowledge of the second order effects, such as population movements, of these policies can inform how to leverage existing resources to encompass climate resilience goals. As an example, we explicitly consider the Child Grant Program (CGP) in Zambia, an unconditional cash transfer which was initiated in 2010 in three rural districts (Kaputa, Kalabo, and Shangombo). Households received approximately $11 per month, representing a significant one-third of their expenditures (Seidenfeld and Handa, 2011). The amount of the transfer was determined by the daily cost requirement to subsidize a meal for each household member over the course of a month. However, stipends did not vary with household size.

Our main objective is to examine how individual migration responses are influenced by variations in temperature and precipitation, and the extent the receipt of a cash transfer influences the use of migration as an adaptation strategy. The analysis relies on climate data merged with georeferenced individual panel data collected from 2010 to 2014 in Zambia in the CGP sites. We use the person-year dataset to identify the direct and heterogeneous causal effects of the CGP on migration behavior. Having access to cash transfers doubles the rate of male, short-distance moves during cool periods irrespective of wealth. Receipt of cash transfers (among wealthier households) during extreme heat causes an additional retention of males. Cash transfers positively spur long-distance migration under normal climate conditions in the long term. They also facilitate short-distance responses to climate, but not long-distance responses that might be demanded by future climate change.

In what follows, we first conceptualize the migration decisions of rural households which are based on the attempts of rural households to manage risk to climate variability in the absence of credit and insurance (Section II). Three hypotheses are formulated based on the previous literature to test how social protection is anticipated to affect migratory responses to climate risk. We proceed to describe the experimental data (Section III) and empirical methodology (Section IV) used to test the hypotheses. The results from the empirical analysis are presented in Section V. Section VI summarizes the findings and discusses their implications for identifying viable policies to facilitate adaptation and/or promote poverty-reduction in the Global South.

II. CONCEPTUAL FRAMEWORK AND HYPOTHESES

A renewed interest in the role of social protection to facilitate mobility stems from the nascent findings that liquidity constraints pose implicit barriers for the rural poor to take advantage of employment opportunities in distant towns, cities or even abroad (Bryan *et al.*, 2014; Angelucci, 2015; Bazzi, 2017; Morten, 2017). Stecklov *et al.* (2005) and Angelucci (2015) exploit the occurrence of a conditional cash transfer program in Mexico, *Oportunidades*, which randomized eligibility status, to identify the causal effect of a positive income shock on migration. Stecklov *et al.* (2005) first show that the receipt of transfers mediates international migration. Restricting the focus to unskilled workers, Angelucci (2015) finds having access to additional income encourages international migration, with virtually no impact on domestic migration. Angelucci (2015) argues the divergent effects on migration patterns lends credence to the role of financial constraints affecting migration, presumably since the costs of moving long-distance are likely more pronounced than moving short distance. Debt patterns confirm her claims. Eligibility into the program does not affect loans at the extensive margin, yet those that already incur debt *and* are eligible to receive the transfer are more likely to increase the amounts that they borrow. Effects are most pronounced for the poor.

The previous literature focuses on the role of social protection during periods of climate normalcy. Two recent working papers explore how social protection programs affect migration during climate anomalous conditions. Chort and Rupelle (2017) evaluate the independent consequences of receiving an agricultural unconditional cash transfer (PROCAMPO) and a disaster fund stipend (FONDEN) in Mexico on documented and undocumented Mexico-US migration flows. Both instruments reduce the flow of undocumented migrants induced by lower than average rainfall levels. Hoddinott and Mekasha (2017) show that the Productive Safety Net Program (PSNP) in Ethiopia also reduces migration during anomalous years but only for girls aged 12 to 18 years. It should be noted that the latter of the two studies has a few distinct features from our CGP evaluation in Zambia. First, the majority of the beneficiaries (85 percent) are required to work off-season in public works programs under the PSNP (Hoddinott and Mekasha, 2017). Thus, the condition of work in exchange for food and cash payments constrains the household by removing a potentially productive worker. Girls may be retained to substitute the absent household labor. Second, the PSNP issues a combination of food and cash payments. The payment modality can bear differential impacts, at least, on consumption patterns (Hidrobo *et al.*, 2014). Since food payments are less fungible, programs offering cash may provide a stronger push if indeed financial barriers inhibit movement.

These preliminary studies suggest the following first hypothesis: *unconditional cash transfers discourage migratory responses to climate variability in the short-term*. We test this hypothesis in the context of the CGP in Zambia. Previous evaluations of the CGP suggest that cash transfers ameliorate push factors (Palermo *et al.*, 2016; Handa *et al.*, 2018), such as food insecurity, known to influence migration (Pankhurst *et al.*, 2013). Asfaw *et al.* (2017) measure how the effect of the cash transfers on food insecurity varies with climate variability. In particular, the authors find that households facing a short-term rainfall shock were more protected from the negative consequences on consumption, caloric intake and dietary diversity. We provide additional evidence that consumption patterns at baseline are negatively associated with short-term temperature shocks (Table A.1). If households in these districts use migration as a risk management strategy to smooth consumption, these findings might lead one to expect a reduction in migration behavior among households receiving the cash transfer and exposed to climate variability.

An additional feature of the CGP that is likely to affect those at risk of migration and apt to move in response to the cash transfer is that women of the household were allocated the cash transfer, given assumptions of their status as primary caregiver (Seidenfeld and Handa, 2011). We therefore expect women to be less likely to migrate in households receiving the cash transfer, if concerns over risk of losing eligibility status exist. Thus, we differentiate the effects of the cash transfer by gender, expecting women's mobility to be differentially affected by receipt of the cash transfer under conditions of extreme climate due to expected income losses.

We next examine the validity of a second hypothesis: *the effect of unconditional cash transfers on the use of migration as an adaptation strategy will be positive for the poor*. Bazzi (2017) provides a theoretical justification for heterogeneous migratory responses to cash transfers. Intuitively, while a positive shock to income can reduce the financial burden of moving, it also can increase the relative returns of staying. Given the observed behavioral changes among the poor in Mexico (Angelucci, 2015) and Indonesia (Bazzi, 2017), the perceived gains in income from financing a family member to migrate outweigh the potential returns from using the migrant's labor at home, especially during years of climate normalcy in Mexico. The intent of the second hypothesis is to understand whether the poor deem investments in migration as beneficial, when simultaneously exposed to a climate shock and a positive income shock.

To examine the longevity of the previous claim, we propose a third hypothesis: *the effects of unconditional cash transfers on the use of migration as an adaptation strategy among the poor will be short-lived*. Short-term financial incentives to migrate have been shown to generate greater migration rates over time even after the payments are terminated (Bryan *et al.*, 2014). As migrant networks develop, the cost of moving declines and the probability of securing a job at the destination increases encouraging migration (Carrington *et al.*, 1996; Munshi, 2003). Furthermore, individual patterns of migration are reinforced through experiential learning (Bryan *et al.*, 2014). The above would suggest that the provision of cash transfers to the poor may reinforce the migratory responses to climate variability through the creation of migrant networks. Alternatively, the migrant networks created from individuals historically taking advantage of job opportunities abroad to help their families adapt offer an additional mechanism for communal resilience through their provision of remittances (Mbaye and Zimmermann, 2016, for a review). Based on insights in rural Mexico (Nawrotzki *et al.*, 2015), we suspect that households residing in communities vulnerable to climate variability will suppress (rather than amplify) migration responses in the long term, if the CGP provokes network formation and communities benefit from remittance receipts.

III. DATA

Child Grant Program and Study Design

The CGP in Zambia was implemented in three districts: Kaputa (northern region), Kalabo (western region), and Shangombo (western region) in Zambia. The districts were targeted due to the extreme vulnerability of children under 5 in these areas, in terms of mortality, morbidity, stunting, and wasting rates (Seidenfeld and Handa, 2011). Households with at least one child under five years old were eligible to participate in the program. The program provided each family $11 per month, approximately one-third of monthly household expenditure at baseline (Seidenfeld and Handa, 2011). The monthly amount was determined to be able to finance a daily meal per household member and was not adjusted by household size. Benefits were paid in cash every two months.

The evaluation study design consisted of first randomly selecting 30 communities in each of the three districts. Once the 90 communities were chosen, with the Zambian Ministry of Community Development and Social Services, a list was developed of eligible households within each community based on the criterion of having at least one child under the age of three years. From each household listing, 28 (out of roughly 100) households were randomly sampled to be part of the evaluation study and surveyed at baseline, with a total sample size of approximately 2,500 households. Following the implementation of the baseline survey, half of the communities were randomized into the treatment group, and the other half were assigned to the control group. All eligible households (and not just those in the evaluation sample) in the treatment communities received transfers.

To perform a broader evaluation of the CGP, surveys were conducted not only at baseline (October to November 2010) but also at first follow-up (FU1, October to November 2012), second follow-up (FU2, October to November 2013), and third follow-up (FU3, October to November 2014). The surveys collected quite extensive information on indicators expected to be influenced by the program, such as morbidity and mortality, education, income, assets, consumption and nutrition. Such information was collected 24-months, 36-months, and 48-months following the baseline to measure short- and medium-term program effects. Of importance is the fact that these rounds were collected when food insecurity is at its seasonal peak, since the anticipated impact is expected to be the largest at that time (Seidenfeld and Handa, 2011). Crops are mainly cultivated during the rainy season, December through March, and harvested through parts of the cold, dry season, April through June (Seidenfeld and Handa, 2011). The hot dry season, September through December, marks a period of low agricultural activity and therefore limited access to food for consumption. It should be noted that the survey team did collect an additional round of data in June to July 2013 that we omit from the analysis. This round was implemented off season, and we lack a pre-intervention round over this period for comparison.

Migration Data

We define the migration behavior of individual household members at baseline through their absence in subsequent rounds. Given the focus of migration as an adaptation strategy, we only consider the moves of those who reportedly left the village. Thus, the migration outcome is a binary variable, in which receives a value of one if the person interviewed at baseline is absent from the household and reported to be at a destination outside of the village at the time of the interview. If the person remained in the village (living in the baseline household or with another household) in a given round, then s/he receives a value of zero for the migration outcome. We further distinguish moves by short-distance (to a nearby village) and long-distance (to another town in Zambia or abroad) in alternative specifications.[2] It is possible that some individuals might have moved and returned to the household in between survey rounds. Thus, our measures of migration would tend to underreport the true number of moves inherent to the sample.

The conceptual framework described in the paper is most appropriate for describing individual migration behavior in result of decisions made by the household to manage risk. We focus on the migration responses of 5,128 individuals, who were ages 15 through 65 at baseline. We observe moves 24, 36, and 48 months following the baseline. Of the sample of working aged individuals, 1.3 percent were missing migration information (65 individuals) [3] and 5.1 percent were not interviewed in subsequent rounds due to the relocation of a household (263). Thus, the final sample used for the analysis consists of 4,802 individuals.

Due to the absence of individual migration information and household attrition, we may be concerned that the observed impacts from the intervention reflect those of more resilient households, or households able to withstand climate variability. The low fraction of individuals who were missing migration information does not differentially impact the composition of the treatment and control groups: 98.9 percent of the control group and 98.6 percent of the treatment group have complete migration information. However, attrition appears to be slightly more pronounced in the treatment group, where 93.9 percent of the original sample is included in our analysis compared to 95.9 percent of the control group. A higher proportion of resilient households in the control group could potentially attenuate the effects of the program on migration.

To determine the extent our results may be influenced by attrition bias, we estimate a linear probability model which correlates the probability of an individual leaving the panel due to household relocation, with the treatment dummy; individual baseline characteristics (female, age is 19–35, 36–55, or >55 years old); household baseline characteristics (number of household members ages 6–12, 13–18, 19–35, 36–55, 56–69, and whether the household’s per capita consumption expenditures were above the median value); contemporaneous rainfall and temperature (levels or anomalies expressed in z scores); and district (Kaputa, Shangombo) and time (36, 48 months) fixed effects. We present the results from stepwise regressions in Table 1, where the simplest model presented in column (1) includes the treatment indicator, district and time fixed effects. The results in columns (1)-(4) show there is no robust relationship between attrition and the treatment indicator. There is a small,

[2]When creating the short- and long-distance migration variables, we exclude the migrants who move to another town in Zambia or abroad from the former binary variable and the migrants who move to a nearby village from the latter binary variable. Because there are few international migrants, we consolidate internal rural-urban migrants and international migrants into one long-distance classification.

[3]In FU2, retrospective information was also collected about location of baseline household members at the time of FU1. In cases where location is missing at FU1, we use the retrospective information at FU2 to measure migration for this round.

weakly significant positive effect of the treatment on attrition in model (1), which disappears after conditioning on the remaining variables. Thus, the attrition regressions validate that our migration effect estimates are less susceptible to bias from household attrition (Table 1).

Climate Data

Using GPS points collected at each household's baseline location, we extract monthly climate data from 1981–2014 from two sources. Temperature values were extracted from the Climatic Research Unit's (CRU) time-series at ~50 km resolution, created via spatial interpolation from over 4000 global weather stations including a large number in Sub-Saharan Africa (UEACRU *et al.* 2017), where CRU data are considered to provide reliable climate information (e.g., Zhang *et al.* 2013). Precipitation values were extracted from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset, which integrates high-resolution satellite imagery to produce a ~5 km resolution product specifically developed for drought monitoring in Africa (Funk *et al.* 2015).[4] These monthly data were transformed into running means at 12-month time scales, and these means were subsequently standardized into z-scores capturing local deviations from the pre-intervention climate (1981–2009). Z-scores represent exogenous climate shocks that are not confounded by baseline climate and have previously been shown to better predict migration in Africa compared to raw climate values (Gray and Wise 2016).

We link the raw climate values and their corresponding z-scores to the person-year data via baseline location and month of follow-up interview. Additional specifications link individuals to climate observed 12 months before the month of interview in order to observe lagged effects. Figures 1 and 2 present the distributions of monthly average rainfall (in millimeters per month) and temperature (in degrees Celsius) one-year prior to the observed migration episodes. Over the period of study, there was considerable variation in rainfall, ranging from a monthly average of 51 to 121 millimeters (Figure 1). The wide range in rainfall values is largely driven by regional differences in climate, where Kaputa district typically experiences an abundance of rainfall relative to the other two western districts (Asfaw *et al.*, 2017). Sufficient overlap occurred in the rainfall exposure of treatment and control groups as expected given the randomization was implemented at the household level. In contrast, temperature values remain concentrated in the range of 22 and 24 degrees Celsius, with the occasional incidence of a "colder" event at 20 degrees Celsius (Figure 2).

Since our primary motivation is to understand migration related to environmental risks, it is fruitful to examine the extent the climate values presented in Figures 1 and 2 relate to the conditions normally experienced by the sample. We therefore also present the distributions of contemporaneous rainfall and temperature z scores, respectively, in Figures 3 and 4. The observed rainfall anomalies appear within the realm of normal, since the majority of the z score values lie between one standard deviation below and above the mean (Figure 3). From the perspective of risk, the sample was much more subjected to colder spells (Figure 4). Although our preferred specifications focus on this component of risk, our empirical

[4]The numbers of pixels representing the rainfall and temperature data in our sample are 293 and 24, respectively.

specifications of migration consider the influence of climate levels, lagged climate factors, as well as differences between positive and negative anomalies.

Descriptive Statistics

Table 2 displays the mean and standard deviations of the outcomes and explanatory variables utilized in the analysis. The majority of working age individuals in the CGP sites are between 19 and 35 years old, living in households with an average of 2 children (ages 6 through 18). From these households, 8 percent of males and 5 percent of females migrated on average at each round. Both men and women slightly favored destinations near their local village relative to another town in Zambia. International migration was rare. Only 0.1 percent of men and women reported moving abroad.

IV. METHODOLOGY

Our primary interest is to quantify whether receiving an unconditional cash transfer T affects migration adaptation strategies, using the following linear probability model:[5]

$$M_{ivt} = \alpha + \delta_t + \delta_d + \beta_T T_v + \beta_{TC} T_v \times C_{vt} + \beta_C C_{vt} + \beta_X X_i + \varepsilon_{ivt}\,. \qquad (1)$$

The outcome M documents the movement of individual i out of the village v in survey year t. We further differentiate between short-distance (destination is in a nearby village) and long-distance (destination is in a town in Zambia or abroad) moves. A vector of climate anomalies C is added to the model to detect the extent migration is used by the household to manage risk. The vector $T \times C$ allows us to capture how the migration coping changes upon receipt of the cash transfer.

Additional explanatory variables are included in (1) to improve the precision of our primary estimates of interest. Vector X_i includes individual and household demographic control variables collected at baseline: categorical variables for age (19–35, 36–55, >55 years old), number of household members by age category (6–12, 13–18, 19–35, 36–55, 56–69 years old), and a dummy variable for above median per capita household consumption expenditure. Fixed effects at the district δ_d and year δ_t account for all time-invariant characteristics at the district level and timevarying macroeconomic variables that may be correlated with climate shocks. Standard errors are clustered at the village level to account for within-village correlation between unobserved factors that affect migration.[6]

We restrict the sample to those who were ages 15 through 65 at baseline to focus on the working population. Separate regressions are estimated for male and female adult samples. Additional specifications replace the contemporaneous climate z scores C, with lagged climate z scores, with current and lagged raw climate values, and differentiate positive from negative anomalies.

[5]Since we do not have a measure of migration at baseline, this is equivalent to a first difference approach comparing the differences between treatment and control outcomes post intervention.
[6]We also provide standard error estimates for select specifications in the Appendix, which cluster at the pixel levels from two separate sources of temperature and precipitation data. The pixel-level clustering accounts for the potential of shared measurement error in climate.

To accept our first null hypothesis, the estimate of β_{TC} in (1) would be negative. The fact that the assignment of who receives the cash transfers is randomly stratified equally across treatment and control communities ensures our ability to interpret β_{TC} as a causal estimate. To internally validate the experimental design, we demonstrate that the baseline outcome and covariates are balanced across treatment and control households in Table 3, and reject the joint statistical significance of the baseline variables on treatment using an F test (p-value=0.29 for the male sample and p-value=0.18 for the female sample).

The estimate β_{TC} can be interpreted in two ways. For the purpose of testing our first hypothesis, we assume it reflects how risk management strategies change with the receipt of a cash transfer. However, it is important to note that the parameter may also be indicative of how migratory responses to the cash transfer vary with climate conditions. To confirm the financial instruments are affecting migration adaptation strategies, we also provide F statistics testing the hypothesis $\beta_{TC}T_v + \beta_C = 0$.

To examine the validity of our second hypothesis, we estimate (1) for different wealth subgroups, using baseline consumption as a proxy.[7] Wealth is defined by whether the household had below or above median per capita consumption expenditure at baseline. We then evaluate whether β_{TC} is positive for the asset poor subgroup to determine if the intervention rendered countervailing effects on the migration of individuals given heterogeneity in wealth.

Finally, we add three more terms to (1) to test our third hypothesis: $\beta_T^H T_i \times H_i$, $\beta_{TC}^H T_i \times C_{vt} \times H_i$, $\beta_{TH}^H C_{vt} \times H_i$. Here, H_i is an indicator for the 2013 survey year. The linear term of H_i in this alternative specification is already present in (1) in our survey fixed effect δ_t. Our third hypothesis explicitly tests whether the triple interacted variable is positive, or $\beta_{TC}^H > 0$. In other words, we are assessing whether tendencies towards climate migration dampen at the end of the CGP.

V. RESULTS

Do Financial Instruments Dampen Migratory Responses to Climate Variability?

We present the estimates of the parameters and standard errors of interest from our preferred specifications of climate in Table 4. Panel A displays the results from the specification that includes the climate z scores and their interaction with the treatment. To first establish what patterns of climate-induced migration are common to the region, we focus on the rainfall and temperature parameter estimates. Migratory responses to changes in climate involve mostly men of the household. Rainfall anomalies consistently have a positive influence on both short- and long-distance male migration. In contrast, temperature anomalies overall cause a retention of men.[8] The magnitudes of the temperature effects on male migration are

[7]We check whether control and treatment groups are comparable in terms of their average values of observable baseline characteristics within wealth groups (Table A.10). We cannot reject that the groups are similar according to F statistics provided in Table A.10. According to the individual t statistics, we observe that the treatment group within the poor (less poor) wealth category has a slightly greater number of people in their household at baseline ages 19–35 (13–18). Since these variables are covariates in the regression model, our intent-to-treat estimates adjusts for such imbalances.

more pronounced when redirecting attention to lagged rather than contemporaneous anomalies (Panel A, Table A.5).[9],[10]

To gauge which type of weather events are influencing male migration, we present the findings from a separate set of specifications in Panel B, which includes four variables that distinguish migration effects by whether the rainfall and temperature anomalies are above or below the mean. For ease of interpretation, we utilize the absolute value of the z score conditional on being above or below the mean for each variable. Here, it becomes evident that conditions that compromise rural livelihoods, such as hot and dry events, are more likely to discourage men from moving. This is consistent with the trapped populations dynamic discussed in the literature (Black *et al.*, 2011) and found in Africa (Gray and Wise, 2016; Nawrotzki and DeWaard, 2018). In contrast, men are more inclined to move both during cooler and wet periods, perhaps to take advantage of economic opportunities or the liquidity available during conditions amenable for agricultural production (Kleemans, 2015).

Given the established environmental migration patterns, we next examine the role of financial instruments through the provision of a cash transfer. According to model (3) (Panels A and B, Table 4), we observe that experiencing a positive shock to household income induces the short- (not long-) distance migration of men during anomalous temperatures. While the results in Panel A (Table 4) indicate that we cannot reject our null hypothesis, $\beta_{TC} < 0$, the interpretation of the coefficient depends on the type of climatic exposure. Turning to the estimates in Panel B (Table 4), we validate the cash transfer augments migration during cold spells by 2.4 percentage points. The additive effect of both exposure to cold spells (0.024) and having received cash under a cold spell (0.030) is approximately 0.054 and statistically significant at the 1 percent critical level (F test, p-value=0.000). This suggests that a one standard deviation decline in temperature (or 0.5 degrees Celsius, Table 2) would not only increase short-distance migration, but households in possession of the cash transfer would send working-age males to nearby villages.

Wealth- and Time-Differentiated Effects

We next examine the extent male migration patterns are influenced by household wealth and the duration in which the household has been receiving the cash transfer. Focusing on the former, Table 5 displays the estimates from (1) for the male household members in poor (below or equal to the median per capita consumption expenditure at baseline) and less poor (above the median per capita consumption expenditure at baseline) households. The evidence presented in column (4) of Panel B indicates we reject our second hypothesis evaluated at cooler temperatures. In particular, the estimated coefficients on the *Temp+* and

[8]Interpretations of the climate coefficients remain the same for models that replace district with village fixed effects. However, we lose precision on the rainfall and temperature parameter estimates in the long-distance migration specifications (columns (5) and (6) in Table A.2). Inferences from specifications that use rainfall-pixel or temperature-pixel clustered standard errors, in lieu of village-clustered standard errors, slightly improve (Tables A.3 and A.4).

[9]We also provide results for versions of equation (1) that include contemporaneous and lagged temperature and rainfall levels. The coefficients on the temperature variables continue to suggest an overall decline in male migration, but are imprecisely estimated due to the lack of temperature variation present in the data (Figure 2). In contrast, the contemporaneous rainfall parameters remain positive and significant for male migration (columns (1) and (5) in Table A.6). Multicollinearity precludes the ability to detect a statistically meaningful effect of both the contemporaneous and lagged climate variables in the same model (Tables A.7 and A.8).

[10]Replacing the annual anomaly variables with wet season anomaly variables produces similar estimates of the temperature and rainfall effects on any migration and the short-distance migration of men (models (1) and (3) in Table A.9).

T x Temp+ variables are imprecisely estimated but similar in magnitude for both poor and less poor households. Furthermore, according to the F test, we cannot reject that the additive effects of both coefficients across subpopulations are equal (F test, p-value=0.447).

Interestingly, evaluating the effects by wealth introduces newer evidence of the availability of cash transfers affecting heat- and dry-related migration. While both types of households tend to retain male household members during warm and dry shocks, the cash transfers generate greater retention rates among wealthier households. In particular, a one-standard deviation (or 0.5 degrees Celsius, Table 2) increase in temperature reduces short-distance migration by an additional 21 percentage points among less poor households. The combined effect of warmer temperatures and its interacted effect with the treatment on male migration is statistically significant from zero and approximately 23 percentage points per 1 standard deviation increase in temperature (F statistic, p-value=0.003). We further reject that the additive effects are equal across wealth groups at the 10 percent critical level (F statistic, p-value=0.085).

There is additional evidence that negative rainfall anomalies have similar consequences as positive temperature anomalies on the migration of men from less poor households. Specifically, a one-standard deviation decline in rainfall (or 19 mm, Table 2) reduces migration by 10 percentage points. While the additive effect for the less poor households is clearly significantly different from zero (F statistic, p-value=0.001), we can only weakly reject that the magnitude of the impact differs by wealth (F statistic, p-value=0.178).

We lastly identify whether the observed adaptation strategies change at later stages of the CGP. We distinguish the effects of the intervention on climate-induced migration over two periods (<48 months vs. 48 months) in Table 6. Although the intervention appeared to have limited effects on the migration patterns of men in the absence of the shock in earlier specifications (Tables 4 and 5), there is weak evidence that participation in the program enhanced the long-distance migration of males by 4.5 percentage points in the long run (column 3, Table 6). With respect to whether there exist any remaining temporal distinctions of the program’s influence on climate-induced migration, the findings are suggestive that the receipt of the cash transfer slightly discourages rainfall-related migration in the long term $\beta_{TC}^{H} < 0$. For example, in column (2), we observe that male short-distance migration increases from 3.9 to 8.5 percent with an increase in the rainfall anomaly by 1 standard deviation. In contrast, 48 months after the program’s inception, we observe the short-distance migration of males declines in response to a similar increase in the rainfall anomaly from 5.1 percent to 0.9 percent. We reject that the additive effects of the contemporaneous rainfall anomaly and its interaction with the treatment on migration over the <48 and 48-month periods are equal to zero at the 10 percent critical level (F test, p-value=0.096). To summarize, the cash transfer may offset short-distance migration driven by positive rainfall anomalies. Since short-distance migration did not generally increase among participants of the program, there is no supporting evidence that the program generated stronger migrant networks nor reduced uncertainty regarding the net benefits of sending a member to migrate. If anything, the cash transfer most likely made staying more desirable to those at risk of migrating due to an environmental shock, given the cumulative income received and the increasing trust that households would receive the payments promised over time.

VI. CONCLUSION

Rural inhabitants in Zambia tend to be immobilized (rather than displaced) during climatic events that jeopardize agricultural production. Cash transfers render use of migration as a climate adaptation strategy attractive in the short term. Having access to the cash transfer doubles the rate of male migration during cool periods. Specifically, a 1-standard deviation (or 0.5 Celsius) decline in temperature encourages 2.4 percent of men without access and 5.4 percent of men with access to the cash transfer to move to nearby villages. These effects are statistically similar among poor and less poor households.

The extent that the cash transfer increases the flexibility of male household members to migrate depends on climatic exposure as well as household wealth. In contrast to behavior observed during cool periods, less poor households tend to reduce the short-distance migration of male household members by 21 percentage points per 1 standard-deviation increase in temperature. Among less poor households, the receipt of cash transfers causes an additional retention of male household members by 2 percentage points. One possible interpretation is that extreme heat poses additional constraints (than cooler conditions) on opportunities to diversify labor in nearby towns. For example, if hot temperatures are more likely to devastate yields, and thus, the purchasing power of farmers, then the demand for hired agricultural wage labor or service labor in nearby towns might similarly decline. The additional, negative effect of the cash transfer on heat-related migration perhaps suggests that a small percentage of households, who might otherwise send a household member to diversify labor (in spite of the dire job prospects), would rather use the money to smooth consumption or endure the shock without bearing the pecuniary or emotional costs associated with the absence of the migrant family member.

The household's reluctance to engage in short-distance migration to diversify labor during periods of income risk becomes more apparent when quantifying the dynamic effects of social protection on mobility. Our empirical estimates imply that cash transfers only directly influence long-distance migration patterns in the long term, not the short-distance patterns which commove with changes in climate. Rather, the short-distance migration observed during anomalous climatic conditions becomes relatively less attractive over time. To give perspective, in comparing the short-term vs. long-term effects of the cash transfers on the propensity to move short-distances under anomalous rainfall conditions, we find the magnitude of rainfall-induced migration dwindles by 80 percent. Households may have substituted long-distance migration (for short-distance migration) in response to the receipt of the cash transfers which may have stimulated household resilience. Given the lack of information on productive practices and income, we cannot rule out that alternative adaptation strategies may also have become more palpable to the household given the accumulation of cash transfers (Jensen *et al.*, 2017).

There is a broader debate over whether concerns regarding climate refugeeism are warranted, or whether victims of climate variability tend to be trapped in place (Black *et al.*, 2011; Gemenne, 2011; Black and Collyer, 2014). The findings support the alternative school of thought in Zambia, rendering broader implications on development strategies in rural Africa. Working-age men in rural Africa are being excluded from outside labor market opportunities during favorable climate conditions due to constraints on mobility, liquidity, family labor supply, among others. The No Lean Season program offers insights on how policymakers may tackle the first barrier. A one-time transportation subsidy prompted households to take the initial risk of allowing family members to seasonally migrate (Bryan *et al.*, 2014). The positive benefits of the experience reinforced migration over time. In contrast, the CGP sheds light on how the provision of cash over an extended period of time can foster migration in the long term. The guaranteed income stream may have lowered the opportunity cost of migration, inclining households to broaden their economic base through migration and potentially increase their wealth (Beegle *et al.*, 2011; Bryan *et al.*, 2014). Wealth begets climate resilience (Barrett and Constas, 2014). Future research is necessary to test the importance of program duration on migration and corroborate whether the patterns observed in the CGP are generalizable to alternate contexts.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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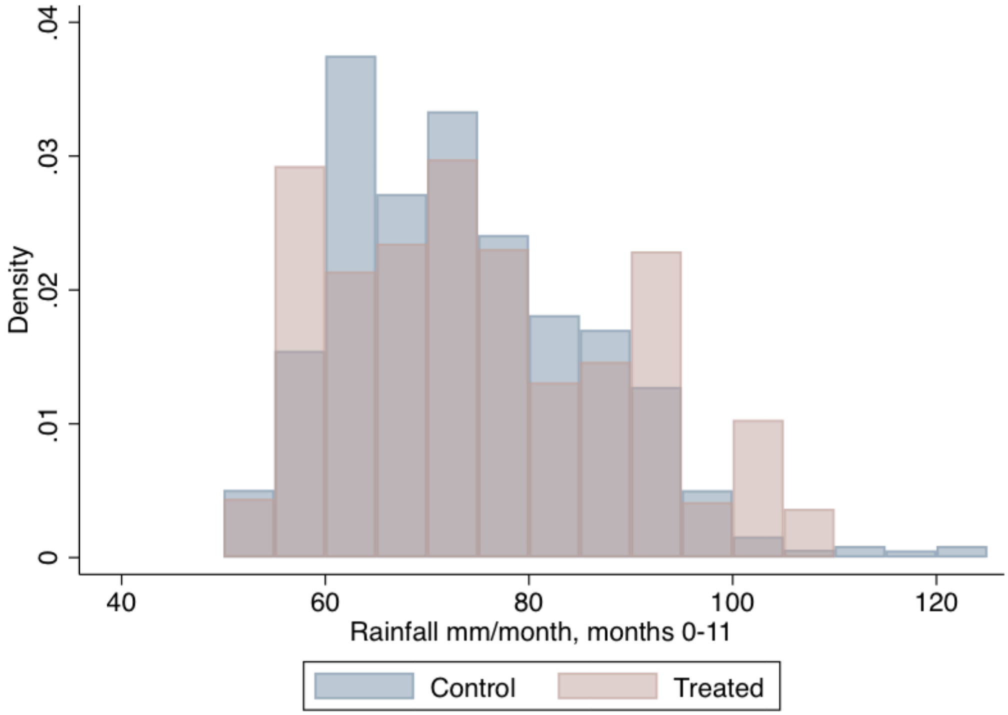

Figure 1:
Distribution of Contemporaneous Rainfall

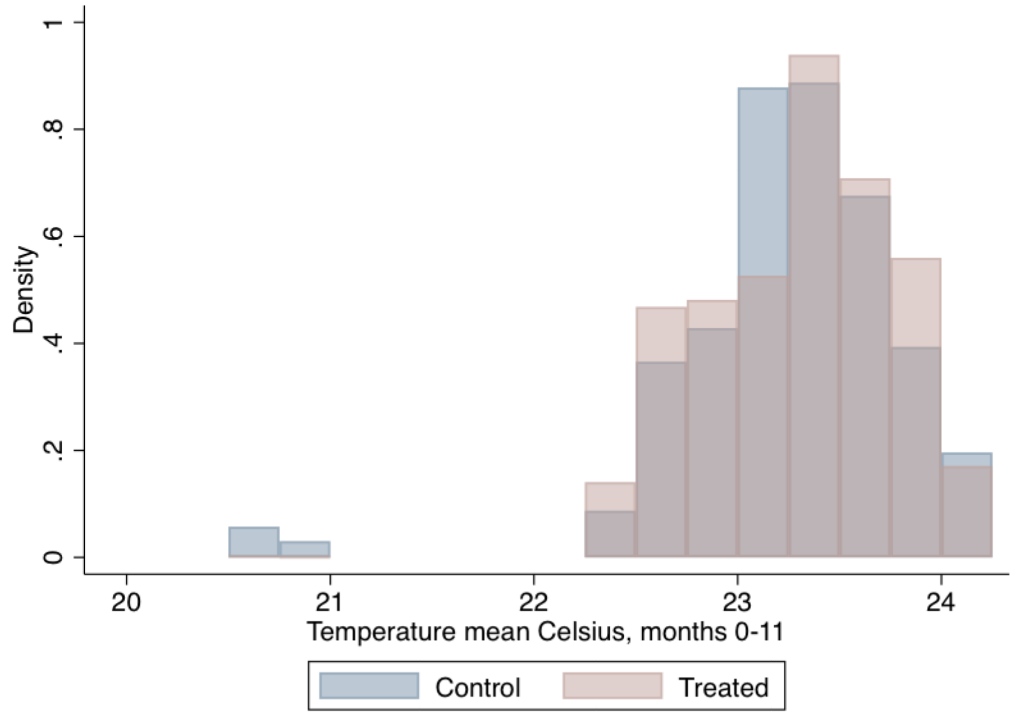

Figure 2:
Distribution of Contemporaneous Temperature

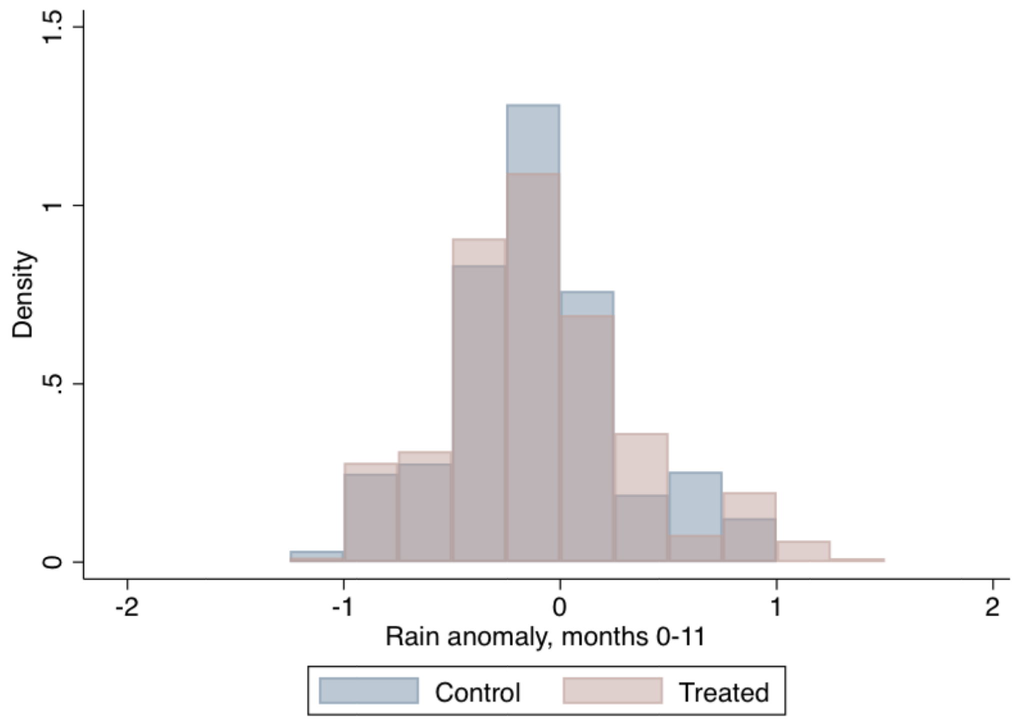

Figure 3:
Distribution of Contemporaneous Rainfall Z score

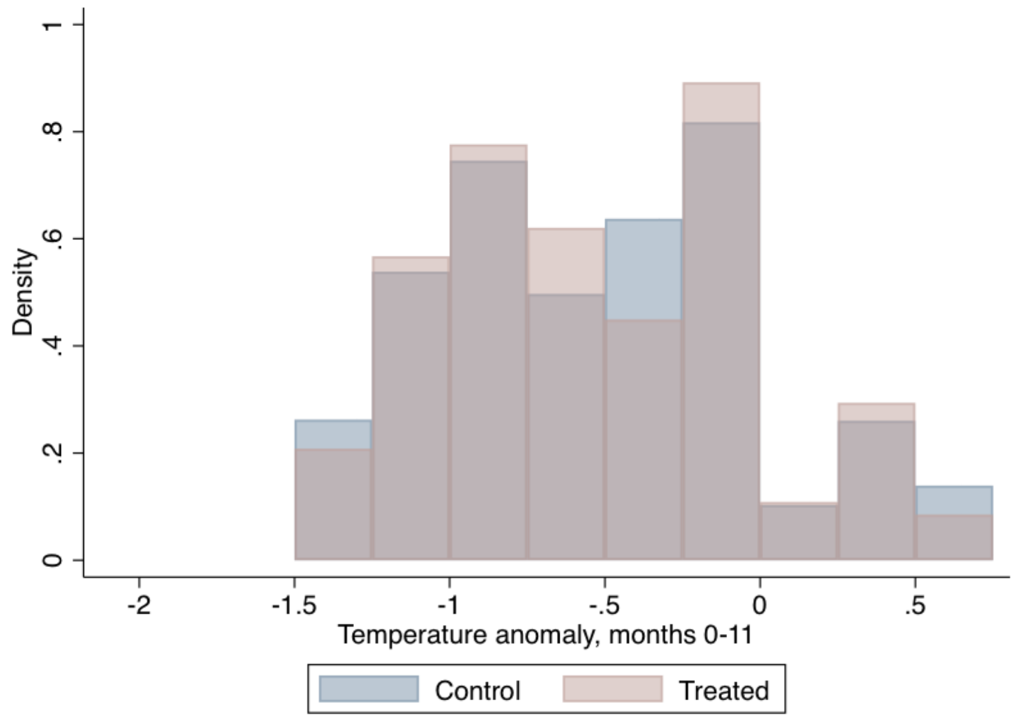

Figure 4:
Distribution of Contemporaneous Temperature Z score

Table 1:

Attrition Analysis

	(1)	(2)	(3)	(4)
Treatment	0.009	0.008	0.008	0.008
	(0.005) *	(0.005)	(0.005)	(0.005)
Kaputa	0.000	−0.001	−0.001	0.001
	(0.007)	(0.009)	(0.008)	(0.008)
Shangombo	−0.008	−0.009	−0.001	−0.010
	(0.008)	(0.008)	(0.008)	(0.008)
36 months	0.024	0.024	0.022	0.018
	(0.004) ***	(0.004) ***	(0.004) ***	(0.008) **
48 months	0.034	0.034	0.030	0.028
	(0.005) ***	(0.005) ***	(0.005) ***	(0.008) ***
Female		−0.002	−0.002	−0.002
		(0.001)	(0.001)	(0.001)
Age is 19 to 35 years old		−0.002	−0.002	−0.002
		(0.003)	(0.003)	(0.003)
Age is 36 to 55 years old		−0.004	−0.004	−0.004
		(0.003)	(0.003)	(0.003)
Age is greater than 55 years old		−0.003	−0.003	−0.003
		(0.007)	(0.007)	(0.007)
Number of people ages 6 – 12		−0.001	−0.001	−0.001
		(0.002)	(0.002)	(0.002)
Number of people ages 13 – 18		0.004	0.004	0.004
		(0.003)	(0.003)	(0.003)
Number of people ages 19 – 35		0.003	0.002	0.003
		(0.004)	(0.004)	(0.004)
Number of people ages 36 – 55		−0.001	−0.001	−0.001
		(0.006)	(0.006)	(0.006)
Number of people ages 56 – 69		−0.004	−0.004	−0.004
		(0.007)	(0.007)	(0.007)
Has above median per capita consumption		−0.001	−0.001	−0.001
		(0.005)	(0.005)	(0.005)
Rainfall mm/month, months 0–11			0.000	
			(0.000)	
Temperature mean Celsius, months 0–11			−0.003	
			(0.004)	
Rain anomaly, months 0–11				0.010
				(0.007)
Temperature anomaly, months 0–11				−0.007
				(0.009)
Constant	−0.001	−0.000	0.028	0.002

	(1)	(2)	(3)	(4)
	(0.006)	(0.009)	(0.089)	(0.009)
R^2	0.01	0.01	0.01	0.01
N	15,384	15,384	15,384	15,384

Notes: Unit of analysis is person-year. The dependent variable reflects whether the person sampled at baseline was removed from the final sample due to the movement of a household. Village-clustered standard errors in parentheses.

* p<0.1

** p<0.05

*** p<0.01.

Table 2:

Summary Statistics

	Male	Female	Total
Moved	0.075 (0.263)	0.051 (0.220)	0.061 (0.240)
Moved to nearby village	0.041 (0.199)	0.029 (0.167)	0.034 (0.182)
Moved to town or other location in Zambia	0.032 (0.176)	0.022 (0.146)	0.026 (0.159)
Moved abroad	0.001 (0.036)	0.001 (0.027)	0.001 (0.031)
Treatment	0.506 (0.500)	0.505 (0.500)	0.506 (0.500)
Age is 19 to 35 years old	0.527 (0.499)	0.638 (0.481)	0.590 (0.492)
Age is 36 to 55 years old	0.295 (0.456)	0.194 (0.395)	0.237 (0.425)
Age is greater than 55 years old	0.022 (0.146)	0.021 (0.144)	0.021 (0.145)
Number of people ages 6 – 12	1.478 (1.198)	1.349 (1.172)	1.404 (1.185)
Number of people ages 13 – 18	0.831 (1.008)	0.735 (0.938)	0.776 (0.970)
Number of people ages 19 – 35	1.503 (0.945)	1.341 (0.936)	1.411 (0.944)
Number of people ages 36 – 55	0.733 (0.810)	0.643 (0.757)	0.682 (0.781)
Number of people ages 56 – 69	0.073 (0.292)	0.095 (0.318)	0.086 (0.307)
Has above median per capita consumption	0.512 (0.500)	0.539 (0.499)	0.527 (0.499)
Rainfall mm/month, months 0–11	74.190 (13.239)	74.968 (13.051)	74.633 (13.137)
Temperature mean Celsius, months 0–11	23.264 (0.508)	23.272 (0.490)	23.269 (0.498)
Rainfall mm/month, months 12–23	83.435 (18.946)	85.326 (20.243)	84.513 (19.717)
Temperature mean Celsius, months 12–23	23.376 (0.473)	23.383 (0.457)	23.380 (0.464)
Rain anomaly, months 0–11	0.105 (0.424)	−0.110 (0.412)	−0.108 (0.417)
Temperature anomaly, months 0–11	0.511 (0.474)	−0.524 (0.473)	−0.518 (0.474)
Rain anomaly, months 12–23	0.381 (0.781)	0.419 (0.804)	0.403 (0.794)
Temperature anomaly, months 12–23	0.316 (0.296)	−0.332 (0.303)	−0.325 (0.300)
Negative rainfall anomaly, months 0–11	0.226 (0.261)	0.224 (0.254)	0.225 (0.257)
Positive rainfall anomaly, months 0–11	0.122 (0.238)	0.114 (0.233)	0.117 (0.235)
Negative temperature anomaly, months 0–11	0.553 (0.402)	0.564 (0.404)	0.559 (0.403)

	Male	**Female**	**Total**
Positive temperature anomaly, months 0–11	0.042 (0.128)	0.040 (0.124)	0.041 (0.126)
Negative rainfall anomaly, months 12–23	0.109 (0.183)	0.101 (0.178)	0.104 (0.180)
Positive rainfall anomaly, months 12–23	0.490 (0.685)	0.520 (0.714)	0.507 (0.702)
Negative temperature anomaly, months 12–23	0.324 (0.286)	0.339 (0.293)	0.333 (0.290)
Positive temperature anomaly, months 12–23	0.009 (0.026)	0.008 (0.025)	0.008 (0.026)
Person-years	6,198	8,208	14,406

Notes: Standard deviations in parentheses. The absolute value of the anomaly is reported for both the negative and positive rainfall and temperature anomalies.

Table 3:

Average Individual and Household Baseline Characteristics by Treatment

	Male			Female		
	Control	**Treated**	**Difference**	**Control**	**Treated**	**Difference**
Age is 19 to 35 years old	0.520	0.533	0.01	0.645	0.631	−0.01
	(0.016)	(0.015)	[0.63]	(0.013)	(0.013)	[0.55]
Age is 36 to 55 years old	0.298	0.292	−0.01	0.201	0.187	−0.01
	(0.014)	(0.014)	[0.73]	(0.011)	(0.010)	[0.45]
Age is greater than 55 years old	0.025	0.019	−0.01	0.021	0.022	0.00
	(0.005)	(0.004)	[0.40]	(0.004)	(0.004)	[0.86]
Number of people ages 6 – 12	1.476	1.479	0.00	1.328	1.369	0.04
	(0.037)	(0.037)	[0.98]	(0.031)	(0.032)	[0.62]
Number of people ages 13 – 18	0.788	0.872	0.08	0.670	0.799	0.13
	(0.032)	(0.031)	[0.33]	(0.025)	(0.026)	[0.07]
Number of people ages 19 – 35	1.456	1.549	0.09	1.292	1.389	0.10
	(0.030)	(0.029)	[0.23]	(0.023)	(0.028)	[0.21]
Number of people ages 36 – 55	0.747	0.720	−0.03	0.608	0.676	0.07
	(0.026)	(0.025)	[0.63]	(0.020)	(0.021)	[0.13]
Number of people ages 56 – 69	0.078	0.068	−0.01	0.092	0.098	0.01
	(0.009)	(0.009)	[0.66]	(0.008)	(0.009)	[0.76]
Has above median per capita consumption	0.493	0.530	0.04	0.532	0.545	0.01
	(0.016)	(0.015)	[0.38]	(0.014)	(0.013)	[0.76]
Mean of 12-month rainfall, 1981–2009	75.295	76.960	1.66	76.304	77.870	1.57
	(0.355)	(0.397)	[0.53]	(0.312)	(0.345)	[0.55]
SD of 12-month rainfall, 1981–2009	16.029	16.262	0.23	16.582	16.798	0.22
	(0.121)	(0.130)	[0.78]	(0.112)	(0.122)	[0.82]
Mean of 12 month-temperatures, 1981–2009	23.517	23.585	0.07	23.541	23.595	0.05
	(0.017)	(0.012)	[0.48]	(0.014)	(0.010)	[0.54]
SD of 12 month-temperatures, 1981–2009	0.518	0.515	−0.00	0.523	0.518	−0.00
	(0.003)	(0.003)	[0.91]	(0.003)	(0.003)	[0.83]
Kaputa	0.356	0.371	0.02	0.322	0.345	0.02
	(0.015)	(0.015)	[0.89]	(0.013)	(0.013)	[0.82]
Shangombo	0.388	0.372	−0.02	0.347	0.335	−0.01
	(0.015)	(0.015)	[0.88]	(0.013)	(0.013)	[0.90]
N	1,020	1,046		1,353	1,383	

Notes: Standard errors reported in parentheses. P values in brackets for t tests of difference in means. F statistic testing joint significance of all variables for male sample is 1.19 (p-value=0.29). F statistic testing joint significance of all variables for female sample is 1.37 (p-value=0.18).

Table 4:

Intent-to-treat and Climate Heterogeneous Effects of Cash Transfer on Migration, Contemporaneous Climate Anomalies

	Any move		**Moves near**		**Moves far**	
	(1) Men	**(2) Women**	**(3) Men**	**(4) Women**	**(5) Men**	**(6) Women**
Panel A: Climate Anomalies						
T	−0.016	0.006	−0.017	0.005	−0.002	0.003
	(0.013)	(0.009)	(0.009) *	(0.006)	(0.009)	(0.006)
T x Rain	0.008	0.013	0.023	0.020	−0.012	−0.005
	(0.020)	(0.014)	(0.015)	(0.010) **	(0.017)	(0.011)
T x Temp	−0.016	0.001	−0.034	−0.004	0.014	0.007
	(0.019)	(0.012)	(0.015) **	(0.009)	(0.013)	(0.008)
Rain	0.078	0.007	0.048	−0.009	0.034	0.017
	(0.023) ***	(0.012)	(0.016) ***	(0.009)	(0.018) *	(0.009) *
Temp	−0.059	−0.004	−0.033	0.002	−0.032	−0.009
	(0.020) ***	(0.010)	(0.014) **	(0.007)	(0.016) **	(0.008)
R^2	0.07	0.09	0.04	0.06	0.04	0.05
F statistic, p-values						
H_a=Rain + T x Rain; H_a =0	0.000	0.135	0.000	0.221	0.106	0.162
H_b=Temp + T x Temp; H_b =0	0.001	0.863	0.000	0.776	0.200	0.200
H_a (1/3/5)= H_a (2/4/6)		0.020		0.002		0.587
H_b (1/3/5)= H_b (2/4/6)		0.012		0.001		0.398
Panel B: Positive vs. Negative Climate Anomalies						
T	−0.004	−0.013	−0.005	−0.000	−0.002	−0.014
	(0.017)	(0.011)	(0.013)	(0.009)	(0.012)	(0.007) *
T x Rain−	−0.031	0.015	−0.037	−0.015	0.002	0.034
	(0.031)	(0.023)	(0.023)	(0.018)	(0.020)	(0.015) **
T x Rain+	−0.058	0.029	0.014	0.014	−0.074	0.027
	(0.063)	(0.058)	(0.045)	(0.032)	(0.053)	(0.042)
T x Temp−	0.012	0.014	0.024	0.010	−0.008	0.004
	(0.018)	(0.012)	(0.014) *	(0.010)	(0.014)	(0.008)
T x Temp+	0.055	0.056	−0.081	0.035	0.136	0.011
	(0.096)	(0.076)	(0.075)	(0.046)	(0.068) **	(0.054)
Rain−	−0.067	−0.020	−0.047	−0.004	−0.019	−0.017
	(0.028) **	(0.018)	(0.022) **	(0.015)	(0.018)	(0.012)
Rain+	0.122	0.003	0.050	−0.018	0.089	0.023
	(0.049) **	(0.044)	(0.033)	(0.022)	(0.042) **	(0.034)
Temp−	0.048	−0.014	0.030	−0.006	0.021	−0.007
	(0.019) **	(0.011)	(0.014) **	(0.008)	(0.015)	(0.008)

	Any move		Moves near		Moves far	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
Temp+	−0.166	−0.076	−0.059	−0.028	−0.132	−0.060
	(0.070) **	(0.054)	(0.050)	(0.027)	(0.051) **	(0.037)
R^2	0.07	0.09	0.05	0.06	0.05	0.05
F statistic, p-values						
H_a=Rain− + T x Rain−; H_a =0	0.001	0.802	0.000	0.177	0.329	0.246
H_b=Rain+ + T x Rain+; H_b =0	0.117	0.395	0.059	0.859	0.674	0.046
H_c=Temp− + T x Temp−; H_c =0	0.004	0.972	0.001	0.760	0.328	0.328
H_d=Temp+ + T x Temp+; H_d =0	0.085	0.703	0.013	0.838	0.925	0.925
H_a (1/3/5)= H_a (2/4/6)		0.007		0.010		0.117
H_b (1/3/5)= H_b (2/4/6)		0.622		0.039		0.522
H_c (1/3/5)= H_c (2/4/6)		0.031		0.010		0.349
H_d (1/3/5)= H_d (2/4/6)		0.307		0.004		0.473
N	6,198	8,208	5,992	8,024	5,941	7,972

Notes: Unit of analysis is person-year. T abbreviates treatment. Rain+ and Temp+ use the absolute values of z scores that are greater than or equal to zero. Rain− and Temp− use the absolute values of z scores that are less than zero. Village-clustered standard errors reported. All specifications include individual and household explanatory variables, as well as district and survey fixed effects. The notation H_a (1/3/5) indicates equation H_a using the estimates from models 1, 3, or 5, respectively, depending on the table column. Thus, H_a (1/3/5)= H_a (2/4/6) is testing whether the expression H_a is equal for men and women using the estimates from models (1/3/5) and (2/4/6), respectively, depending on the table column.

* $p<0.1$

** $p<0.05$

*** $p<0.01$.

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Table 5:

Intent-to-treat and Climate Heterogeneous Effects of Cash Transfer on Male Migration, by Wealth

	Any move		Moves near		Moves far	
	(1) Poor	(2) Less Poor	(3) Poor	(4) Less Poor	(5) Poor	(6) Less Poor
Panel A: Climate Anomalies						
T	−0.001	−0.026	−0.017	−0.012	0.015	−0.016
	(0.018)	(0.016)	(0.015)	(0.010)	(0.010)	(0.012)
T x Rain	0.005	0.007	0.014	0.029	−0.005	−0.020
	(0.022)	(0.028)	(0.021)	(0.021)	(0.021)	(0.021)
T x Temp	0.006	−0.032	−0.018	−0.041	0.023	0.003
	(0.026)	(0.023)	(0.023)	(0.017) **	(0.015)	(0.018)
Rain	0.064	0.089	0.057	0.040	0.010	0.053
	(0.021) ***	(0.030) ***	(0.019) ***	(0.018) **	(0.017)	(0.024) **
Temp	−0.055	−0.061	−0.043	−0.025	−0.019	−0.038
	(0.022) **	(0.026) **	(0.020) **	(0.015)	(0.014)	(0.022) *
R^2	0.09	0.07	0.07	0.04	0.04	0.05
F statistic, p-values						
H_a=Rain + T x Rain; H_a =0	0.001	0.006	0.000	0.007	0.730	0.095
H_b=Temp + T x Temp; H_b =0	0.033	0.004	0.001	0.000	0.798	0.798
H_a (1/3/5)= H_a (2/4/6)		0.459		0.966		0.237
H_b (1/3/5)= H_b (2/4/6)		0.222		0.828		0.185
Panel B: Positive vs. Negative Climate Anomalies						
T	−0.001	−0.009	−0.024	0.009	0.018	−0.018
	(0.025)	(0.023)	(0.021)	(0.016)	(0.015)	(0.018)
T x Rain−	−0.014	−0.035	−0.006	−0.052	−0.008	0.012
	(0.047)	(0.037)	(0.037)	(0.027) *	(0.028)	(0.033)
T x Rain+	−0.060	−0.033	0.007	0.053	−0.058	−0.091
	(0.071)	(0.101)	(0.071)	(0.058)	(0.052)	(0.075)
T x Temp−	0.002	0.021	0.025	0.020	−0.019	0.005
	(0.026)	(0.024)	(0.024)	(0.017)	(0.016)	(0.019)
T x Temp+	0.126	−0.037	0.018	−0.210	0.111	0.165
	(0.091)	(0.160)	(0.088)	(0.107) *	(0.070)	(0.108)
Rain−	−0.043	−0.092	−0.052	−0.050	0.007	−0.039
	(0.036)	(0.034) ***	(0.035)	(0.022) **	(0.020)	(0.029)
Rain+	0.125	0.104	0.074	0.009	0.056	0.116
	(0.055) **	(0.069)	(0.052)	(0.043)	(0.039)	(0.050) **
Temp−	0.042	0.047	0.035	0.023	0.013	0.022
	(0.024) *	(0.023) **	(0.022)	(0.016)	(0.017)	(0.019)
Temp+	−0.157	−0.177	−0.084	−0.019	−0.084	−0.194
	(0.065) **	(0.104) *	(0.056)	(0.078)	(0.046) *	(0.070) ***

	Any move		Moves near		Moves far	
	(1) Poor	(2) Less Poor	(3) Poor	(4) Less Poor	(5) Poor	(6) Less Poor
R^2	0.09	0.07	0.07	0.04	0.04	0.06
F statistic, p-values						
H_a=Rain− + T x Rain−; H_a =0	0.123	0.001	0.043	0.001	0.964	0.231
H_b=Rain+ + T x Rain+; H_b =0	0.185	0.356	0.139	0.154	0.962	0.658
H_c=Temp− + T x Temp−; H_c =0	0.075	0.013	0.009	0.006	0.692	0.692
H_d=Temp+ + T x Temp+; H_d =0	0.630	0.083	0.341	0.003	0.622	0.622
H_a (1/3/5)= H_a (2/4/6)		0.112		0.178		0.448
H_b (1/3/5)= H_b (2/4/6)		0.953		0.785		0.692
H_c (1/3/5)= H_c (2/4/6)		0.444		0.447		0.198
H_d (1/3/5)= H_d (2/4/6)		0.197		0.085		0.589
N	3,027	3,171	2,931	3,061	2,893	3,048

Notes: Unit of analysis is person-year. T abbreviates treatment. Rain+ and Temp+ use the absolute values of z scores that are greater than or equal to zero. Rain− and Temp− use the absolute values of z scores that are less than zero. Village-clustered standard errors reported. All specifications include individual and household explanatory variables, as well as district and survey fixed effects. The notation H_a (1/3/5) indicates equation H_a using the estimates from models 1, 3, or 5, respectively, depending on the table column. Thus, H_a (1/3/5)= H_a (2/4/6) is testing whether the expression H_a is equal for men from poor and less poor households using the estimates from models (1/3/5) and (2/4/6), respectively, depending on the table column.

* $p<0.1$

** $p<0.05$

*** $p<0.01$

Table 6:

Intent-to-treat and Climate Heterogeneous Effects of Cash Transfer on Male Migration, by Time

	(1) Any move	(2) Moves near	(3) Moves far
T	−0.010	−0.002	−0.010
	(0.017)	(0.014)	(0.013)
T x 48 months	0.032	−0.009	0.045
	(0.034)	(0.027)	(0.026) *
T x Rain	0.024	0.046	−0.016
	(0.030)	(0.026) *	(0.020)
T x Rain x 48 months	−0.112	−0.060	−0.069
	(0.067) *	(0.049)	(0.062)
T x Temp	−0.016	−0.024	0.004
	(0.017)	(0.014) *	(0.012)
T x Temp x 48 months	0.052	0.000	0.061
	(0.053)	(0.041)	(0.037)
Rain	0.069	0.039	0.030
	(0.028) **	(0.024) *	(0.019)
Rain x 48 months	0.102	0.051	0.077
	(0.060) *	(0.038)	(0.061)
Temp	−0.034	−0.022	−0.014
	(0.019) *	(0.014)	(0.013)
Temp x 48 months	−0.099	−0.048	−0.069
	(0.041) **	(0.025) *	(0.033) **
R^2	0.07	0.05	0.05
F statistic, p-values			
H_a=Rain + T x Rain; H_a =0	0.003	0.001	0.398
H_b=Temp + T x Temp; H_b =0	0.036	0.012	0.519
H_a=Rain x 48 months + T x Rain x 48 months	0.122	0.096	0.861
H_b=Temp x 48 months + T x Temp x 48 months	0.951	0.972	0.966
N	6,198	5,992	5,941

Notes: Unit of analysis is person-year. T abbreviates treatment. Village-clustered standard errors reported. All specifications include individual and household explanatory variables, as well as district and survey fixed effects.

* $p<0.1$

** $p<0.05$

*** $p<0.01$