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Coping with Weather Shocks

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Abstract

Accounting for multiple responses to weather shocks drastically changes policy implications for adaptation to increasingly variable weather. Kenyan households react to temperature anomalies by sending migrants, by transiting to less climate-sensitive occupations, and by changing livestock species. Evidence suggests these are short-term adjustments, which respond significantly to common interventions. Randomised income transfers cushion consumption losses and decrease adaptation pressure, such as migration. Better infrastructure, instead, eases occupational transitions, reducing alternative adjustments, including migration and livestock composition. A model of joint migration, occupation, and livestock choices reveals long-term effects of these short-term shocks. Transitions to non-agriculture first act as a substitute for migration and subsequently as a stepping stone for later migration.

JEL classification

J61, O15, R23

Keywords

migration, weather shocks, coping strategies, development policies

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1 Introduction

Policy makers seek to formulate interventions that help vulnerable populations to adapt to increasingly variable weather shocks (Paris Agreement, Article 7, 2015). To design such policies, however, it is crucial to understand how individuals and communities respond to disruptions in the weather (United Nations Environment Programme, 2023). Much academic work has focused on migration as a response to weather events (see e.g. Munshi 2003; Jayachandran 2006; Gröger and Zylberberg 2016; Bazzi 2017; Albert et al. 2022; Imbert and Ulyssea 2022, and the surveys by Cattaneo et al. 2019; Hoffmann et al. 2020). Yet, the World Bank (2020) stresses that migration should be considered together with alternative, in-place adaptations, such as occupational sectors, crop or livestock compositions. Accounting for such coping strategies has profound policy implications. Interventions easing in-place coping, such as switching out of agriculture, may ease migration pressure. Conversely, local non-agricultural employment may be a first step towards later migration, creating dynamic complementarities. Understanding these dynamics is important. In the short term, households need assistance in coping with weather shocks. In the longer term, it may be optimal to help households transition to less sensitive economic activities.

This is the first paper to examine how common policy interventions change migration responses to weather shocks whilst accounting for alternative, in-place adaptation strategies. The setting for our analysis is the pastoral regions of northern Kenya, which experienced frequent heat waves. These regions exhibit strong variation in two prototypical policy dimensions: they were exposed to a randomized income support programme and vary substantially in the level of local infrastructure. Both policy dimensions may have distinct effects. They can ease and thus increase migration; conversely, they may decrease migration by facilitating alternative coping strategies or increasing income to buffer welfare losses. To investigate which of these mechanisms prevail, we consider two relevant coping strategies in addition to migration: occupational sector choice and livestock composition. We find that transfers received under the randomised income support programme are spent on food, buffering the adverse welfare effects of weather shocks, and thus decrease the need to adapt. Better infrastructure, by contrast, helps households transit to less weather sensitive activities, thus lowering migration pressure. To compare distinct policies at equal costs and to assess whether short-term coping strategies can have longer term impacts, we set up a dynamic model of migration, occupation, and livestock choices. Our model reveals that temporary shocks can have persistent effects on both sectoral composition and migration. Whilst transitions to non-agricultural occupations initially serve as an alternative to migration, their higher incomes an lower migration costs also act as a stepping stone for costly migration in the longer run.

To investigate changes in coping strategies, we combine granular climatic information with data from a randomised controlled trial and with geo-coded infrastructure information. Specifically, we overlay the geographic location of respondents to the Hunger Safety Net Programme evaluation survey (HSNP, a household panel in northern Kenya spanning 2010 to 2012) with air temperature drawn from the ERA5 database, and calculate local temperature anomalies, which are plausibly exogenous.[1]

In line with policy reports highlighting the importance of financial access and infrastructure (e.g. World Bank, 2020), we explore the role of these policy dimensions. For income support, we exploit the random allocation of unconditional cash transfers under the HSNP. Households in a randomly selected half of locations were given unconditional bi-monthly cash transfers amounting to 28% of median household consumption. Importantly, these transfers are unconditional on households sending a migrant. To investigate the importance of broader infrastructure, we use geo-coded data on several dimensions of infrastructure: overland roads (which ease transport of goods and people), digital infrastructure, such as electricity and mobile phone coverage (which can catalyse all sorts of economic activities), and health and educational infrastructure in each location. Causal identification in our main analysis derives from exogenous deviations in temperature from local longer-run levels and trends. Nevertheless, we also instrument the interaction of infrastructure with temperature shocks using lightning strike frequency (Manacorda and Tesei, 2020) and terrain ruggedness (Nunn and Puga, 2012). Furthermore, using geo-coded data on population density, we show that the effects are not driven by urbanised areas.

Our results show that in years after which local dry season temperature was above its local long-term median, households are 2.8 percentage points more likely to send a member outside the district, with stronger effects for higher temperature cut-offs or when we consider deviations from local trends rather than levels. Given a sample mean of 4 percent, these are large effects, highlighting the importance of weather shocks for migration decisions.[2] Despite livestock rearing being an important economic activity in this context, only 8.4% of household members who left the district are reported to follow animals as a reason for their absence. We also find that abnormally hot years decrease household consumption. As such, sending a migrant is a rational response, since for the average household that sent a migrant, these transfers contribute 10% of household consumption (see also Kinnan et al., 2018). We find no effect on entire households migrating.

Both random income transfers and better infrastructure significantly attenuate the effect of heat shocks on migration. Interacting our two policies with heat shocks shows that unconditional cash transfers from the HSNP or a one standard deviation improve-

[1]Indeed, we find no relation between these local anomalies and household characteristics. We also explore the role of rainfall, but find it not to be the driving dimension in our context.

[2]Migration in our context is largely temporary. The vast majority (82.8%) of households with a migrant do not report any absence of members the following year.

ment in local infrastructure respectively offset about 70% and 90% of temperature's effect on migration. We show that our estimates are unchanged when we allow for differential effects of heat shocks by sector or urbanity of a location. However, as we explain below, the mechanisms behind these two policies are very different.

To examine migration responses in relation to in-situ adaptation, we use detailed information on households' economic activities and analyse two additional coping strategies: occupational sector choice and livestock composition. Our results show that in abnormally hot years, the likelihood of household members entering non-agricultural occupations increases by almost 11 percentage points. Most of this effect comes from households diversifying and working in both agricultural and non-agricultural occupations, in line with these being short-term adjustments to temporary shocks. Considering the large proportion of households involved with pastoralism (63%), we analyse the impact of shocks depending on the type of livestock households own. We find that consumption losses are less pronounced for households owning camels, which are more heat resistant than cows, the other commonly owned large kind of livestock (Watson et al., 2016). Both types of animals are used for milk and meat production. The choice of livestock hence is a further potential shock coping strategy. In fact, our estimates show that heat shocks increase the likelihood of households owning camels by 4.4. percentage points, mainly driven by households already herding other animals. At the same time, there are strong negative effects on cattle ownership. This substitution of one type of livestock with another potentially circumvents credit constraint. We find very different effects of infrastructure and income transfers on in-place adaptation. Whereas infrastructure substantially increases the effect of heat on local transitions out of agricultural occupations, cash transfers buffer consumption losses after heat shocks. We also find no direct effect of HSNP transfers on migration or other mitigation strategies.

Taken together, our findings suggest that, whilst both better infrastructure and random income receipt decrease temperature's effect on migration, the mechanisms underlying these effects are very different. Infrastructure eases local adaptation as an alternative to migration after temperature shocks. We find that following a heat shock, previously agricultural households are more likely to work in non-agricultural occupations (without migrating) when local infrastructure is better. By contrast, our results show that in abnormally hot years, HSNP recipients are more likely to spend the transfers on food and less on clothing suggesting that income supports alleviates the most severe hardship and offsets adjustment pressure. We find no evidence for transfers being used to set up non-agricultural businesses.

An upshot of our reduced form analysis is that any policy prediction requires a joint modelling of migration and sectoral choice. We do this in the last, structural part of the paper. In our dynamic model, forward-looking households decide on sending a migrant, whether to work in non-agricultural occupations and on livestock type. In line with reduced form estimates showing that consumption losses are significantly stronger for agricultural households without camels, we let temperature depress earnings differentially by occupational sector and camel ownership. Moreover, we allow the costs of migration, sector and livestock changes to vary with past income as an approximation to financial constraints as well as with local infrastructure. When sending a migrant, households enjoy remittances, which again vary with temperature.

The structural model accounts for the forward-looking nature of costly choices, and thus allows us to take a more dynamic perspective. We first estimate a temperature transition matrix. Based on expectations over the probability of a heat shock conditional on previous period temperature, households maximize dynamic values by deciding on migration, sector and livestock. We identify the model's parameters using static and dynamic moments, including the main effects of our reduced-form estimations. Our estimates suggest that infrastructure most strongly reduces the cost of entering non-agricultural occupations, thus mitigating the migration response to temperature shocks through the substitutability of different coping strategies.

Our model reveals that occupational transitions first decrease and subsequently increase migration. Immediately after a weather shock, transition into non-agricultural occupations offers an alternative to migration thus attenuating it as an adaptive response to higher temperature. However, because non-agricultural incomes are higher and because migration is less costly for non-agricultural households, migration increases in the future. As such, our model shows that a temporary temperature shock can have long lasting effects on both occupational compositions and migration patterns. The indirect effect of infrastructure through occupational change has important policy implications. Infrastructure improvements initially reduce migration responses to a temperature shock by more than cash transfers of equal aggregate cost. However, by catalysing transitions into higher paying non-agricultural occupations, infrastructure also lowers the relative cost of future migration, thus leading to migration increases in the long run. In terms of targeting sub-populations, we find that policies have the strongest impact in agricultural locations with poor infrastructure.

These findings have wide-ranging policy implications. By jointly analysing occupational choice and migration, our analysis is able to link commonly used policies, such as infrastructure investment and income support programmes, to migration. Large sums of money are regularly spent on infrastructure projects. The World Bank pledged 390 million USD to improve digital infrastructure in Kenya. Whilst in our model we allow for infrastructure investments to reduce migration costs, empirically we find that the reduction is far stronger for sectoral transition costs. Our analysis thus highlights that such interventions can have the additional effect of first attenuating but subsequently increasing migration responses to weather shocks.

Our paper contributes to several strands of the literature. In a first instance, our focus on weather fluctuations contributes to the micro-development literature linking migration to climatic shocks such as hurricanes, (Mahajan and Yang, 2020), typhoons (Gröger and Zylberberg, 2016), regional dryness (Albert et al., 2022), rainfall (Munshi, 2003; Jayachandran, 2006; Bazzi, 2017; Kleemans and Magruder, 2018), temperature (Mueller et al., 2014; Jessoe et al., 2018), droughts (Gray and Mueller, 2012; Imbert and Ulyssea, 2022; Di Falco et al., 2024), or combinations thereof (Bohra-Mishra et al., 2014); see also the surveys by Cattaneo et al. (2019), Cui and Feng (2020), Ferris (2020), and Hoffmann et al. (2020). Whilst the omission of other choices does not necessarily bias the reduced form effects of weather shocks on migration, it will affect policy simulations and predictions.

Our paper also advances the fast growing literature on the interaction between migration and other choices. Morten (2019) and Meghir et al. (2021) analyse migration in relation to informal risk sharing, whereas Diop (2022) considers the interdependency between a policy subsidizing fertilizers on the one hand and migration on the other. We add novel insights to this literature by highlighting occupational choice and livestock ownership as important additional responses of high policy relevance. This multiplicity of adjustment margins also speaks to the climate-economy literature (see Dell et al., 2014; for an overview, and Hsiang, 2010; Dell et al., 2012; Aragón et al., 2021; Somanathan et al., 2021; Balboni et al., 2024; for examples) highlighting the effect of the weather on—among many other things—economic productivity. Our paper contributes to these studies by highlighting the interaction between such adaptation mechanisms with migration decisions. By pointing out several, different ways in which households respond to weather shocks, our analysis also speaks to a body of research that investigates similar adjustments to climatic trends on a more aggregate scale (see, for instance, Cattaneo and Peri, 2016; Marchiori et al., 2012; Conte et al., 2021; Burzyński et al., 2022; Conte, 2022; Bertoli et al., 2022; Waldinger, 2022; Cruz, 2023). In some contexts, forced adjustments—including migration—following adverse events have been found to yield long-term benefits to affected individuals or their offspring (Chyn, 2018; Nakamura et al., 2021; Sarvimäki et al., 2022).

Our paper furthermore adds to the large literature evaluating the effects of randomized cash transfers on migration (see Clemens, 2021; Niehaus and Suri, 2024). Our analysis differs in two important ways: first, most of the literature considers cash transfers that are conditional on certain choices (such as public works programme participation in Gazeaud et al., 2020), or tied to a specific purpose (such as transportation in Bryan et al., 2014). Instead, receipt is universal in our setting.[3] Second, whereas existing studies evaluate the effects of a transfer itself, our interest is in its interaction with weather shocks. Analyses of general equilibrium effects of cash transfers are provided by Cunha et al. (2019) and

[3]Since the main migration outcome in our context is the migration of a single household member, transfers, which are paid at the household level, in fact are also not conditional on not migrating.

Egger et al. (2022). Finally, our investigation of infrastructure development as a policy alternative to direct cash transfers adds to a nascent literature that links this to migration, such as Fuchs et al. (2023) and Gamso and Yuldashev (2018), who find that World Bank projects and other development aid attenuate emigration pressure in recipient countries. In a similar vein, Fried and Lagakos (2021) find that the economic development following an electrification wave in Ethiopia lowered out-migration.

2 Background and Data

The setting for our analysis is the pastoral semi-arid region of northern Kenya, where individuals experience frequent heat waves.

2.1 Hunger Safety Net Programme evaluation data

We use a household panel dataset collected to evaluate the Hunger Safety Net Programme (HSNP), an unconditional cash transfer. In the Kenyan districts Mandera, Marsabit, Turkana and Wajir, 2,436 households in 40 locations were interviewed in three annual waves spanning 2010-2012. Table 1 shows that the characteristics of HSNP households are very similar to those interviewed in the same four districts by the nationally representative 2009 Kenyan Demographic Health Survey (DHS). The vast majority of agricultural occupations consists of livestock herding. For completeness, we define agricultural occupations to also include the the small percentage of households active in crop production.

As part of the HSNP evaluation, half the locations were randomly selected via public lottery to receive unconditional cash transfers—see map A2b in Appendix A. The value of bi-monthly transfers increased from KES 2,150 initially to KES 3,500 (corresponding to USD 65.50 and 92.20, PPP adjusted, respectively). Over a year, the sum of six payments amounts to 28% of median yearly household consumption. After the data collection, the scheme was extended to control locations.

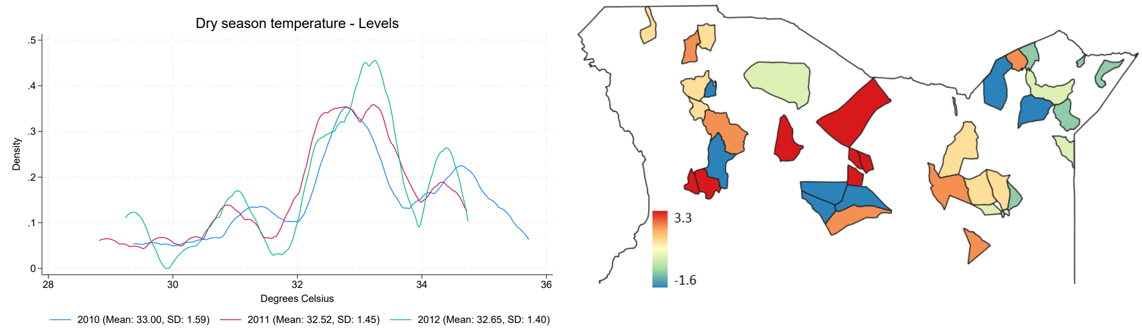
2.2 Weather in northern Kenya

Meteorological data are taken from the ECMWF2-ERA5 reanalysis (Hersbach et al., 2020).[4] We employ data on monthly averages for surface air temperature (in °C) measured at 12noon. We focus specifically on deviations in dry season temperature, which is important for herding animals (the major occupation of respondents in our context), from local long-run levels that we calculate from data over decade before the start of the panel survey. For the HSNP sample, air temperature during the dry seasons of 2010-2012 has a mean of 32.7°C, a median of 32.9°C and a standard deviation of 1.50°C. Figure 1a

[4] The data are freely available at `https://cds.climate.copernicus.eu`.

Figure 1: Temperature in northern Kenya

(a) Distribution by year (b) Temperature anomalies across space



Notes: Figures report geographical and temporal variation in temperature. Panel a) reports densities of previous dry season temperatures for years 2010, 2011, and 2012. Panel b) shows mean deviations in dry season temperature 2010-2012 from local long-term median calculated using data over the previous decade.

shows the cross-sectional distributions of previous dry season temperature for the three years covered by the HSNP (2010 to 2012) along with its means and standard deviations and illustrates that dry season temperatures fluctuate considerably across space and over time. The large panel variation in temperature shocks is corroborated in figure 1b, which plots anomalies for each of the 40 locations from 2010 to 2012. The figures show both considerable variation across space for each year and across time within each location.

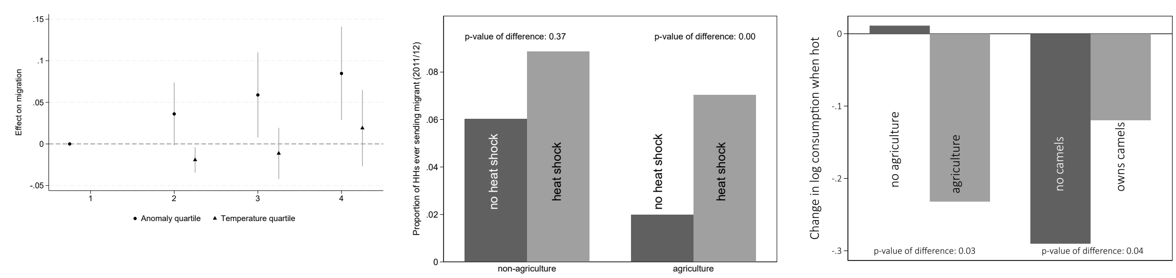
Measurement of weather shocks. To isolate the causal effect of temperature, we follow standard practice in the literature and calculate yearly deviations from local long-term conditions (often referred to as anomalies). We focus on temperature during the previous year's dry season (January, February, and June to September) when grazing is at its shortest.[5] For each of the 40 locations covered by the HSNP evaluation data, we calculate the long-term median for dry season temperature by using data from 2000 to 2009. Appendix figure A1a shows dry season temperature anomalies from 2010 to 2012. The figure highlights the high degree of variation. For our main specification we then define a variable taking the value 1 if the dry season temperature in the year before interview was higher than the local long-term median. We cross-check this specification with a large number of different weather measurements (see appendix table A4). To account for long-run climatic trends, we also re-estimate our main specifications using a dummy for realised temperature exceeding *predicted* temperature using long-run trends (see appendix table A8).

Rainfall. We also examine the effect of rainfall, which in broader sub-Saharan analyses has been shown to be a relevant measure (see, e.g., McGuirk and Nunn, forthcoming).

[5] `https://fews.net/east-africa/kenya/seasonal-calendar/december-2013`, accessed January 2023.

Figure 2: Temperature and migration in northern Kenya

(a) Temperature anomalies and levels (b) Migration by occupational sector (c) Consumption by sector and livestock



Notes: Panel (a) reports effect of temperature anomalies and temperature levels on migration, conditional on household and year effects; dependent variable takes value 1 if at least one household member left the district of residence; circles and triangles denote point estimates for coefficients on dummies for 2nd, 3rd, and 4th quartiles of temperature anomalies and temperature levels, respectively; vertical lines indicate 95% confidence intervals. Panel (b) reports average proportion of households sending at least one migrant between 2011 and 2012, distinguishing households without members working in agriculture and households with at least one member working in agriculture, and those experiencing a heat shock from those that do not. Panel (c) plots changes in log household consumption expenditure net of remittances and cash transfers when local dry season temperature exceeds the local long-term median, controlling for year and household fixed effects. All standard errors and p-values are based on spatial heteroskedasticity- and autocorrelation-robust (HAC) standard errors with 50km radius and two year lag.

For the context of northern Kenya, instead, we find that rainfall is not relevant. While there is close to no rainfall during dry seasons, the anecdotal danger of high temperatures is that water holes run dry more quickly. Accordingly, appendix tables A1 and A5 show that rainfall is not important for consumption and for migration.

2.3 Livelihoods and infrastructure in northern Kenya

With the highest rate of rural poverty in the country (KNBS, 2007), individuals living in the semi-arid regions of northern Kenya are persistently impoverished.

Measurement of coping strategies. We consider three coping strategies relevant in our context. Migration: We measure migration rates using detailed information on household members' whereabouts contained in the household roster. During baseline, the HSNP collects information on all household members. The two follow up surveys inquired whether each roster member still resides in the household. This is similar to the way migration is measured by Di Falco et al. (2024), and by Gray and Mueller (2012). If a member does not reside in the household anymore, the questionnaire records their new location as any of the following i) *same village* (7.0%), ii) *same cluster* (5.2%), iii) *same district* (3.7%), or iv) *outside of the district* (4.0%). It is this last, strictest, category we use to define our migration indicators.[6] Given that all major urban centres in Kenya

[6]Among those, only 8.4% of absent members are reported to have *Moved to follow the animals (herding)*, which may be explained by the large size of districts (55,712km^2 on average).

Table 1: Descriptives

	(1)	(2)		(3)	(4)	(5)	(6)
	Panel A			**Panel B**			
Data source	HSNP (2010)			HSNP (2010)		DHS (2009)	
	Mean	SD		Mean	SD	Mean	SD
Member migrated (2011-12)	0.04	(0.20)	**Age**	23.7	(20.9)	20.0	(19.0)
Works only in agriculture (2010)	0.60	(0.49)	**HH size**	5.89	(2.28)	5.27	(2.33)
Works only in non-agriculture (2010)	0.25	(0.43)	**Owns livestock**	0.79	(0.40)	0.76	(0.43)
Works in both (2010)	0.13	(0.33)	**Owns mobile phone**	0.16	(0.36)	0.20	(0.40)
Owns camels (2010)	0.36	(0.48)	**Owns cart**	0.06	(0.23)	0.07	(0.25)
Mean temperature (2009-11)	32.7	(1.50)	**Owns mosquito net**	0.68	(0.47)	0.66	(0.47)
Households			2,436				
Locations			40				

Notes: Table reports summary statistics of the Hunger Safety Net Programme evaluation data. Panel A: reports summary statistics of key variables used in estimations. Panel B: compares characteristics of Hunger Safety Net Programme respondents with 2009 Demographic Health Survey respondents, a nationally representative survey of Kenyan households.

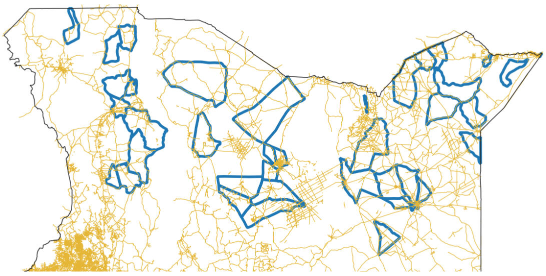
are located outside the four districts, this corresponds to classical rural-urban migration. Appendix figure A1b reports the geographic variation in local migration intensities and shows that changes in migration are not driven by, for instance, single districts. Among households who report absent households members in 2011, 82.8% have no absentees the following year, indicating that migration is largely temporary in our setting. As is commonly documented in the literature, migrants in our context are predominantly young, comparatively well educated, and most likely the child of the household head (see appendix figure A3a). These migrants support their household financially. Appendix figure A8 shows that, when exposed to a heat shock, households which sent a migrant receive considerably more transfers per capita than households without migrants.

Occupational sector: Throughout the three rounds, the HSNP questionnaires inquire about the major activities of all household members. We define a household being active in the *agricultural* sector if at least one member's main activity is either pastoralism or agriculture (crop production). A household is classified as active in non-agriculture if at least one member's main activity is collecting bush products (either for sale or consumption), self-employed, paid work (including casual labour), or help in family business. The baseline HSNP survey reveals that livestock rearing and (to a lesser extent) agriculture were the primary sources of livelihood: 73 percent of households have at least one member working in these occupations (see table 1). Panel (c) of appendix figure A1 shows the geographical distribution.

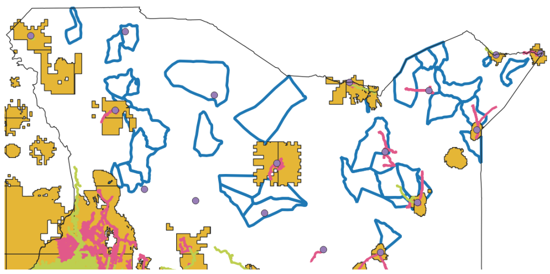
Livestock ownership: In each round, the HSNP inquires about the types of livestock

Figure 3: Infrastructure in northern Kenya

(a) Road network



(b) GSM coverage and electricity



Notes: Figure reports road, electricity, and mobile phone network in northern Kenya. 40 HSNP locations are outlined in blue. Panel (a) reports major and secondary roads in Kenya in yellow (Source: Digital Chart of the World). Panel (b) reports electricity access via cable or minigrid (Source: World Bank Off-Grid Project) in pink and green and GSM second generation mobile phone network coverage in yellow (Source: Bartholomew Collins).

each household owns with possible animals being listed as camels, cattle, goats, and sheep. For the whole sample, 79 percent of all households own some livestock and 36 percent own camels. Research by Watson et al. (2016) shows the value of camels as a comparably heat resistant species for pastoralists in northern Kenya. Panel (d) of appendix figure A1 shows the geographical distribution.

Infrastructure measurement. We consider a range of infrastructure dimensions, which catalyse economic activities in different ways. First, we use geo-coded information on mobile phone network coverage from the Global System for Mobile Communications Authority provided by Collins Bartholomew. Less than half the locations were covered by GSM networks.[7] Second, using maps denoting major and minor roads, we calculate road density as the kilometres of roads by square kilometre for each sub-location.[8] The average value for our sample is less than 3 meters of paved road per square kilometer. Third, we identify whether each sub-location has access to electricity via kv11 or kv33 cables or via mini-grids.[9] See figure 3. We complement these three geo-coded features with the number of educational and health facilities as reported by the HSNP. Our main infrastructure measure is the normalized first principal component of these dimensions. Appendix table A7 shows that the results remain robust if we consider these measurements separately (roads, phone and electricity, and facilities).

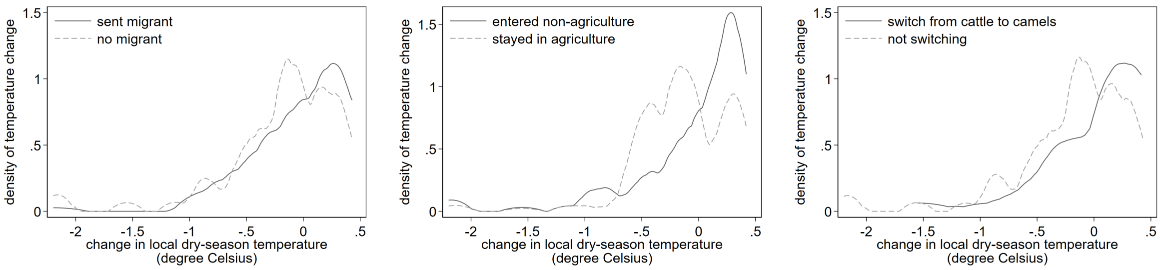
[7]We define a location to have GSM coverage if any of its area is covered by GSM. Of the 40 locations, 21 locations have no GSM coverage; for 4 locations GSM signal covers between 1% and 9%, for 5 locations it covers 10-19%, for 3 it covers 20-49%, and for 4 locations it covers 50-99% of a location's area. For 3 locations, the whole area is covered.

[8]Source: Digital Chart of the World (`https://www.diva-gis.org/gdata`)

[9]Source: The World Bank Kenya Off-Grid Solar Access Project (`https://energydata.info/dataset/kenya-overview-of-off-grid-electricity-service-areas`.)

Figure 4: Temperature, migration, sector and livestock choice

(a) Sending a migrant (b) Changing sector (c) Changing livestock



Notes: Figure displays distributions of year-to-year changes in local dry season temperature, separately for household with different migration, sector and livestock choices reported in 2011 and 2012. Panel (a) distinguishes households sending a member outside the district in the year following the displayed change in temperature from households that have not. Panel (b) conditions on households exclusively being active in agriculture in the previous period, and distinguishes households having at least one member entering a non-agricultural occupation in the year following the displayed change in temperature from households that do not. Panel (c) distinguishes households that owned cattle but no camels the previous period and own camels but no cattle in the year following the displayed change in temperature from households that do not make this switch.

2.4 Descriptive evidence

In line with migration being temporary in our setting, it is predominantly used as an adaptation to short-term shocks. Regressing an indicator for a household sending a migrant on quartiles of temperature anomalies and temperature levels, figure 2a shows that migration responds to anomalies but not to levels pointing towards migration being a coping strategy for unexpected, short-term temperature fluctuations.

We further find that households surveyed by the HSNP react to heat shocks in three different ways. Figure 4a displays the distributions of year-to-year changes (to 2011 and 2012) in dry season temperature separately for households that send a migrant in the year following the displayed change and for households that do not. The figure shows a clear positive correlation between temperature changes and migration.[10] Distinguishing households by sector of economic activity, figure 2b shows that agricultural households experiencing a heat shock are more likely to send a migrant in later years. Yet, the baseline migration rate is higher among non-agricultural households, with dynamic implications for policies targeting occupational choice also for longer-term migration outcomes. Due to endogenous sector choice, we do not interpret these results as causal.

Second, we also find a positive relation between temperature changes and households entering non-agricultural occupations—see Figure 4b. Third, the results show that in areas with temperature increases households are more likely to switch their livestock from cattle to heat resistant camels (figure 4c).

[10] Relatively large negative temperature changes derive from exceptionally high temperatures in Turkana in 2010. Excluding Turkana from our estimations leaves the results unchanged and only marginally changes the estimate of a temperature shock on migration to 2.2 percentage points.

3 Responses to weather shocks

This section estimates the extent to which the effect of temperature shocks on different coping strategies is mitigated by policy variables. The outcomes we consider are sending a migrant, working in agricultural versus non-agricultural occupations and the ownership of certain types of livestock. We then estimate the following regression:

$$coping_{it} = \beta_1 hot_{l_i,t} + \beta_2 hot_{l_i,t} \times policy_{l_i} + \iota_i + \tau_t \times policy_{l_i} + \epsilon_{it}, \qquad (1)$$

where $coping_{it}$ alternatively indicates whether at least one member has left household i in year t to move out of the district, whether at least one household member works in livestock or arable farming, whether the household owns at least one camel, or whether the household owns at least one cattle (see Section 2.1 for definitions of these variables). The treatment $hot_{l_i,t} = 1$ if the temperature during the dry season in household i's location l_i in the year prior to interview was above the long-term median in location l_i calculated using temperatures from the last decade. Moreover, $policy_{l_i}$ denotes either location l_i's treatment status in the randomized unconditional cash transfer programme or the level of local infrastructure. Throughout, we condition on household (ι_i) and year (τ_t) fixed effects. To allow for differential variation over time across locations with different $policy_{l_i}$ realizations, we also include an interaction between the policy variable and year dummies ($\tau_t \times policy_{l_i}$). Controlling for household fixed effects, equation (1) accounts for any local differences in outcomes. This avoids the assumption that economic activity adjusts to long-term temperature levels. Column (5) in appendix table A6 shows that the effect of temperature anomalies is similar across all quintiles (aside from the highest). Since all household members are present at baseline by construction, the estimation is based on the years 2011 and 2012 when the outcome is sending migrant. For other outcomes, instead, we can include the 2010 baseline and use all three waves of the panel. We report spatial correlation- and and heteroskedasticity-robust (Conley, 1999) standard errors with auto-correlations (HAC) as in Hsiang (2010).[11]

3.1 Temperature shocks and migration in Kenya

Among our three coping strategies, migration has arguably received most attention by researchers and policy makers. Given that interest, we document the effect of weather shocks on migration and carry out a large number of checks to show that the effect of weather shocks on migration is robust in the north Kenyan setting.

In our setting, the identifying variation in $hot_{l_i,t}$ is based on yearly temperature deviations from long-term local climatic conditions (as calculated over the past decade),

[11] We allow for spatial correlation within a 50km radius and two years lag. We consider alternative specifications in appendix table A2.

in line with previous studies (e.g. Barrios et al., 2010; Harari and La Ferrara, 2018). Column (1) of table 2 shows a positive effect of temperature shocks on migration with a 2.8 percentage point higher propensity for households to send a migrant after abnormally hot dry seasons. Compared to the sample mean of 4 percent, this is a large effect in line with policy reports highlighting weather to be a major driver of migration (IOM, 2020). Instead, we find no effect on the (low) rate at which entire households leave the sample, see column (1) in appendix table A4. Column (2) of that table estimates the effect on migration, including to destinations within the district, and finds a smaller effect (relative to the sample mean).

Identification. The use of weather *anomalies* is common practice in the literature (see Dell et al., 2014) as these are plausibly unrelated to underling factors, such as institutions. Panel (a) of appendix figure A5 investigates the exogeneity of temperature anomalies by correlating the $hot_{l_i,t}$ dummy with household characteristics at baseline. Since the household fixed effects in our regressions account for any time-constant variation, we also investigate the correlation between household characteristics and temporal *changes* in temperature (2010 to 2012) in panel (b). We find no correlation.

Alternative temperature measurements. In appendix table A4, we show that the effects are robust to different measurements of temperature shocks. These include: dry season temperature in degrees Celsius (column 3), rainy season temperature (columns 4 and 5), stricter cut-off definitions (80^{th} and 90^{th} percentile in columns 6 and 7), dry season temperature quartiles (column 8), and controlling for one lead and lag of temperature shocks (column 9).

Temperature deviations from long-term trends. One possible concern is that $hot_{l_i,t}$ picks up long-run increases in temperature. We address this concern by defining an alternative dummy for whether temperature lies above the predicted time trend. For each location, we regress dry season temperature from 2001 to year $t-1$ on a time trend. Thereafter, we predict temperature in t for each location and survey year (2010 to 2012). Finally, we define an indicator variable equal to one if realised temperature exceeds our prediction. Appendix table A8 shows very similar patterns to our main estimates. One possible interpretation is that deviations from long-term trends capture *unexpected* temperature shocks, calling for short-term, temporary adaptations.

Moreover, in column (5) of appendix table A6, we divide locations into quintiles based on the long run temperature and estimate the effect of temperature anomalies along its distribution. We find that the effect of anomalies is similar for the first four quintiles. Only for the hottest quintile is there no effect, which is characterised by very high temperatures ranging from 33.56^{o}C to 34.24^{o}C.

Rainfall. Appendix table A5 shows that rainfall shocks are not a driver of migration in our context. The coefficients on rainfall anomalies during dry and rainy seasons are small and their inclusion does not reduce the size of the temperature coefficients. As outlined earlier, there is little rainfall during dry season in northern Kenya and high temperature make water holes that are vital for livestock run dry faster.

3.2 Temperature shocks, migration, and policies

In this section, we show that the widely documented effect of weather shocks on migration can significantly be attenuated by policies. Temperature shocks affect output in weather sensitive sectors (see Dell et al., 2014). The ensuing negative impact on household consumption (more on this below) acts as a direct push factor for migration. As such, any policy that helps households to attenuate the negative consequences of higher temperatures can potentially decrease the effect on migration. For $policy_{l_i}$ in equation (1), we consider two major types of policy: income transfers and infrastructure improvements.

Income transfers and migration. To examine whether disposable income influences the effects of weather shocks, we exploit the random allocation of unconditional cash transfers to households by the HSNP. Hence $policy_{l_i} = 1$ if location l_i was randomly chosen to receive HSNP transfers. The results in column (2) of table 2 show that receiving unconditional cash transfers offsets a large part of the effect of temperature on migration. Note that due to household fixed effects (ι_i), we cannot estimate the direct effect of unconditional cash transfers. However, column (1) of appendix table A13 suggests that (controlling for district fixed effects) HSNP transfers themselves have no significant direct effect on migration in our context.

Infrastructure and migration. To investigate the importance of infrastructure, we extract the first principal component from geo-coded data on the overland road network, geo-coded data on mobile phone coverage and electricity (mainland electricity lines and electricity minigrids), and information drawn from the HSNP on educational and health facilities in each location (see section 2.3). For interpretability, we normalize this principal component to have a minimum value of 0 and a standard deviation of 1.[12]

Column (3) of table 2 shows that when interacting this index with $hot_{l_i,t}$, infrastructure significantly attenuates the effect of temperature on migration. A one standard deviation improvement in infrastructure from the lowest value decreases the effect of temperature by 89%. In columns (1) to (6) of appendix table A7, we use the three broad components

[12] Whilst an extrapolation suggests that infrastructure improvements could reverse temperature's effect on migration, this would apply for only a small subset of locations, as the distribution of infrastructure is very skewed (skewedness 2.52). Our results are robust to dropping these locations in column (3) of appendix table A12. In appendix table A10, we show that coefficient magnitudes are similar when we discretize infrastructure.

of our infrastructure measure (roads, electricity/GSM (once as a dummy and once as a z-score), and education/health facilities) separately and find that the effect of temperature shocks decreases along each of them. Moreover, we re-estimate our effects excluding educational or healthcare facilities and find that our results remain robust. Local market integration, including faster commuting, is one channel through which roads and other infrastructure support non-agricultural activity (cf Egger et al., 2024).[13] In columns (5) and (6) of table A12 we re-estimate our main models dropping the district of Marsabit, where besides the HSNP also a livestock insurance was introduced (Jensen et al., 2017).

Policies and consumption. Infrastructure significantly changes the effect of temperature on consumption shown in figure 2c. Appendix figure A4 shows that in locations with lower levels of infrastructure, per capita consumption decreases with higher temperatures. In locations with good infrastructure the consumption-temperature gradient is flat. Instead, whilst the introduction of the randomized cash transfer programme raises consumption, the lack of adjustment in economic activities implies that consumption nonetheless decreases at higher temperatures.

Instrumenting infrastructure. Whilst receipt of randomized unconditional cash transfers is exogenous by design, infrastructure is not. Note that we are interested in the *interaction* of infrastructure with quasi-random temperature shocks (conditional on household and year fixed effects), rather than the direct effect of infrastructure. Nonetheless, we instrument infrastructure in location l_i using two local geographical features. First, lightning strike frequency has been shown to damage electrical infrastructure such as telephone antennae used for GSM and electrical grids (Manacorda and Tesei, 2020), which both are parts of our infrastructure measure. Second, terrain ruggedness makes overland transportation hard (Nunn and Puga, 2012) and is thus related to our measure for roads. We extract the first principal component of these two variables and use the interaction with $hot_{l_i,t}$ as an instrument for the $hot_{l_i,t} \times policy_{l_i}$ interaction. Due to the conditioning household and year effects, the instrument's identifying variation only derives from the interaction with the time-varying hot dummy. As column (1) of appendix table A12 shows, the instrumental variables parameter estimates are almost identical to their OLS counterparts in column (3) of table 2, with an F-statistic of 20.4. First stage estimates are reported in appendix table A7 and illustrated graphically in appendix figure A7.

[13] Commuting rather than temporary migration to Kenya's urban centers, all of which are south of the districts Mandera, Marsabit, Turkana and Wajir, and at more than 360km road distance from the respective district centres, is unlikely.

Table 2: Temperature, coping strategies and policies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable = 1 if											
	at least one household member migrated			at least one household member works in agriculture			household owns camels			household owns cattle		
Sample mean		0.04			0.65			0.36			0.22	
High temperature	0.028	0.054	0.049	−0.047	−0.048	−0.020	0.044	0.018	0.085	−0.073	−0.109	−0.068
	(0.013)	(0.012)	(0.014)	(0.017)	(0.027)	(0.019)	(0.025)	(0.040)	(0.025)	(0.027)	(0.029)	(0.039)
High temperature × UCT		−0.040			−0.011			0.038			0.050	
		(0.018)			(0.033)			(0.047)			(0.032)	
High temperature × Infrastructure (SD)			−0.045			−0.056			−0.105			−0.020
			(0.013)			(0.014)			(0.022)			(0.037)
HH and year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
UCT×year effects		YES			YES			YES			YES	
Infrastructure×year effects			YES			YES			YES			YES
Households	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436

Notes: Table reports effect of temperature on migration, occupational sector choice and camel ownership in northern Kenya; dependent variable in columns (1)-(3) takes value 1 if at least one household member left the district of residence; dependent variable in columns (4)-(6) takes value 1 if at least one household member works in agricultural occupations (herding or agriculture); dependent variable in columns (7)-(9) takes value 1 if household owns at least one camel; dependent variable in columns (10)-(12) takes value 1 if household owns at least one cattle; data in columns (1)-(3) are drawn from follow up 1 (2011) and follow up 2 (2012) of the HSNP; data in columns (4)-(12) include also the baseline (2010); *High temperature* = 1 if the dry season temperature in the location is above the long-run median for that location; *UCT* = 1 if the location was randomly chosen to receive unconditional cash transfers (UCT) under the Hunger Safety Net Programme; *Infrastructure (SD)* is the first principal component of road network, electricity grid, GSM mobile telephone, education and health infrastructure in a location (normalised to have minimum value = 0 and standard deviation = 1); HAC standard errors with 50km radius and two year lag reported in parentheses.

Results are not driven by urbanised areas. A possible concern is that infrastructure acts as a proxy for more developed or urban areas where there are fewer agricultural households, mechanically decreased the effect of temperature on migration. We show that this is not the case. First, we re-estimate equation (1) adding an interaction term between the hot dummy and an indicator for the household working in agriculture and the results remain robust (see Column (2) of appendix table A12). This interaction will pick up any differential migration responses to heat shocks between agricultural and non-agricultural households. Second, we calculate the share of households in each location working in agriculture and re-estimate equation (1) excluding locations below the 25th percentile (i.e. the least agricultural locations). Column (3) shows very similar effects for this sample. Third, we identify particularly developed or urban areas using geo-coded information on population density (see map A2e in Appendix A).[14] Column (4) shows very similar results when we exclude the two locations with the highest population densities, see figure A2f.

Heterogeneity by income at baseline. For some households, cash transfers may help overcome binding financial constraints. Distinguishing households by consumption expenditure in 2010, column (1) of appendix table A6 shows that receiving unconditional cash transfers under the HSNP increases (rather than decreases) the effect of temperature shocks for the poorest quartile. This is in line with studies documenting that at low levels, additional income is used to fund migration (Clemens, 2021). For the largest part of our sample, by contrast, cash transfers attenuate the effect of heat shocks (see column 2).[15] Instead, the coefficient on the infrastructure interaction does not vary, see columns (3) and (4).

3.3 Sector and livestock as additional coping strategies

A recent World Bank report (2020) highlights the importance of in-place adaptations, such as occupational sectors, crop or livestock compositions. Although rural-urban migration often coincides with a change from agricultural to non-agricultural work, our data show substantial local occupational transitions within rural areas (see also Budí-Ors, 2024, for similar patterns in Indonesia). Descriptive evidence suggests that in northern Kenya, the negative effect of temperature on household welfare varies significantly with the sector household members work in and with the livestock they own. Figure 2c shows that high temperatures depress per capita consumption significantly more for agricultural

[14] `https://energydata.info/dataset/kenya-population-density-2015/resource/a57fce6f-b00c-428f-b1f9-86855c64b9df`, accessed February 2024.

[15] This does not contradict the generally higher migration rates among richer households. In fact, we do document such a positive relation in appendix figure A11, which our model presented below is able to replicate.

than for non-agricultural households. While, we do not interpret these changes as causal, they are (like the estimates in table 2) net of household and year effects. The two bars on the right of figure 2c further indicate a significantly milder loss in consumption for households that own camels.

Given these differential impacts, and since most respondents are pastoralists (see Section 2.3), occupational and livestock composition changes are plausible coping strategies. In fact, several papers highlight sectoral transitions as an important adjustment mechanism, see, for instance, Colmer (2021), Macours et al. (2022), and Liu et al. (2023). Emerick et al. (2016) demonstrate the potential of adopting more resistant crop types. Appendix figure A3b provides suggestive evidence that occupational choice provides a possible alternative to migration highlighting how households either change sector or migrate. We model these different, but potentially joint responses explicitly in Section 4.

Temperature and occupational sector choice. We re-estimate equation (1) using the dependent variable $A_{it} = 1$ if at least one member of household i in year t works in the agricultural sector.[16] The estimate in column (4) of table 2 shows that in years when dry season temperature is above the long-run median, households are almost 5 percentage points less likely to work in agriculture. Our results remain robust to controlling for one and two years lag of temperature shocks (appendix table A3). Below we provide several pieces of evidence suggesting that observed changes are most likely short-term adjustments.

Temperature and livestock choice. We re-estimate equation (1) using a dependent variable which takes the value one if household i owns at least one camel or any cattle in year t. In line with the descriptive evidence shown in figure 4c, the estimate in column (7) of table 2 indicates that in years after which the dry season temperature exceeded the long-run median, households are 4.4 percentage points more likely to own at least one camel. We also estimate temperature's effect on cattle, which are the least heat resistant type of commonly owned livestock. Column (10) shows a negative effect. Below we provide evidence that the positive effect of heat shocks on camel ownership is driven by households already owning other livestock.

Income transfers, infrastructure, sector and livestock choices. We do not find that the effect of temperature shocks on occupational sector choice or livestock changes varies much with random receipt of cash transfers, see columns (5), (8), and (11) of table 2. In columns (2) to (4) of appendix table A13, we also estimate the direct effect of HSNP transfers and find no changes.

[16] Since occupational and livestock information is provided in all three rounds, we use the years 2010, 2011, and 2012 for both estimations.

Different from cash transfers, the parameter estimates in column (6) of table 2 show that the effect of temperature shocks on households moving out of the agricultural sector is significantly stronger for those living in locations with better infrastructure. A one standard deviation increase from the lowest infrastructure level more than triples occupational sector changes. By the same token, in columns (9) and (12) of table 2 we find that increases in camel and decreases in cattle ownership are significantly weaker in areas with better infrastructure.

For robustness, we re-estimate the effect of temperature semi-parametrically across deciles of the deviations from local long-term medians for three equidistant levels of infrastructure: minimum, mean(approximately 1.5 standard deviations above the minimum), and 1.5 standard deviations above the mean. Appendix figure A6 confirms the magnifying effect of infrastructure (aside from the two highest deciles).

Responses reflect short-term coping strategies. We find that the transition to non-agriculture after heat shocks consists predominantly of households diversifying by working in both agriculture and non-agriculture, as opposed to leaving agriculture completely. Column (2) of appendix table A11 shows that after hot dry seasons, the probability of households working exclusively in non-agriculture only increases by a statistically insignificant 2.8 percentage point. By contrast, the probability of households working in both agriculture and non-agriculture increases by more than 8 percentage points (column (3)), suggesting that the adaptations we document are mostly short-term coping strategies unlikely to require large capital investments.

The temporary nature of coping strategies is further corroborated by the results in appendix table A9. The table indicates that last dry season's temperature is considerably more important for households working in both agricultural and non-agricultural occupations. Temperatures in earlier years, by contrast, are determinants of households working exclusively in non-agricultural occupations, which more likely involves more significant capital investments.

In line with the above, columns (4) and (5) of appendix table A11 indicate that the effect of heat shocks on camel acquisitions is driven by households already owning livestock at baseline (in 2010) which may avoid binding financial constraints. This tallies with the estimates in appendix table A13 showing no direct effect of HSNP on purchases of livestock.

3.4 Different pathways of impact of transfers and of infrastructure

Using detailed information from the HSNP questionnaires, we provide evidence suggesting that income transfers and better infrastructure decrease temperature's effect on migration (section 3.1) in very different ways. After heat shocks, HSNP recipients are more likely to use transfers for purchases on food. By contrast, agricultural households transition to non-agricultural occupations at faster rates when local infrastructure is of better quality.

HSPN cushions negative consumption effect of heat shocks. Figure 2c shows a strong negative effect of heat shocks on household consumption expenditure. We show that HSNP transfers are used to offset these losses by using information in the HSNP evaluation questionnaire where the randomly treated households were asked in the two follow ups what they used the pecuniary transfers for. Columns (1) to (4) of table 3 show the effect of heat shocks on a selection of uses. Columns (1) and (2) show that in abnormally hot years households are more likely to use the HSNP transfer to buy food (which is also the most common use) and to buy livestock. It appears that these increases in expenditures are offset by decreases in expenditures on clothing (column (3)). By contrast, the effect of heat on HSNP being used for setting up new businesses is a precisely estimated zero (column (4)).

Infrastructure catalyses employment transitions out of agriculture. To provide more details on the occupational transitions shown in columns (4) to (6) of table 2, we select households working exclusively in agriculture at the beginning of the sample period and follow these over time. Column (5) of table 3 shows that following heat shocks transitions from agricultural to non-agricultural occupations are significantly stronger when local infrastructure is better, and that this change is driven primarily by households entering non-agricultural occupations in addition to continued work in agriculture by some household members (column (7)).

The mirror image of this is shown in columns (8) and (9). The higher sectoral transitions in high infrastructure locations come at the expense of adjustments in livestock composition. This suggests that sectoral transition is a substitute both to migration and to changes in livestock composition. We carry out the same check as in Section 3.2 and find that our results hold also when we exclude the most densely populated and least agricultural locations in appendix table A12.

4 A Dynamic Model of Temperature, Migration, Sector, and Livestock Choices

4.1 Purpose of model and intuitive overview

Section 3 has documented that households use several strategies to cope with temperature shocks. Exploring the dynamic interactions between these choices as well as evaluating counterfactual policies, requires an explicit joint modelling of coping strategies over time.

Table 3: Cash transfers buffer shocks, infrastructure eases sectoral transitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	A: Use of cash transfer				**B:** Infrastructure & transitions				
Dependent variable	=1 if HH spent HSNP on				=1 if HH members work in	members work in		=1 if household	
	food	live-stock	clothes	set up shop	non-agri	non-agri only	for both sectors	owns camels	
Sample mean	0.86	0.08	0.28	0.02	0.30	0.10	0.20	0.56	0.59
High temp.	0.058	0.031	−0.072	0.005	−0.036	−0.055	0.019	0.261	0.280
	(0.026)	(0.027)	(0.055)	(0.009)	(0.053)	(0.028)	(0.066)	(0.043)	(0.049)
High temp. × Infra (SD)					0.268	0.085	0.184	−0.332	−0.340
					(0.051)	(0.026)	(0.051)	(0.044)	(0.048)
Sample	HSNP treatment HHs				Exclusively in agriculture in 2010				+ animals in 2010
HH & year FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Households	1,224	1,224	1,224	1,224	983	983	983	983	949

Notes: Table reports effect of temperature on use of HSNP transfer and on occupational sector and livestock choices; dependent variable in columns (1)-(4), takes value 1 if the HSNP transfer is used for the purchase of food, livestock, clothes or the start of a small business, respectively; dependent variable in column (5) takes value 1 if at least one member of the household works in non-agricultural occupation (self-employment, wage employment, collecting bush products for sale or consumption, or helping in family business) dependent variable in column (6) takes value 1 if all household members work in non-agricultural occupations; dependent variable in column (7) takes value 1 if household members work in both agricultural and non-agricultural occupations; dependent variable in columns (8) and (9) takes value 1 if household owns any camels; sample in columns (1) to (4) consists of HSNP recipients only, sample in columns (5) to (8) is conditional on whole household working in agriculture in 2010, sample in column (9) furthermore is conditional on household owning any livestock in 2010; data are drawn from follow up 1 (2011), and follow up 2 (2012) of the HSNP; *High temp* = 1 if the dry season temperature in the location is above the long-run median for that location; *Infra (SD)* is the first principal component of road network, electricity grid, GSM mobile telephone, education and health infrastructure in a location (normalised to have minimum value = 0 and standard deviation = 1); HAC standard errors with 50km radius and two year lag reported in parentheses.

In our model, households are forward looking and base their choices on expectations regarding future earnings, which, in turn, depend on expected future heat shocks. In each period households maximise their income via three costly choices: sending a migrant, having household members work in a non-agricultural occupation, and rearing camels. The cost of each option varies with local infrastructure, a household's previous activity, and—to approximate financial constraints—with household income in the previous period. If households send a migrant, they receive remittances. We allow for high temperature to differentially affect payoffs from all these choices. High temperatures change earnings as well as transfers received. Crucially, the extent to which heat alters incomes depends on the household's occupation and the type of livestock owned. For instance, high temperature shocks depress earnings less in non-agricultural than in agricultural occupations. In addition, our model allows infrastructure to have an activity-specific effect on productivity.

Our model serves four main purposes. First, the model enables us to simulate different policies at equal costs, thus allowing for adequate comparisons and for more credible policy predictions. Second, a reduced form setting cannot distinguish the relationships between three choices taken simultaneously. Third, the model allows us to investigate dynamics. For instance, transitions to non-agricultural occupations increase migration in later periods thus showing how short term strategies can have long term effects. Fourth, we incorporate expectations using a Markov process based on data from the previous decade. This feature allows for updating beliefs, since it captures the empirical fact that having just experienced an unusually high temperature realization makes higher temperatures more likely in the next season.

4.2 Model setup

Locations are differentially exposed to shocks, and further differ in the level of infrastructure and treatment status in the randomized cash transfer programme. Temperature shocks affect consumption both through a direct impact on earnings, through an effect on choices that may offset part of that effect, as well as through a potential change in the level of transfers received from migrant members or households' broader network. Households differ in size, and all choices depend on idiosyncratic preference shocks. We incorporate two distinct types of dynamics in the model. First, households are forward looking, and thus anticipate future benefits of changing sector or livestock, for instance. Second, the costs of all choices are functions of lagged outcomes, in particular lagged income as an approximation for financial constraints. Households have three adjustment options: (i) sending a household member to migrate, (ii) changing to a sector of employment where incomes are less affected by temperature shocks, and (iii) raising camels as opposed to other species.

Notation. Each period t, household i chooses $m_{it} \in \{0, 1\}$, indicating whether a household member is sent as migrant.[17] The household further decides on the sector $s_{it} \in \{A(griculture), N(on-agriculture)\}$ in which its members are economically active, where N indicates that at least one household member is active in a non-agricultural occupation. Finally, households choose whether their animals include camels or not, indicated by $a_{it} \in \{C(amels), O(ther)\}$. Each of these choices will potentially respond to heat shocks. To be consistent with the estimations in Section 3, we use the same indicator $hot_{l_i,t}$ for previous dry season temperature being above the local long-run median in location l_i. Different from above, however, we assume that $hot_{l_i,t}$ follows a Markov process, whose transition matrix we estimate from temperature realizations across time and space for the year 2001-2012 (see appendix table A14). Agents observing $hot_{l_i,t}$ thus form expectations about $hot_{l_i,t+z}, \quad z = 1, 2, ...$

Earnings and remittances. Households value per capita consumption c_{it}, which is financed through income y_{it}. This income derives from sector-specific wages w_{it}, migrant remittances $r^m(hot_{l_i,t})$ or other transfers $r^o(hot_{l_i,t})$ from the social network, each of which may vary with temperature shocks and serve as insurance (Yang and Choi, 2007). We scale all income sources to per capita levels by dividing by the number of adult equivalent household members. Finally, a household enjoys unconditional cash transfers $hsnp_{l_i,t}$ from the HSNP, if its location is randomly allocated to the treatment group. Per capita consumption in a household of size n_i then is given by

$$c_{it} = y_{it} = w_{it} + r^m(hot_{l_i,t})m_{it} + r^o(hot_{l_i,t}) + hsnp_{l_i,t}/n_i. \tag{2}$$

Infrastructure development, which is one of the simulated policies we evaluate in the counterfactual analysis of Section 4.5, may trigger equilibrium effects as well as direct productivity changes that affect earnings regardless of households' choices. We thus model earnings as

$$\ln w_{it} \quad = \quad \phi_s + \psi_a + \mu_s hot_{l_i,t} + \mu_a hot_{l_i,t} + \nu_s d_{l_i} + \nu_a d_{l_i} + v_{it}, \tag{3}$$

which differ by sector of economic activity s_{it} and by whether their livestock a_{it} includes camels (log wage levels ϕ_s and ψ_a). In addition, earnings are a function of the local level of infrastructure development d_{l_i} (through parameters ν_s and ν_a) and of temperature shocks $hot_{l_i,t}$ (through parameters μ_s and μ_a), the impacts of which again vary with sector and livestock type. For consistency, we use the same measure for infrastructure introduced in Section 3.1.

Since we observe that both migrant and non-migrant transfers vary with households'

[17] We do not observe any household in our data that sends more than one member to migrate.

exposure to heat shocks, we predict transfers received as described in Appendix D. As our model focuses on the household rather than the individual migrant, its choices depend on remittance receipt rather than migrants' potentially under-estimated total income (Baseler, 2023), their exact destination or migrants' disutility from migration (Imbert and Papp, 2020).

Migration, sector change and livestock costs. Migration, sector changes and changes in livestock are costly, with costs depending both on a household's previous activity and the level of infrastructure development d_{l_i} in its location l_i. Given the literature on financial constraints to migration (see, for instance, Bryan et al., 2014; Bazzi, 2017; Gazeaud et al., 2020; Clemens, 2021; Görlach, 2023), we let migration (as well as the other) costs be a function of a household's previous income y_{it-1} as an approximation to the stock of assets, which is the key variable in financial constraints. Studies in this literature face the common problem of separately identifying the direct effect of income on consumption on the one hand and the effect it has on financial constraints on the other. We rely on a timing assumption, which amounts to assuming that costs are to be paid upfront and can be covered by past incomes, whereas choices are made based on expected utility in the current period. We denote costs by $\delta^m_{it} = \delta^m(d_{l_i}, y_{it-1}, s_{it-1})$ for migration choice m, $\eta^s_{it} = \eta^s(d_{l_i}, y_{it-1}, s_{it-1})$ for the choice of sector s, and $\kappa^a_{it} = \kappa(d_{l_i}, y_{it-1}, a_{it-1})$ for camel acquisition.[18]

Choices. We assume a dynamic nested logit structure for the discrete choices we want to model. Households decide on migration, sector of economic activity and livestock composition, maximizing the value

$$V_{it} = \max_{m\in\{0,1\}} \tilde{V}^m_{it} - \delta^m_{it} + \varepsilon^m_{it}, \tag{4}$$

which describes the value maximizing migration decision. This choice further entails the optimal sector choice

$$\tilde{V}^m_{it} = \max_{s\in\{A,N\}} \tilde{V}^s_{it} - \eta^s_{it} + \varepsilon^s_{it} \tag{5}$$

and the optimal livestock decision

$$\tilde{V}^s_{it} = \max_{a\in\{C,O\}} \tilde{V}^a_{it} - \kappa^a_{it} + \varepsilon^a_{it}. \tag{6}$$

[18]We assume that the costs of staying in the same sector ($s = s_{it-1}$) or maintaining the same type of livestock ($a = a_{it-1}$) are zero. For sector and livestock changes, as well as for migration, we assume that costs are log linear functions of d_{l_i} and y_{it-1}, see Appendix D.

With these choices, the dynamic value function is

$$\tilde{V}_{it}^{a} \quad = \quad u(c_{it}) + \beta \mathrm{E}[V_{it+1}]. \tag{7}$$

Flow utility is given by $u(c_{it}) = \frac{c_{it}^{1-\gamma}-1}{1-\gamma}$, with relative risk aversion γ. Consumption c_{it} is a function of household i's choices (m, s, a), see equations (2) and (3). The terms ε_{it}^{m}, ε_{it}^{s} and ε_{it}^{a} capture unobserved idiosyncratic taste shocks for each option. In line with the reduced form estimations in Section 3, we assume that households use the previous dry season's temperature realization $hot_{l_i,t}$ as a basis for their choices. The expectation E[$\cdot$] in equation (6) is over the future realizations of taste shocks ε_{it}^{m}, ε_{it}^{s} and ε_{it}^{a}, earnings shocks v_{it}, as well as over future temperature. We model the latter as a Markov process whose transition probabilities we estimate based on the 2001-2012 temperature transitions in all HSNP locations. Table A14 in Appendix D lists these probabilities. The estimated transition matrix, for instance, implies that if last year's dry season was abnormally hot, with probability 0.8 this year's will also be.

4.3 Identification and estimation

We first estimate transfers received as a function of temperature shocks, separately for households with and without a migrant (see Appendix D). Appendix figure A8 shows the estimated parameters of these relations. All preference, wage and cost parameters are then estimated jointly by indirect inference, targeting observed static and dynamic conditional moments related to livestock composition, sector of economic activity, migration, consumption expenditure per capita by sector, type of livestock, infrastructure, heat exposure, as well as the variance of log expenditure.[19] See below and Appendix D for details. Solving for the choice probabilities implied by the model requires a specification of the distributions of preference shocks ε_{it}^{a}, ε_{it}^{m} and ε_{it}^{s} as well as solving for the value functions. We assume that these shocks are extreme value distributed with spread parameters σ_a, σ_m and σ_s, leading to logistic closed form solutions for agents' choice probabilities. In addition, we assume that idiosyncratic shocks v_{it} to log wages are normally distributed with variance σ_y^2. We then solve the model by value function iteration, assuming a discount factor $\beta = 0.95$, as estimated for instance by Attanasio et al. (2011).

Identification. We estimate the model's 30 structural parameters by targeting 38 static and dynamic moments from the HSNP data. Note that in indirect inference estimation, the targeted moments may derive from auxiliary regressions, and that consistent

[19]We target expenditure (the left hand side of equation (2)) rather than income, because the former is measured more precisely. Furthermore, because many respondents in our data work on own account, income information leaves unclear whether it refers to revenues or profits (Deaton, 1997).

estimation of the structural parameters does not require consistency on part of the auxiliary regressions (Gourieroux et al., 1993).

While all moments identify the model's parameter jointly, appendix table A15 lists all parameter and the moments contributing most directly to their identification. Our targeted moments include the reduced form coefficients from columns (2) and (3) of table 2, which help identify preference parameters γ and σ_m. The spread parameter σ_m is inversely related to the elasticity of migration and thus pinned down by the migration response to shocks irrespective of HSNP receipt or infrastructure (coefficients on $High\ temperature$ in columns (2) and (3) table 2). The degree to which income variation translates into changes in utility and thus in migration pressure depends on the curvature γ of the utility function, which thus is identified by the change in the migration response to temperature shocks when households receive cash transfers, corresponding to the coefficient $High\ temperature \times UCT$ in column (2) of table 2. The cost $\delta^m(d_{l_i}, y_{it-1}, s_{it-1})$ of sending a migrant in our model is a function of local infrastructure, of whether the household was active in a non-agricultural activity, and—to approximate financial constraints—on previous income. To identify these relations as well as the level of the migration cost, we target both the overall share of households sending a migrant (irrespective of shocks) and coefficients from a regression of an indicator $\mathbb{1}[m_{it} = 1]$ for sending a migrant on HSNP treatment status, the level of local infrastructure d_{l_i}, and indicators $\mathbb{1}[s_{it-1} = A]$ and $\mathbb{1}[s_{it-1} = N]$.

Similarly, the effects of hot_{it} on households being active in non-agricultural occupations and on households owning camels identify σ_s and σ_a, which are again inversely related to the respective choice elasticities. The costs $\eta^s(d_{l_i}, y_{it-1}, s_{it-1})$ of changing sector are identified by the coefficients from two regressions of, respectively an indicator $\mathbb{1}[s_{it} = N]$ for switching to non-agriculture among households with $s_{it-1} = A$ and an indicator $\mathbb{1}[s_{it} = A]$ for switching to agriculture among households with $s_{it-1} = N$, each on HSNP treatment status, d_{l_i}, and a constant. The costs $\kappa^a(d_{l_i}, y_{it-1}, a_{it-1})$ of changing livestock, in turn, are pinned down by the coefficients from two regressions of, respectively, an indicator $\mathbb{1}[a_{it} = C]$ for switching to camels among households with $a_{it-1} = O$ and an indicator $\mathbb{1}[a_{it} = NC]$ for switching to exclusively other livestock among households with $a_{it-1} = C$, each on HSNP treatment status, d_{l_i}, and a constant. We also include the coefficients of column (5) of table 3, the share of households with at least some members working in non-agricultural occupations and the share owning camels among their livestock among the estimation moments.

Conditional on pre-estimated transfer functions $r^m(hot_{l_it})$ and $r^o(hot_{l_it})$, observed HSNP transfers, and assumption (2), we identify the earnings equation parameters ϕ_s, ψ_a, μ_s, μ_a by targeting mean log per capita expenditure and the coefficients from a fixed effects regression of log per capita expenditure on sector, livestock type, as well as on hot_{it}, interacted with both sector and livestock type. Parameters ν_s and ν_a, which determine how earnings depend on local infrastructure, are identified through coefficients from regressions of log per capita expenditure on local infrastructure, separately for households in agriculture, non-agriculture, and households with and without camels among their livestock. Finally, we target the variance of per capita consumption expenditure to pin down σ_y^2.

Figure A9 visualizes the gradient matrix of moments with respect to parameters. The fact that this matrix has full rank, formally demonstrates local identification of all parameters under the model. Appendix figure A10 and table A16 show that the model fits these moments well. Figure A11 in the appendix further shows a good fit also for important moments not targeted in the estimation. Our model matches very well the share of households sending a migrant along the distribution of consumption expenditure (which in our model equals total household income).

Parameter estimates. We list all structural parameter estimates of our model in appendix table A17. Absent any endogenous response, we estimate a strong negative effect of $\exp(\mu_0) - 1 = -35\%$ of heat on earnings, which applies to agricultural households that do not own camels. This effect is cut by about one half for both non-agricultural households and for households owning camels ($\mu_{NA} \approx \mu_C \approx 0.2$). Earnings are $\exp(\nu_0) - 1 = 20\%$ higher in locations with better infrastructure, with an additional $\exp(\nu_{NA}) - 1 = 9\%$ for non-agricultural occupations. Our estimate for relative risk aversion $\gamma = 0.61$ is similar to those by Rendon and Cuecuecha (2010) and Imai and Keane (2004), who estimate relative risk aversion to be 0.56 and 0.74, respectively. We estimate a migration elasticity of $1/\sigma_\varepsilon = 3.8$, comparable to the elasticity of 4.5 estimated by Morten and Oliveira (2024) for internal migration in Brazil. For inner-European migration, Ortega and Peri (2013) by contrast estimate a lower elasticity of 1.8. We estimate lower elasticities for sector and livestock choices. The cost of sending a migrant is slightly lower for non-agricultural than for agricultural households ($\delta_{NA} < \delta_A$), and decreases with lagged earnings by about $1 - \exp(\delta_y) = 10\%$ per 100 USD PPP per capita. Sector transition costs are most notably affected by infrastructure, which reduces the cost of entering non-agricultural occupations by $1 - \exp(\eta_d^{NA}) = 50\%$ per standard deviation of infrastructure.

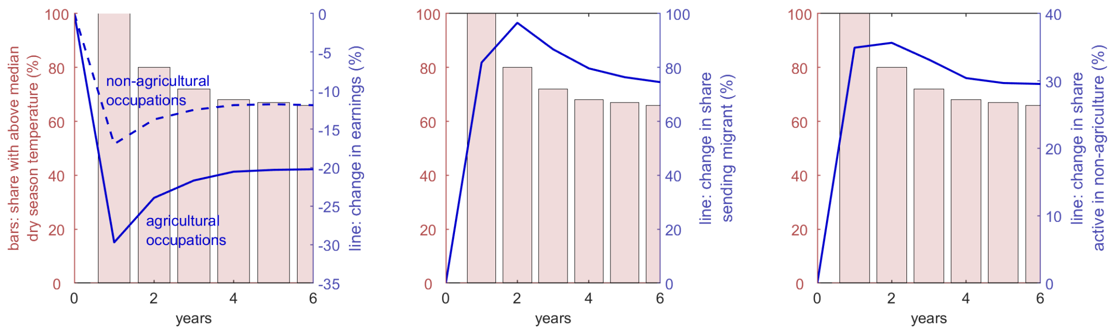
4.4 Dynamic migration and sector responses to heat shocks

To illustrate dynamic adjustments, we simulate a temperature shock and its path in later periods as predicted by the estimated Markov process. The red bars in figure 5 show how locations transition from having a dry season temperature below the local median in period 0 to all experiencing above median dry season temperatures in period 1. In line with the Markov process outlined above, the probability that dry season temperature continues to be above the median quickly declines and converges to around 66%.

Delayed increase in migration after heat shocks. The effect of this temperature shock on income is displayed in panel (a) of figure 5 (scale on the right axis). In line with the descriptive evidence of figure 2c, high temperature reduces income by about 20% on average, and primarily so in agricultural occupations. Migration responses are shown in panel (b). The probability of sending a migrant approximately doubles in the first period. A notable feature is that the higher migration rate in period 1 does not decrease immediately in period 2, whilst temperature does. The reason for this lag is that higher temperature in period 1 caused households to transition into non-agricultural occupations (shown in panel (c)), which have higher migration rates irrespective of temperature shocks—recall the higher baseline migration rate among non-agricultural households in figure 2b.

Figure 5: Dynamic adjustments to a temperature shock

(a) Income (b) Migration (c) Non-agricultural work



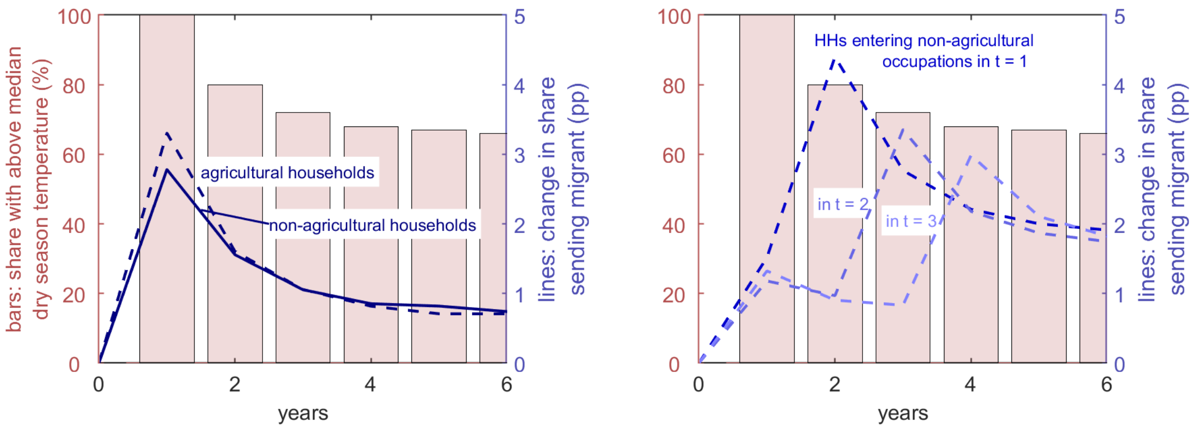
Notes: Figure shows dynamic effects of temperature shock on income, migration and the non-agricultural share. In period 0, no location has high temperature; in period 1, all locations have high temperature; in periods 2, 3, ..., temperature evolves stochastically following the estimated Markov process. Red bars show probabilities that temperature is high. Panel (a): Blue line shows change in income relative to period 0; panel (b): Blue line shows change in share of households sending a migrant relative to period 0; panel (c): Blue line shows change in share of households active in non-agricultural occupations relative to period 0.

Sectoral transitions and delayed migration increase. The mechanism behind this lagged increase in migration is visualized in figure 6, which simulates the same heat shock as in figure 5. Panel (a) of the figure shows the migration response for households that stay in the same sector for at least 10 periods after the shock. Migration rates for these households peak in period 1. The figure displays a slightly stronger sensitivity for households whose members work in agriculture only. For better comparison of the different groups, we display changes in percentage points rather than in percent. Panel (b) focuses on households that initially (in period 0) are exclusively active in agriculture. Different lines single out households which enter non-agricultural occupations in periods 1, 2 and 3. The figure shows that migration rates continue to increase among these households one period after they transit to non-agricultural occupations. This migration increase happens despite the share of locations with above dry season temperature continuing to decline. The reason for this persistence is that non-agricultural households have a higher baseline migration rate irrespective of temperature fluctuations, see figure 2b.

Figure 6: Mechanisms behind migration dynamics

(a) Non-switching agricultural vs non-agricultural households

(b) Transition to non-agricultural occupations boosts later migration



Notes: Figure shows dynamic effects of temperature on migration by sector. In period 0, no location has high temperature; in period 1, all locations have high temperature; in periods 2, 3, ..., temperature evolves stochastically following the estimated Markov process. Red bars show probabilities that temperature is high. Blue lines show changes in share of households sending a migrant relative to period 0. Panel (a): Lines show migration response by households that do not switch sector in the first 10 years following the shock; solid line denotes households active in non-agricultural occupations; dashed line denotes households that are exclusively active in agricultural occupations. Panel (b): Lines show migration response by households exclusively active in agriculture in period 0, but entering non-agricultural occupations in periods 1, 2 or 3.

4.5 Comparing policies at equal costs

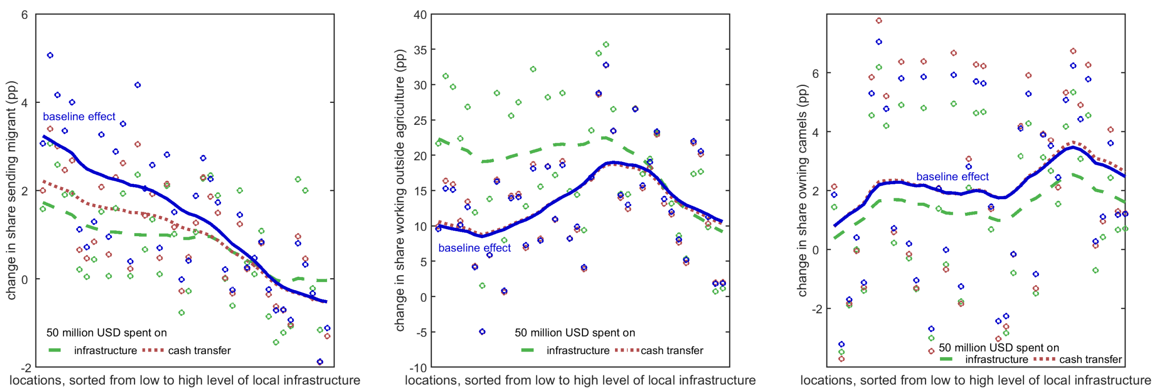
Besides its dynamic perspective, an advantage of the model is that, in the presence of expected non-linearities, it allows a comparison of different policies at comparable scales. We carry our the following thought experiment: spending an annual amount of 50 million USD to develop infrastructure or transferring the same amount directly as unconditional cash payments to households.

Comparing policies' aggregate costs. For infrastructure, we focus on building overland roads for which reliable cost estimates are readily available from the World Bank's Road Costs Knowledge System (ROCKS) Database, which has been used for instance by Collier et al. (forthcoming). We account for the contribution of roads to the broader infrastructure index used in the model, see Appendix D.2 for details. Based on the estimates for Kenya, 50 million USD per year spent on a uniform expansion of the road network in the four HSNP districts Mandera, Marsabit, Turkana and Wajir would raise our infrastructure measure by 0.0365 standard deviations. The World Bank estimates that roads in Africa have a life span of about 20 years, after which they typically require resurfacing. Hence, to account for the longer-run effect of infrastructure investment, we multiply the above number with 20. As a second policy, the same annual 50 million USD paid out as unconditional cash transfers in these districts would imply a transfer of about 64 USD PPP per adult equivalent capita or 289 USD PPP per household, about half the amount paid out by the HSNP.

Spatial distribution of policy effects. Figure 7 shows the results across different locations, sorted by their level of infrastructure. Blue circles in panel (a) indicate the percentage point increase in migration after a temperature shock. The two policies we consider reduce the effect of temperature shocks on migration primarily among these more rural locations with lower infrastructure. The effect of temperature shocks on migration is reduced more strongly when the annual 50 million USD are spent on road construction than as cash transfers. Panel (b) shows that the reduction in the effect of temperature on migration through infrastructure coincides with an increase in the share of households entering non-agricultural occupations. Thus, a clear policy implication from our model is that, when the objective is a facilitation of in-place adaptation to temperature shocks funds should be channelled towards rural locations.

Figure 7: Spatial heterogeneity with cash transfers and infrastructure

(a) Migration (b) Non-agricultural work (c) Camel ownership

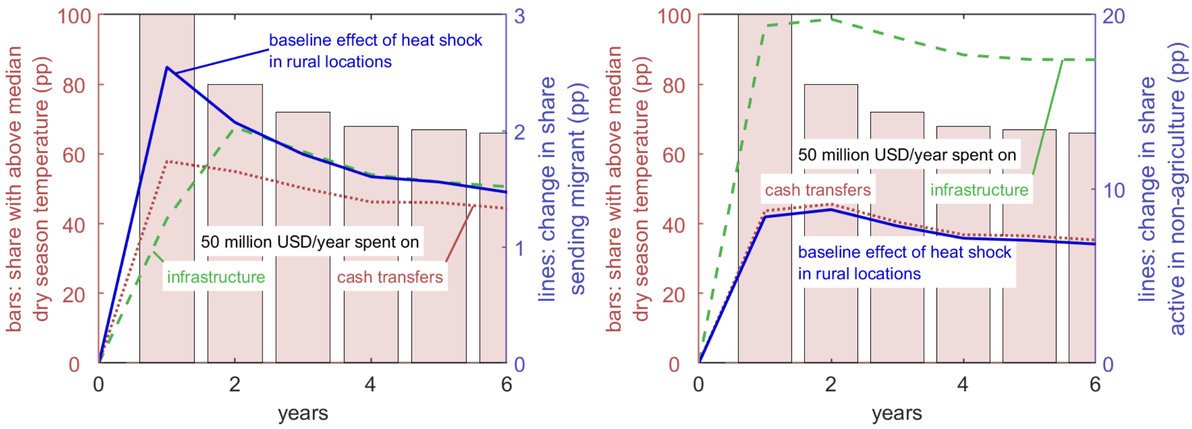


Notes: Figure shows changes in the simulated effects of a temperature shock by policy. Panel (a) displays changes in the effect on sending a migrant; panel (b) in the effect on working in non-agricultural occupations; panel (c) in the effect on owning camels. Circles indicate effects of temperature shock on shares of households within each location sending a migrant, with locations sorted horizontally by their level of infrastructure. Lines show effects smoothed across locations. Blue solid lines indicate effects without any policy; green dashed lines indicate effects if 50 million USD per year are spent on road construction; red dotted line indicates effects if 50 million USD per year are spent as unconditional cash transfers.

Dynamic policy effects. Our model reveals that the two policies have very different longer term effects. Figure 8 simulates the same responses as in figure 5 with and without each of the policies, focusing on rural locations, showing migration rates and sectoral transitions over The figure provides three important insights. First, panel (a) reveals that for this set of rural locations, the immediate effect of high temperature on migration in period 1 is reduced more strongly through infrastructure than though cash transfers of equal aggregate cost. Second, panel (b) displays a strong boost in the effect of the temperature shock on non-agricultural work when infrastructure improves. Cash transfers, instead have a negligible effect on sector transitions. Third, and perhaps most importantly, the rise in non-agricultural work leads to a delayed but sizeable increase in migration rates from period 2 onwards. This is due to infrastructure helping agricultural households to enter non-agricultural occupations, which, however, have higher baseline migration rates. At the same aggregate cost, the longer-term impact of cash transfers on migration in response to temperature shocks thus exceeds that of infrastructure investment.

Figure 8: Dynamic adjustment with cash transfers and infrastructure

(a) Migration (b) Non-agricultural work

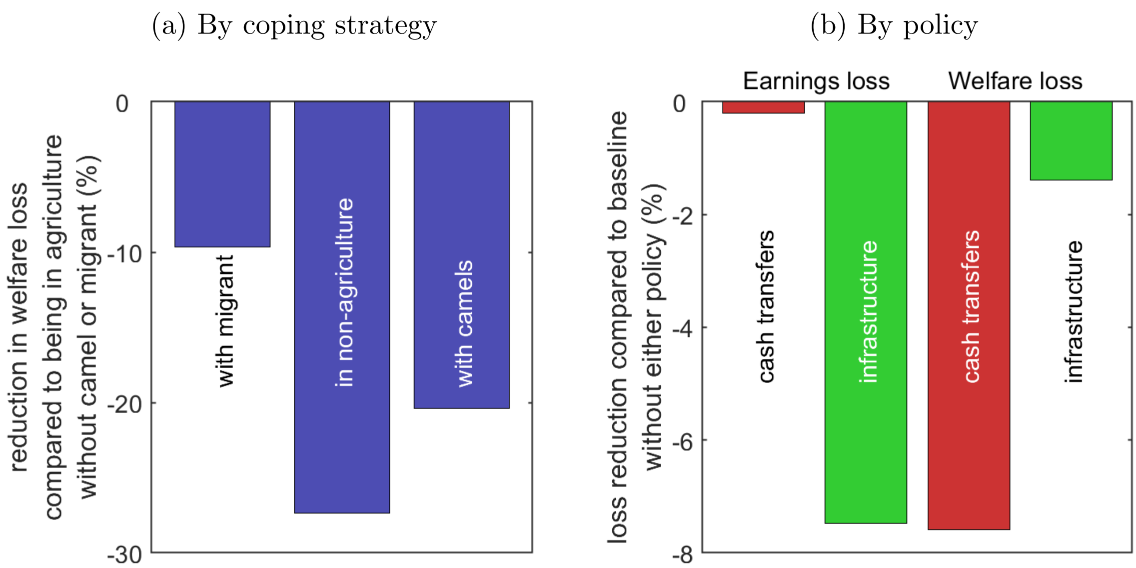


Notes: Figure shows dynamic effects of temperature shock on migration and the non-agricultural share by policy in the bottom quartile of locations in terms of infrastructure. In period 0, no location has high temperature; in period 1, all locations have high temperature; in periods 2, 3, ..., temperature evolves stochastically following the estimated Markov process. Red bars show probabilities that temperature is high. Panel (a): Blue solid line shows change in share of households in low infrastructure locations sending a migrant relative to period 0 without any policy; green dashed line shows change in migration if 50 million USD per year are spent on road construction in the districts Mandera, Marsabit, Turkana and Wajir; red dotted line shows change in migration if 50 million USD per year are spent as unconditional cash transfers in the same districts. Panel (b): Blue solid line shows change in share of households in low infrastructure locations active in non-agricultural occupations relative to period 0 without any policy; green dashed line shows change in non-agricultural share if 50 million USD per year are spent on road construction in the districts Mandera, Marsabit, Turkana and Wajir; red dotted line shows change in non-agricultural share if 50 million USD per year are spent as unconditional cash transfers in the same districts.

Welfare effects. Our model can be used to calculate the welfare effects of different choices and policies. Since utility has no scale, we calculate changes in the expected welfare loss following a temperature shock relative to a baseline loss. Panel (a) of figure 9 shows that relative to a household exclusively working in agriculture without camels and no migrant the welfare loss from high temperature is weakened most, by 27%, for households that have members working in non-agricultural occupations. More generally, in-place adaptations turn out to be effective strategies to cope with temperature shocks. For comparison, having a migrant household member reduces the welfare loss by 10%.

Panel (b) of figure 9 displays reductions in earnings and welfare losses through different policies at a common aggregate cost of 50 million USD per year relative to a baseline with no policy in place. In line with the smaller earnings losses in non-agricultural occupations shown in figure 5a and the acceleration of occupational change through infrastructure, earning losses are strongly reduced under better infrastructure. Instead, cash transfers—while supporting households consumption—have little effect on their earnings. Yet, since occupational change comes at a cost to households, the welfare effect of infrastructure is dominated by cash transfers given directly to households.

Figure 9: Welfare effects of different adjustments



Notes: Figure shows changes in welfare losses following a temperature shock. Panel (a): Losses for households that have a migrant, are active in non-agricultural occupations or own camels are shown relative to the loss for households whose members work exclusively in agriculture without camels and no migrant. Panel (b): Losses with cash transfers or infrastructure improvements of an aggregate cost of 50 million USD per year are shown relative to the loss absent either policy intervention. Changes in welfare losses are calculated based on expected values V_{it} in the model (see equation (4)).

5 Conclusion

The Intergovernmental Panel on Climate Change (IPCC, 2022) emphasizes that adaptation strategies to weather shocks are vital to reduce risks and enhance resilience for low-income groups in the face of increased climate variability. This paper provides new insights about the inter-relationships between different adaptation strategies to higher temperatures and how they interact which common policy margins—income support and infrastructure development. First, whilst the theoretical direction of effects is ambiguous, we find that in the Kenyan context both income transfers and better infrastructure significantly weaken the effect of heat on out-migration. These effects, however, operate via two very different channels: whereas better infrastructure eases the transition to non-agricultural occupations, cash transfers are used to soften adverse consumption shocks. Second, using a dynamic model that considers migration jointly with other coping strategies, we document important differences in these policies' short- versus long-run impacts. Whilst, at the same aggregate cost, infrastructure mitigates more of the immediate effect of temperature shocks on migration than cash transfers, the non-agricultural work infrastructure boosts serves as a steppingstone for future migration. Thus, our paper illustrates how temporary weather shocks can lead to long-lasting impacts on both occupational structures and migration trends. The finding that weather related shocks drive population movements as well as local, in-place adaptations stresses the importance for policy predictions of modelling migration jointly with other choices. Labor markets have been identified as a key dimension of adjustment to climatic change (World Bank, 2022). Although the importance of rising temperatures as a push factor of migration is well documented, adequate policy responses remain underdeveloped (Carleton et al., 2024). If well-designed, policies can support transitions that yield longer-term benefits to adapting households. Our joint modelling of choices indicates that infrastructure development can support both welfare improving local occupational change and facilitate longer-term mobility. The importance of the occupation and production technology choices we highlight suggests novel avenues for research.

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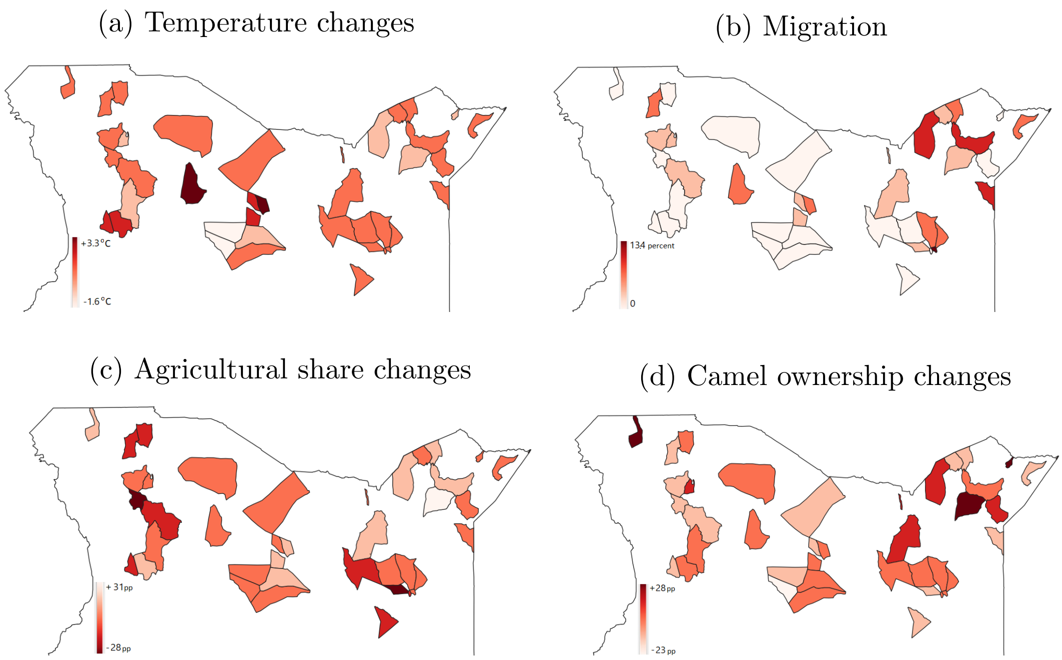
Supplemental Appendix

(for online publication only)

A Additional maps and material

Figure A1: Main outcomes



(a) Temperature changes

(b) Migration

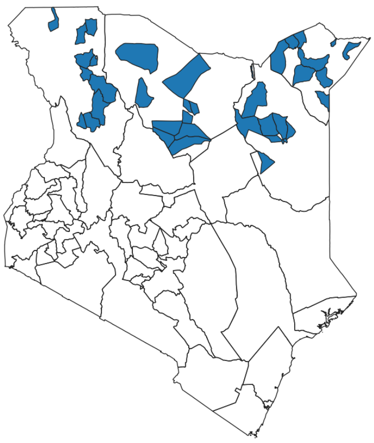
(c) Agricultural share changes

(d) Camel ownership changes

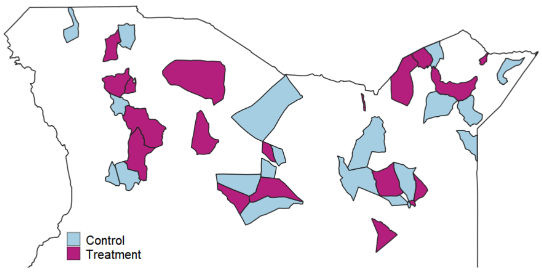
Notes: Figure reports temperature, migration, changes in sector and camel ownership for the 40 locations covered by the HSNP data. Panel (a) shows mean deviations in dry season temperature 2010-2012 from local long-term median. Panel (b) shows the proportion of households for which a member moved out of the district. Panel (c) shows the change in households for which at least one member works in the agricultural sector. Panel (d) shows the change in households that own at least one camel.

Figure A2: Spatial patterns

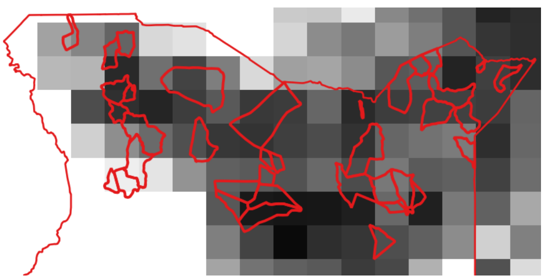
(a) Locations in Kenya



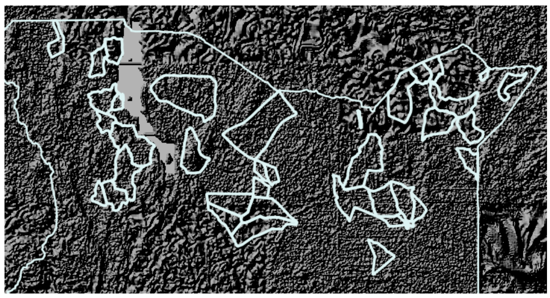
(b) HSNP random treatment status



(c) Lightning strikes

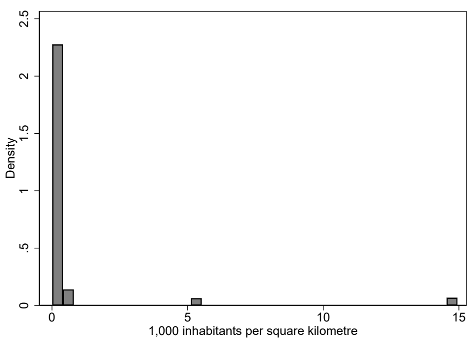


(d) Terrain ruggedness



(e) Population density

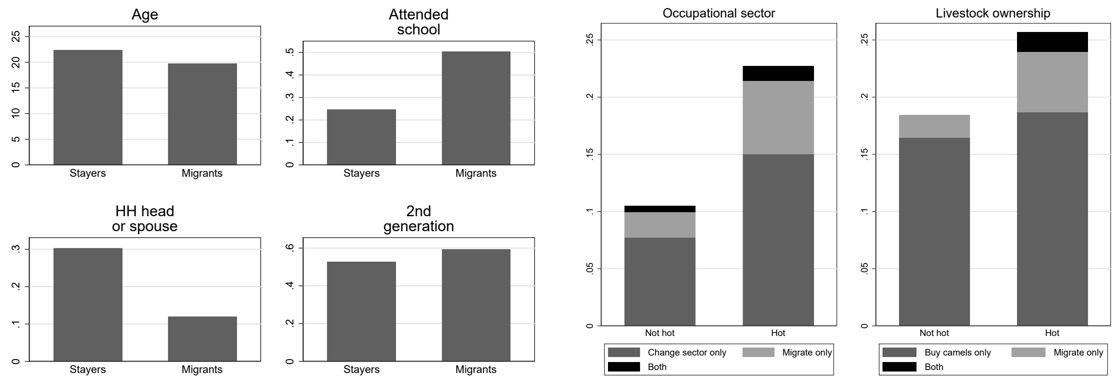
(f) Population density distribution



Notes: Map (a) shows the 40 locations covered by the HSNP along with Kenya's 47 districts. Map (b) shows the 40 locations covered by the HSNP by random receipt of unconditional cash transfer (treatment) and no receipt (control). Map (c) shows the 40 locations covered by the HSNP along with number of lightning strikes as reported by NASA. Map (d) shows the 40 locations covered by the HSNP along with terrain ruggedness. Map (e) shows the 40 locations covered by the HSNP along with population density. Figure (f) shows distribution of population density across the 40 locations covered by the HSNP (in 1,000 inhabitants/sq km).

Figure A3: Temperature and migration in northern Kenya

(a) Migrant characteristics (b) Reactions to temperature shocks



Notes: Panel a reports individual characteristics of individuals (age, educational attainment, and relationship to household head) by migration status, educational attainment reported for respondents aged 16 or older. Panel b reports proportion of households changing sector, sending migrants or both by experience of heat shock (left two bars); and proportion of households switching to camel ownership, sending migrants or both by experience of heat shock (right two bars).

Table A1: Variation in consumption by rainfall and temperature

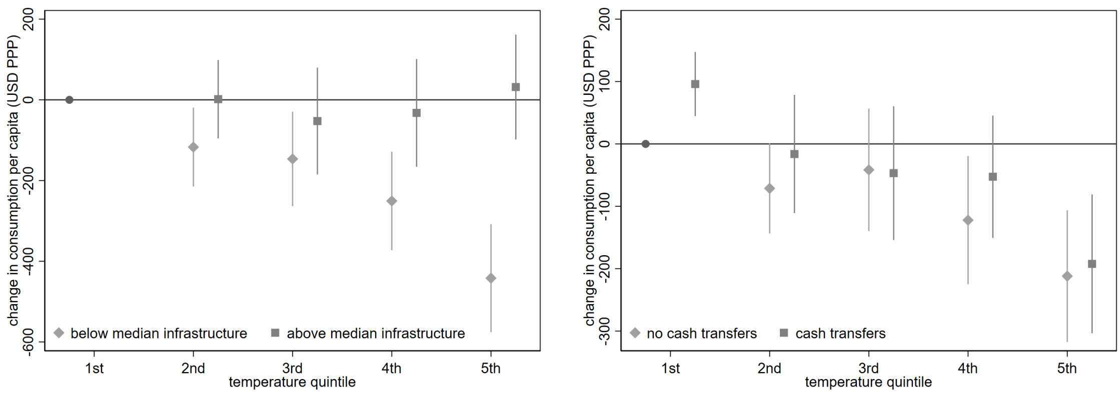
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable = log(consumption per adult equivalents in household)							
	All households				Agricultural households			
Rainfall, z-score (dry season)	0.110 (0.040)		0.031 (0.033)		0.103 (0.043)		0.020 (0.022)	
Rainfall, z-score (rainy season)		−0.141 (0.059)		−0.120 (0.068)		−0.067 (0.051)		−0.028 (0.052)
Temperature, z-score (dry season)			−0.675 (0.169)	−0.703 (0.141)			−0.715 (0.131)	−0.743 (0.122)
HH & Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Households	2,436	2,436	2,436	2,436	1,554	1,554	1,554	1,554

Notes: Table reports effect of weather shocks on consumption in northern Kenya; dependent variable is the log of a household's total consumption value over the number of adult equivalent household members; *Rainfall, z-score (dry season)* denotes z-score of rainfall during dry season; *Rainfall, z-score (rainy season)* denotes z-score of rainfall during rainy season; *Temperature, z-score (dry season)* denotes z-score of dry season temperature; sample in columns (1)-(4) includes all households, sample in columns (5)-(8) only households with at least one member active in either livestock or crop production; spatial heteroskedasticity- and autocorrelation-robust (HAC) standard errors with 50km radius and two year lag reported in parentheses.

Figure A4: Temperature and consumption losses by cash transfers and infrastructure

(a) By infrastructure

(b) By cash transfers



Notes: Figure reports variation in households' consumption value over the number of adult equivalent household members by local dry season temperature. Panel a distinguishes households in locations with above and below median infrastructure level. Panel b distinguishes households in treatment and control locations of the randomized HSNP cash transfer programme; since cash transfer are introduce in 2011, the effect of cash transfers in the lowest temperature quartile is identified.

B Balance checks

This appendix provides evidence for the exogeneity of temperature shocks, temperature time trends, and of unconditional cash transfers under the HSNP. To that end, we regress shocks (respectively dummies for HSNP receipt, for dry season temperature being above long-term median, and temperature growth from 2010 to 2012) on a number of household characteristics drawn from the baseline survey in 2010.

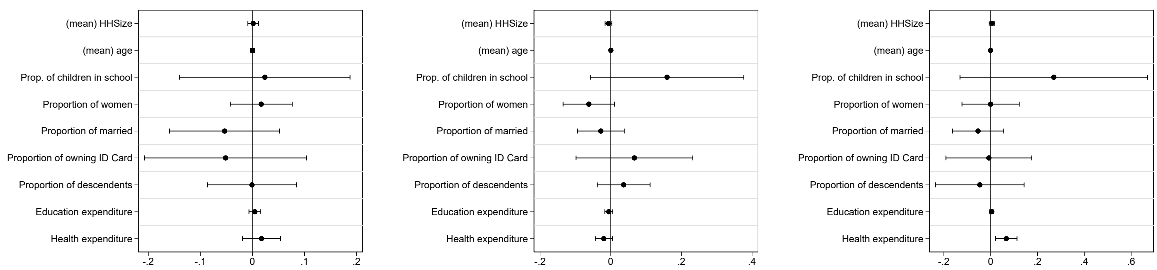
High temperature dummy. For each of the 40 HSNP locations, we compute the long-run median of temperature during the dry season using the years 2000 to 2009. Whilst the long-run temperature during dry seasons is likely to be correlated with various unobservable factors, such as institutions, for instance, whether temperature in any particular year is above (or below) the median is likely to be exogenous. Panel (a) of figure A5 shows correlations between the *High temperature* dummy and household characteristics.

Temperature trends. Since the household fixed effects in our regressions difference out any time-constant variation, we carry out an additional balancing check. In panel (b) we regress differences between the 2012 and 2010 dry season temperatures on household characteristics and, as before, find no correlation to household characteristics at baseline.

HSNP tansfers. Half of the 40 HSNP locations were assigned to the treatment group, which received unconditional cash transfers from follow up 1 (in 2011) onwards. Treatment status was assigned via public lottery. Panel (c) shows correlations between the *HSNP transfer* dummy and household characteristics.

Figure A5: Balancing tests

(a) High temperature dummy (b) Temperature trends (c) HSNP transfer



Notes: Figures report correlations between temperature shocks, temperature growth and cash transfer dummies on the one hand and household characteristics on the other; circles denote point estimates and horizontal lines 95% confidence intervals based on HAC standard errors with 50km radius and two year lag; data are drawn from the 2010 baseline of the HSNP; Panel (a): dependent variable = 1 if the dry season temperature in the location is above the long-run median for that location; Panel (b): dependent variable is dry season temperature 2012 minus dry season temperature 2010; Panel (c): dependent variable = 1 if location was randomly selected to receive unconditional cash transfers under HSNP scheme.

C Robustness

Table A2: Alternative clustering methodologies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable = 1 if											
	at least one household member migrated			at least one household member works in agriculture			household owns camels			household owns cattle		
Sample mean		0.04			0.65			0.36			0.22	
High temperature	0.028	0.054	0.049	−0.047	−0.048	−0.020	0.044	0.018	0.085	−0.073	−0.109	−0.068
HAC 50km, 2 lags	(0.013)	(0.012)	(0.014)	(0.017)	(0.027)	(0.019)	(0.025)	(0.040)	(0.025)	(0.027)	(0.029)	(0.039)
HAC 100km, 2 lags	(0.010)	(0.012)	(0.013)	(0.028)	(0.034)	(0.024)	(0.025)	(0.034)	(0.020)	(0.033)	(0.034)	(0.038)
HAC 50km, no lags	(0.009)	(0.009)	(0.009)	(0.029)	(0.049)	(0.039)	(0.024)	(0.046)	(0.030)	(0.029)	(0.042)	(0.041)
Clustered at location	(0.014)	(0.013)	(0.014)	(0.020)	(0.027)	(0.023)	(0.027)	(0.041)	(0.026)	(0.026)	(0.033)	(0.038)
High temperature × UCT		−0.040			−0.011			0.038			0.050	
HAC 50km, 2 lags		(0.018)			(0.033)			(0.047)			(0.032)	
HAC 100km, 2 lags		(0.012)			(0.023)			(0.037)			(0.027)	
HAC 50km, no lags		(0.013)			(0.037)			(0.046)			(0.032)	
Clustered at location		(0.018)			(0.032)			(0.048)			(0.033)	
High temperature × Infrastructure (SD)			−0.045			−0.056			−0.105			−0.020
HAC 50km, 2 lags			(0.013)			(0.014)			(0.022)			(0.037)
HAC 100km, 2 lags			(0.013)			(0.017)			(0.022)			(0.037)
HAC 50km, no lags			(0.009)			(0.072)			(0.040)			(0.058)
Clustered at location			(0.014)			(0.016)			(0.021)			(0.036)
Households	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436

Notes: Table replicates results in table 2 using different clustering methodologies: Heteroskedasticity- and autocorrelation-robust (HAC) standard errors with 50km radius and 2 years lag, HAC standard errors with 100km radius and 2 years lag, HAC standard errors with 50km radius and no lags, and standard errors clustered at the location level. Same notes as table 2 apply.

Table A3: Controlling for past temperature shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable = 1 if											
	at least one household member migrated			at least one household member works in agriculture			household owns camels			household owns cattle		
Sample mean		0.04			0.65			0.36			0.22	
High temperature	0.047	0.079	0.065	−0.075	−0.095	−0.046	0.039	0.009	0.082	−0.048	−0.073	−0.048
	(0.011)	(0.016)	(0.008)	(0.025)	(0.033)	(0.024)	(0.026)	(0.039)	(0.021)	(0.023)	(0.026)	(0.034)
High temperature × UCT		−0.044			0.015			0.043			0.030	
		(0.019)			(0.025)			(0.045)			(0.028)	
High temperature × Infrastructure (SD)			−0.048			−0.061			−0.118			−0.000
			(0.013)			(0.012)			(0.016)			(0.036)
High Temperature (lag 1)	0.021	0.026	0.016	−0.075	−0.072	−0.069	−0.038	−0.042	−0.041	0.093	0.090	0.095
	(0.008)	(0.010)	(0.011)	(0.041)	(0.043)	(0.039)	(0.041)	(0.042)	(0.045)	(0.033)	(0.035)	(0.037)
High Temperature (lag 2)	−0.021	−0.026	−0.033	−0.042	−0.048	−0.048	0.006	0.003	0.006	0.024	0.020	0.024
	(0.008)	(0.010)	(0.023)	(0.034)	(0.033)	(0.034)	(0.025)	(0.025)	(0.026)	(0.014)	(0.016)	(0.016)
HH and year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
UCT×year effects		YES			YES			YES			YES	
Infrastructure×year effects			YES			YES			YES			YES
Households	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436

Notes: This table replicates the main results of the paper shown in Table 2 on page 17 of the manuscript with the addition of lagged temperature shocks. *High Temperature (lag 1)* = 1 if the dry season temperature in the location one-year prior is above the long run median for that location. This corresponds to the one-year lag of the variable High Temperature. *High Temperature (lag 2)* = 1 if the dry season temperature in the location two years prior is above the long run median for that location. This corresponds to the two-year lag of the variable High Temperature. All other notes are identical to Table 2.

Table A4: Alternative migration and temperature measurements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Dependent variable =1 if						
	HH leaves	Mem leaves (any dest.)	household member migrated out of district						
Sample mean:	0.029	0.174	0.040	0.040	0.040	0.040	0.040	0.040	0.040
High temperature	0.012	0.077							0.039
	(0.010)	(0.029)							(0.012)
Temperature in °C (dry season)			0.083		0.080				
			(0.036)		(0.038)				
Temperature in °C (rainy season)				−0.027	−0.011				
				(0.025)	(0.029)				
High temperature (> 80 pctl)						0.037			
						(0.017)			
High temperature (> 90 pctl)							0.097		
							(0.045)		
2nd temperature quartile								0.035	
								(0.019)	
3rd temperature quartile								0.055	
								(0.032)	
4th temperature quartile								0.090	
								(0.038)	
HH & Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Households	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436
Lag & lead									YES

Notes: Table reports effect of temperature shocks on migration in northern Kenya; dependent variable in column (1) takes value 1 if household leaves sample the following period; data for column (1) are drawn from the baseline (2010) and follow up 1 (2011) of the HSNP; dependent variable in column (2) takes value 1 if at least one household member left the households (to any destination); dependent variable in columns (3)-(8) takes value 1 if at least one household member left the district of residence; data for columns (2)-(8) are drawn from follow up 1 (2011) and follow up 2 (2012) of the HSNP; *High temperature* = 1 if the dry season temperature the year before interview in the location is above the long-run median for that location; *Temperature in ^oC (dry season)* denotes dry season temperature in degree Celsius; *Temperature in ^oC (rainy season)* denotes rainy season temperature in degree Celsius; *High temperature (> 80 pctl)* and *High temperature (> 90 pctl)* = 1 if the dry season temperature the year before interview in the location is above the long-run 80th and 90th percentile, respectively; *2nd temperature quartile*, *3rd temperature quartile*, and *3rd temperature quartile* = 1 if dry season temperature anomalies fall into the second, third, or highest quartile, respectively; column (9) also controls for one year lag and lead of variable *High temperature*; HAC standard errors with 50km radius and two year lag reported in parentheses.

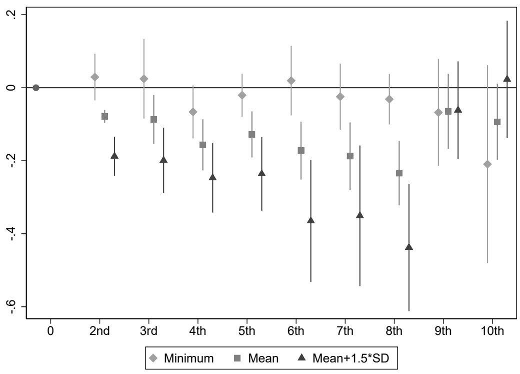
Table A5: Temperature and rainfall

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable =1 if household member migrated out of district (mean: 0.040)							
Rainfall, z-score	−0.003	0.001	−0.003				−0.000	−0.005
(dry season)	(0.005)	(0.005)	(0.005)				(0.007)	(0.005)
Rainfall, z-score				−0.001	−0.003	−0.003	−0.003	−0.005
(rainy season)				(0.007)	(0.004)	(0.006)	(0.006)	(0.007)
Temperature, z-score		0.120			0.120		0.116	
(dry season)		(0.055)			(0.052)		(0.057)	
Temperature, z-score							−0.016	−0.028
(rainy season)							(0.044)	(0.038)
High temperature			0.027			0.030		0.028
(dry season)			(0.014)			(0.013)		(0.013)
HH & Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Households	2,583	2,436	2,436	2,436	2,436	2,436	2,436	2,436

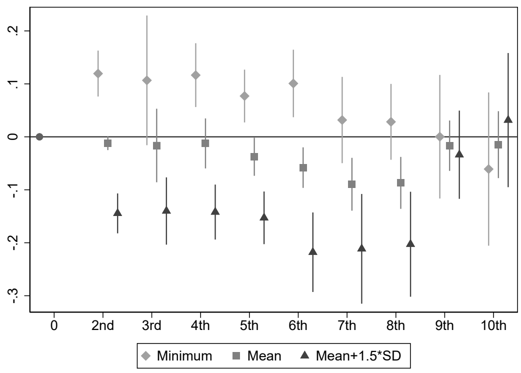
Notes: Table reports effect of weather shocks on migration in northern Kenya; dependent variable takes value 1 if at least one household member left the district of residence; *Rainfall, z-score (dry season)* denotes z-score of rainfall during dry season; *Rainfall, z-score (rainy season)* denotes z-score of rainfall during rainy season; *Temperature, z-score (dry season)* denotes z-score of dry season temperature; *Temperature, z-score (rainy season)* denotes z-score of rainy season temperature; *High temperature* = 1 if the dry season temperature the year before interview in the location is above the long-run median for that location; HAC standard errors with 50km radius and two year lag reported in parentheses.

Figure A6: Effect of temperature deciles on occupation and livestock by infrastructure

(a) Working in agriculture



(b) Owning camels



Notes: Figures show estimates based on equation (1). Diamonds, squares, and triangles denote coefficient estimates on deciles of temperature anomalies evaluated at lowest, mean, and 1.5 standard deviations above mean of level of infrastructure, respectively; dependent variable = 1 if at least one member works in an agricultural occupation in panel (a) and if household owns at least one camel in panel (b); vertical lines denote 95% confidence intervals based on HAC standard errors with 50km radius and two year lag.

Table A6: Migration response by baseline income and temperature

	(1)	(2)	(3)	(4)	(5)
	Dependent variable = 1 if at least one household member migrated (mean: 0.04)				
Sample	poor	rest	poor	rest	all
High temperature	−0.008	0.052	0.038	0.056	
	(0.013)	(0.016)	(0.010)	(0.015)	
High temperature × UCT	0.044	−0.057			
	(0.017)	(0.021)			
High temperature × Infrastructure (SD)			−0.030	−0.052	
			(0.015)	(0.012)	
High Temperature × (in 1st LR quintile)					0.062
					(0.039)
High Temperature × (in 2nd LR quintile)					0.114
					(0.084)
High Temperature × (in 3rd LR quintile)					0.101
					(0.107)
High Temperature × (in 4th LR quintile)					0.155
					(0.067)
High Temperature × (in 5th LR quintile)					−0.020
					(0.024)
HH and year effects	YES	YES	YES	YES	YES
Households	609	1,827	609	1,827	2,436

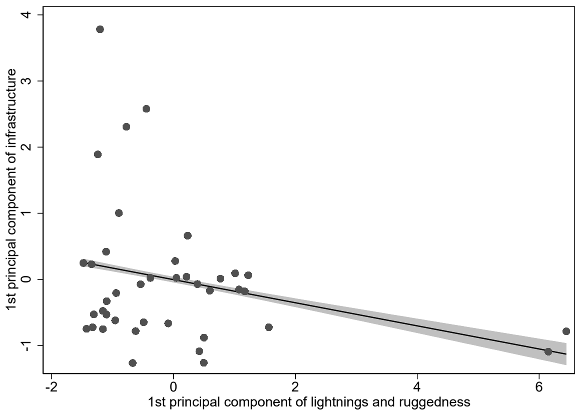
Notes: Table reports effect of temperature on migration in northern Kenya; dependent variable takes value 1 if at least one household member left the district of residence; data are drawn from follow up 1 (2011) and follow up 2 (2012) of the HSNP; *High temperature* = 1 if the dry season temperature in the location is above the long-run median for that location; $UCT = 1$ if the location was randomly chosen to receive unconditional cash transfers (UCT) under the Hunger Safety Net Programme; *Infrastructure (SD)* is the first principal component of road network, electricity grid, GSM mobile telephone, education and health infrastructure in a location (normalised to have minimum value = 0 and standard deviation = 1); sample in columns (1) and (2) consists of households in lowest quartile of 2010 consumption distribution; sample in columns (3) and (4) consists of households in highest three quartiles of 2010 consumption distribution; *High temperature (in nth LR quintile)* is the interaction between High temperature and a dummy for the long run median temperature in location i being in the nth quintile. HAC standard errors with 50km radius and two year lag reported in parentheses.

Table A7: Infrastructure - measurements and first stages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable							
	=1 if member left hh						High temp × infrastr	
High temperature	0.077	0.029	0.038	0.056	0.045	0.041		1.101
	(0.012)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)		(0.123)
High temperature × Roads (SD)	−0.119							
	(0.038)							
High temperature × Digital (Dummy)		−0.022						
		(0.017)						
High temperature × Digital (SD)			−0.034					
			(0.012)					
High temperature × Facilities (SD)				−0.037				
				(0.012)				
High temperature × Infrastructure (SD)					−0.043	−0.033		
					(0.013)	(0.014)		
High temperature × IV							1.415	−0.268
							(0.255)	(0.060)
Estimator	OLS	OLS	OLS	OLS	OLS	IV	OLS	OLS
Excl facilities					YES	YES		
HH & Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Households	2,436	2,436	2,436	2,436	2,436	2,436	2,436	2,436

Notes: Table reports alternative measures for infrastructure and first stages. Dependent variable in columns (1) to (6) takes value 1 if at least one household member left the district of residence; dependent variable in columns (7) and (8) is our infrastructure index in standard deviations. *High temperature × Roads (SD)* denotes the interaction between the hot dummy and the number of roads per area in standard deviations. *High temperature × Digital (Dummy)* denotes the interaction between the hot dummy and a dummy = 1 if the location has either electricity (via kv11 or k33 cable or via minigrid) or GSM coverage. *High temperature × Digital (SD)* denotes the interaction between the hot dummy and the first principal componnt of electricity (via kv11 or k33 cable or via minigrid) or GSM coverage in standard deviations. *High temperature × Facilities (SD)* denotes the interaction between the hot dummy and the number of health or education facilities in a location in standard deviations. *High temperature × IV* denotes the interaction between the hot dummy and the first principal component of lightning strikes and terrain ruggedness. Columns (5) and (6) define the infrastructure index excluding health and educational facilities. Column (6) instruments infrastructure with the first principal component of lightning strikes and terrain ruggedness; HAC standard errors with 50km radius and two year lag.

Figure A7: First stage illustration



Notes: Figure illustrates the relationship between infrastructure and our instrument. The vertical axis denotes our infrastructure index. The horizontal axis denotes the first principal component of the number of lightning strikes and terrain ruggedness. Line indicates slope coefficient with 95% confidence interval in grey, applying as weights the sample size in each location.

Table A8: Temperature deviations from long-term trends

	(1)	(2)	(3)
Dependent variable	=1 if at least one HH member migrated		
Mean			
Hotter than predicted by trends	0.058 (0.029)	0.147 (0.013)	0.096 (0.037)
Hotter × UCT		−0.144 (0.017)	
Hotter × Infrastructure (SD)			−0.024 (0.008)
HH and year effects	YES	YES	YES
Households	2,436	2,436	2,436

Notes: Table replicates main results using a different definition of temperature shocks. *Hotter than predicted by trends*=1 if actual temperature is higher than temperature as predicted by past temperatures. Dependent variable = 1 if at least one household member left the district; HAC standard errors with 50km radius and two year lag reported in parentheses.

Table A9: Lagged temperature

	(1)	(2)	(3)
	Dependent variable =1 if		
	anyone works in non-agri	exclu-sively in non-agri	both in agri & non-agri
High temperature	0.111	0.052	0.059
	(0.034)	(0.033)	(0.027)
High temperature (1 year lag)	0.020	0.093	−0.073
	(0.023)	(0.037)	(0.046)
High temperature (2 years lag)	−0.008	0.020	−0.027
	(0.040)	(0.040)	(0.030)
HH & Year FE	YES	YES	YES
Households	2,436	2,436	2,436

Notes: Table reports effect of temperature shocks on migration and occupations in northern Kenya; dependent variable in column (1) = 1 if at least one household member works in a non-agricultural occupation; dependent variable in column (2) = 1 if all household members work in non-agricultural occupations; dependent variable in column (3) = 1 if at least one household member works in a non-agricultural and at least one in an agricultural occupation; data are drawn from all three rounds of the HSNP; *High temperature* = 1 if the dry season temperature the year before interview in the location is above the long-run median for that location; *High temperature (1 year lag)* = 1 if the dry season temperature two years before interview in the location is above the long-run median for that location; *High temperature (2 years lag)* = 1 if the dry season temperature three years before interview in the location is above the long-run median for that location; HAC standard errors with 50km radius and two year lag reported in parentheses.

Table A10: Discretized infrastructure

	(1)	(2)	(3)	(4)
	Dependent variable = 1 if household			
	sends migrant	active in agriculture	owns camels	owns cattle
Sample mean	0.04	0.65	0.36	0.22
High temperature	0.033	−0.031	0.075	−0.079
	(0.011)	(0.018)	(0.022)	(0.034)
High temperature	−0.026	−0.054	−0.115	−0.011
× **High infrastructure**	(0.016)	(0.022)	(0.025)	(0.041)
HH and year effects	YES	YES	YES	YES
Households	2,436	2,436	2,436	2,436

Notes: Table replicates estimation in table 2, but discretizes infrastructure; dependent variable in column (1) takes value 1 if at least one household member left the district of residence; dependent variable in column (2) takes value 1 if at least one household member works in agricultural occupations (herding or agriculture); dependent variable in column (3) takes value 1 if household owns at least one camel; dependent variable in column (4) takes value 1 if household owns at least one cattle; data in column (1) are drawn from follow up 1 (2011) and follow up 2 (2012) of the HSNP; data in columns (2)-(4) include also the baseline (2010); *High temperature* = 1 if the dry season temperature in the location is above the long-run median for that location; *High infrastructure* = 1 if the first principal component of road network, electricity grid, GSM mobile telephone, education and health infrastructure in a location is above the median; HAC standard errors with 50km radius and two year lag reported in parentheses.

Table A11: Responses are short-run coping strategies

	(1)	(2)	(3)	(4)	(5)
	Panel A: Occupations			**Panel B:** Livestock	
Dependent variable	=1 if HH members work in			=1 if HH owns	
	non-agri	non-agri only	both sectors	camels	
Sample mean	0.55	0.32	0.24	0.44	0.07
High temperature	0.109 (0.026)	0.028 (0.018)	0.082 (0.023)	0.118 (0.044)	−0.004 (0.240)
HH and year effects	YES	YES	YES	YES	YES
Sample		All		Animals in '10	No animals in '10
Households	2,436	2,436	2,436	1,908	528

Notes: Table reports effect of temperature on occupational sector choice and camel ownership in northern Kenya; dependent variable in column (1) = 1 if at least one household member works in a non-agricultural occupation; dependent variable in column (2) = 1 if all household members work in a non-agricultural occupation; dependent variable in column (3) = 1 if household members work in both agricultural and non-agricultural occupations; columns (4) and (5): =1 if household owns any camels; data are drawn from baseline (2010), follow up 1 (2011), and follow up 2 (2012) of the HSNP; samples in columns (4) and (5) respectively are conditional on household owning and not owning any type of livestock in 2010; *High temperature* = 1 if the dry season temperature in the location is above the long-run median for that location; *Infrastructure (SD)* is the first principal component of road network, electricity grid, GSM mobile telephone, education and health infrastructure in a location (normalised to have minimum value = 0 and standard deviation = 1); HAC standard errors with 50km radius and two year lag reported in parentheses.

Table A12: Migration, occupation, and infrastructure - robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable =1	if household member migrated out of district (mean: 0.04)					if household members work in agri. sector	in both sectors	in agri. sector	in both sectors
High temperature	0.038	0.050	0.035	0.044	0.050	0.019	−0.043	0.050	0.019
	(0.011)	(0.017)	(0.012)	(0.016)	(0.017)	(0.027)	(0.070)	(0.030)	(0.066)
High temperature × Infrastructure (SD)	−0.029	−0.045	−0.043	−0.045		−0.068	0.219	−0.089	0.184
	(0.010)	(0.013)	(0.028)	(0.013)		(0.031)	(0.080)	(0.028)	(0.061)
High temperature × UCT					−0.043				
					(0.023)				
HH & Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
IV for infrastructure	YES								
High temp. × Agri.		YES							
Kleibergen-Paap F-Stat	20.4								
Sample	All	All	Agricultural locations	No Marsabit	No Marsabit	HHs exclusively in agriculture at baseline in agricultural locations		in sparsely populated locations	
Households	2,436	2,436	1,873	1,814	1,814	950	950	983	983

Notes: Table reports effect of heat shocks on migration and sectoral choice by local infrastructure; dependent variables takes value 1 if: at least one household member left the district of residence (columns (1) to (5)), if at least one household member works in an agricultural occupation (columns (6) and (8)), and if at least one member works in a non-agricultural and at least one member in an agricultural occupation (columns (7) and (9)); *High temperature* = 1 if the dry season temperature in the location is above the long-run median for that location; *Infrastructure (SD)* is the first principal component of road network, electricity grid, GSM mobile telephone, education and health infrastructure in a location (normalised to have minimum value = 0 and standard deviation = 1); *UCT* = 1 if location received unconditional cash transfers under the HSNP; *Agri.* = 1 if at least one household member worked in agricultural occupation; column (1) instruments *infrastructure* with first principal component of lightning strikes and terrain ruggedness; sample consists of rounds 2011 and 2012, sample in columns (1) and (2) consists of all households, sample in column (3) consists of locations where share of agricultural households lies above the 25th percentile, sample in columns (4) and (5) excludes households located in district of Marsabit; sample in columns (6) and (7) consists of locations where share of agricultural households lies above the 25th percentile, and conditions on whole household working in agriculture in 2010; sample in columns (8) and (9) drops locations with population densities of 1,000 inhabitants per square kilometres or above, and conditions on whole household working in agriculture in 2010; HAC standard errors with 50km radius and two year lag reported in parentheses.

Table A13: Direct effect of HSNP transfers

	(1)	(2)	(3)	(4)
	Dependent variable =1 if household			
	member migrated	works in non-agri.	owns camels	owns cattle
HSNP	0.009	0.010	−0.002	−0.005
	(0.009)	(0.032)	(0.019)	(0.027)
District & Year FE	YES			
HH & Year FE		YES	YES	YES
Households	2,436	2,436	2,436	2,436

Notes: Table reports effect of unconditional cash transfers under the HSNP on migration, occupations, and livestock ownership in northern Kenya; dependent variable takes value 1 if at least one household member left the district of residence (column (1)), if at least one household member works in a non-agricultural occupation (column (2)), and if household owns any camels (column (3)) or cattle (column (4)); *HSNP* = 1 if household's location was randomly chosen to receive unconditional cash transfers under the HSNP from 2011 onwards; sample in column (1) consists of rounds 2011 and 2012 only (since we do not measure migration at baseline); HAC standard errors with 50km radius and two year lag reported in parentheses.

D Model appendix

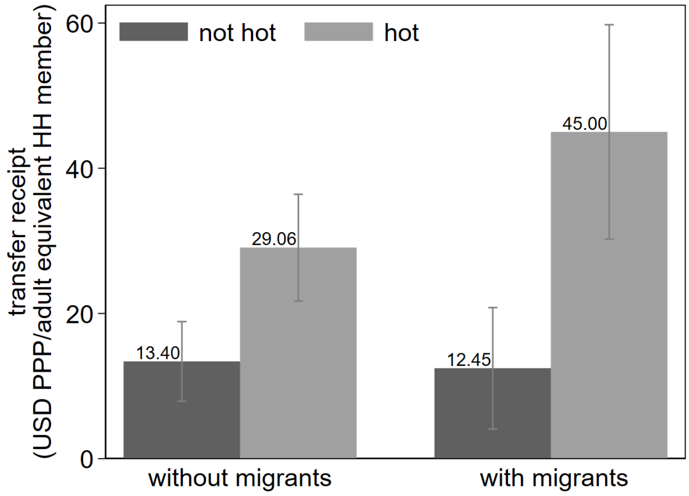
D.1 Specification details and parameter estimates

We assume that the costs of sending a household member to migrate, entering a new sector or changing livestock, each depends on lagged income y_{it-1} and on the level of infrastructure development d_{l_i}. The cost of changing sector s, which enters the household's sector choice problem (5), is given by $\eta^s_{l_i,y_{it-1},s_{it-1}} = \exp(\eta^s_{s_{it-1}} + \eta^s_y y_{it-1} + \eta^s_d d_{l_i})$. We assume that staying in the same sector is costless. That is, $\eta^s_{l_i,y_{it-1},s} = 0$. The cost of changing livestock, which enters the livestock choice (6), is given by $\kappa^a_{l_i,y_{it-1},a_{it-1}} = \exp(\kappa^a_{a_{it-1}} + \kappa^a_y y_{it-1} + \kappa^a_d d_{l_i})$. Finally, the cost of sending a migrant, which enters the household's migration choice problem (4), is given by $\delta^1_{l_i,y_{it-1},s_{it-1}} = \exp(\delta_{s_{it-1}} + \delta_y y_{it-1} + \delta_d d_{l_i})$. Column (2) of table A17 lists these sets of parameters.

Since we observe that both migrant and non-migrant transfers vary with households' exposure to heat shocks, we predict transfers received through a household's non-migrant network as $r^o_{l_i,t} = \hat{\rho}^o_0 + \hat{\rho}^o_1\ hot_{l_i,t}$, based on a regression of observed transfers on temperature shocks. When a household sends a member to migrate, its income is further augmented by migrant remittances $r^m_{l_i,t} = \hat{\rho}^m_0 + \hat{\rho}^m_1\ hot_{l_i,t}$. The coefficients in these equations are shown in figure A8.

Figure A10 shows the fit of the model to the empirical moments targeted in the estimation, which are also listed in table A16. Figure A11 shows the model fit for migration rates by earnings groups, which are not targeted in the estimation.

Figure A8: Transfer receipt by migrant and non-migrant households



Notes: Figure reports transfer receipt for households in northern Kenya by exposure to temperature shocks; the left set of bars shows the total amount of transfers received per adult equivalent household member for households of which no household member left the district of residence; the right set of bars shows the total amount of transfers received per adult equivalent household member for households of which at least one member left the district of residence; data are drawn from follow up 1 (2011) and follow up 2 (2012) of the HSNP; *not hot* and *hot* distinguish whether dry season temperature in the location the year before the interview was above the long-run median for that location; whiskers indicate 95% confidence intervals with clustering at location level.

Table A14: Transition matrix for above median dry season temperature

	$hot_{l_i,t+1}$	
$hot_{l_i,t}$	0	1
0	0.624	0.376
1	0.196	0.804

Notes: Table displays transition probabilities for dry season temperature in a location being above the local long-term median; calculation based on data for years 2001-2012.

D.2 Estimating the cost of infrastructure in Kenya

In our model, costs and earnings are functions of a location's level of infrastructure, measured in standard deviations. We calculate the monetary cost of this measure based on the cost of road construction, for which better data are available than for the other dimensions of infrastructure we consider. First, we draw on the detailed estimates for

Table A15: Identification of model parameters

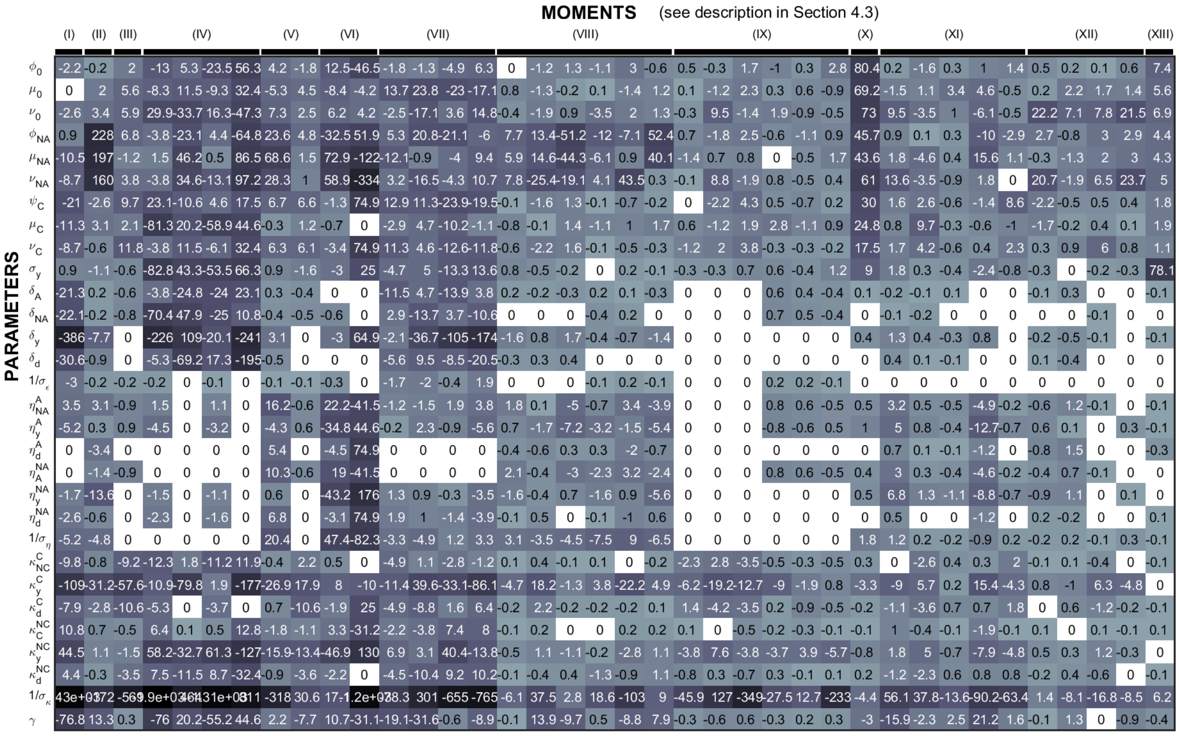
Parameters	Moments
γ, σ_m	Coefficients in columns (2) and (3) of table 2
σ_s	Effect of hot_{it} on household being active in non-agricultural occupations
σ_a	Effect of hot_{it} on household owning camels
$\delta^m(d_{l_i}, y_{it-1}, s_{it-1})$	Shares of households sending a migrant; coefficients from a regression of an indicator $\mathbb{1}[m_{it} = 1]$ for sending a migrant on HSNP treatment status, the level of local infrastructure d_{l_i}, and indicators $\mathbb{1}[s_{it-1} = A]$ and $\mathbb{1}[s_{it-1} = N]$
$\eta^s(d_{l_i}, y_{it-1}, s_{it-1})$	Share with at least some members working in non-agricultural occupations; coefficients in column (5) of table 3; coefficients from two regressions of, respectively an indicator $\mathbb{1}[s_{it} = N]$ for switching to non-agriculture among households with $s_{it-1} = A$ and an indicator $\mathbb{1}[s_{it} = A]$ for switching to agriculture among households with $s_{it-1} = N$, each on HSNP treatment status, d_{l_i}, and a constant
$\kappa^a(d_{l_i}, y_{it-1}, a_{it-1})$	Share owning camels among their livestock; coefficients from two regressions of, respectively, an indicator $\mathbb{1}[a_{it} = C]$ for switching to camels among households with $a_{it-1} = O$ and an indicator $\mathbb{1}[a_{it} = NC]$ for switching to exclusively other livestock among households with $a_{it-1} = C$, each on HSNP treatment status, d_{l_i}, and a constant
ϕ_s, ψ_a, μ_s, μ_a	Mean log per capita expenditure; coefficients from a fixed effects regression of log per capita expenditure on sector, livestock type, as well as on hot_{it}, interacted with both sector and livestock type
ν_s, ν_a	Coefficients from regressions of log per capita expenditure on local infrastructure, separately for households in agriculture, non-agriculture, and households with and without camels among their livestock
σ_y^2	Variance of per capita consumption expenditure

Notes: Table lists which estimation moments contribute most directly to identification of different model parameters. Not that all moments contribute to the joint estimation of parameters under the model.

country specific road construction costs provided by the World Bank's Road Costs Knowledge System (ROCKS) Database.[20] The median cost for a two-lane bituminous road in Kenya in the listed projects is 419,381 USD per kilometer. The total area of the districts Mandera, Marsabit, Turkana and Wajir extends over 222,847 square kilometers, so that an additional kilometer of road network raises road density by $1/222,847 = 4.487 \cdot 10^{-6}$ kilometers of road per square kilometer. Conditional on the other dimensions of infrastructure we consider (electricity access, GSM coverage, presence of education and health

[20] See `https://collaboration.worldbank.org/content/sites/collaboration-for-development/en/groups/world-bank-road-software-tools.html`, last accessed 25 July 2023.

Figure A9: Gradient matrix of moments with respect to parameters.



Notes: Figure visualizes the responsiveness of targeted moments (here measured in standard deviations) with respect to the model's structural parameters. Darker shading indicates stronger absolute dependence of moments with respect to parameters. Moments are: (I) share of households sending a migrant; (II) share active in non-agricultural occupations; (III) share owning camels among their livestock; (IV) coefficients from columns (2) and (3) of table 2; (V) effects of hot_{it} on household being active in non-agricultural occupations and on household owning camels; (VI) coefficients from column (5) of table 3; (VII) coefficients from a regression of an indicator $\mathbb{1}[m_{it} = 1]$ for sending a migrant on HSNP treatment status, d_{l_i}, and indicators $\mathbb{1}[s_{it-1} = A]$ and $\mathbb{1}[s_{it-1} = N]$; (VIII) coefficients from two regressions of, respectively an indicator $\mathbb{1}[s_{it} = N]$ for switching to non-agriculture among households with $s_{it-1} = A$ and an indicator $\mathbb{1}[s_{it} = A]$ for switching to agriculture among households with $s_{it-1} = N$, each on HSNP treatment status, d_{l_i}, and a constant; (IX) coefficients from two regressions of, respectively, an indicator $\mathbb{1}[a_{it} = C]$ for switching to camels among households with $a_{it-1} = O$ and an indicator $\mathbb{1}[a_{it} = NC]$ for switching to exclusively other livestock among households with $a_{it-1} = C$, each on HSNP treatment status, d_{l_i}, and a constant; (X) mean log per capita expenditure; (XI) coefficients from a fixed effects regression of log per capita expenditure on sector, livestock type, as well as on hot_{it}, interacted with both sector and livestock type; (XII) coefficients from regressions of log per capita expenditure on local infrastructure, separately for households agriculture, non-agriculture, and households with and without camels among their livestock; (XIII) variance of log per capita expenditure conditional on year and location effects. See also text of Section 4.3.

facilities), one standard deviation of additional road density ($3.791 \cdot 10^{-3}$ kilometers of road per square kilometer) raises our standardized measure for infrastructure on average by 0.258 standard deviations. One additional kilometer of road constructed in the districts Mandera, Marsabit, Turkana and Wajir thus raises our infrastructure as measured

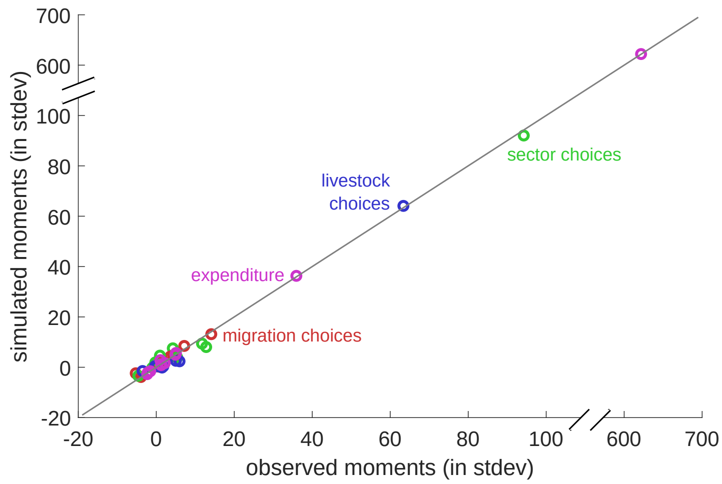
Table A16: Estimation moments

Moment group	Data moment	Standard error	Model moment	Moment group	Data moment	Standard error	Model moment
(I)	0.040	(0.003)	0.037	(IX)	0.006	(0.046)	0.018
(II)	0.554	(0.006)	0.541		−0.049	(0.014)	−0.021
(III)	0.359	(0.006)	0.363		0.184	(0.037)	0.094
(IV)	0.051	(0.007)	0.060		−0.016	(0.052)	0.025
	−0.035	(0.009)	−0.034		0.078	(0.053)	−0.006
	0.045	(0.010)	0.045		0.203	(0.034)	0.081
	−0.040	(0.008)	−0.017	(X)	6.057	(0.010)	6.060
(V)	0.109	(0.026)	0.194	(XI)	0.092	(0.088)	0.250
	0.044	(0.025)	0.008		0.190	(0.087)	0.144
(VI)	−0.009	(0.037)	0.073		−0.341	(0.221)	−0.349
	0.224	(0.019)	0.176		−0.106	(0.048)	−0.104
(VII)	0.006	(0.008)	0.001		−0.210	(0.090)	−0.246
	0.019	(0.004)	0.018	(XII)	0.200	(0.040)	0.224
	0.005	(0.007)	0.013		0.133	(0.106)	0.090
	0.024	(0.007)	0.028		0.159	(0.121)	0.142
(VIII)	−0.065	(0.097)	0.031		0.202	(0.041)	0.205
	−0.127	(0.027)	−0.093	(XIII)	0.430	(0.012)	0.435
	0.654	(0.051)	0.410				
	−0.063	(0.061)	−0.015				
	0.047	(0.050)	0.228				
	0.285	(0.053)	0.208				

Notes: Moments targeted in the estimation of the model detailed in Section 4.2. The first and the fifth column indicate the group of moments (see also text of Section 4.3): (I) share of households sending a migrant; (II) share active in non-agricultural occupations; (III) share owning camels among their livestock; (IV) coefficients from columns (2) and (3) of table 2; (V) effects of hot_{it} on household being active in non-agricultural occupations and on household owning camels; (VI) coefficients from column (5) of table 3; (VII) coefficients from a regression of an indicator $\mathbb{1}[m_{it} = 1]$ for sending a migrant on HSNP treatment status, d_{l_i}, and indicators $\mathbb{1}[s_{it-1} = A]$ and $\mathbb{1}[s_{it-1} = N]$; (VIII) coefficients from two regressions of, respectively an indicator $\mathbb{1}[s_{it} = N]$ for switching to non-agriculture among households with $s_{it-1} = A$ and an indicator $\mathbb{1}[s_{it} = A]$ for switching to agriculture among households with $s_{it-1} = N$, each on HSNP treatment status, d_{l_i}, and a constant; (IX) coefficients from two regressions of, respectively, an indicator $\mathbb{1}[a_{it} = C]$ for switching to camels among households with $a_{it-1} = O$ and an indicator $\mathbb{1}[a_{it} = NC]$ for switching to exclusively other livestock among households with $a_{it-1} = C$, each on HSNP treatment status, d_{l_i}, and a constant; (X) mean log per capita expenditure; (XI) coefficients from a fixed effects regression of log per capita expenditure on sector, livestock type, as well as on hot_{it}, interacted with both sector and livestock type; (XII) coefficients from regressions of log per capita expenditure on local infrastructure, separately for households agriculture, non-agriculture, and households with and without camels among their livestock; (XIII) variance of log per capita expenditure conditional on year and location effects. Columns respectively list the empirical moments, their standard error, and the corresponding model predictions.

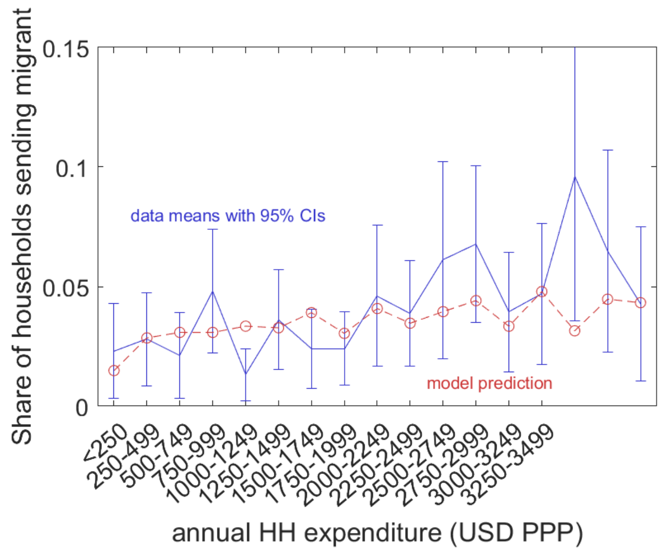
in our model by $4.487 \cdot 10^{-6} \cdot 3.791 \cdot 10^{-3} \cdot 0.258 = 3.060 \cdot 10^{-4}$ standard deviations. Correspondingly, 50 million USD spent on road construction in these northern Kenyan districts raises infrastructure by $50,000,000/419,381 \cdot 3.060 \cdot 10^{-4} = 0.037$ standard deviations. Multiplying this by 20, the World Bank's estimated expected years of life span for roads in Africa, yields an effect on infrastructure of 0.74 standard deviations. If paid out as unconditional cash transfers, the same 50 million USD would imply a transfer of 64.20

Figure A10: Model fit



Notes: Figure plots moments simulated from the model against the same moments observed in the data, each in standard deviations of the empirical moments. See table A16 for a list.

Figure A11: Fit to non-targeted moments



Notes: Figure compares migration rates predicted by the model (red dashed lines) to those observed in the data (in blue, with 95% confidence intervals), each by income groups. Source: HSNP evaluation data 2010-2012.

USD PPP per adult equivalent in these districts.

Table A17: Structural parameter estimates

(1)			(2)		
Earnings and preferences			Cost parameters		
Earnings parameters:			Migration cost:		
Baseline effects:			δ_A	1.396	(0.294)
ϕ_0	5.971	(0.083)	δ_{NA}	1.144	(0.268)
μ_0	-0.426	(0.100)	$\delta_y \times 100$	-0.106	(0.024)
ν_0	0.179	(0.030)	δ_d	-0.005	(0.107)
Effects of non-agri:			Sector transition cost:		
ϕ_{NA}	-0.187	(0.033)	η^A_{NA}	0.642	(0.317)
μ_{NA}	0.170	(0.037)	$\eta^A_y \times 100$	-0.042	(0.092)
ν_{NA}	0.083	(0.030)	η^A_d	-0.001	(0.290)
Effects of camels:			η^{NA}_A	0.166	(0.462)
ψ_C	-0.228	(0.090)	$\eta^{NA}_y \times 100$	-0.003	(0.096)
μ_C	0.240	(0.093)	η^{NA}_d	-0.695	(0.270)
ν_C	-0.024	(0.077)	Livestock trans. cost:		
Log earnings variance:			κ^C_{NC}	5.234	(0.185)
σ_y	0.8763	(0.015)	$\kappa^C_y \times 100$	-0.007	(0.020)
Preference parameters:			κ^C_d	0.206	(0.132)
γ	0.6063	(0.073)	κ^{NC}_C	7.261	(0.472)
$1/\sigma_\epsilon$	3.8422	(1.078)	$\kappa^{NC}_y \times 100$	-0.391	(0.054)
$1/\sigma_\eta$	0.5466	(0.101)	κ^{NC}_d	0.156	(0.264)
$1/\sigma_\kappa$	0.0124	(0.002)			

Notes: Structural parameters of the model detailed in Section 4.2. Coefficients δ_y, η^A_y, η^{NA}_y, κ^C_y and κ^{NC}_y are scaled by 100, so that they indicate the change in log costs per 100 USD PPP in lagged earnings. Asymptotic standard errors in parentheses.