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Labor Adaptation to Climate Variability in Eastern Africa

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Contents

Tables

Figures

ABSTRACT

As countries design climate change adaptation policies, it is important to understand how workers alter behavior in response to changes in temperature. Nonetheless, the impact of temperature on labor markets is poorly documented, especially in Africa. We address this gap by analyzing panel surveys of labor choices by sector, contractual arrangement, and migration status in four East African countries. Merging survey information with high-resolution climate data, we assess how workers shift employment in response to temperature anomalies. Results suggest important distinctions between rural and urban areas. In urban areas, only agricultural self-employment and migration are responsive to temperature, with participation in both activities decreasing at high extremes. Urban out-migration is used as a tool to increase incomes in “good” years rather than an adaptation mechanism during bad years. In contrast, out-migration appears to be a means of adapting to high temperatures in rural areas, especially among households with relatively little agricultural land. The combined impact of these forces suggests that a 2 standard deviation increase in temperature results in a 7 percent increase in urban unemployment and no significant impact on rural unemployment.

Keywords: migration, labor, adaptation, climate, development, Africa

JEL Classification: J22, O13, O15, Q54, Q56

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1. INTRODUCTION

Despite international efforts to curb greenhouse gas emissions, in coming decades Africa is likely to experience warming in excess of two standard deviations above the mean (IPCC 2013; Niang et al. 2014). Heat stress adversely impacts plant growth (Schlenker, Hanemann, and Fisher 2006; Seo et al. 2009; Hsiang 2010; Lobell, Schlenker, and Costa-Roberts 2011; Lobell, Sibley, and Ortiz-Monasterio 2012), and may affect productivity in other sectors as well (Dell, Jones, and Olken 2012; Burke, Hsiang, and Miguel 2015). Adaptation is a key component of the United Nations Framework Convention on Climate Change agreements and development assistance. Yet, how workers in developing countries can adapt is poorly understood, especially in Africa.

We address this knowledge gap by conducting a cross-country analysis of labor adaptation using panel surveys in four African countries. Workers can adapt to weather anomalies through sectoral reallocation (Kochar 1999; Rose 2001; Dimova et al. 2015; Mathenge and Tschirley 2015), migration (Barrios, Bertinelli, and Strobl 2006; Halliday 2006; Dillon, Mueller, and Salau 2011; Gray and Mueller 2012a,b; Marchiori, Maystadt, and Schumacher 2012; Gray and Bilsborrow 2013; Mueller, Gray, and Kosec 2014; Henderson, Storeygard, and Deichmann 2015), or human capital investment (Graff-Zivin, Hsiang, and Neidell 2015). Worker endowments affect ability to adapt. For example, liquidity constraints (Bryan, Chowdhury, and Mobarak 2014; Kleemans 2014), language barriers, and a lack of transferable skills can dampen the returns on migration (Chiswick and Miller 2003). Moreover, the existence of labor markets segmented by location (such as urban manufacturing jobs) or gender (such as domestic or security work) suggest that adaptation may vary by worker location and sex.

Our study is the first to analyze how workers adapt their behavior to temperature anomalies using individual panel microdata on participation in agricultural and nonagricultural wage and self-employment sectors, schooling, and migration in multiple African countries. We use high-resolution temperature data to extend previous findings on climate change and adaptation in the literature (Schlenker, Hanemann, and Fisher 2006; Seo et al. 2009; Hsiang 2010; Lobell, Schlenker, and Costa-Roberts 2011; Gray and Mueller 2012a; Mueller, Gray, and Kosec 2014; Burke and Emerick 2015). We further consider nonlinear relationships between climate and worker behavior (Burke, Hsiang, and Miguel 2015; Henderson, Storeygard, and Deichmann 2015). Previous macroeconomic research utilizes urbanization as a migration proxy (Barrios, Bertinelli, and Strobl 2006; Poelhekke 2011; Henderson, Storeygard, and Deichmann 2015), we instead explicitly measure the impact of temperature on migration in both rural and urban areas.

We find that temperature anomalies contribute to economic stress in urban areas. As temperatures rise, overall urban out-migration declines, while rural out-migration increases, but only for households with low assets. At the same time, fewer urban workers engage in agricultural self-employment. These findings indicate potential climate vulnerability in urban populations and are consistent with evidence in the geography literature that urban out-migration to rural areas occurs in years with favorable agronomic conditions (Potts 1995; Tacoli 2001; Potts 2013). Under a temperature increase of 2 standard deviations, the combined impact of reduced migration and reduced agricultural self-employment leads to a 7 percent increase in urban unemployment.[1] Climate change will thus likely affect broader development goals (Barrett and Constas 2015) in urban areas, requiring concerted international effort to invest in programs that promote economic growth and facilitate worker adaptation.

In what follows, we first present a theoretical model formalizing the household decision to maximize utility by allocating each member's participation in a number of activities (Section 2). We use this model as the basis for the specification and interpretation of the labor participation regressions in Section 3. Section 4 details the construction of labor and temperature anomaly variables. Section 5 presents the results, and Section 6 concludes.

[1]The IPCC's fifth assessment report projects temperature increases above two standard deviations for most of Africa (IPCC 2013).

2. THEORETICAL MODEL

Households choose how to allocate each member's time to maximize expected utility in period t. There are J households, indexed $j = 1,2,...,J$. Each household has I_j individuals, indexed $i = 1,2,...,I_j$. Apart from leisure, each individual allocates time among K income generating activities, $k = 1,2,...,K$. Let $\mathbf{y}_{ijt} \in R_+^K$ denote income-generated from each of these activities in a given period.[2] Let H denote the time constraint faced by all individuals. The vector $\mathbf{h}_{ijt} \in R_+^K$ denotes the allocation of time for individual i in household j across each income generating activity. Leisure, s, is time left over after engaging in income-generating activity: $s_{ijt} = H - \sum_{k=1}^{K} h_{ijkt}$, with $\mathbf{s}_{jt} \in R_+^{I_j}$ denoting the leisure hours for each member of household j at time t.

Let the twice-differentiable function y_k denote returns on labor in activity k. Marginal returns on labor for each activity are nonnegative and nonincreasing: $\partial y_k \partial h_k \geq 0$ and $\partial^2 y_k \partial h_k^2 \leq 0$. We further assume income from one activity is independent of time spent on other activities in any period. Income from each source is also a function of M individual characteristics: $\mathbf{x}_{ijt} = (x_{ijt1},...,x_{ijtM})'$.[3]

The location dummy serves as a proxy for unobserved climate-dependent differences in returns on labor. Suppose, for example, that rural labor markets are dominated by agriculture and urban labor markets are dominated by nonagricultural sectors. Additionally, consider a year with favorable growing conditions in all locations to increase the returns on labor in agriculture in both rural and urban areas. Due to the larger amount of agricultural land relative to labor in rural areas, however, one might expect the returns to migration from urban to rural to increase, and the returns on migration from rural to urban to decrease.

Household wealth may also affect returns on a given activity. If credit markets are imperfect, lack of household assets may create a barrier to entry into self-employed activities if they require an initial fixed investment. In such cases, we would expect the returns on self-employment to be higher for individuals in wealthier households, reducing the relative attractiveness of other activities such as migration.

Let Y_{ijt} denote the income for individual i in household j in period t:

$$Y_{ijt}(\mathbf{h}_{ijt};\mathbf{x}_{ijt}) = \sum_{k=1}^{K} y_{ijkt}(h_{ijkt};\mathbf{x}_{ijt}). \tag{1}$$

Assuming that money generates the same level of utility regardless of source, the household utility maximization problem can be broken into two stages. In stage one, conditional on a vector of individual leisure time, $\mathbf{s}_{jt}$, the household chooses how to allocate each individual's remaining time to maximize household income, π_{jt}:

$$\pi_{jt}(\mathbf{s}_{jt}) \quad = \quad \max_{\mathbf{h}_{1jt},...,\mathbf{h}_{I_j} \geq \mathbf{0}} \left\{ \sum_{i=1}^{I_j} Y_{ijt}(\mathbf{h}_{ijt};\mathbf{x}_{ijt}) : \sum_{k=1}^{K} h_{ijkt} = H - s_{ijt} \text{ for all } i,j,t \right\}. \tag{2}$$

Let λ_{ijt} denote the Lagrange multiplier for the constraint that the labor/leisure combination not exceed available hours. The Kuhn-Tucker conditions are, for all i, j, and t,

[2]For our application, K = 6 activities: agricultural self-employment, nonagricultural self-employment, migrant income, agricultural wage employment, nonagricultural wage employment, and school. Although school does not generate current income, we model its return as the expected present value of additional future income.

[3]For our application M = 5 characteristics: gender, a rural dummy, household wealth (proxied by landholding), and local temperature and rainfall shocks. The last four are common to members of a household.

$$
\begin{aligned}
\frac{\partial y_{ijkt}}{\partial h_{ijkt}} - \lambda_{ijt} &\leq 0 \text{ for all } k; && (3) \\
h_{ijkt}\left[\frac{\partial y_{ijkt}}{\partial h_{ijkt}} - \lambda_{ijt}\right] &= 0 \text{ for all } k, && (4) \\
\lambda_{ijt}\left[H - s_{ijt} - \sum_{k=1}^{K} h_k\right] &= 0, && (5) \\
\lambda_{ijt} &\geq 0. && (6)
\end{aligned}
$$

At the optimum, the λ_{ijt} are equal to the shadow value of an additional hour H. Assuming π_{jt} is differentiable and concave in $\mathbf{s}$, the envelope theorem implies

$$
\begin{aligned}
\frac{\partial \pi_{jt}}{\partial s_{ijt}} - \lambda_{ijt} &\leq 0 \text{ for all } i, j, t && (7) \\
and s_{ijt}\left[\frac{\partial \pi_{jt}}{\partial s_{ijt}} - \lambda_{ijt}\right] &= 0 \text{ for all } i, j, t; && (8) \\
\text{with } s_{ijt} &\geq 0 \text{ for all } k. && (9)
\end{aligned}
$$

Together, these equations indicate that at the optimum, the marginal return on each activity equals the shadow value of time. As a corollary, holding leisure constant, a change in a factor x that affects productivity can have nonmonotonic impact on hours spent in an activity, even if the impact on productivity is monotonic.

This result is most easily seen for the case in which $k = 2$. Suppressing subscripts i, j, and t, for an interior solution for both activities, $h_2 = H - s - h_1$ and equation (3) simplifies to

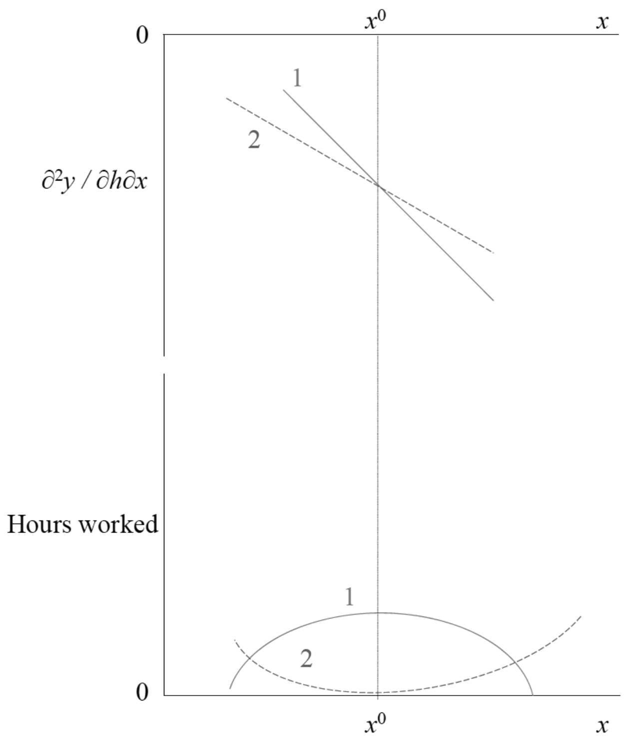
$$
\frac{\partial y_1}{\partial h_1} - \frac{\partial y_2}{\partial h_2} = 0. \tag{10}
$$

Differentiating with respect to hours spent in activity 1 and an environmental variable x (for example, temperature) yields

$$
\frac{\mathrm{d}h_1}{\mathrm{d}x} = -\frac{\frac{\partial[\partial y_1 \partial h_1]}{\partial x} - \frac{\partial[\partial y_2 \partial h_2]}{\partial x}}{\frac{\partial[\partial y_1 \partial h_1]}{\partial h_1} - \frac{\partial[\partial y_2 \partial h_2]}{\partial h_2}\frac{\partial h_2}{\partial h_1}}. \tag{11}
$$

The denominator of the right-hand side of this expression is negative due to the concavity assumption on y. Thus the impact of a change in temperature on hours spent in activity 1 depends on the relative magnitude of its impact on the marginal product of labor in each activity. Suppose, as illustrated in Figure 2.1, temperature adversely affects the marginal return on labor for both activities, but at different rates, such that $\partial^2 y_1 \partial h_1 \partial x, \partial y_2 \partial h_2 \partial x < 0$ and $\partial^3 y_2 \partial h_2 [\partial x]^2 > \partial^3 y_1 \partial h_1 [\partial x]^2$. The upper panel illustrates a case in which the two curves depicting the change in marginal return with respect to temperature cross; marginal returns are decreasing in temperature for each activity, but at a faster rate for activity 1. As shown in the lower panel, the hours observed in each activity would be non-monotonic functions of temperature. Increases in temperature lead to an increase in activity 1 and a decrease in activity 2 only until x^0, after which time spent in activity 2 increases and time spent in activity 1 decreases.

Figure 2.1 Labor supply response to temperature



Source: Authors.

In the second stage of the labor allocation problem, the household chooses the amount of leisure for each individual to maximize overall utility, u,

$$V(H)_{jt} = \max_{s_{ijt} \leq H} \left\{ u_{jt}(\mathbf{s}_{jt}, \pi_{jt}(\mathbf{s}_{jt})) \right\}. \tag{12}$$

We assume $u(\cdot)$ to be differentiable with $\partial u \partial s, \partial u \partial \pi > 0$ and $\partial^2 u [\partial s]^2, \partial^2 u [\partial \pi]^2, \partial^2 u \partial s \partial \pi < 0$. Letting μ denote the Lagrange multiplier for the constraint that leisure be no greater than total available time, H, the Kuhn-Tucker conditions for a solution to equation (12) are, for all i, j, and t,

$$\frac{\partial \pi_{jt}}{\partial s_{ijt}} + \frac{\frac{\partial u_{jt}}{\partial s_{ijt}}}{\frac{\partial u_{jt}}{\partial \pi_{jt}}} + \mu_{ijt} \geq 0; \tag{13}$$

$$s_{ijt} \left[\frac{\partial \pi_{jt}}{\partial s_{ijt}} + \frac{\frac{\partial u_{jt}}{\partial s_{ijt}}}{\frac{\partial u_{jt}}{\partial \pi_{jt}}} + \mu_{ijt} \right] = 0; \tag{14}$$

$$\mu_{ijt} [H - s_{ijt}] = 0; \tag{15}$$

$$\mu_{ijt} \geq 0; \tag{16}$$

$$s_{ijt} \geq 0. \tag{17}$$

Let h^*_{ijkt} denote the time allocations that solve the above system of equations. A climate variable x impacts household labor allocation not only through its impact on relative marginal returns but also in the allocation of leisure time across individuals. For an interior solution in which all members have leisure between 0 and H, differentiation of equation (13) yields

$$\frac{\mathrm{d}s_{ijt}}{\mathrm{d}x} = -\frac{\frac{\partial\left[\partial\pi_{jt}\partial s_{ijt}\right]}{\partial x_{jt}} + \frac{\partial\left[\partial u_{jt}/\partial s_{ijt}\partial u_{jt}/\partial\pi_{jt}\right]}{\partial x_{jt}}}{\frac{\partial\left[\pi_{jt}\partial s_{ijt}\right]}{\partial s_{ijt}} + \frac{\partial\left[\partial u_{jt}/\partial s_{ijt}\partial u_{jt}/\partial\pi_{jt}\right]}{\partial s_{ijt}}}. \tag{18}$$

The denominator is less than 0 due to the concavity assumption on u. From equation (7), the loss in income resulting from an additional hour of leisure to individual i is equal to the shadow value of time, which in turn depends on the impact of x on the marginal product of each activity:

$$\frac{\partial\left[\partial\pi_{jt}\partial s_{ijt}\right]}{\partial x_{jt}} < 0 \iff \frac{\partial\lambda}{\partial x_{jt}} > 0. \tag{19}$$

The second term in the numerator represents the change in the marginal rate of substitution between leisure and income arising from a change in x. Assuming that x has no amenity value (that is, it affects the marginal utility of leisure not directly, but only through its effect on income), we can rewrite this expression

$$\frac{\partial\left[\frac{\partial u_{jt}\partial s_{ijt}}{\partial u_{jt}\partial\pi_{jt}}\right]}{\partial x_{jt}} = \frac{\frac{\partial\pi_{jt}}{\partial x_{jt}}\left[\frac{\partial\left[\partial u_{jt}\partial s_{ijt}\right]}{\partial\pi_{jt}}\frac{\partial u_{jt}}{\partial\pi_{jt}} - \frac{\partial\left[\partial u_{jt}\partial\pi_{jt}\right]}{\partial\pi_{jt}}\frac{\partial u_{jt}}{\partial s_{ijt}}\right]}{\left[\partial u_{jt}\partial\pi_{jt}\right]^2} > 0 \text{ iff } \frac{\partial\pi_{jt}}{\partial x_{jt}} > 0. \tag{20}$$

Suppose an increase in temperature increases household income ($\partial\pi_{jt}\partial x_{jt} > 0$) without increasing individual i's marginal return on labor ($\partial\lambda\partial x \leq 0$). This situation may occur if temperature increases average productivity without affecting marginal productivity, or if it increases marginal productivity for an activity in which i does not participate. In such a case, the household's value for leisure increases (since it has more income), and the marginal income generated by work does not increase. Thus, by (19) and (20) individual i's leisure time does not decrease.

Conversely, if an increase in temperature reduces household income and increases i's marginal return on labor, her leisure time will not increase. Otherwise, the impact of a change in x on household income is ambiguous and possibly nonlinear. As suggested by Schlenker, Hanemann, and Fisher (2006), Burke, Hsiang, and Miguel (2015) and others, an increase in temperature from a low base may have beneficial impacts on both agricultural and industrial productivity, whereas the same change from a high base may have an adverse impact.

Taken together, these results suggest that the impact of temperature on labor market participation is likely to be nonlinear through at least two channels. If climate has nonlinear impacts on household income, those effects will transmit to individual labor market participation rates via the household leisure allocation problem. Second, even if the impact on marginal productivity is linear, allocation of time across activities may be nonlinear if the impact of climate variables on marginal productivity differs by activity. In the next section, we discuss how we apply this theoretical model to the data to provide a foundation for our empirical analysis.

3. EMPIRICAL MODEL

We focus on individual participation in each activity because hours worked were not collected at the individual level for each activity across countries. The conceptual framework introduced in the previous section allows us to infer the impact of climate on each income-generating activity through its effect on agents' choices of activities. We direct our attention to corner solutions in which an individual does not engage in a particular activity. It is optimal to allocate a strictly positive amount of individual i's time to activity k, only if the marginal income for that activity equals the marginal rate of substitution between household income and leisure for that individual. From equations (3), (7), and (13),

$$h^*_{ijkt} > 0 \iff \frac{\partial y_{ijkt}}{\partial h_{ijkt}} = \frac{\frac{\partial u_{jt}}{\partial s_{ijt}}}{\frac{\partial u_{jt}}{\partial \pi_{jt}}}. \tag{21}$$

Corner solutions in which an individual allocates no time to activity k arise if the marginal income from that activity is less than the marginal rate of substitution evaluated at $h_{ijkt} = 0$,

$$h^*_{ijkt} = 0 \iff \frac{\partial y_{ijkt}}{\partial h_{ijkt}} < \frac{\frac{\partial u_{jt}}{\partial s_{ijt}}}{\frac{\partial u_{jt}}{\partial \pi_{jt}}}. \tag{22}$$

If random error enters equations (21) and (22), the probability that an agent engages in activity k can be expressed as

$$\begin{aligned} 1 - \Pr[h_{ijkt} = 0] &= 1 - \Pr\left[\frac{\partial y_{ijkt}}{\partial h_{ijkt}} - \frac{\frac{\partial u_{jt}}{\partial s_{ijt}}}{\frac{\partial u_{jt}}{\partial \pi_{jt}}} < 0\right] && (23) \\ &= L_k(\mathbf{x}_{ijt}). && (24) \end{aligned}$$

Our empirical approach approximates equation (24) with a linear probability model for each activity.

We let the indicator variable, L_{ijkt}, take a value of 1 if an individual i in household j engages in labor activity k at any point in year t. Using a linear approximation, we estimate the probability model described in equation (24):

$$\begin{aligned} L_k(\mathbf{x}_{ijt}) &\approx \sum_{m=1}^{M} \beta_m x_{ij\ell t} + \sum_{m=M-1}^{M} \beta_{mm} x^2_{ijmt} + \beta_{M-1,M} x_{ijM-1t} x_{ijMt}; && (25) \\ L_{ijkt} &= \sum_{m=1}^{M} \beta_m x_{ijmt} + \sum_{m=M-1}^{M} \beta_{mm} x^2_{ijmt} + \beta_{M-1,M} x_{ijM-1t} x_{ijMt} + \varepsilon_{ijkt}. && (26) \end{aligned}$$

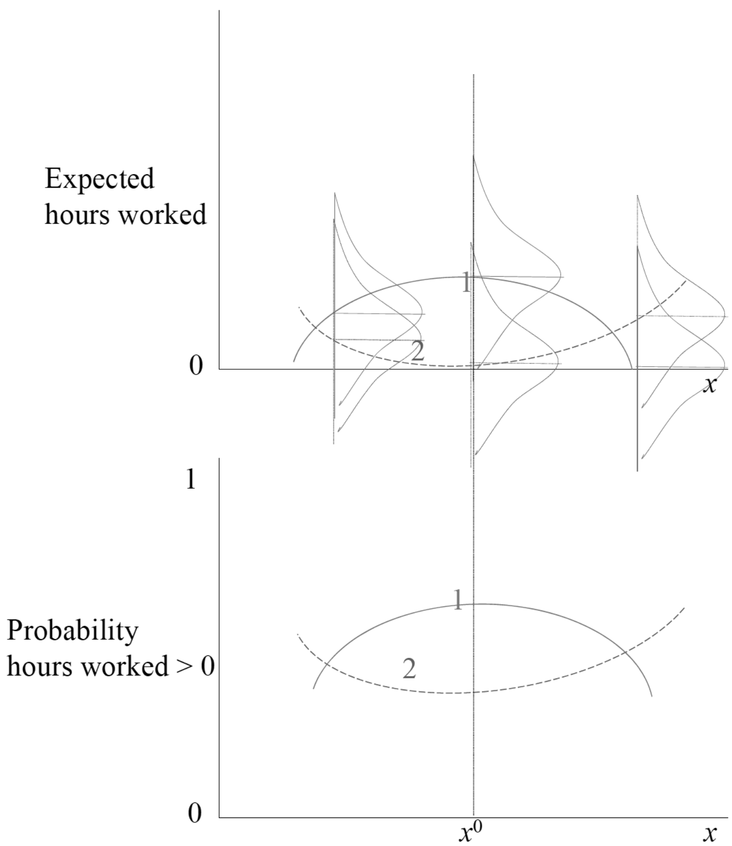
Here, M and $M-1$ are the indexes for the two climate variables, temperature and rainfall.[4] We include quadratic terms in these variables to allow for the possible nonlinear relationship between climate and labor decisions described in Section 2.

Section 2 framed the discussion largely in terms of hours worked in a deterministic framework. It is straightforward to extend these results to an analysis of corner solutions in the presence of random error. The top panel of Figure 3.1 adds statistical noise to the lower panel of Figure 2.1, reframing hours worked

[4]Although we focus on temperature, we condition estimates on rainfall, its interaction with temperature, and rainfall squareed due to their correlation with temperature (Auffhammer et al. 2013).

as expected hours worked, conditional on temperature (and other observables). The dashed bell-shaped curves reflect the probability distribution of realized hours worked in each activity across the sample of survey respondents for a given temperature. The horizontal distance from the dashed curve to its base represents the probability density of workers who allocate the indicated number of hours to a given activity at the indicated temperature. The highest point on the probability distribution curve corresponds to the expected hours worked at that temperature. The area between the distribution curve and its base, above the horizontal axis, represents the probability that a randomly selected individual dedicates a positive amount of time to an activity at a given temperature. This probability is depicted as a function of temperature in the lower panel. As shown, the nonlinearity in expected hours worked as a function of temperature translates to a nonlinearity in the probability of working at all. It is this latter relationship that we model in equation (26).

Figure 3.1 Labor participation response to temperature



Source: Authors.

We first estimate this model with a fixed-effects error structure. Focusing on the sample of workers 15–65 years old, we include individual γ and region-specific time τ fixed effects in each regression to reduce the potential influence of confounding factors on our parameters of interest; $\gamma_{ij} + \tau_t + \eta_{ijkt} = \varepsilon_{ijkt}$. Suppressing the i, j, and t subscripts, we estimate parameters of equation (26) with the following regressions for each activity k:

$$L_k = \beta_0 + \sum_{m=M-1}^{M} \left[\beta_m x_m + \beta_{mm} x_m^2\right] + \beta_{M-1,M} x_{M-1} x_M + \gamma + \tau + \eta_k. \quad (27)$$

Weather shocks are represented by the z-scores of the current outcomes relative to the historical distribution. Given our interest in adaptation to warming, our discussion emphasizes parameter estimates for the temperature variables while controlling for rainfall. Standard errors are clustered at the baseline enumeration area level. All regressions are weighted by inverse probability weights accounting for attrition and the sampling scheme (see Section 4).

Our main specifications use pooled samples from the four countries, differentiating effects by worker location (rural, urban). To explore how individual and household characteristics affect marginal weather impacts, we stratify the sample by gender and small or large household asset wealth as proxied by landholdings.[5]

[5] Rural-urban classifications are taken from the baseline surveys. A binary household landownership variable is created to reflect whether the household's landholdings are below or above the country's median household landholdings. The median acreage values are 1.41 for Ethiopia, 0.87 for Malawi, 1.75 for Tanzania, and 2.06 for Uganda.

4. DATA

We use the following panel databases from the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) collected in four east African countries: Ethiopia (2011–2012, 2013–2014), Malawi (2010–2011, 2012–2013), Tanzania (2008–2009, 2010–2011, 2012–2013), and Uganda (2009–2011, 2010–2011,2011–2012). The number of panel households surveyed ranges from 3,200 in Uganda to 4,000 in Ethiopia. We use these data to construct variables describing individuals' occupation and migration outcomes over time, education, gender, baseline age, and household location and land. The final dataset consists of 55,277 person-years.

Surveys record whether an individual was engaged in one or more of the following activities at some time during the previous 12 months: agricultural self-employment, agricultural wage employment, nonagricultural self-employment, nonagricultural wage employment, and school.[6] We also construct a migration variable indicating whether the household member was away from the household for at least 1 of the previous 12 months.[7] Those who do not participate in any of the labor markets, migrate, or attend school are considered unemployed.

We merge the person-year database with secondary climate data derived from NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) using the survey interview date and global positioning system (GPS) coordinates of the household's location at baseline.[8] MERRA uses a reanalysis approach to integrate data from NASA's collection of Earth-observing satellites in a way consistent with physical models of the Earth system. This methodology produces subdaily data at a resolution of 0.50 latitude $\times$ 0.67 longitude covering the modern satellite era (Rienecker and et al. 2011). This dataset has the virtue that the observational network is equally dense around the globe. Previous work has shown that these data are able to predict migration patterns in Ethiopia, Bangladesh, and Pakistan (Gray and Mueller 2012a,b; Mueller, Gray, and Kosec 2014). We extract monthly values of mean daily rainfall and temperature for the years 2000 through 2014. To account for varying historical climates across the study locations and for lagged effects on employment outcomes, we take the mean of these monthly values over a 24-month period ending in month t, and use these values to derive z-scores characterizing deviations in climate relative to all other consecutive periods of 24 months in the dataset.[9] The z-scores are equivalent to the climate anomalies commonly used to measure climatic variation over time.[10]

Descriptive Statistics

Table 4.1 describes the population, aged 15–65 years old, engaged in each activity by location.[11] Overall, most individuals are self-employed in agriculture, although the proportion varies greatly between rural areas (85 percent) and urban areas (35 percent). Rural workers rely primarily on self-employed farming, with 8 and 7 percent participation in agricultural and nonagricultural wage markets, respectively. A greater

[6]Agricultural self-employment participation was recorded in seasonal on-farm labor and livestock modules. Agricultural annd nonagricultural wage employment participation was obtained from wage modules. Nonagricultural self-employment data were taken from nonfarm enterprise modules. Employment modules were available in every country and had the respondent reference employment over a 12-month recall period. The number of family members documented in the enterprise module varied by country. In Tanzania, all individuals engaged in the enterprise were documented in the first two waves, but a maximum of six workers per enterprise were identified in the last round. For the other countries, surveys reported identities of at most two owners per enterprise. Details regarding enterprise staff are restricted to at most five for hired labor in the Ethiopia survey, at most two for any type of worker in the Malawi survey, and at most five of any type of worker in Uganda. Despite evidence on the small size of enterprises (Fox and Sohnesen 2012), nonagricultural self-employment may be underreported, especially in Ethiopia and Malawi.

[7]One limitation of this migration variable is that it is likely inclusive of moves unrelated to employment, which we are unable to verify because the motivation for temporary migration was not asked.

[8]To ensure confidentiality, surveys introduce a location error of 2–5 km.

[9]We use 24-month rather than 12-month periods in order to include all events between panel rounds.

[10]We normalize climate variables based on the distribution of rainfall and temperature during the years 2000–2014 in order to capture a time period that would be behaviorally relevant to both young and old workers.

[11]All statistics use baseline sampling weights provided by the LSMS-ISA.

percentage (but still a small fraction) of rural workers are self-employed in the nonagricultural sector (15 percent) and sectors attracting temporary migrants (10 percent). In contrast, workers in urban settings appear much more specialized in nonagricultural wage employment (24 percent) and nonagricultural self-employment (24 percent). Even a slightly greater percentage of urban workers have migrated temporarily in the last 12 months (16 percent). These findings potentially suggest that the opportunities for diversification may be somewhat more limited in rural settings.

Table 4.1 Worker characteristics

Characteristics	Pooled	Urban	Rural
Wage: Agriculture	0.07	0.03	0.08
	(0.00)	(0.00)	(0.00)
Self-employed: Agriculture	0.78	0.35	0.85
	(0.01)	(0.02)	(0.01)
Wage: Nonagriculture	0.09	0.24	0.07
	(0.00)	(0.01)	(0.00)
Self-employed: Nonagriculture	0.16	0.24	0.15
	(0.00)	(0.01)	(0.01)
Migrated	0.11	0.16	0.10
	(0.00)	(0.01)	(0.00)
School	0.14	0.19	0.13
	(0.00)	(0.01)	(0.00)
Unemployed	0.07	0.18	0.05
	(0.00)	(0.01)	(0.00)
Rainfall (z-score)	-0.13	-0.26	-0.11
	(0.02)	(0.03)	(0.03)
Temperature (z-score)	0.39	0.60	0.35
	(0.03)	(0.03)	(0.03)
Large landowner	0.59	0.24	0.65
	(0.01)	(0.03)	(0.01)
Female	0.52	0.52	0.51
	(0.00)	(0.01)	(0.00)
Observations	55,277	14,073	41,204

Source: Authors' calculations.

Notes: Table includes means and enumeration-area clustered standard errors in parentheses. All activity variables refer to whether the individual engaged in the activity in the previous 12 months except school, which refers to current school year. Large landowner indicates whether individual belonged to a household with above median landownership in baseline year. Observations are person-years. Sampling weights applied to calculation of summary statistics.

We measure variations in household vulnerability to climate along two dimensions: location and asset wealth (household-owned landholdings). The majority of households live in rural areas.[12] Sixty-five percent of rural workers live in households with landholdings above their country's median, while only 24 percent of urban workers live in households with landholdings above their country's median. Our period of coverage is limited by the timing of the LSMS-ISA, which spans a six-year period. The statistics in Table 4.1 indicate that rainfall in this period was slightly below historical averages, with a z-scores of 0.26 and 0.11 below the mean in urban and rural areas, respectively. In addition to exposure to lower than average rainfall, all countries experienced relatively warm temperatures. Urban workers faced greater exposure to heat, with average temperature z-scores of 0.60, compared with average z-scores of 0.35 in rural areas.

Table 4.2 indicates that in both rural and urban areas, wage markets and school are dominated by men, whereas the majority of unemployed are women. The sharpest geographic distinction is in migration; in urban areas migration is equally split by gender, while only 40 percent of rural migrants are female.

[12] The Ethiopia sample excludes metropolitan areas, such as Addis Ababa, because the baseline sampling frame was representative of only rural areas and small towns (with a population of fewer than 10,000 people) in all regions except Afar and Somalie.

Table 4.2 Occupational characteristics

Characteristics	Agriculture Wage	Agriculture Self-employed	Nonagriculture Wage	Nonagriculture Self-employed	Migrated	School	Unemployed
Urban							
Female	0.47	0.56	0.32	0.54	0.50	0.46	0.65
	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Age	34.01	33.56	32.70	34.81	26.17	17.32	28.28
	(1.08)	(0.38)	(0.45)	(0.35)	(0.38)	(0.18)	(0.42)
Primary education	0.51	0.54	0.49	0.58	0.54	0.53	0.59
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Secondary education	0.08	0.12	0.34	0.19	0.27	0.17	0.13
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Observations	341	4,496	3,410	3,682	2,178	2,746	2,591
Rural							
Female	0.43	0.51	0.25	0.53	0.40	0.41	0.68
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Age	32.32	32.66	32.67	33.55	27.66	16.68	27.81
	(0.34)	(0.15)	(0.34)	(0.26)	(0.33)	(0.12)	(0.45)
Primary education	0.39	0.30	0.43	0.35	0.39	0.36	0.26
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Secondary education	0.02	0.02	0.20	0.05	0.07	0.04	0.03
	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
Observations	3,306	3,3265	3,348	6,854	4,061	6,072	2,908

Source: Authors' calculations.

Notes: Table includes means and enumeration-area clustered standard errors in parentheses. All activity variables refer to whether the individual engaged in the activity in the previous 12 months except school, which refers to current school year. Large landowner indicates whether individual belonged to a household with above median landownership in baseline year. Observations are person-years. Sampling weights applied to calculation of summary statistics.

Average age is similar across activities and locations, with the exceptions of migration, school, and unemployment. Respondents engaging in these three activities tend to be younger. This age profile is similar in both locations.

Urban areas draw relatively highly educated workers. Approximately one-third of nonagricultural wage workers and migrants in urban areas have completed a secondary education. These occupations in rural areas also attract highly educated labor, albeit at a more modest scale. Only 20 percent of nonagricultural wage workers and 7 percent of migrants in rural areas have completed their secondary education.

Finally, the unemployed (excluding those who attend school) bear differential skills in rural and urban locations. This group of workers lacks experience irrespective of location because they tend to be younger than workers participating in most other labor markets. However, the urban unemployed possess qualifications akin to those of farmers, with a slightly greater percentage having completed a primary education. In contrast, the rural unemployed tend to be less educated than farmers, with 13 percent fewer having completed their primary education.

Attrition

We focus on the sample of baseline households that completed surveys in each subsequent wave. Individuals in a household are omitted from the sample if the household moved out of its original residence or if the household questionnaire was incomplete in follow-up rounds. Within households that remained in the sample, individuals who left the survey in later rounds are also dropped from the main sample. This allows us to stratify the sample into groups of nonattritors and attritors (households and individuals surveyed at baseline who are unidentifiable in later rounds). Approximately 15 percent of individuals who were in the 15–65 age category at baseline were unable to be tracked over time.

For each country, we estimate probit models to determine which factors influence the probability that baseline individuals stay in the sample in later waves. The baseline covariates in the regressions include individual gender and age, and the natural logarithms of the number of children, adults, and household land owned. We further include the attrition rate of the enumeration area (EA)[13] and indicators that represent the interviewers' identities in the follow-up rounds to reflect the role of field practices on survey quality (Maluccio 2004; Thomas et al. 2012).

Table 4.3 displays results from individual probit regressions. Youth are less likely to appear in Uganda and more likely to appear in Ethiopia. Households with more children and more land may be over-represented in Tanzania and Malawi, respectively. The EA attrition rate (Ethiopia and Malawi only) and interviewer indicators are strongly correlated with remaining in the sample. The latter is determined by the Chi-squared tests of joint parameter significance presented at the bottom of Table 4.3, where the P-values are all below 0.10.

Table 4.3 Determinates of remaining in sample

Variable	Ethiopia	Malawi	Tanzania	Uganda
Female	-0.063	0.008	-0.062	-0.004
	(0.046)	(0.086)	(0.039)	(0.036)
Age 20–29	0.368***	-0.121	0.055	-0.112*
	(0.082)	(0.110)	(0.066)	(0.060)
Age 30–39	0.719***	-0.004	0.133*	0.258***
	(0.118)	(0.135)	(0.072)	(0.057)
Age 40–49	0.864***	0.193	0.333***	0.427***
	(0.121)	(0.167)	(0.080)	(0.062)
Age 50–59	0.790***	-0.116	0.245***	0.649***
	(0.136)	(0.248)	(0.094)	(0.074)
Age 60–65	0.762***	0.182	0.235	0.695***
	(0.195)	(0.299)	(0.166)	(0.117)
Log(Children)	0.088	-0.075	0.160***	0.077
	(0.054)	(0.093)	(0.045)	(0.056)
Log(Adults)	-0.461***	-0.361**	-0.182**	-0.586***
	(0.154)	(0.146)	(0.084)	(0.093)
Log(Land owned)	-0.017	0.329**	0.062*	0.043
	(0.074)	(0.128)	(0.033)	(0.040)
Log(Attrition rate)	-2.300**	2.611*	0.399	0.006
	(1.122)	(1.347)	(0.433)	(0.770)
χ^2	5.845	206.988	78.503	123.271
P-value	0.054	0.000	0.016	0.000
Observations	7,266	4,377	8,800	6,372

Source: Authors' calculations.

Notes: Observations are baseline individuals. Children, adults, and land owned measured at household level. Attrition rate is individuals who left the sample from a given enumeration area divided by total individuals from the enumeration area at baseline; calculation excludes surveyed individual. Indicators for the interviewer presiding over the survey are included. χ^2 statistic tests joint significance of interviewer indicators and attrition rate. A value of 1 was added to all variables before taking logs. $^*p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

For the main analysis, we draw from models estimated in Table 4.3 to account for selective attrition using the approach in Fitzgerald, Gottschalk, and Moffitt (1998). Restricted versions of models in Table 4.3 are also estimated, excluding the EA attrition rate and enumerator indicators (our excluded instruments). The ratio of the predicted values from the restricted and unrestricted probit regressions is used to create inverse probability weights, which we apply to individual labor participation regressions.

[13] To provide attrition rates exogenous to the individual, we exclude the individual from the calculation.

5. RESULTS

The motivation for the analysis is to understand how workers in eastern Africa adapt to temperature extremes. We consider occupational mobility between local agricultural and nonagricultural sectors, between local self-employment and wage labor, and across space (migration). The main results suggest an important distinction between rural and urban areas. To better understand the drivers of this result, we estimate separate regressions that interact climate variables with landownership and gender. In all cases, we focus on those results for which the temperature coefficients linear, squared, or both are statistically significant for the omitted category (using a *t*-test of the temperature parameters) or the included category (using an F-test of the combination of the parameters on the temperature variable and its interaction with the included categorical variable).

Parameters in Table 5.1 suggest that temperature has a significant effect on labor choices only in urban areas.

Table 5.1 Labor participation response to temperature by location

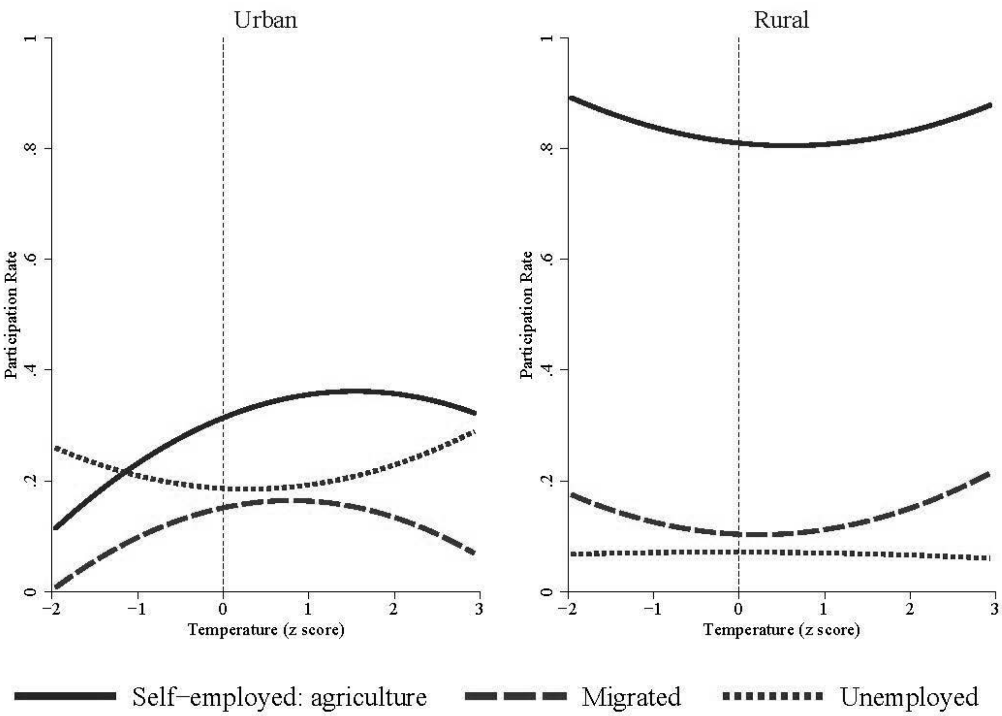
		Self-employed				
Variable	Wage	Agriculture	Non agriculture	Migrated	School	Unemployed
Temp	-0.014	0.059***	-0.016	0.025	0.008	-0.005
	(0.016)	(0.021)	(0.018)	(0.016)	(0.011)	(0.017)
Temp^2	0.005	-0.020**	-0.009	-0.021*	-0.003	0.015**
	(0.007)	(0.009)	(0.008)	(0.011)	(0.005)	(0.007)
Temp × Rural	0.015	-0.072***	0.021	-0.025	-0.006	0.004
	(0.017)	(0.023)	(0.019)	(0.021)	(0.012)	(0.018)
Temp^2 × Rural	-0.010	0.034***	0.006	0.036**	0.000	-0.016
	(0.009)	(0.013)	(0.010)	(0.016)	(0.006)	(0.010)
F-test P values						
Temp × (1+Rural)=0	0.892	0.169	0.425	0.991	0.631	0.898
Temp^2 × (1+Rural)=0	0.335	0.140	0.596	0.186	0.316	0.869
R^2	0.029	0.006	0.084	0.012	0.059	0.016
Observations	55,277	55,277	55,277	55,277	55,277	55,277

Source: Authors' calculations.
Notes: Parameters displayed with standard errors in parentheses clustered at baseline enumeration level. Regressions use inverse probability weights to account for attrition and sampling scheme. Observations are person years. Temp is temperature z-score. Rural is a dummy variable for rural location. Other controls include quadratic rainfall z-score terms, and individual and region × time effects. *P< 0.1, **P< 0.05, ***P< 0.01.

For all outcomes, we cannot reject that the combination of the linear or squared temperature variables and their interaction with the rural dummy yields 0 effect on labor participation. Figure 5.1 illustrates agricultural self-employment and migration. Both have inverted U shapes, which are complemented by a U-shaped unemployment response. Temperature z-scores of 1.48 and 0.60 standard deviations above the mean achieve maximum participation rates in agricultural self-employment and migration, respectively.[14]

[14]The complete regression results displayed in Appendix Table A.1 show that rainfall variability, the principal measure of income risk in previous work (Kochar 1999; Rose 2001; Barrios, Bertinelli, and Strobl 2006), also influences migration among rural workers.

Figure 5.1 Labor participation response to temperature by location



Source: Authors' calculations.

One explanation for the occurrence of the peaks of the respective curves near 1 standard deviation above the mean temperature may be that agricultural productivity is highest in this temperature range. Consequently, at this range people in urban areas are most likely to engage in small-scale self-employed agricultural production. Similarly, if temperatures in rural and urban areas are correlated,[15] there may be an increase in labor demand for harvest under favorable growing conditions. As a result, urban dwellers may have a higher probability during these moderately warmer times of temporarily migrating to rural areas, either to help with family farms or to participate in the wage labor market (Potts 1995; Tacoli 2001; Potts 2013). Taken together, these results suggest that urban residents are able to take advantage of relatively benign temperatures (within 1 standard deviation above the mean) to engage in agricultural self-employment and migration. These opportunities may disappear, however, when temperatures are very high.

We find no evidence that urban wage markets or nonagricultural self-employment absorb the workers who cease participation in agricultural self-employment or migration at high temperatures.[16] Nor does participation in school increase. Instead, unemployment significantly increases under periods of heat stress: a temperature increase of 2 standard deviations above the mean corresponds to a 7 percent increase in urban unemployment.

The reduction in agricultural self-employment appears to be driven by constraints on maintaining crops in urban areas. To shed further light on this question, we disaggregate self-employed agricultural workers into those who work exclusively in crop production, those who work exclusively in livestock production, and those engaged in both crop and livestock activities. Results in Appendix Table A.2 suggest that the agricultural self-employment temperature response is driven by the sample of individuals

[15]Mean temperatures in the urban and rural samples appear qualitatively similar in Table 4.1.

[16]Table 5.1 consolidates agricultural and nonagricultural wage participation into a single "wage" category. As shown in Appendix Table A.1, temperature does not significantly affect participation in either wage market when analyzed separately.

exclusively engaged in crop production. Thus, despite the fact that a relatively large percent of self-employed urban agricultural workers rely exclusively on livestock as a means of production (Table A.3), the effects are driven by adjustments (or lack thereof) in crop-related activities.[17]

We next consider whether temperature responses differ by gender. Results in Table 5.2 indicate that the urban agricultural self-employment response holds regardless of gender. Only male workers show temperature-sensitive migration choices, however, and only urban male unemployment appears to be affected by temperature.[18] In rural areas, male agricultural self-employment participation is significant and the opposite of that for urban areas, suggesting increasing marginal returns in periods of high temperature. We find that all other rural activities are insensitive to temperature when disaggregating effects by gender.

We further explore whether labor choices are driven by a lack of sufficient savings to maintain an enterprise (De Mel, McKenzie, and Woodruff 2012) or finance a move (Lucas 2015) following a s hock. If this type of barrier to entry exists, we would expect to see adaptation measures such as nonagricultural self-employment and migration increase with extreme temperatures, but only among households with relatively large landownership. Table 5.3 presents the results from regressions, stratified by worker location, that include variables which interact temperature and a dummy for having large landholdings. In both rural and urban areas, the agricultural self-employment, migration, and unemployment (urban sample only) results are significantly different from 0 only for individuals in households with relatively small baseline landholdings. Disaggregating effects by landholdings generates two new findings: in rural areas, both nonagricultural self-employment and unemployment appear sensitive to temperature, but only for large landholders.

Figure 5.2 shows the participation rate curves follow closely those presented in previous figures for the land poor. Relationships between participation rates and temperature appear relatively flat for the land rich. Adjustments in participation in agricultural self-employment among small landowners may be driven by the increase in the demand for labor once family members migrate. Lack of assets does not pose a significant barrier to using migration as a safety valve for employment in years with high temperatures. In rural areas, only large landowners face a significant inverted U-shaped temperature response in nonagricultural self-employment, and a corresponding. significant U-shaped response in unemployment.

[17]We explored the possibility that the effects on agricultural self-employment were driven by adjustments in livestock production In rural areas, high temperatures often require more labor-intensive livestock management practices, such as relocating livestock as grazing land becomes exhausted, to maintain the optimal herd (Box 1971; Lybbert et al. 2004; Maystadt and Ecker 2014). We posited that urban dwellers may be unlikely to adopt similar practices due to a lack of access to grazing land and constraints on traveling with livestock. We disaggregate the agricultural self-employment outcome into those who work exclusively in crop production, those who work exclusively in livestock production, and those engaged in both crop and livestock activities. Appendix Table A.2 demonstrates that the adaptations observed in the agricultural self-employment regression are driven by the sample of individuals exclusively engaged in crop production.

[18]According to the F-statistics, female migration response is not significantly different from 0. For the unemployment outcome, we reject the null hypothesis that the combined effect of temperature squared is 0. However, the parameter estimate on the coefficient of temperature squared interacted with the female dummy variable is rather small.

[19]Although the temperature coefficients in the unemployment regression are not significantly different from 0 for small landholders, the F-tests support a nonzero temperature effect for large landholders.

Table 5.2 Labor participation response to temperature by location and gender

Variable	Urban: Self-employed Agriculture	Urban: Self-employed Non agriculture	Urban: Migrated	Urban: School	Urban: Un employed	Rural: Self-employed Agriculture	Rural: Self-employed Non agriculture	Rural: Migrated	Rural: School	Rural: Un-employed
Temperature	0.071***	-0.024	0.040*	0.002	-0.013	-0.013	0.006	0.004	0.010	-0.007
	(0.027)	(0.026)	(0.021)	(0.015)	(0.019)	(0.009)	(0.009)	(0.014)	(0.008)	(0.006)
Temperature^2	-0.020**	-0.011	-0.030**	-0.009	0.015*	0.015*	-0.001	0.016	-0.002	-0.001
	(0.010)	(0.012)	(0.013)	(0.007)	(0.009)	(0.009)	(0.008)	(0.012)	(0.005)	(0.006)
Temperature×Female	-0.021	0.015	-0.029	0.012	0.013	0.001	-0.000	-0.007	-0.015	0.013
	(0.024)	(0.031)	(0.025)	(0.020)	(0.025)	(0.012)	(0.013)	(0.013)	(0.010)	(0.010)
Temperature^2×Female	-0.000	0.005	0.018	0.012	0.001	-0.003	-0.003	-0.002	-0.002	-0.000
	(0.009)	(0.013)	(0.012)	(0.009)	(0.011)	(0.008)	(0.009)	(0.009)	(0.007)	(0.008)
F-test P-values										
Temp×(1+Female) = 0	0.024	0.709	0.559	0.322	0.996	0.337	0.567	0.807	0.505	0.538
Temp^2×(1+Female) = 0	0.030	0.449	0.295	0.638	0.095	0.277	0.475	0.271	0.334	0.900
R^2	0.009	0.159	0.016	0.074	0.039	0.007	0.060	0.011	0.059	0.008
Observations	14,073	14,073	14,073	14,073	14,073	41,204	41,204	41,204	41,204	41,204

Source: Authors' calculations.

Notes: Parameters displayed with standard errors in parentheses clustered at baseline enumeration level. Regressions use inverse probability weights to account for attrition and sampling scheme. Observations are person years. Temp is temperature z-score. Female is a dummy variable for gender. Other controls include quadratic rainfall z-score terms, and individual and region × time effects.*P<0.1, **<0.05, ***P<0.01.

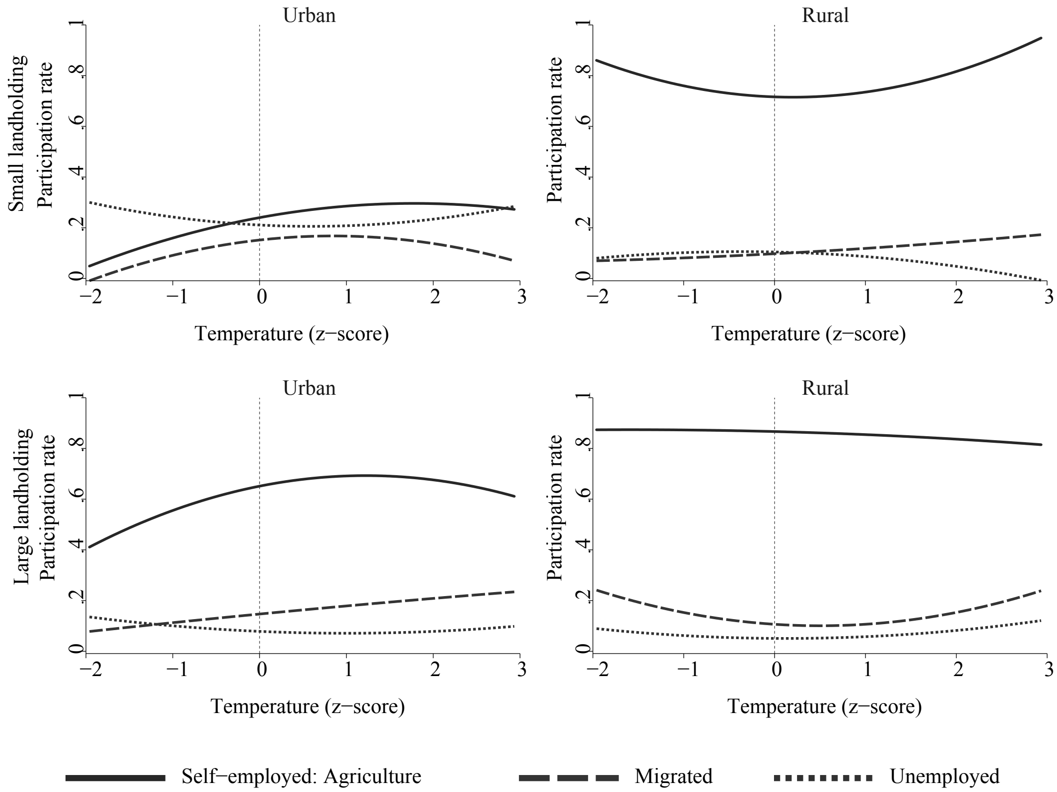
5.3 Labor participation response to temperature by location and landholding

	Urban					Rural				
	Self-employed					Self-employed				
Variable	Agriculture	Non agriculture	Migrated	School	Un employed	Agriculture	Non agriculture	Migrated	School	Un-employed
Temperature	0.061***	0.005	0.030*	-0.003	-0.014	-0.002	-0.004	0.021*	0.001	-0.013
	(0.021)	(0.017)	(0.018)	(0.013)	(0.020)	(0.018)	(0.009)	(0.013)	(0.010)	(0.012)
Temperature^2	-0.018**	-0.013	-0.022*	0.003	0.014*	0.031*	0.014	0.002	-0.005	-0.010
	(0.009)	(0.008)	(0.012)	(0.005)	(0.008)	(0.016)	(0.009)	(0.009)	(0.005)	(0.013)
Temperature×Land	-0.009	-0.064	-0.004	0.055*	0.004	-0.010	0.011	-0.035**	0.004	0.015
	(0.062)	(0.054)	(0.053)	(0.030)	(0.035)	(0.019)	(0.011)	(0.016)	(0.011)	(0.013)
Temperature^2×Land	-0.010	0.007	0.021	-0.030	-0.007	-0.034**	-0.026**	0.021	0.002	0.019
	(0.031)	(0.023)	(0.027)	(0.019)	(0.017)	(0.017)	(0.010)	(0.016)	(0.006)	(0.014)
F-test P values										
Temp×(1+Land) = 0	0.380	0.274	0.584	0.055	0.724	0.176	0.386	0.374	0.356	0.720
Temp^2×(1+Land) = 0	0.356	0.809	0.963	0.143	0.621	0.665	0.033	0.152	0.427	0.027
R^2	0.012	0.160	0.018	0.073	0.041	0.011	0.061	0.012	0.057	0.010
Observations	14,073	14,073	14,073	14,073	14,073	41,204	41,204	41,204	41,204	41,204

Source: Authors' calculations.

Notes: Parameters displayed with standard errors in parentheses clustered at baseline enumeration level. Regressions use inverse probability weights to account for attrition and sampling scheme. Observations are person years. Temp is temperature z-score. Land is a dummy variable for above median household landownership. Other controls include quadratic rainfall z-score terms, and individual and region × time effects. *P<0.1, **<0.05, ***P<0.01.

Figure 5.2 Labor participation response to temperature by location and landholding



Source: Author calculations.

6. CONCLUSION

We find that temperature changes significantly affect worker behavior in East Africa. Workers in urban areas appear to fare worse than those in rural areas, challenging the conventional narrative of rural vulnerability to climate. Temperature impacts are nonlinear, with extremes in urban areas causing a decline in agricultural self-employment and migration. There do not currently appear to be many opportunities to adapt to temperature shocks by shifting to wage labor or nonagricultural sectors, or going to school. Instead, extreme temperatures causes a rise in urban unemployment.

In rural areas, temperature increases primarily affect workers with relatively small household assets. In contrast to their urban counterparts, these workers increase both agricultural self-employment and migration (as in Asia and Africa, see Gray and Mueller 2012b; Mueller, Gray, and Kosec 2014; Dillon, Mueller, and Salau 2011; Gray and Wise 2016). They do not appear, however, to diversify into nonagricultural self- or wage employment as observed in Asia by Kochar (1999) and Rose (2001).

The heightened role of temperature has surfaced in discussions of environmental migration (Gray and Mueller 2012b; Mueller, Gray, and Kosec 2014), but there are few studies that demonstrate how these effects spill over into auxiliary labor markets in the developing-country context (for an analysis in the United States, see Graff-Zivin and Neidell 2014). These findings have implications on how we perceive environmental displacement and adaptation in Africa. The fact that workers reduce their supply of labor in some markets (without concurrent increases in their supply of labor in other markets) suggests that urban labor markets are unable to accommodate workers displaced by temperature shocks, and there may be a need for increased social protection in these areas.

APPENDIX: SUPPLEMENTARY TABLES

Table A.1 Labor participation response to temperature and rainfall by location

	Agriculture		Nonagriculture					
Variable	**Wage**	**Self-employed**	**Wage**	**Self-employed**	**Wage**	**Migrated**	**School**	**Unemployed**
Rain	0.001	0.027*	-0.013	0.014	-0.014	0.012	0.003	-0.007
	(0.005)	(0.016)	(0.013)	(0.015)	(0.014)	(0.014)	(0.009)	(0.013)
Rain^2	-0.005*	0.003	-0.008	-0.024***	-0.012*	-0.020***	0.009**	0.014*
	(0.003)	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.004)	(0.007)
Temp	-0.005	0.059***	-0.008	-0.016	-0.014	0.025	0.008	-0.005
	(0.006)	(0.021)	(0.015)	(0.018)	(0.016)	(0.016)	(0.011)	(0.017)
Temp^2	0.003	-0.020**	0.001	-0.009	0.005	-0.021*	-0.003	0.015**
	(0.003)	(0.009)	(0.006)	(0.008)	(0.007)	(0.011)	(0.005)	(0.007)
Rain × Temp	-0.006	-0.014	0.007	-0.015	0.003	-0.037***	-0.005	0.016
	(0.005)	(0.014)	(0.011)	(0.015)	(0.014)	(0.014)	(0.007)	(0.014)
Rain × Rural	0.010	-0.040**	0.010	0.012	0.022	-0.033*	-0.003	0.004
	(0.007)	(0.018)	(0.014)	(0.016)	(0.016)	(0.018)	(0.010)	(0.015)
Rain^2 × Rural	-0.006	-0.001	0.004	0.010	-0.001	0.029***	-0.008	-0.016*
	(0.005)	(0.010)	(0.007)	(0.010)	(0.008)	(0.010)	(0.005)	(0.009)
Temp × Rural	0.011	-0.072***	0.004	0.021	0.015	-0.025	-0.006	0.004
	(0.008)	(0.023)	(0.016)	(0.019)	(0.017)	(0.021)	(0.012)	(0.018)
Temp^2 × Rural Rain ×	-0.008*	0.034***	0.000	0.006	-0.010	-0.036**	0.000	-0.016
	(0.005)	(0.013)	(0.007)	(0.010)	(0.009)	(0.016)	(0.006)	(0.010)
Temp × Rural	-0.003	0.028	-0.006	0.003	-0.012	0.069***	-0.007	-0.018
	(0.007)	(0.019)	(0.012)	(0.017)	(0.014)	(0.022)	(0.009	(0.018)
R^2	0.019	0.006	0.013	0.084	0.029	0.012	0.059	0.016
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Source: Authors' calculations.
Notes: Parameters displayed with standard errors in parentheses clustered at baseline enumeration level. Regressions use inverse probability weights to account for attrition and sampling scheme. Observations are person years. Temp and rain are z-scores for temperature and rainfall. Rural is a dummy variable for rural location. Other controls include individual and region × time effects.*P<0.1, **P<0.05, ***P<0.01.

Table A.2 Agricultural self-employment response to temperature and rainfall by location and type

	Agricultural self-employment		
Variable	**Crop**	**Livestock**	**Both**
Rain	0.048***	-0.020**	-0.001
	(0.017)	(0.009)	(0.010)
$Rain^2$	-0.008	0.001	0.010**
	(0.008)	(0.004)	(0.005)
Temp	0.054***	-0.008	0.013
	(0.017)	(0.013)	(0.015)
$Temp^2$	-0.013**	-0.004	-0.003
	(0.007)	(0.005)	(0.005)
Rain×Temp	-0.034***	0.009	0.011
	(0.012)	(0.007)	(0.008)
Rain×Rural	-0.060***	0.019*	0.000
	(0.020)	(0.010)	(0.013)
$Rain^2$×Rural	0.001	-0.003	0.001
	(0.012)	(0.005)	(0.010)
Temp×Rural	-0.065***	0.006	-0.013
	(0.021)	(0.013)	(0.018)
$Temp^2$×Rural	0.038***	-0.001	-0.004
	(0.012)	(0.006)	(0.009)
Rain×Temp×Rural	0.054***	-0.017*	-0.009
	(0.020)	(0.009)	(0.015)
R^2	0.003	0.003	0.006
Observations	55,277	55,277	55,277

Source: Authors' calculations.
Notes: Parameters displayed with standard errors in parentheses clustered at baseline enumeration level. Regressions use inverse probability weights to account for attrition and sampling scheme. Observations are person years. Temp and rain are z-scores for temperature and rainfall. Rural is a dummy variable for rural location. Other controls include individual and region × time effects.*P<0.1, **P<0.05, ***P<0.01.

Table A.3 Agricultural self-employment by type

Employment type	**Urban**	**Rural**
Crop	0.57	0.57
	(0.02)	(0.01)
Livestock	0.13	0.02
	(0.01)	(0.00)
Both	0.30	0.40
	(0.02)	(0.01)
Observations	4,496	33,265

Source: Authors' calculations.
Notes: Observations are person-years. Sampling weights applied to calculation of mean. Standard errors in parentheses clustered by enumeration area.

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