Labor Response to Climate Variation in Eastern Africa

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Understanding how climate variability affects workers is crucial to adaptation policy design. We develop a multi-activity labor allocation model of individual responses to climate shocks. Combining high-resolution climate data with panel surveys of labor participation by sector, contractual arrangement, and migration status, we apply the model to assess responses to local temperature anomalies in four East African countries. Non-agricultural activities are hardest hit by high temperatures, particularly in urban areas. Results suggest a ceteris paribus 2 standard deviation temperature increase above the 2000–2014 mean in urban areas could double the percent of people who are not employed.

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Africa is likely to experience warming in excess of two standard deviations above the mean by the late 20th century (IPCC, 2013). Heat stress adversely impacts plant growth (Schlenker et al., 2006; Seo et al., 2009; Lobell et al., 2011, 2012), and may affect productivity in other sectors (Hsiang, 2010; Dell et al., 2012; Heal and Park, 2013; Burke et al., 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 respond to temperature is poorly understood, especially in Africa. We address this knowledge gap by analyzing labor response to temperature in four East African countries.

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Previous work has analyzed labor response to climate anomalies through sectoral reallocation (Kochar, 1999; Rose, 2001; Mathenge and Tschirley, 2015; Colmer, 2016), migration (Dillon et al., 2011; Gray and Mueller, 2012a,b; Gray and Bilsborrow, 2013; Mueller et al., 2014; Gray and Wise, 2016), human capital investment (Graff-Zivin et al., 2015), or leisure (Graff-Zivin and Neidell, 2014). To our knowledge, this study is the first to analyze how temperature affects individual worker choices among income-generating activities.[1] We use individual panel microdata on participation in agricultural and non-agricultural wage and self-employment occupations, schooling, and migration across four East African countries. High-resolution temperature data allow us to extend previous findings on economic impacts of climate change (Schlenker et al., 2006; Seo et al., 2009; Hsiang, 2010; Lobell et al., 2011; Gray and Mueller, 2012a; Mueller et al., 2014; Burke and Emerick, 2016).

The granularity of occupational choice and migration data opens lines of inquiry unavailable to previous macroeconomic work. First, by using individual panel data on labor participation, we are better able to distinguish causal effects of temperature from selection by incorporating individual fixed effects into our empirical models. Individual fixed effects control for time invariant characteristics, such as ability and skill, thereby assuaging concerns that the estimated effects of interest are driven by poorly skilled individuals self-selecting into occupations vulnerable to climate. Second, having detailed information on all worker activities allows us to capture extensive margins of labor allocation often overlooked when focusing on primary employment or restricting participation by the allocation of hours spent on one activity. Third, in contrast with macroeconomic studies that use urbanization as a proxy for internal migration (Barrios et al., 2006; Poelhekke, 2011; Henderson et al., 2017), data on individual migration decisions do not run the risk of conflating other factors such as geographic changes in urban boundaries, fertility, and mortality, with migration. Fourth, unlike studies that focus on aggregate international migration flows (Cai et al., 2016; Cattaneo and Peri, 2016), we can identify individual characteristics that influence propensity to migrate in response to

[1] Graff-Zivin and Neidell (2014) examine how temperature affects labor-leisure choices for U.S. workers, and Colmer (2016) analyzes Indian district-by-sector data.

changing climate. Fifth, we can exploit the heterogeneity in the sample to understand the degree to which climate affects worker responses across and within sectors. For example, if increasing temperatures reduce agricultural productivity, it is useful to understand whether the non-agricultural sector can absorb displaced workers. Moreover, wage employment may be more accessible to low-income households rather than self-employment given capital constraints or other barriers to entry. Finally, the ability to monitor overall employment allows us to gain insight into welfare implications of climate shocks, even in the absence of income data.

Non-monotonic responses to climate play an important role in the theoretical and empirical results. Previous work interpreted non-monotonic temperature impacts as being driven by productivity: a temperature increase may be beneficial in cool climates, but detrimental in warmer areas. We develop a worker time allocation that shows how non-monotonic labor responses can occur in warm climates where the productivity impact is likely to be monotonic. That is, even in countries where the marginal productivity impact of an increase in temperature is unambiguously negative for all occupations, participation in an occupation may increase or decrease as temperature rises due to differences in productivity changes relative to other occupations. We show how corner solutions to this theoretical model can be used to derive regression equations for the binary labor force participation responses common in developing country surveys.

Empirical results suggest that temperature anomalies contribute to economic stress (as measured by the percentage of labor force who is not employed) in urban areas. As temperatures rise, fewer urban workers engage in non-agricultural self-employment and urban temporary out-migration declines. These findings indicate potential adverse climate productivity impacts for urban populations. Further disaggregation of non-agricultural self-employment reveals that the adverse temperature impacts are restricted to those occupations dependent upon agricultural inputs. Participation in these occupations significantly declines at high temperatures, while participation in other occupations significantly increases, albeit at a lower rate.[2] Combined with evidence from the geography literature

[2]This phenomenon occurs in rural areas as well.

that urban out-migration to rural areas occurs in years with favorable agronomic conditions (Potts, 1995; Tacoli, 2001; Potts, 2013), these results suggest that the adverse urban labor force temperature impacts may be occurring indirectly through an agricultural productivity channel.

Under a temperature increase of 2 standard deviations, the combined impact of reduced migration and reduced non-agricultural self-employment leads to an estimated 9.4 percentage point increase in urban adults who are not employed.[3] Although rural areas also experience a decline in non-agricultural self-employment, it is not accompanied by an increase in the percentage of adults who are not employed, perhaps due to the relative availability of agricultural self-employment as a back-stop occupation for these workers. Climate change will thus likely affect development goals (Barrett and Constas, 2015) in urban areas, underscoring the need for programs to promote economic growth and facilitate worker adaptation.

Section I presents a theoretical model formalizing worker decisions to maximize utility by allocating time across several activities. We use this model to specify and interpret labor participation regressions in Section II. Section III details construction of labor and climate variables. Section IV presents empirical results, and Section V concludes.

I. Theoretical Model

We begin with a labor choice model in section I.A, allowing for optimal reallocation of time across activities in response to short-term changes in climate.[4] The model predicts substitution between labor activities can drive non-monotonic relationships, even if climate's productivity impact is monotonic. It also highlights the importance of considering multiple activities (as opposed to just the primary occupation) since overall labor force participation rates allow one to deduce whether climate shocks adversely impact productivity. We close with two extensions: discrete labor choices

[3]The IPCC's fifth assessment report projects temperature increases above two standard deviations for most of Africa in 2081-2100 relative to 1986-2005. The change in terms of ° C depends on the assumed GHG concentration trajectory – less than 2° C for scenario RCP 2.6 and from 3–5° C for RCP 8.5 (see Figure SPM 8, IPCC, 2013).

[4]Since relatively few agents in our sample either work for wages or hire workers, we employ a non-recursive model in which production and leisure decisions are jointly determined (see, e.g., Singh et al., 1986).

to relate the model to the empirics (section I.B); and the special cases of backstop occupations, barriers to entry, and upstream linkages as factors limiting adaptation (section I.C).

A. *Labor Allocation Model*

Individuals allocate time across activities to maximize utility. There are K income-generating activities, $k = 1, 2, ..., K$.[5] Let $\bar{h}$ denote the time constraint. The vector $\mathbf{h} \in \mathbb{R}^K_+$ denotes the allocation of time across each income generating activity. Leisure, s, is time left over after engaging in income-generating activities: $s = \bar{h} - \sum_{k=1}^{K} h_k$.[6]

The twice-differentiable function $y_k(h_k)$ denotes returns to labor in activity k. Labor is an essential input such that $y_k(0) = 0$. Marginal returns for each activity are nonnegative and nonincreasing, ${}^{\partial y_k}/_{\partial h_k} \geq 0$ and ${}^{\partial^2 y_k}/_{\partial h_k^2} \leq 0$, and independent of time spent on other activities. Income from each source is also a function of J binary characteristics, $\mathbf{d} = (d_1, ..., d_J)'$, such as location (rural, urban), gender (male, female), or household assets (small, large).[7] An individual's anticipated income from a labor allocation depends on recent local climate (temperature and rainfall) shocks, $\mathbf{z} = (z_1, ..., z_M)'$.[8] We assume that climate directly impacts the labor market by affecting occupational productivity, not the desirability of leisure.[9] Our model shows how workers optimally adjust their time in response to these productivity shocks.

Given the set of potential income-generating activities, the individual maximizes a twice continuously-differentiable strictly quasiconcave utility function of an aggregate consumption good,

[5]For our application, $K = 6$ activities: agricultural self-employment, nonagricultural self-employment, temporary migration, 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.

[6]Leisure can be more generally interpreted as time dedicated to non-income generating household activities including rest, childcare, cooking, etc. We assume that leisure is voluntary, given returns to labor in each activity.

[7]Climate's impact on returns to an activity may vary by location. Suppose, for example, that rural labor markets are dominated by agriculture and urban labor markets are dominated by nonagricultural sectors. A year with favorable growing conditions in all locations increases returns to labor in agriculture in both rural and urban areas. Due to the larger amount of agricultural land relative to labor in rural areas, returns to migration from urban areas may increase more than returns to migration from rural areas. Gender or wealth may also affect returns to a given activity. Gender discrimination, for example, may create real or perceived lower returns to education for girls. With imperfect credit markets, lack of household assets may create a barrier to entry into self-employed activities or migration if they require an initial fixed investment. In such cases, returns to these activities may be higher for individuals in wealthier households.

[8]In principle, climate may affect returns to labor both through local and remote productivity effects. An example of the latter would be if a drought were to cause workers in the countryside to migrate to cities and thereby depress urban wages. Lacking data on migrant destinations, however, we only control for local impacts.

[9]Graff-Zivin and Neidell (2014) consider the impact of temperature on climate controlled versus outdoor leisure.

c (with price normalized to unity), and leisure s, given income and time constraints:

$$\max_{c,s} \left\{ U(c,s) : c = \pi(\mathbf{h};\mathbf{d},\mathbf{z}); s = \bar{h} - \sum_{k=1}^{K} h_k \right\}, \tag{1}$$

where π denotes total income,

$$\pi(\mathbf{h};\mathbf{d},\mathbf{z}) = \sum_{k=1}^{K} y_k(h_k;\mathbf{d},\mathbf{z}). \tag{2}$$

Increasing temperature may have a non-monotonic impact on productivity, being beneficial at low temperatures and harmful at higher temperatures. Previous work has discussed how this phenomenon might translate to non-monotonic climate impacts on GDP or international migration (Burke et al., 2015; Cai et al., 2016). Our model yields several results that we exploit to empirically evaluate climate variation effects on labor market participation across activities. In particular, it predicts under what conditions one might expect two additional sources of a non-monotonic impact of temperature on labor supply[10] in a given occupation, even if the productivity impact is monotonic: a backward-bending labor supply curve and substitution across activities. Propositions 1 and 2 show that, even in the absence of a non-monotonic productivity impact, non-monotonic labor responses can arise from the shape of the total (across activities) labor supply curve or substitution across activities. Proposition 3 shows how overall employment rates can be used to infer productivity and welfare impacts. The Appendix contains proofs for the two-activity case.

PROPOSITION 1: *Let temperature have a monotonic productivity impact in each activity, and the worker be in an upward-sloping range of the total labor supply curve. For interior solutions, changing temperature can cause a non-monotonic labor response in each activity. The impact on total hours worked in both activities is monotonic.*

Proposition 1 rules out both non-monotonic productivity impacts and a backward-bending labor

[10]Here, we mean hours supplied as a function of marginal return.

supply curve as possible sources of a non-monotonic labor response to temperature.[11] Instead, it focuses on substitution among income-generating activities. Suppose, as illustrated in Figure 1, an increase in temperature adversely affects marginal returns to labor for both activities, but at different rates.[12] The upper graph illustrates a case in which the two curves depicting the change in marginal return with respect to temperature cross only once; marginal returns are decreasing in temperature for each activity, but at a faster rate for activity 1. As shown in the lower graph, despite the monotonic relationship between temperature and productivity in each activity, the hours observed in each activity could be non-monotonic functions of temperature. Increases in temperature lead to an increase in activity 1 and a decrease in activity 2 only until z^0, after which time spent in activity 2 increases and time spent in activity 1 decreases. An implication of Proposition 1 is that one cannot infer a directional productivity impact of a climate shock by observing labor participation in a given activity. In the example given, an increase in temperature can cause an increase in hours worked in each activity (at the expense of the other) even if it has a negative productivity impact in both.

PROPOSITION 2: *Suppose an increase in temperature has an identical negative impact on marginal productivity in each activity. For an interior solution, workers may respond to a small temperature increase by reducing labor supply to each activity, but increase labor supply in each activity in response to a large increase in temperature.*

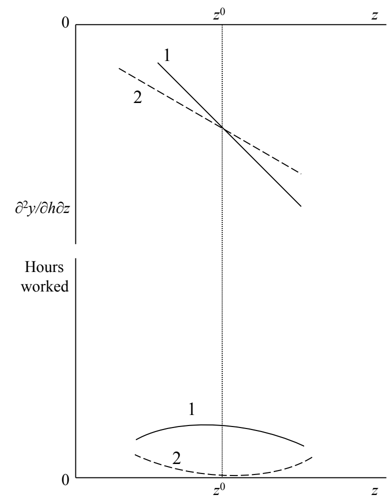
The hypothesis of Proposition 2 rules out non-monotonic productivity impacts and substitution across activities as possible sources of a non-monotonic labor response to temperature, focusing on total labor supply curvature alone. Figure 2 depicts hours employed in each activity as a function of temperature. Suppose increasing temperature reduces productivity in both activities in the same way.[13] A backward-bending labor supply curve can cause hours employed in each activity

[11] To develop intuition for these results, we consider the effect of climate-productivity shocks on labor supply in the special case of a single income-generating activity with the possibility of a backward-bending supply curve in the Appendix. The main model allows the labor supply function to have backward-bending properties and permits multiple income-generating activities.

[12] Specifically, $\partial^2 y_1/\partial h_1 \partial z, \partial y_2/\partial h_2 \partial z < 0$ and $\partial^3 y_2/\partial h_2 \partial z^2 > \partial^3 y_1/\partial h_1 \partial z^2$.

[13] Mathematically, $\partial^2 y_1/\partial h_1 \partial z = \partial^2 y_2/\partial h_2 \partial z < 0$.

Figure 1. Climate-induced substitution across activities



Note: Increasing temperature, z, reduces marginal productivity in both activities, but at different rates. Workers may initially respond by shifting time from activity 2 to activity 1, but reverse this response after the impact on marginal productivity in activity 1 falls below that of activity 2. Variable definitions: y income generated by activity 1 or 2, h hours engaged in activity 1 or 2, z temperature z-score.

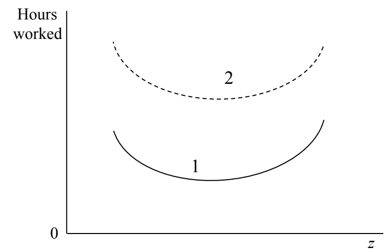
to be U-shaped functions of z. They may initially decrease for low z (the upward sloping portion of the labor-supply curve).[14] As z rises and further reduces productivity, individuals may enter the backward-bending portion of the supply curve after which labor supply increases in order to maintain a minimal income. This phenomenon has implications for interpretation of empirical specifications of labor response to climate variation. If parameters estimated by the econometric model suggest an inverted-U functional form, then the existence of a backward-bending supply curve for poor individuals cannot entirely explain the results.

Propositions 1 and 2 discuss temperature's impact on hours worked in each income-generating activity, and motivate the interpretation of empirical specifications between labor choice and climate. Proposition 3 shows how this translates into overall labor force participation decisions, reflecting an individual's ability to adapt to temperature.

PROPOSITION 3: *(a) If a temperature increase does not negatively (positively) affect productivity it cannot induce a worker who is employed (not employed) to become not employed (employed). (b)*

[14] By "upward sloping" we refer to a situation in which labor supply is an increasing function of the return to labor.

Figure 2. Effect of backward-bending labor supply on worker response to climate



Note: As increasing temperature, z, reduces marginal productivity in both activities 1 and 2, workers initially respond by working less in each. Once incomes have been sufficiently reduced, they respond to further increases in z by working more due to the need to maintain a subsistence income.

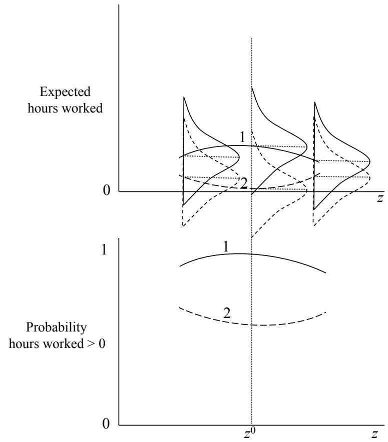
A temperature increase that causes an employed worker to become not employed reduces welfare.

The first two propositions show that the directional effect of a change in climate on engagement in any given activity is ambiguous, even if climate has a monotonic productivity impact. Part (a) of Proposition 3 states that changes in the tendency to be employed overall depends upon productivity. Decreases in overall employment require climate to have an adverse productivity impact in at least one activity, while increases in overall participation rates require climate to have a positive productivity impact in at least one activity. Part (b) allows one to infer a welfare impact from observed temperature-induced changes in employment.

The model has several implications for empirical analysis of labor responses to climate change. First, it highlights the importance of choosing an empirical specification sufficiently flexible to permit non-monotone relationships between temperature and labor allocations within an activity. Other work, e.g., Schlenker et al. (2006) and Burke and Emerick (2016), has also stressed the importance of allowing for a non-monotonic relationship between temperature and productivity since a temperature increase may be beneficial at low temperatures, but harmful at high temperatures. Here we have shown that it is equally important to allow such flexibility even in temperature ranges where one might expect the productivity impact to be uniformly positive or negative.

Second, care must be taken when interpreting the channel through which climate affects labor supply in individual activities. It may seem natural, for example, to interpret an increase in agricul-

Figure 3. Labor participation response to temperature



Note: Variable definition: z temperature z-score.

tural employment as evidence of an increase in agricultural productivity. Instead, we have shown that agricultural employment may increase even if productivity decreases – either because of a backward-bending labor supply curve or a greater loss in marginal productivity in another activity. Thus, climate productivity data cannot unambiguously predict labor responses. Conversely, labor markets only reveal climate productivity impacts via changes in overall participation rates.

B. Discrete Labor Choices

Bringing this model to the data faces a practical challenge since it focuses on a continuous time allocation variable whereas surveys, particularly in developing countries, often provide information for discrete participation variables (e.g., whether the respondent engaged in a family non-farm enterprise in the past year). The Appendix provides detailed implications of replacing continuous with discrete choice variables. Here, we provide the intuition for how this modification affects predictions.

Consider an unobserved latent variable that determines hours worked by an individual: hours worked equals the latent variable if the latent variable is positive, otherwise hours worked equals zero. Reframing the lower panel of Figure 1, the top panel of Figure 3 depicts the expected value of the latent variable as a function of temperature and its sample distribution for two activities. The bell-shaped curves reflect the probability distributions of unobserved heterogeneity in the sample of survey responses around the mean for a range of temperatures. The horizontal distance from the bell curve to its base represents the probability density of workers corresponding to a particular value of the latent variable for a given activity at the indicated temperature. The top of the bell curve corresponds to the expected (latent) hours observed working 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. The lower panel depicts this probability as a function of temperature, showing how nonlinearity in expected hours worked can translate to nonlinearity in the participation probability.

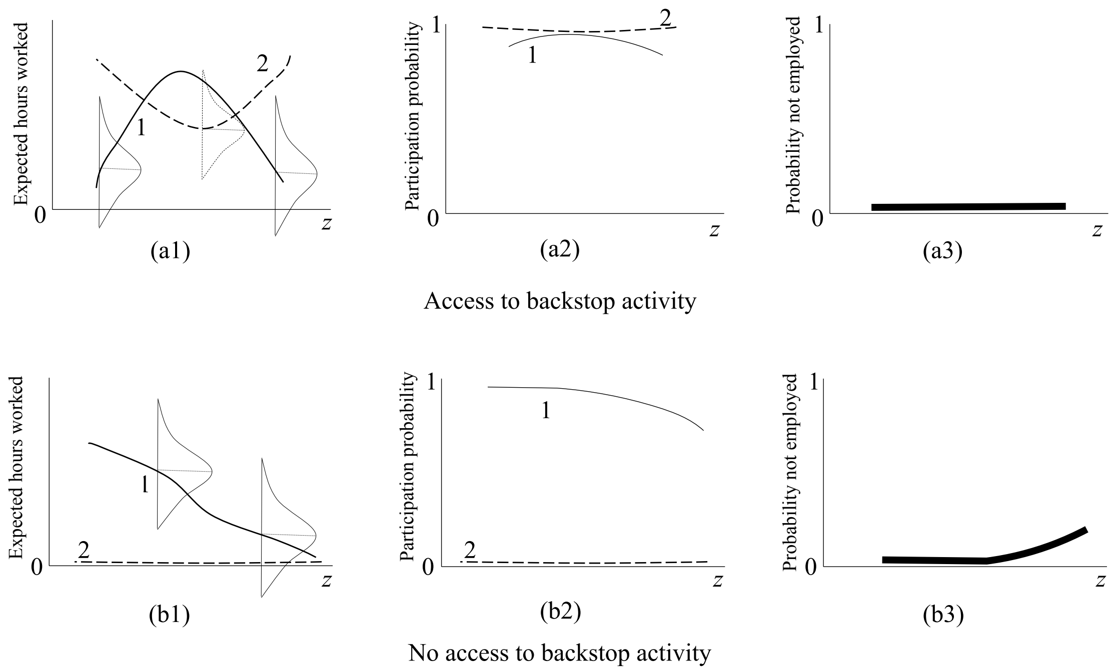
C. Special Cases

Here we consider three special cases to the general model that we encounter in the empirical analysis: backstop occupations, barriers to entry, and downstream sectors.

Backstop occupations. Although the model predicts changes in continuous time allocation in response to climate shocks, these changes may not always be observed in discrete participation decisions. As an example, consider the case in which there is a backstop activity that has sufficiently high initial marginal returns to labor that an individual will always allocate strictly positive hours regardless of climate. Agricultural self-employment may fit this description if workers with suitable land almost always engage in subsistence livestock or gardening activities. Further suppose that increasing temperature negatively affects productivity in both another activity, 1, and the backstop activity, 2, as depicted in panel (a1) of Figure 4.[15] The key difference between panel (a2) of Figure 4 and the lower panel of Figure 3 is that the probability of not engaging in the backstop activity is negligible. In such a case, observed participation in activity 1 follows an inverted-U shape while there is no discernible impact of climate on the backstop, and, as shown in panel (a3), individuals

[15]That is, as in Figure 1 an increase in temperature adversely affects productivity in both activities, but at different rates such that substitution between activities creates non-monotonic responses for each.

Figure 4. Special cases: backstop and barrier to entry



Note: The figure depicts behavior of individuals with, panels (a1)–(a3), and without, panels (b1)–(b3), access to a "backstop" activity 2 in which it is profitable to engage, regardless of climate, z. Although hours employed in backstop changes with z, the probability that an individual engages in the activity remains near one for those who have access to it. These individuals always participate in the labor market in some form, even if probability of engagement in activity 1 declines. In contrast, for individuals who do not have access to the backstop activity, the probability of not being employed increases as the probability of engaging in activity 1 declines.

are always employed in at least one activity.

Barriers to entry. Some workers may face barriers to entry in one or more activities due to unobserved heterogeneity. Taking the backstop example further, suppose that land markets are illiquid such that some workers face high unobserved costs to acquiring or selling land suitable for agricultural self-employment. In such a case, the net marginal product of engaging in this activity is almost always non-positive for individuals without access. Consequently, they only engage in the non-backstop activity, as depicted in panel (b1) of Figure 4. If temperature shocks adversely affect productivity in activity 1, hours worked decreases monotonically with z, as does observed participation in the activity, as depicted in panel (b2), and probability of not being employed (panel (b3)).

Unable to directly observe the barrier to entry, the researcher only observes aggregate participation in each activity across the sample (a combination of panels (a3) and (b3)). Based on the relative proportion of the types in the sample, there is a probability of engaging in the backstop activity that does not depend on climate, and a probability of engaging in the other activity that decreases with z. The combined impact is that the percentage of people who are not employed increases in z, but only as the proportion of individuals with barriers to entry exit the non-backstop activity.

Upstream linkages. There may be activities for which climate does not directly affect the production technology, yet affects demand for labor via its impact on inputs from upstream activities. As a concrete example consider two activities: upstream agricultural fruit production and downstream non-agricultural activity, fruit-trading. For simplicity suppose that fruit-trading requires two inputs, fruit and labor, and that temperature does not directly affect the marginal product of labor (holding the other input constant). That is, the ability of a worker to sell a given quantity of fruit is independent of z. Temperature does, however, affect the productivity of fruit growers such that the supply of produce falls as z increases. If labor and fruit are complementary inputs in the trading sector (there are limited opportunities to increase fruit sales by substituting more labor for less fruit) then the marginal product of labor in the fruit trade may fall with z through the indirect impact on agriculture rather than the direct impact on trading itself.

II. Empirical Model

The goal of the empirical analysis is to identify the impact of a recent temperature shock on the probability that an individual engages in each income-generating activity or suspends employment altogether, conditional on rainfall. Individual fixed effects control for time invariant factors directly affecting occupational choice. Interacting temperature and rainfall with time-invariant worker characteristics (local population density, gender, household assets), however, allows us to discern how these factors influence climate impacts. The conceptual framework described in the previous section and the Appendix shows how to infer the climate impact on worker behavior via its effect on the probability that an individual engages in each activity. Here, we provide a detailed empirical model derived from this framework.

We estimate a linear probability model for the sample (15–65 year olds):[16]

$$L_{ikt} = f(\beta_k; \mathbf{z}_{it}, \mathbf{d}_i) + \gamma_{ik} + \tau(\alpha_k; t_k) + \varepsilon_{ikt}. \tag{3}$$

The dependent variable is the binary indicator, L_{ikt}, taking a value of 1 if an individual i engages in labor activity k at any point in the survey period t (typically the past year), zero otherwise. The vector $\mathbf{d}_i$ is a set of dummy variables for observable individual characteristics such as gender, household assets, and baseline urban versus rural location. Individual fixed effects γ_{ik} and a time trend $\tau(\cdot)$, reduce the potential influence of confounding factors such as innate ability and business cycle employment trends that could bias estimates of parameter vectors α_k and β_k.

Climate shocks are represented by the z-scores of the preceding 24-month average value relative to the historical 2000–2014 distribution. Use of a 24-month average reflects the fact that there may be a lagged response to temperature effects and is empirically supported by previous studies of lagged climate effects on labor outcomes (Gray and Mueller, 2012a; Mueller et al., 2014).[17]

We cluster standard errors by baseline enumeration area to account for potential non-independence and/or serial autocorrelation within these units. Regressions are also weighted by inverse probability weights accounting for sampling scheme and selective attrition (Fitzgerald et al., 1998).[18] To facilitate comparison with the literature, we include conventional standard errors and significance as well as q-values corrected for false discovery rates due to multiple outcomes (Anderson, 2008).[19]

Our main specification stratifies by urban and rural populations, including quadratic climate shocks to allow for the non-monotonic impacts discussed in Section I, and a quadratic time trend to

[16]The linear probability model allows us to control for unobserved time-invariant confounders influencing non-exclusive outcomes without causing sample selection bias. Fixed-effects logit or probit models drop observations that have no variation in the dependent variable. In the agricultural employment regression, for example, a fixed effect logit model would drop subsistence farmers who worked at least one hour in every survey year. In contrast, the linear probability model allows us to maintain the same sample size across all outcomes, avoiding bias due to dropping the portion of the sample that lacks variation in a particular outcome.

[17]To test the robustness of our results to alternate definitions of climate exposure, in the Appendix we validate the effects are robust to the use of 12-month measures of anomalies and raw temperature data.

[18]See Appendix A.A2 for attrition weight methodology. Results are not sensitive to attrition weights.

[19]We calculate q-values using the *False Discovery Rate Control* procedure described in Anderson (2008) and the accompanying Stata code posted at `are.berkeley.edu/~mlanderson/ARE_Website/Research.html`.

control for common cross-country regional business cycles:[20]

$$
\begin{aligned}
(4) \qquad & f^{Main}(\cdot) = \sum_{\ell=1}^{2} d_{i\ell} \left[\sum_{m=1}^{2} \left[\beta_{k\ell m} z_{imt} + \beta_{k\ell mm} \left[z_{imt} \right]^2 \right] + \beta_{k\ell 12} z_{i1t} z_{i2t} \right] \\
& \tau^{Main}(\cdot) = \alpha_{0k} t + \alpha_{1k} t^2 \\
& \text{for } \ell = \{\text{rural, urban}\}, \qquad m = \{\text{temperature, rain}\}.
\end{aligned}
$$

In the Appendix, we validate that the main results are robust to alternative time trend specifications allowing for country-specific cycles, distinct cross-country cycles for urban and rural areas, and distinct country-specific urban and rural cycles. The Appendix also contains analysis sub-stratifying the sample by gender and household asset size (as proxied by landholdings) as follows:

$$
\begin{aligned}
(5) \qquad & f^{Sub}(\cdot) = \sum_{j=1}^{2} \sum_{\ell=1}^{2} d_{ij} d_{i\ell} \left[\sum_{m=1}^{2} \left[\beta_{jk\ell m} z_{imt} + \beta_{jk\ell mm} \left[z_{imt} \right]^2 \right] + \beta_{jk\ell 12} z_{i1t} z_{i2t} \right] \\
& \text{for } j = \{\text{female, male}\} \text{ or } \{\text{large, small}\}; \ell = \{\text{rural, urban}\}; m = \{\text{temperature, rain}\}.
\end{aligned}
$$

III. Data

Individual labor decisions come 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 (2009–2010, 2010–2011, 2011–2012). The LSMS-ISA are nationally representative panel household surveys. One unique feature of the surveys are that they ask common questions on agriculture and other aspects of behavior across several countries facilitating generalization of inferences across contexts. The number of households surveyed ranges from 3,200 in Uganda and Malawi to 4,000 in Ethiopia and Tanzania.[21] The data allow us to construct variables for individ-

[20] Although the countries in our sample have two to three reporting years, we construct a common quadratic trend across countries exploiting the fact that different countries do not necessarily have the same reporting years.

[21] Additional details regarding each survey and round can be found from the Basic Information Documents posted online at http://go.worldbank.org/BCLXW38HY0.

ual occupation and migration outcomes over time, and gender, age, household location and land ownership at baseline. The final dataset contains 55,277 person-years.[22]

Surveys record individual engagement 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. We create binary variables that indicate whether the individual engaged in each separate activity in the last 12 months.[23] Labor participation is not mutually exclusive across activities, meaning any given worker can participate in more than one activity at once. We also construct a migration variable indicating whether the individual was away from the household for at least 1 of the previous 12 months.[24]

We merge these data 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 household baseline location.[25] MERRA uses reanalysis to integrate data from NASA's collection of Earth-observing satellites consistent with physical models of the Earth. It produces subdaily data at a resolution of 0.50° latitude $\times$ 0.67° longitude covering the modern satellite era (Rienecker, 2011). An advantage of these data is that the observational network is equally dense around the globe. They have been used to predict migration patterns in Ethiopia, Bangladesh, and Pakistan (Gray and Mueller, 2012a,b; Mueller et al., 2014).

We extract monthly values of mean daily rainfall and temperature, and take the mean of these monthly values over a 24-month period ending in month t. To account for varying historical climates across study locations and for lagged effects on employment outcomes, we use these values

[22] Appendix Figure A2 illustrates the spatial distribution of survey enumeration areas.

[23] Agricultural self-employment participation was recorded in seasonal on-farm labor and livestock modules. Agricultural and nonagricultural wage employment participation was obtained from wage modules. Non-agricultural 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), non-agricultural self-employment may be underreported, especially in Ethiopia and Malawi.

[24] Migration may include movement for non-economic motives.

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

to derive z-scores characterizing deviations in climate relative to all other consecutive 24-month periods between 2000 and 2014.[26]

The z-scores are anomalies commonly used to measure climatic variation over time (see, for example, Hansen et al., 2012). Use of z-scores, versus raw or demeaned variables, helps ensure results are applicable across heterogeneous areas. Suppose, for example, that large temperature deviations are far more likely to occur in dry climates. Using demeaned temperature as an explanatory variable would imply that our results for extreme temperatures would be driven by (and only applicable to) dry areas. In contrast, by construction z-scores of a given magnitude should have a similar probability of occurring across all areas. In addition, Gray and Wise (2016) have shown z-scores to be stronger predictors of labor outcomes in Africa. Temperature z-scores in our sample range from -2.0 to 2.9, with the roughly bimodal distributions (using sampling weights) depicted in Appendix Figure A3. The average value of a standard deviation in temperature ranges from 0.29° C in Ethiopia to 0.44° C in Tanzania.[27]

Surveys provide rural and urban classifications. Definitions, however, vary by country. To apply a uniform classification, we merge georeferenced population density from the 2010 Gridded Population of the World (GPW V4) using baseline EA GPS coordinates (Center for International Earth Science Information Network, 2016). We use 400 persons per km^2 as the threshold defining urban and rural EAs, a benchmark applied in most censuses (Qadeer, 2010).

Table 1 describes the working age (15–65) population engaged in each activity by location.[28] Most individuals are self-employed in agriculture, although the proportion varies greatly between rural areas (84 percent) and urban areas (51 percent). Rural workers rely primarily on self-employed farming, with 9 and 7 percent participation in agricultural and non-agricultural wage markets, respectively. A slightly greater percentage of rural workers are self-employed in the non-agricultural sector (15 percent) and sectors attracting temporary migrants (11 percent). In contrast, workers

[26] This time period was chosen to be relevant for young and old workers.
[27] Raw temperature data for the four countries are summarized in Appendix Table A.2.
[28] All summary statistics use baseline sampling weights provided by the LSMS-ISA.

Table 1—Worker characteristics

	Urban	Rural	Total
Occupational participation rates			
Agriculture			
Wage labor	0.03	0.09	0.07
Self-employed	0.51	0.84	0.78
Non-agriculture			
Wage labor	0.18	0.07	0.09
Self-employed	0.23	0.15	0.16
Migrate	0.12	0.11	0.11
School	0.18	0.13	0.14
Non-participant	0.14	0.06	0.07
Climate			
Temperature z-score	0.52	0.35	0.39
	(0.97)	(0.99)	(0.99)
Rainfall z-score	-0.07	-0.15	-0.13
	(0.88)	(0.84)	(0.85)
Other			
Female	0.52	0.51	0.52
Large landowner	0.40	0.55	0.52
Observations	15,241	40,036	55,277

Note: Table includes means (proportions for binary variables) and standard deviations 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, where the medians vary by country and rural-urban classification. Observations are person-years aged 15–65. Sample weights applied.

in urban settings appear to be more active in non-agricultural wage employment (18 percent) and non-agricultural self-employment (23 percent). A slightly greater percentage of urban workers have migrated temporarily in the last 12 months (12 percent).

Main results measure variations in climate responses by rural and urban locations.[29] The majority of households live in rural areas.[30] Fifty-five percent of rural workers live in households with landholdings above the country rural median, while only 40 percent of urban workers live in households with landholdings above the country urban median.

The coverage period is limited by the six-year span of LSMS-ISA. Table 1 indicates that rainfall in this period was 0.07 and 0.15 standard deviations below historical averages in urban and rural areas. In addition, the sample experienced historically warm temperatures. Urban workers faced greater exposure to heat variation, with average temperature z-scores of 0.52, compared to 0.35 in rural areas.

[29] In the Appendix, we further stratify the sample by gender and assets (proxied by household landholdings).

[30] The Ethiopia sampling frame is representative of only rural areas and small towns (fewer than 10,000 people) except Afar and Somalie regions. It thus excludes metropolitan areas such as Addis Ababa.

Table 2—Occupational characteristics

	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban							
Female	0.39	0.53	0.30	0.52	0.47	0.44	0.65
Age	35.80	33.57	33.22	34.71	26.23	17.54	28.53
Primary Education	0.41	0.36	0.46	0.45	0.51	0.50	0.55
Secondary Education	0.03	0.06	0.33	0.15	0.26	0.13	0.14
Observations	370	5,932	3,258	3,364	2,001	3,003	2,707
Rural							
Female	0.44	0.51	0.26	0.54	0.41	0.42	0.67
Age	32.13	32.59	32.35	33.48	27.65	16.56	27.65
Primary Education	0.40	0.31	0.45	0.38	0.40	0.36	0.28
Secondary Education	0.02	0.03	0.20	0.05	0.07	0.04	0.02
Observations	3,277	31,829	3,500	7,172	4,238	5,815	2,792

Note: Table includes means (proportions for binary variables), conditional on the individual participating in a given activity. 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. Observations are person-years. Sample weights applied.

Table 2 indicates that agricultural wage markets and school attendance are dominated by men in both rural and urban areas, whereas a greater percentage of women is not employed. The sharpest geographic distinction is in migration; in urban areas migration is almost equally split by gender, while only 41 percent of rural migrants are female.

Average age is similar across activities and locations, with the exceptions of migration, school, and not employed. Respondents engaging in these three activities tend to be younger. This age profile is similar in both locations.

Urban areas have relatively highly educated workers. Approximately one third of non-agricultural wage workers and one fourth of 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 non-agricultural wage workers and 7 percent of migrants in rural areas have completed secondary education.

Those who are currently not employed have different skills in rural and urban locations. Individuals who are not employed in urban areas possess qualifications similar to those of the non-agricultural self-employed, with a slightly greater percentage having completed a primary education. In contrast, those in rural areas who are not employed tend to resemble farmers, with only 3 percent fewer having completed primary education.

Appendix Table A.3 describes self-employed activities by sector. The main sources of income for the agricultural self-employed are livestock and its byproducts (31 percent), followed by cash (18 percent) and cereal (14 percent) crops. The distinguishing features of the urban agricultural self-employment sector is that a greater percentage of workers are engaged in cash crops (35 relative to 15 percent) and fewer manage livestock (23 relative to 32 percent). Across countries, Ethiopia possesses the largest share of workers engaged in cash crops on average (26 percent), whereas Malawi holds the greater share of workers in livestock (52 percent).

The majority of workers in non-agricultural self-employment engage in trade and repair. The pattern is similar for rural and urban areas, but there is cross-country variation. Over half of the workers in non-farm enterprises in Tanzania and Malawi are involved in this activity. The trade and repair subsector can be particularly vulnerable to climate variability since the demand for such goods and services can decline with the purchasing power of low-income households (Mueller and Quisumbing, 2011).

IV. Results

A. Labor Response to Temperature

Workers can respond to high temperatures by adjusting behavior in several dimensions: from self-employed to wage labor, from agricultural to non-agricultural activities, from local to distant locations, or by engaging in more educational or non-income generating household activity. As discussed in Section I, theory alone offers little guidance regarding the direction of these changes. If higher temperatures reduce marginal productivity of labor, a backward-bending labor supply curve may cause leisure to decrease for subsistence households. Similarly, the choice of income-generating activity is affected by temperature's marginal productivity impact *relative* to other activities, not just by the absolute impact. Thus, even in the absence of backward-bending labor supply, increasing temperature may increase participation in an activity for which it has a negative productivity impact if the impact on other activities is worse. These responses may be non-monotonic even if temperature has a monotonic impact on each activity.

Estimating temperature impacts on agricultural yields or industrial productivity alone is therefore insufficient for predicting labor response in a particular activity; it is necessary to observe individual responses directly.[31] Our empirical analysis yields several insights. Table 3 presents parameters and standard errors of the climate variables estimated using our preferred specification for each occupational activity.[32] The intuition underlying the results is most easily described with graphs of the predicted probabilities of engagement in each activity over the range of temperature z score values observed in the data, holding all other variables fixed at observed values.

Despite well-documented impacts of temperature on agricultural yields, the curves shown in Figure 5 suggest the strongest participation response to temperature may not be in agriculture directly. Rather, non-agricultural self-employment declines with temperature, while agricultural self-employment does not.[33] The temperature impact is monotonically decreasing in both urban and rural areas for all observed temperatures.[34]

The impact is similar in rural and urban areas; neither the difference between the two linear terms nor the difference between squared terms is statistically significant at conventional levels (linear F statistic P-value=0.104; squared F statistic P-value=0.128). An increase in the temperature z-score from zero to one is associated with a drop in non-agricultural self-employment participation from 29.5 to 21.0 percent and 17.1 to 12.0 percent in urban and rural areas, respectively (Appendix Table A.6). These responses are not sensitive to replacing the quadratic time trend with separate

[31]Alternatively, with sufficient data, in principle one might be able to estimate relative productivity impacts across multiple sectors to develop an empirically-calibrated structural model along the lines of Figure 1. However, climate productivity data is scarce, particularly for non-agricultural sectors.

[32]To facilitate comparison with earlier results in the literature, we report standard significance levels (indicated by stars) and in brackets q-values adjusted for multiple hypothesis testing.

[33]Schooling participation is similarly unaffected.

[34]Gender does not appear to affect the non-agricultural self-employment response to high temperatures in urban or rural areas (Figure A4 and Table A.4). Referring to Figure A5, high temperature's adverse impact on non-agricultural self-employment is qualitatively similar for large and small landowners in both rural and urban areas. Table A.5 includes corresponding estimates. Here, we utilize household landownership as a proxy for wealth. Landholdings are defined as large or small based on one's relative size to the median landholdings in rural or urban areas in each country.

Table 3—Climate impacts on labor participation rates by activity

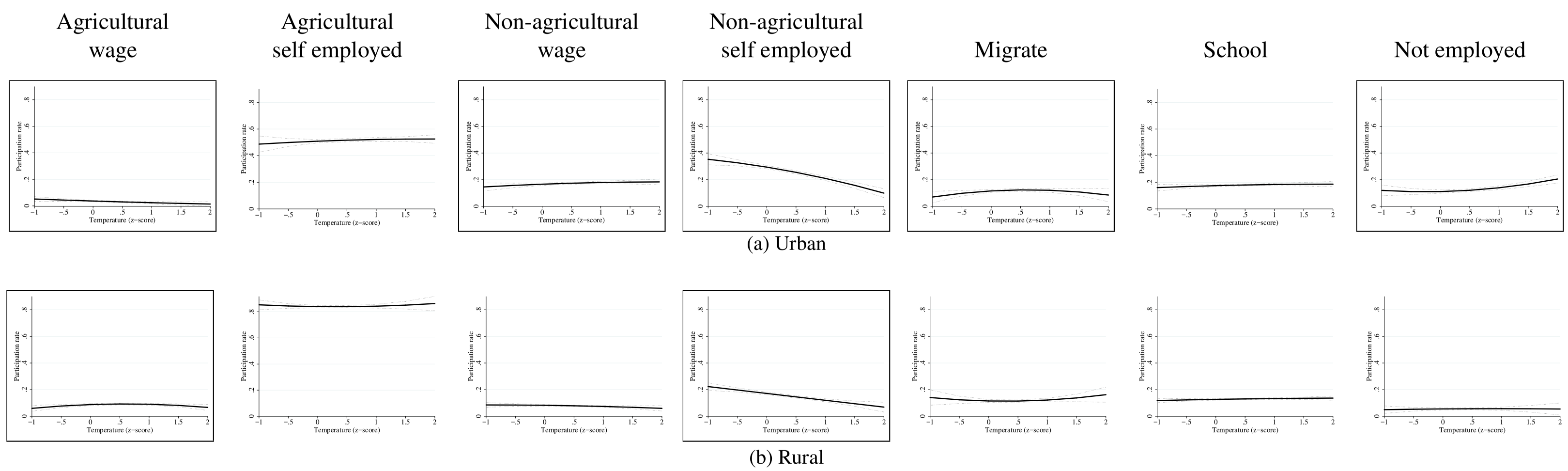
	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.014**	0.017	0.016**	-0.070***	0.024**	0.012	0.010
	(0.005)	(0.017)	(0.008)	(0.012)	(0.011)	(0.007)	(0.011)
	[0.046]	[0.367]	[0.086]	[0.001]	[0.058]	[0.149]	[0.367]
Temperature^2	0.001	-0.005	-0.004	-0.013**	-0.020**	-0.003	0.019***
	(0.003)	(0.010)	(0.004)	(0.006)	(0.010)	(0.004)	(0.006)
	[0.665]	[0.665]	[0.612]	[0.080]	[0.080]	[0.612]	[0.008]
Rain	-0.009	0.006	0.012	-0.022	0.003	-0.000	0.001
	(0.006)	(0.012)	(0.010)	(0.016)	(0.011)	(0.008)	(0.013)
	[0.472]	[0.988]	[0.472]	[0.472]	[0.988]	[0.988]	[0.988]
Rain^2	-0.002	-0.009	-0.008*	-0.007	-0.014***	0.004	0.014**
	(0.002)	(0.006)	(0.005)	(0.007)	(0.006)	(0.004)	(0.006)
	[0.326]	[0.284]	[0.224]	[0.380]	[0.069]	[0.386]	[0.102]
Rain × Temperature	0.004	-0.004	-0.009	0.025*	-0.020*	-0.002	0.002
	(0.005)	(0.011)	(0.009)	(0.014)	(0.011)	(0.008)	(0.013)
	[0.705]	[0.872]	[0.705]	[0.296]	[0.296]	[0.872]	[0.872]
Rural ×							
Temperature	0.014**	-0.005	-0.004	-0.050***	-0.004	0.007	0.003
	(0.005)	(0.008)	(0.004)	(0.007)	(0.012)	(0.004)	(0.005)
	[0.040]	[0.654]	[0.500]	[0.001]	[0.756]	[0.271]	[0.654]
Temperature^2	-0.013***	0.008	-0.003	0.000	0.017	-0.001	-0.002
	(0.005)	(0.009)	(0.003)	(0.007)	(0.012)	(0.003)	(0.007)
	[0.033]	[0.726]	[0.726]	[0.990]	[0.597]	[0.917]	[0.917]
Rain	0.008	-0.009	-0.011**	0.001	-0.023**	0.004	-0.000
	(0.006)	(0.008)	(0.005)	(0.007)	(0.012)	(0.005)	(0.006)
	[0.452]	[0.523]	[0.121]	[0.990]	[0.163]	[0.524]	[0.990]
Rain^2	-0.005	0.001	0.004	0.004	0.014*	-0.001	-0.005
	(0.004)	(0.007)	(0.003)	(0.006)	(0.008)	(0.004)	(0.006)
	[0.686]	[0.934]	[0.686]	[0.780]	[0.457]	[0.841]	[0.694]
Rain × Temperature	-0.010	0.004	0.008	0.012	0.037**	-0.004	-0.004
	(0.006)	(0.015)	(0.006)	(0.010)	(0.018)	(0.005)	(0.012)
	[0.367]	[0.801]	[0.367]	[0.389]	[0.338]	[0.526]	[0.801]
P values for F test:							
urban × temp. = rural × temp.	0.000	0.223	0.014	0.104	0.042	0.529	0.534
urban × temp.^{2} = rural × temp.^{2}	0.009	0.341	0.824	0.128	0.014	0.733	0.022
R^2	0.007	0.003	0.008	0.051	0.011	0.058	0.012
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sample and attrition weights applied.

linear trends for rural and urban areas within each country, a common linear trend across countries, separate linear trends for each country, and linear urban and rural trends common across countries.[35]

[35] Results presented in Appendix Figures A6–A8 and Tables A.7–A.11.

Figure 5. Predicted labor participation response to temperature by activity and location



Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which linear or quadratic temperature response parameters are significantly different from zero with q <10 percent.

Participation in agricultural wage labor also decreases at higher temperatures in both urban and rural areas. The effect is non-monotonic in rural areas over the relevant temperature range (participation only increases until about 0.5 standard deviations above the mean), while it is almost linear in urban areas. Urban migration rates are highest during moderate temperatures, while participation in the urban non-agricultural wage activity is highest at relatively high temperatures.[36] Urban workers increase participation in non-agricultural wage employment at about the same rate as they decrease their agricultural wage labor (0.016 compared to -0.014 with q-values of 0.046 and 0.086, respectively). There are no analogous offsetting responses to agricultural wage labor in rural areas.

Interestingly, urban workers experience more disruptive outcomes, in terms of overall reductions in overall employment rates, despite evidence of labor substitution across activities. The percentage of people who are not employed in urban areas follows a U-shaped curve,[37] roughly inverse to the combination of non-agricultural self-employment and migration, whereas the rural impact of temperature on the probability of not being employed is not statistically significant.[38] Together, these estimates suggest that the increase in urban non-agricultural wage labor is not sufficient to absorb workers who no longer migrate or engage in non-agricultural self-employment. The percentage of people in urban areas who are not employed increases from 11.1 percent at mean 2000–2014 temperatures to 13.9 percent at one standard deviation above the mean. At two standard deviations, the percentage of people not employed reaches 20.5 (Appendix Table A.6).

As discussed in Section I, caution should be exercised in interpreting these results. It may seem

[36]Only men have a significant inverted U-shaped migration curve (Figure A4). This difference may partly be explained by marital customs. Due to the dominance of patrilocal residence in many countries (Ember, 1975), women may be more likely to migrate for non-economic reasons than men. Consequently, temperature may be less likely to affect marginal returns to migration from females, leading to a less significant participation response. Furthermore, for migration, temperature impacts also vary by wealth (Figure A5). Whereas individuals in urban households with small landownership experience the high temperature decline in migration observed in the main results, individuals from large landowning households actually increase migration. These results are consistent with findings that suggest access to capital may make temporary migration more profitable for the impoverished (Bryan et al., 2014).

[37]The proportion of men and women that are not employed in urban areas increases during temperature extremes (Figure A4). However, small landowners experience the corresponding increase in the probability of not being employed observed in the main results, whereas large landowners do not (Figure A5).

[38]Results are robust to using 12, rather than 24, month climate anomalies (Table A.12), using sample rather than attrition weights (Table A.13), and dropping individuals who change location between survey rounds (Table A.14). Corroborating earlier work, raw temperature values are not as strong of a predictor on labor outcomes as temperature anomalies (Table A.15). Spatial dependence in the error term among close enumeration areas does not appear to bias inferences, as the results are robust to substituting district-clustered for enumeration area-clustered standard errors (Table A.16).

natural to attribute an increase in non-agricultural wage participation to a temperature-induced increase in productivity. Yet, this phenomenon is also consistent with temperature adversely affecting urban non-agricultural wage labor productivity at a slower rate than its adverse impact on agricultural wage labor. By Proposition 3, however, the increase in the percentage of urban adults who are not employed suggests an adverse temperature productivity impact in one or more urban activities.

In contrast, the fact that participation in agricultural wage labor and non-agricultural self-employment declines with temperature in rural areas without a corresponding increase in the percentage who are not employed does not provide conclusive evidence of an adverse productivity impact. Since there is not a corresponding increase in participation in other activities, these workers may be engaged in multiple activities at lower temperatures. For example, they may engage in both agricultural and non-agricultural self-employment at lower temperatures, but use agricultural self-employment as a backstop occupation at higher temperatures. In the next section, we explore possible mechanisms consistent with these results.

B. *Potential mechanisms*

Our main finding in the previous section is that although high temperatures cause a decline in non-agricultural self-employment in both rural and urban areas, it only leads to a reduction in overall employment rates in urban areas. In light of previous research showing strong adverse temperature impacts on agricultural productivity, our results raises two questions: Why is the decrease in employment only observed in urban areas? and Why is there a decline in *non*-agricultural self employment? In this section, we explore the potential for barriers to entry to a backstop occupation or upstream input linkages to explain these findings.

Barriers to entry to a backstop occupation. Agricultural self-employment has the highest predicted participation rate in both urban and rural areas. The fact that engagement in this activity is insensitive to temperature (Figure 5) suggests that it may serve as a backstop occupation as described in Section I. Even if increasing temperature reduces profitable work opportunities, workers

Table 4—Proportion of sample engaged in multiple activities in one year

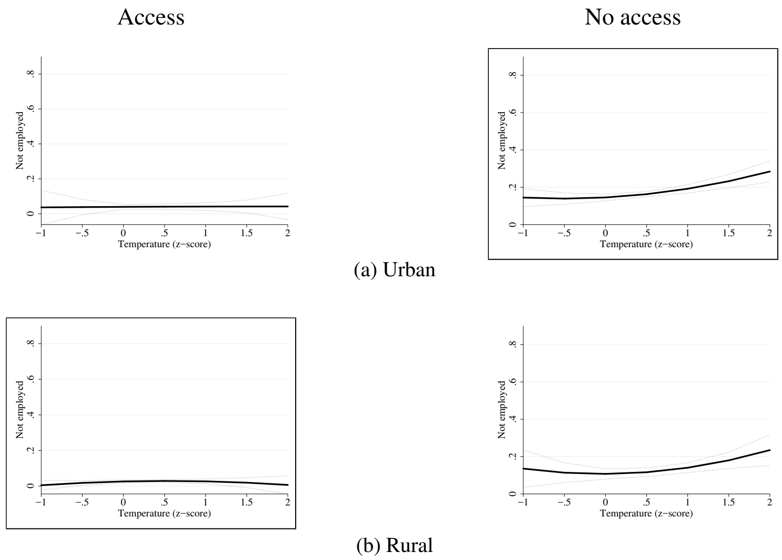
		If employed			
			activity besides agricultural self-employment		
Population Density	Never employed	Only agricultural self-employment	Only concurrent (Access)	Only alone (No access)	Concurrent and alone
Urban	0.03	0.20	0.27	0.37	0.13
Rural	0.01	0.34	0.46	0.08	0.11

Note: "Only" signifies that individual only reports participating in given activity over course of panel. "Concurrent" signifies the individual reports participating in agricultural self-employment and another activity in the same year. "Alone" signifies individual reports participating in another activity, but not agricultural self-employment. "Concurrent and alone" signifies the individual reports another activity alone in one year and both agricultural self-employment and another activity in a different year. Columns sum to 1 in each row. Sample weights applied.

may continue to engage in this activity rather than leave the labor market. If there are no barriers to entry, then observable characteristics should not be correlated with the probability of not being employed at high temperatures. If, on the contrary, the increase in the percentage of people who are not employed at high temperatures is not randomly distributed across the sample, this may indicate potential barriers to entry to the backstop activity for a subset of individuals.

One possible explanation for the vulnerability of urban workers to variation in temperature is that some face greater obstacles to engaging in the backstop activity than rural residents due to a characteristic not directly observable in the data. For example, land suitable for agriculture may be relatively scarce in urban areas, or a greater proportion of urban workers may lack skills necessary for agricultural work. We consider two types of workers. The first type simultaneously engages in both agricultural self-employment and another activity at moderate temperatures, while the second does not. The first type evidently does not face any barriers to engaging in agricultural self-employment, while the second may or may not face such barriers. If there were no barriers preventing one from working in agricultural self-employment, then both worker types should have an equal probability of not being employed at high temperatures, i.e., the probability of not being employed at high temperatures should be independent of whether one engages in agricultural self employment at moderate temperatures. To test this explicitly, we need to refine the empirical specification since Eq. (4) estimates aggregate temperature effects for both types.

Figure 6. Predicted temperature response for not being employed by access to agricultural self-employment



Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which linear or quadratic temperature response parameters are significantly different from zero with q <10 percent. "Access" is defined as engaging in agricultural self-employment in same year as engages in another activity. "No access" is defined as not engaging in agricultural self-employment in same year as engages in another activity.

As a crude test of the above hypothesis, we take the sample of individuals who have ever participated in any activity besides agricultural self-employment and focus on two groups: those who only report engaging in another activity in years that they report engaging in agricultural self-employment (access) and those who only report engaging in another activity in years when they do not report agricultural self-employment (no-access).[39] We compare temperature employment impacts across the two groups.[40]

Figure 6 illustrates response rates implied by the estimated parameters from this regression. The results are stark, particularly in urban areas.[41] Employment rates are near 100 percent and invariant to temperature for those who have engaged in agricultural self-employment alongside another ac-

[39] We do not estimate (or claim) a causal relationship between access and employment. Rather, we evaluate whether it is plausible that lack of access is correlated with an unobservable barrier to entry that impedes employment at high temperatures.

[40] Table 4 reports the proportion of the rural and urban sample in each category. We modify regression Eq. (5) with not employed as the dependent variable by replacing {male, female} with {access, no-access}. There are three other groups included in the regression for completeness: those who only participate in agricultural self-employment, those who are never employed, and those who report participating in agricultural self-employment concurrently with another activity in one round and report participating in another activity without agricultural self-employment in another.

[41] Appendix table A.17 presents estimates and standard errors.

tivity. For those without access, temperature increases lead to a sharp highly significant increase in urban residents reporting no employment.

These results are consistent with the stylized facts described by the theoretical model case presented in Figure 4. In both rural and urban areas, there is a segment of the population that does not have access to the agricultural self-employment backstop activity, and who are not employed at higher temperatures. Overall, people are less likely to engage in agricultural self-employment in urban areas (see Table 1). Table 4 shows that the percentage of urban individuals in the "no access" group is much is much larger (37 percent) than in rural areas (8 percent). Since the employment results presented in Table 3 and Figure 5 aggregate over both groups of individuals, we only observe a statistically significant decrease in labor force participation in urban areas.

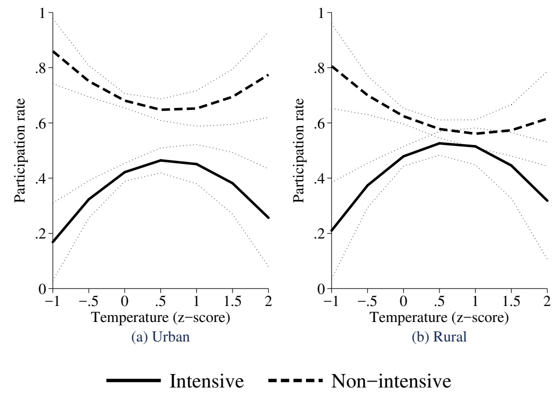
Lack of liquidity in land suitable for agriculture and relatively higher land rental prices in urban areas may offer an explanation for why urban workers may not be able to readily use agricultural self-employment as a backstop occupation (Holden and Otsuka, 2014). If it is easier to engage in self-employed agriculture if one owns an agricultural plot than if one does not, and more individuals in rural areas have access to such plots, then it may be more difficult or costly for urban residents to engage in self-employed agriculture even if the temperature productivity impacts are similar.

Upstream linkages. The decline in participation in non-agricultural self-employment in response to increasing temperature raises the question of how climate affects this sector. It may be that temperature affects participation indirectly via an impact on upstream agricultural sectors. In other contexts, however, research has found that high temperatures may adversely affect industrial productivity (Heal and Park, 2013).

To shed light on this issue, we subdivide the non-agricultural self-employment participation into activities that rely and do not rely on agricultural inputs.[42] Figure 7 shows a statistically significant inverted U-shape participation curve for non-agricultural self-employment activities that are agricultural-input intensive in both rural and urban areas. These results are consistent with a sce-

[42]Estimates of parameters and standard errors are reported in Table A.18

Figure 7. Predicted temperature response for non-agricultural self-employment by agricultural input intensity



Note: Dotted lines depict 95 percent confidence intervals.

nario in which rising temperature reduces agricultural yields, and the corresponding reduction in output reduces employment opportunities for small-scale buyers and sellers of agricultural produce in both urban and rural areas.

V. Conclusion

Given well-documented temperature impacts on productivity and labor decisions elsewhere, it is unsurprising that our results indicate that temperature significantly affects occupational participation decisions in East Africa. What remains puzzling is that this effect is most pronounced in the non-agricultural activity, both in rural and urban areas, and that temperature extremes reduce urban migration. This reduction in urban migration is consistent with the drought-driven urbanization discovered in Henderson et al. (2017). Our findings suggest that, in the short run, climate-driven urban population growth may be in part influenced by the inability of urban workers to migrate in search for work during hotter temperatures.

Henderson et al. (2017) argue that that climate-driven urbanization predominates in areas with a higher concentration of manufacturing industries with tradable goods outside districts. The intuition is that areas with manufacturing goods oriented outside of the district can attract labor out of the agricultural sector. By evaluating the specific labor activities of individuals, we provide additional insights on why towns and cities servicing agriculture may be particularly vulnerable. We show that non-agricultural self-employment reliant on agricultural inputs is most jeopardized by extreme temperatures.

Urban areas fare worse than rural areas, as the proportion of people exiting the urban labor force increases at high temperatures. This result challenges the conventional narrative of rural vulnerability to climate, and, by virtue of our theoretical model, implies that urban welfare is adversely affected by the temperature shock. We illustrate which factors appear associated with the vulnerability of urban workers. Additionally, urban workers are less likely to engage in a backstop occupation. Unlike their urban counterparts, rural workers are able to use agricultural self-employment (the primary activity of most) as a backstop when exposed to economic shocks.

The role of temperature has surfaced in discussions of environmental migration but few studies have examined its effect on individual worker decisions across multiple activities. Our findings have implications for how we perceive environmental displacement and adaptation policy in Africa. They suggest that urban labor markets may need increased social protection due to an inability to absorb workers displaced by temperature shocks.

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Appendix

A1. Theoretical Model

The utility maximization problem can be framed as allocating time **h** to solve:

$$\max_{\mathbf{h}\in\Re_{+}^{K}} \left\{ U\left(\pi(\mathbf{h};\mathbf{d},\mathbf{z}), \bar{h} - \sum_{k=1}^{K} h_k \right) \right\}. \tag{A1}$$

Eq. (A1) is a standard household production labor supply model modified to allow for multiple activities and a marginal product of labor that is a function of climate. Necessary conditions for a solution include for all $k \in (1,...,K)$

$$\frac{\partial y_k}{\partial h_k} - \frac{\frac{\partial U}{\partial s}}{\frac{\partial U}{\partial c}} \leq 0; \qquad h_k\left[\frac{\partial y_k}{\partial h_k} - \frac{\frac{\partial U}{\partial s}}{\frac{\partial U}{\partial c}}\right] = 0. \tag{A2}$$

An interior solution requires the marginal return to labor for all income-generating activities to be equal to the marginal rate of substitution of leisure for consumption:

$$\frac{\partial y_j}{\partial h_j} = \frac{\partial y_k}{\partial h_k} = \frac{\frac{\partial U}{\partial s}}{\frac{\partial U}{\partial c}}, \text{ for all } j,k \in (1,...,K). \tag{A3}$$

For an interior solution with $K = 2$ activities, differentiating Eq. (A2) with respect to h_1, h_2, and

z, and letting $\partial y/\partial h = \partial y_i/\partial h_i = \partial y_j/\partial h_j$ denote the solution to Eq. (A3) yields:

$$\begin{bmatrix} C_i \\ C_j \end{bmatrix} = \begin{bmatrix} A_i & B \\ B & A_j \end{bmatrix} \times \begin{bmatrix} \frac{\mathrm{d}h_i}{\mathrm{d}z} \\ \frac{\mathrm{d}h_j}{\mathrm{d}z} \end{bmatrix}, \text{ where for } k = i, j; i \neq j$$

$$A_k = \overbrace{\frac{\partial^2 U}{\partial c^2}\left[\frac{\partial y}{\partial h}\right]^2}^{a} + \overbrace{\frac{\partial U}{\partial c}\frac{\partial^2 y_k}{\partial h_k^2}}^{b_k} - \overbrace{2\frac{\partial^2 U}{\partial c \partial s}\frac{\partial y}{\partial h}}^{c} + \overbrace{\frac{\partial^2 U}{\partial s^2}}^{d}$$

$$B = \overbrace{\frac{\partial^2 U}{\partial c^2}\left[\frac{\partial y}{\partial h}\right]^2}^{a} - \overbrace{2\frac{\partial^2 U}{\partial c \partial s}\frac{\partial y}{\partial h}}^{c} + \overbrace{\frac{\partial^2 U}{\partial s^2}}^{d}$$

$$C_k = -\overbrace{\frac{\partial U}{\partial c}\frac{\partial^2 y_k}{\partial h_k \partial z}}^{e_k} - \overbrace{\sum_{m=1}^{2}\frac{\partial y_m}{\partial z}\left[\frac{\partial^2 U}{\partial c^2}\frac{\partial y}{\partial h} - \frac{\partial^2 U}{\partial c \partial s}\right]}^{f}$$

The solution to this system of equations is:

$$\begin{aligned}
\frac{\mathrm{d}h_i}{\mathrm{d}z} &= \frac{C_i A_j - C_j B}{A_i A_j - B^2} = \frac{[e_j - e_i][a - c + d] - [e_i + f]b_j}{b_i b_j + [a + c + d][b_i + b_j]} \\
&= \frac{D_i - E_i}{F}, \text{ where} \\
D_i &= \left[\frac{\partial^2 y_j}{\partial h_j \partial z} - \frac{\partial^2 y_i}{\partial h_i \partial z}\right]\left[\frac{\partial^2 U}{\partial s^2} + \frac{\partial y}{\partial h}\left[\frac{\partial^2 U}{\partial c^2}\frac{\partial y}{\partial h} - 2\frac{\partial^2 U}{\partial c \partial s}\right]\right] \\
E_i &= \frac{\partial^2 y_j}{\partial h_j^2}\left[\frac{\partial U}{\partial c}\frac{\partial^2 y_i}{\partial h_i \partial z} + \sum \frac{\partial y_k}{\partial z}\left[\frac{\partial^2 U}{\partial c^2}\frac{\partial y}{\partial h} - \frac{\partial^2 U}{\partial c \partial s}\right]\right] \\
F &= \frac{\partial U}{\partial c}\frac{\partial^2 y_i}{\partial h_i^2}\frac{\partial^2 y_j}{\partial h_j^2} + \left[\frac{\partial^2 U}{\partial s^2} + \frac{\partial y}{\partial h}\left[\frac{\partial^2 U}{\partial c^2}\frac{\partial y}{\partial h} - 2\frac{\partial^2 U}{\partial c \partial s}\right]\right]\sum \frac{\partial^2 y_k}{\partial h_k^2}.
\end{aligned} \tag{A4}$$

Although $F > 0$, the signs of D_i and E_i are ambiguous.

Special Case: Backward-Bending Supply Curve and Single Income Activity

For ease of exposition, we replace the climate vector $\mathbf{z}$ with the scalar temperature, z, and consider the special case of a single income-generating activity y. Suppose an increase in temperature monotonically reduces productivity, such that $\partial^2 y/\partial h \partial z < 0$. For an interior solution, differentiation of Eq.

(A2) yields:

$$\text{(A5)} \qquad \frac{\mathrm{d}h}{\mathrm{d}z} = -\frac{\frac{\partial U}{\partial c}\frac{\partial^2 y}{\partial h \partial z} + \frac{\partial y}{\partial z}\left[\frac{\partial^2 U}{\partial c^2}\frac{\partial y}{\partial h} - \frac{\partial^2 U}{\partial s \partial c}\right]}{\frac{\partial y}{\partial h}\left[\frac{\partial^2 U}{\partial c^2}\frac{\partial y}{\partial h} - 2\frac{\partial^2 U}{\partial c \partial s}\right] + \frac{\partial U}{\partial c}\frac{\partial^2 y}{\partial h^2} + \frac{\partial^2 U}{\partial s^2}}.$$

The denominator of Eq. (A5) is negative due to the concavity of the utility function, but the sign of the numerator is ambiguous. The latter can be broken into two components, a productivity effect and a leisure substitution effect. The first term in the numerator is negative, reflecting the fact that the climate shock reduces productivity and hence marginal utility of an hour of labor. The second term is positive, reflecting the fact that the reduction in income caused by the productivity shock also reduces the value of leisure.

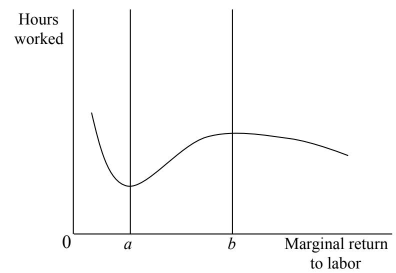
Backwards-bending labor response curves arise if the second term is greater in absolute value than the first. The marginal utility of consumption may be sufficiently low for wealthy individuals that they increase work hours due to an adverse productivity shock. Alternatively, they may reduce work hours in the presence of a positive shock.

Poor households may also experience a backward-bending labor supply curve (Dessing, 2002). Suppose that the decrease in marginal utility decelerates with wealth, $\partial^3 U / \partial c^3 > 0$, or the increase in marginal utility of leisure from an increase in consumption decreases with wealth, $\partial^3 U / \partial s \partial c^2 < 0$. These conditions are continuous analogs of the Dessing (2002) subsistence constraint. In such cases, labor supply can have the S-shape depicted in Figure A1, a downward-sloping function of marginal return to labor at low and high incomes, and upward sloping in between. Since the countries analyzed here are poor, for the remainder of the discussion we use the term backward-bending labor supply to refer to the downward-sloping range of the labor supply curve for low-income individuals. That is, even relatively wealthy individuals in our sample are likely to be to the left of point b in Figure A1.

PROOF OF PROPOSITION 1:

Suppose $E_i \geq 0$ (labor supply curve is upward sloping), and $\partial^2 y_j / \partial h_j \partial z < \partial^2 y_i / \partial h_i \partial z < 0$. In this case

Figure A1. S-shaped labor supply curve



Note: As poor workers approach subsistence level below *a* they respond to reduced returns to labor by increasing work hours. Due to their low marginal utility of consumption, wealthy workers respond to increased returns to labor by reducing work hours above point *b*.

$D_i > 0$. Hours allocated to i increase if $D_i > E_i$. Total employed hours decreases:

$$\text{(A6)} \qquad \frac{\mathrm{d}h_i}{\mathrm{d}z} + \frac{\mathrm{d}h_j}{\mathrm{d}z} = \frac{D_i + D_j - [E_i + E_j]}{F} = -\frac{E_i + E_j}{F} < 0.$$

■

PROOF OF PROPOSITION 2:

Suppose $\partial^2 y_i / \partial h_i \partial z = \partial^2 y_j / \partial h_j \partial z < 0$. Then $\mathrm{d}h_i / \mathrm{d}z$ has the same sign as $-E_i$, the first term of which is negative and the second positive. Workers between a and b in Figure A1 respond to marginal increases in z by reducing labor supply. If consumption falls such that $\partial^3 U / \partial c^3$ or $\partial^3 U / \partial c^2 \partial s$ are sufficiently small, individuals respond to further increases in temperature by increasing hours worked.

■

PROOF OF PROPOSITION 3:

(a) For workers who are employed: Let $h_k > 0$ for at least one activity and $\partial^2 y_k / \partial h_k \partial z > 0$, for all k. In Eq. (A4), the term $D_i \geq 0$ for at least one activity for which $h > 0$ (by Eq. (A5) this term disappears for the single activity case). At the limit $\sum_{k=1}^{K} \partial y_k / \partial z = 0$ as $\sum_{k=1}^{K} h_k \to 0_+$. Thus, for some strictly positive number of hours worked, $E_i < 0$. The right hand side of Eq. (A4) is greater than zero and a marginal increase in temperature cannot further reduce hours worked. For workers who are not employed: Let $h_k = 0$ and $\partial^2 y_k / \partial h_k \partial z < 0$, for all k. By Eq. (A2), $\partial U / \partial c \, \partial y_i / \partial h_i < \partial U / \partial s$. Regardless of the individual's unearned income level, an adverse climate shock has no impact on total earned income (since none is generated). Therefore $\partial U/\partial s$ remains unchanged while $\partial U/\partial c \, \partial y_i/\partial h_i$ decreases, resulting in no increase in labor market participation. (b) Let $U(\pi_1, s_1; z_1)$ be the utility obtained by the solution to the worker's optimization problem at temperature z_1, with $\pi_1 > 0$ (i.e., the worker is optimally employed). Let $U(0, s_2; z_2)$ be the utility obtained at the solution given temperature z_2 (the worker is optimally not employed). It must be the case that $U(\pi_1, s_1; z_1) > U(0, s_2; z_1) = U(0, s_2; z_2)$, where the first relationship follows from the strict quasiconcavity of U and the second follows from the assumption that utility obtained from leisure is independent of z. ■

From continuous to discrete labor choices

An individual allocates time to activity k, only if the marginal return to k equals the marginal rate of substitution between income and leisure. Analogous to the Heckman (1976) two-step procedure, let $\tilde{\mathbf{h}}_k(z)$ be an unobserved latent variable solving Eq. (A2) without the non-negativity constraint,

$$\tilde{h}_k(z) = \left\{ h_k : \frac{\partial y_k(h_k)}{\partial h_k} = \frac{\frac{\partial U(c,s;\mathbf{h})}{\partial s}}{\frac{\partial U(c,s;\mathbf{h})}{\partial c}} \right\}. \tag{A7}$$

Introducing random unobserved individual heterogeneity u_i, let the value of the latent variable for individual i be

$$h^*_{ik} = \tilde{h}_k(z) + u_{ik}. \tag{A8}$$

Let the observed participation indicator L_{ikt} take a value of 1 if an individual engages in activity k, zero otherwise

$$L_{ik} = \begin{cases} 1 & \text{if } \tilde{h}_k(z) + u_{ik} > 0 \\ 0 & \text{if } \tilde{h}_k(z) + u_{ik} \leq 0. \end{cases} \tag{A9}$$

The probability that an individual engages in an activity is then

$$\Pr[L_{ik} = 1] = \Pr[\tilde{h}_k(z) > -u_{ik}]. \tag{A10}$$

Regression Eq. (3) is a linear approximation to this expression.

Table A.1—Determinants of remaining in sample

	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)
ln(1 + Household members age 2-15)	0.088	-0.075	0.160***	0.077
	(0.054)	(0.093)	(0.045)	(0.056)
ln(1+ Household members above age 15)	-0.461***	-0.361**	-0.182**	-0.586***
	(0.154)	(0.146)	(0.084)	(0.093)
ln(1 + Land area owned)	-0.017	0.329**	0.062*	0.043
	(0.074)	(0.128)	(0.033)	(0.040)
ln(1 + EA 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

Note: 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 and interview month and year are included. χ^2 statistic tests joint significance of interview 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.

A2. Attrition weights

We focus on the sample of baseline households that completed surveys in each subsequent round. A household is omitted from the sample if it moved out of its original residence and was not interviewed or if the household questionnaire was incomplete for some other reason in follow-up rounds. This procedure 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 in the 15–65 age category at baseline were unable to be tracked over time.[43]

For each country, we estimate probit models to determine which factors influence the probability that baseline individuals stay in the sample in later rounds. The baseline covariates in the regressions

[43]Including movers who left the baseline enumeration area in our main sample raises possible concerns regarding interpretation of results (e.g., if rural workers moved to urban areas), and assignment of baseline location climate variables. Approximately 1.9 percent of our sample moved between rounds 2 and 3 of the Uganda or Tanzania surveys, but were assigned baseline climate from round 1. Appendix Table A.14 shows results are robust to excluding tracked movers, those who were interviewed in rounds 2 (or 3) but live in a new enumeration area.

include individual gender and age, and the natural logarithms of the number of children, adults, and household land owned. We also include attrition rates of baseline individuals from the EA,[44] indicators for the baseline interview month and year, and indicators of baseline interviewers to reflect the role of field practices on survey quality (Maluccio, 2004; Thomas et al., 2012).

Table A.1 displays probit regression results. 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. The EA attrition rate (Ethiopia and Malawi only) and interviewer indicators are strongly correlated with remaining in the sample. The latter is determined by χ^2 tests of joint parameter significance presented at the bottom of Table A.1, which indicates we cannot reject that the EA attrition rate and interview variable coefficients jointly are equal to zero at the 10 percent level.

We estimate restricted versions of models in Table A.1, excluding the EA attrition rate and interview indicators (our excluded instruments) to account for selective attrition (Fitzgerald et al., 1998).[45] The ratio of predicted values from restricted and unrestricted probit regressions is used to create the inverse probability weights applied to labor participation regressions.

[44] Individuals excluded from calculation of own attrition rate. Attrition rates based on round 2 (and 3 if available).

[45] We are unable to include climate variables in the attrition model since they are highly correlated with the excluded instruments (the interviewer indicators and village attrition rate), which are defined at a similar geographic level.

A3. Appendix Figures

Figure A2. Enumeration Areas

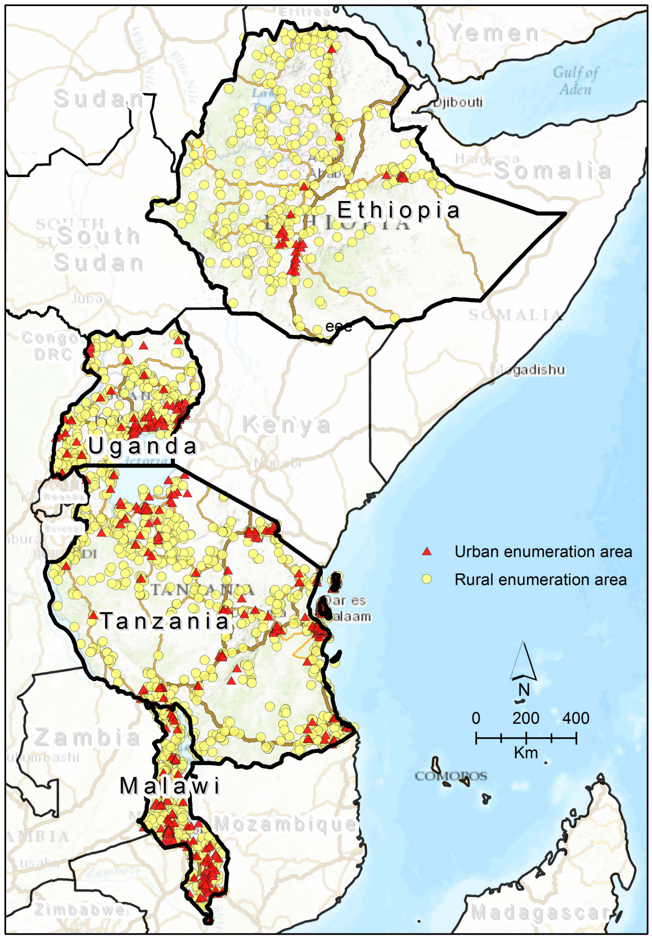
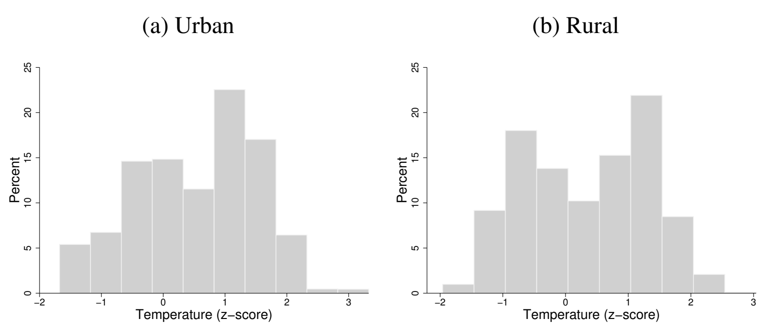
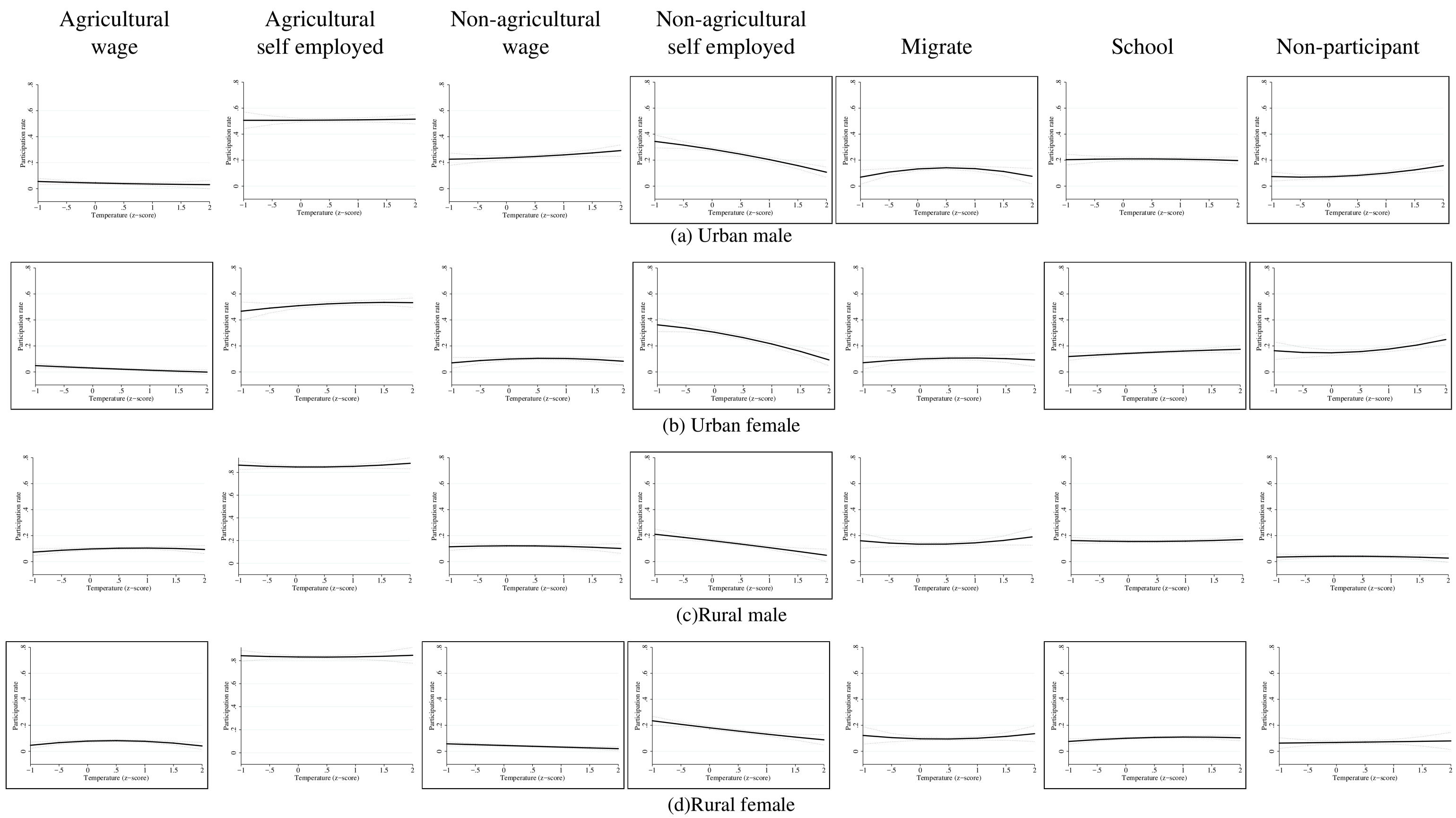


Figure A3. Distribution of temperature anomolies



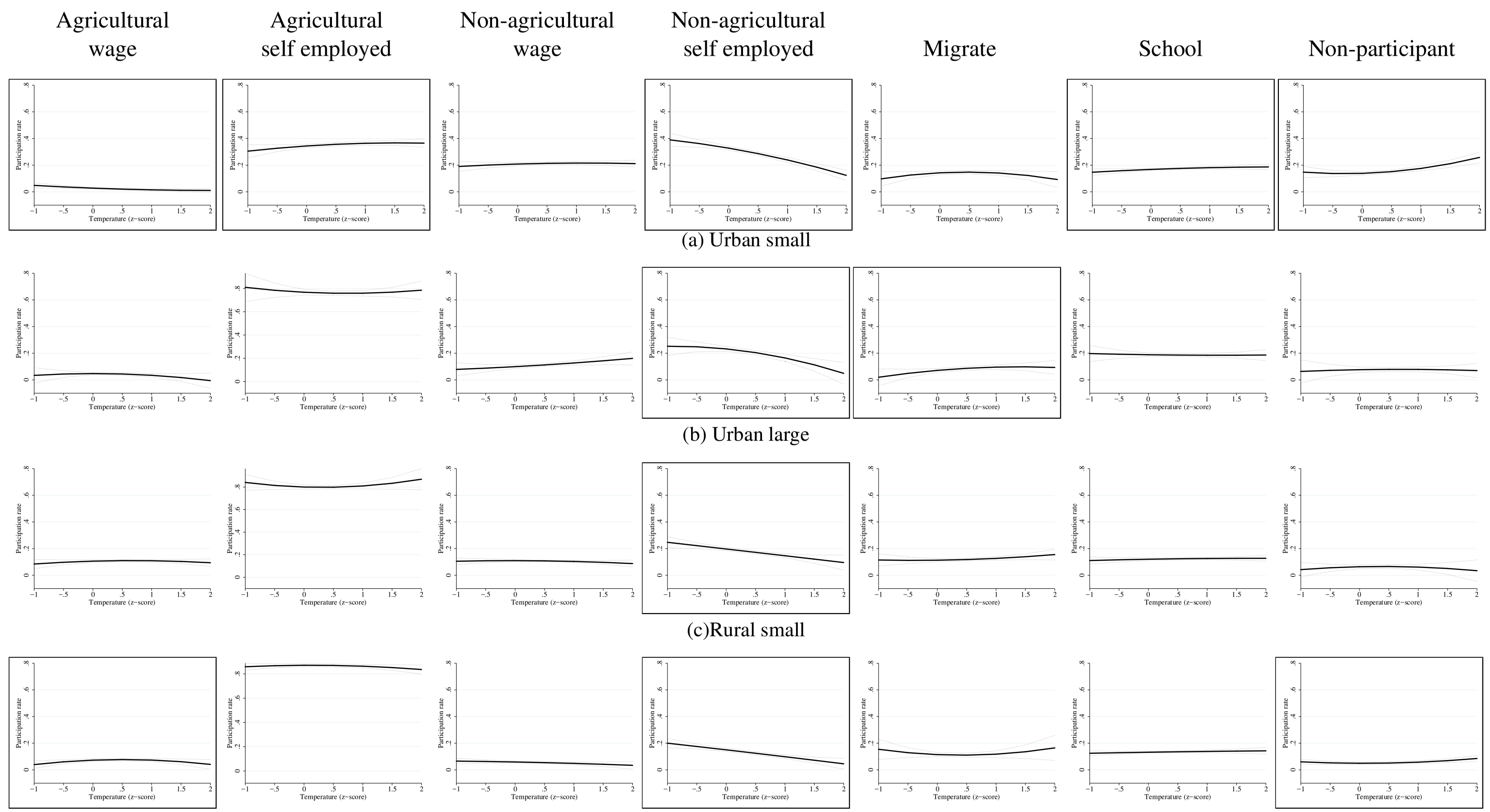
Note: Frequency adjusted using survey sampling weights.

Figure A4. Predicted temperature response by activity, location, and gender



Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which linear or quadratic temperature response parameters are significantly different from zero with q <10 percent.

Figure A5. Predicted labor response by household land ownership



(a) Urban small

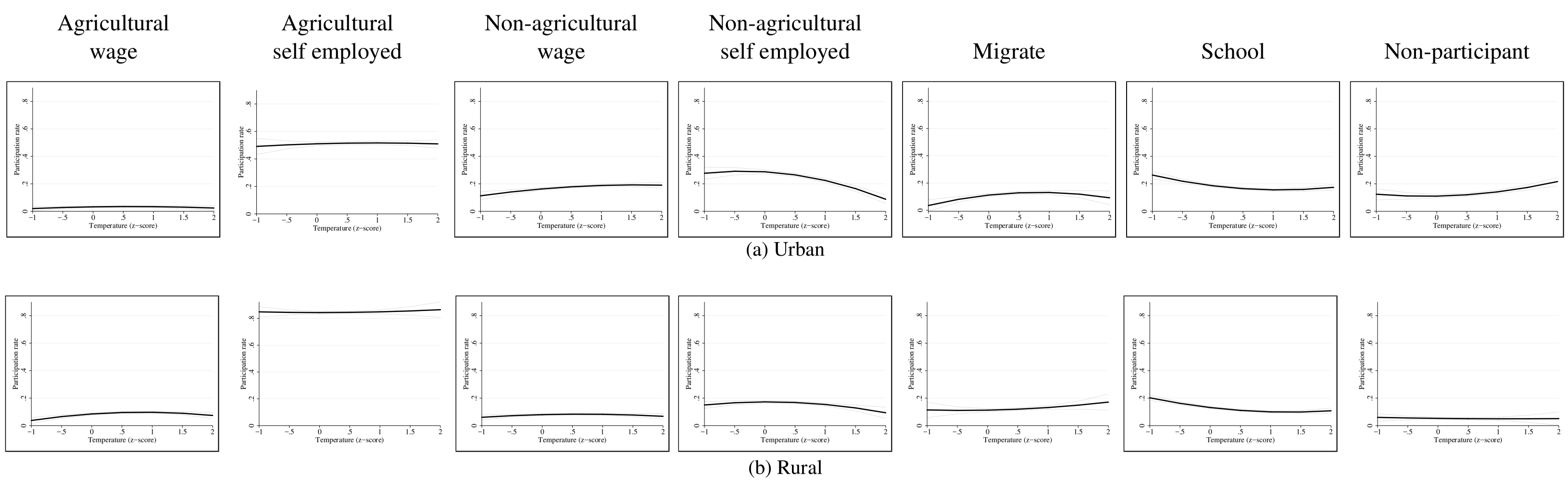
(b) Urban large

(c)Rural small

(d)Rural large

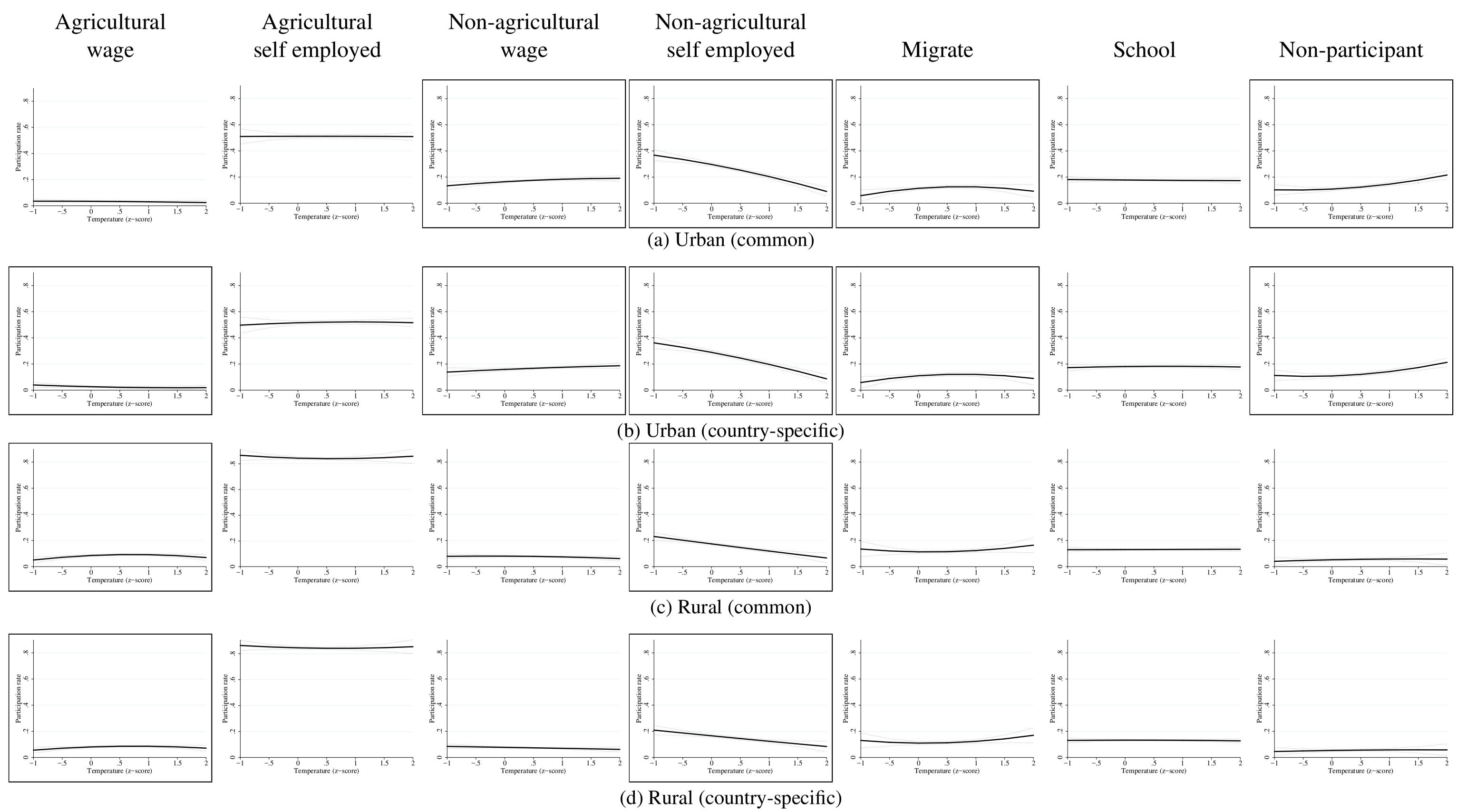
Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which linear or quadratic temperature response parameters are significantly different from zero with q <10 percent.

Figure A6. Predicted labor response, no time trend



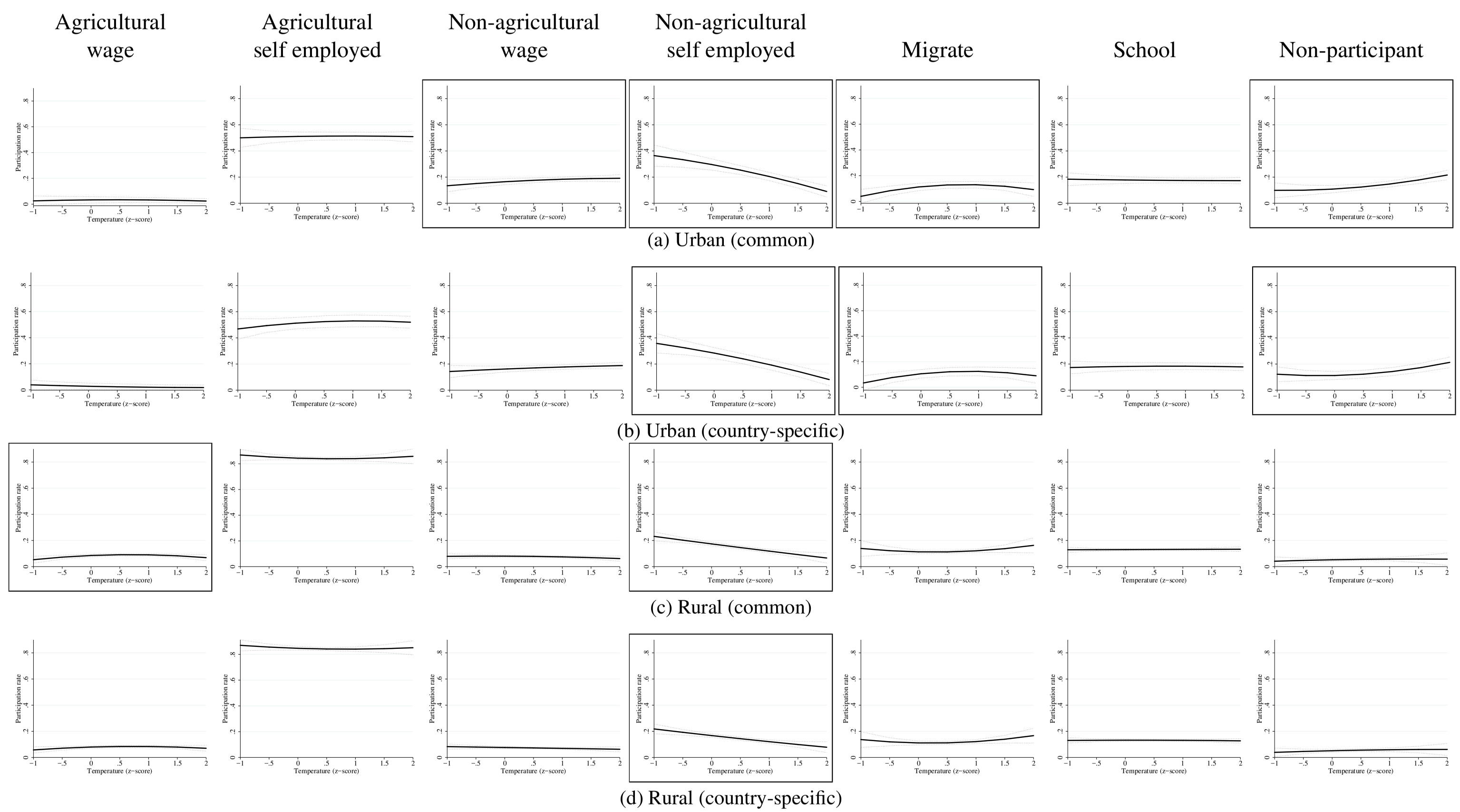
Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which linear or quadratic temperature response parameters are significantly different from zero with q <10 percent.

Figure A7. Predicted labor response, common and country-specific linear trend



Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which linear or quadratic temperature response parameters are significantly different from zero with q <10 percent.

Figure A8. Predicted labor response, common and country-specific linear trends by population density



Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which linear or quadratic temperature response parameters are significantly different from zero with q <10 percent.

A4. Appendix Tables

Table A.2—Raw temperature data by country (° C)

	Ethiopia	Malawi	Tanzania	Uganda
Mean	19.80	22.40	23.35	23.85
	(2.56)	(1.34)	(2.12)	(1.76)
Standard Deviation	0.29	0.43	0.44	0.35
	(0.17)	(0.05)	(0.16)	(0.13)

Note: "Mean" is 24-month mean temperature averaged across individuals. "Standard Deviation" is the standard deviation of temperatures in the 24-month period averaged across individuals. Standard deviations of these averages in parentheses. Sampling weights applied.

Table A.3—Primary self-employed income source by activity (percent)

				Total by country			
	Urban	Rural	Total	Ethiopia	Malawi	Tanzania	Uganda
Agricultural							
Cash crop	0.35	0.15	0.18	0.26	0.17	0.11	0.16
Cereal	0.09	0.14	0.14	0.14	0.09	0.13	0.17
Fruits and vegetables	0.11	0.08	0.08	0.05	0.06	0.09	0.16
Livestock	0.23	0.32	0.31	0.39	0.52	0.25	0.18
Nuts and pulses	0.04	0.09	0.09	0.04	0.13	0.12	0.13
Oil seeds	0.00	0.04	0.03	0.04	0.00	0.03	0.02
Roots and tubers	0.00	0.02	0.02	0.04	0.00	0.00	0.00
Other	0.06	0.07	0.07	0.02	0.03	0.11	0.08
Observations	5,932	31,829	37,761	9,645	5,627	13,812	8,677
Non-agricultural							
Mining	0.02	0.03	0.02	0.04	0.01	0.02	0.01
Manufacturing	0.11	0.18	0.16	0.19	0.30	0.13	0.14
Electricity and water	0.05	0.05	0.05	0.18	0.00	0.00	0.00
Construction	0.02	0.01	0.01	0.02	0.01	0.01	0.00
Trade and repair	0.47	0.43	0.44	0.30	0.57	0.61	0.27
Hotel and restaurant	0.06	0.05	0.06	0.03	0.03	0.10	0.01
Transport	0.07	0.07	0.07	0.18	0.04	0.03	0.02
Services	0.08	0.05	0.06	0.02	0.06	0.08	0.06
Other	0.02	0.04	0.04	0.05	0.01	0.01	0.06
Observations	3,364	7,172	10,536	2,420	1,478	3,454	3,184

Note: Primary crop is the greatest source(s) of agricultural household income. Cash crops include black wattle, chat, cocoa, coffee, cotton, gesho, jute, kapok, phrethrum, rubber sisal, sugar cane, tea, tobacco, and wattle. The cereal crop category comprises barley, maize, millet, oats, rice, sorghum, teff, and wheat. Livestock includes meat and livestock byproducts. Proportions do not sum to one due to ties and missing values. Sampling weights applied.

Table A.4—Labor response differentiated by gender

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature × male	-0.009	0.002	0.016	-0.069***	0.031**	0.002	0.013
	(0.008)	(0.018)	(0.012)	(0.014)	(0.013)	(0.010)	(0.009)
	[0.314]	[0.893]	[0.314]	[0.001]	[0.073]	[0.893]	[0.314]
Temperature^2 × male	0.002	0.001	0.006	-0.009	-0.031***	-0.004	0.015**
	(0.005)	(0.011)	(0.008)	(0.008)	(0.012)	(0.006)	(0.006)
	[0.835]	[0.914]	[0.704]	[0.608]	[0.062]	[0.704]	[0.073]
Rain × male	-0.015	-0.008	0.009	-0.011	0.003	-0.013	0.013
	(0.009)	(0.014)	(0.015)	(0.019)	(0.015)	(0.012)	(0.012)
	[0.665]	[0.665]	[0.665]	[0.665]	[0.826]	[0.665]	[0.665]
Rain^2 × male	-0.001	-0.000	-0.006	-0.013	-0.017**	0.007	0.009*
	(0.003)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.005)
	[0.683]	[0.989]	[0.645]	[0.259]	[0.215]	[0.638]	[0.259]
Rain × temperature × male	0.008	0.008	-0.003	0.017	-0.023	-0.000	-0.002
	(0.009)	(0.012)	(0.014)	(0.016)	(0.014)	(0.011)	(0.011)
	[0.861]	[0.861]	[0.990]	[0.861]	[0.839]	[0.990]	[0.990]
Temperature × female	-0.018***	0.031	0.016	-0.071***	0.017	0.021**	0.007
	(0.005)	(0.019)	(0.010)	(0.015)	(0.012)	(0.009)	(0.018)
	[0.002]	[0.180]	[0.184]	[0.001]	[0.196]	[0.044]	[0.699]
Temperature^2 × female	0.001	-0.010	-0.013*	-0.016**	-0.011	-0.002	0.022**
	(0.003)	(0.011)	(0.007)	(0.007)	(0.010)	(0.005)	(0.009)
	[0.725]	[0.497]	[0.129]	[0.085]	[0.446]	[0.725]	[0.085]
Rain × female	-0.004	0.020	0.015	-0.034*	0.003	0.012	-0.011
	(0.006)	(0.018)	(0.011)	(0.020)	(0.013)	(0.012)	(0.020)
	[0.671]	[0.526]	[0.526]	[0.526]	[0.798]	[0.526]	[0.671]
Rain^2 × female	-0.003	-0.017*	-0.011*	-0.000	-0.012*	-0.000	0.019
	(0.002)	(0.010)	(0.006)	(0.009)	(0.007)	(0.004)	(0.012)
	[0.174]	[0.174]	[0.174]	[0.968]	[0.174]	[0.968]	[0.174]
Rain × temperature × female	0.001	-0.016	-0.015	0.032*	-0.017	-0.004	0.006
	(0.003)	(0.015)	(0.011)	(0.019)	(0.014)	(0.011)	(0.022)
	[0.819]	[0.508]	[0.508]	[0.508]	[0.508]	[0.819]	[0.819]
P values for F test:							
temp. × male = temp. × female	0.223	0.046	0.969	0.878	0.322	0.135	0.732
temp.^{2} × male = temp.^{2} × female	0.906	0.126	0.132	0.451	0.033	0.834	0.489

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sampling and attrition weights applied.

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Table A.4 – continued from previous page

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Rural ×							
Temperature × male	0.014**	-0.004	0.003	-0.051***	-0.003	-0.002	0.001
	(0.007)	(0.008)	(0.007)	(0.009)	(0.012)	(0.006)	(0.005)
	[0.140]	[0.817]	[0.817]	[0.001]	[0.817]	[0.817]	[0.817]
Temperature^2 × male	-0.009	0.011	-0.006	-0.002	0.018	0.005	-0.004
	(0.006)	(0.009)	(0.006)	(0.009)	(0.012)	(0.005)	(0.006)
	[0.466]	[0.466]	[0.466]	[0.787]	[0.466]	[0.466]	[0.518]
Rain × male	0.004	-0.009	-0.010	0.003	-0.020	-0.002	0.005
	(0.008)	(0.009)	(0.008)	(0.010)	(0.012)	(0.008)	(0.006)
	[0.842]	[0.667]	[0.589]	[0.842]	[0.589]	[0.842]	[0.667]
Rain^2 × male	-0.009*	-0.001	0.005	-0.002	0.012	0.001	0.005
	(0.005)	(0.008)	(0.005)	(0.007)	(0.009)	(0.006)	(0.005)
	[0.592]	[0.946]	[0.592]	[0.946]	[0.592]	[0.946]	[0.592]
Rain × temperature × male	-0.009	0.006	0.010	0.002	0.034*	0.003	-0.002
	(0.008)	(0.014)	(0.010)	(0.013)	(0.019)	(0.008)	(0.009)
	[0.710]	[0.902]	[0.710]	[0.902]	[0.539]	[0.902]	[0.902]
Temperature × female	0.014**	-0.005	-0.012***	-0.048***	-0.005	0.015***	0.004
	(0.006)	(0.009)	(0.004)	(0.009)	(0.014)	(0.005)	(0.007)
	[0.031]	[0.720]	[0.007]	[0.001]	[0.741]	[0.008]	[0.720]
Temperature^2 × female	-0.017***	0.006	0.000	0.003	0.015	-0.007*	0.000
	(0.005)	(0.011)	(0.003)	(0.008)	(0.014)	(0.004)	(0.010)
	[0.010]	[0.980]	[0.980]	[0.980]	[0.623]	[0.293]	[0.980]
Rain × female	0.012*	-0.008	-0.012***	-0.001	-0.027**	0.010	-0.005
	(0.007)	(0.011)	(0.004)	(0.009)	(0.014)	(0.006)	(0.009)
	[0.177]	[0.691]	[0.041]	[0.935]	[0.175]	[0.205]	[0.694]
Rain^2 × female	-0.001	0.002	0.001	0.009	0.016*	-0.004	-0.014*
	(0.005)	(0.010)	(0.003)	(0.007)	(0.008)	(0.004)	(0.009)
	[0.866]	[0.866]	[0.850]	[0.520]	[0.341]	[0.520]	[0.341]
Rain × temperature × female	-0.010	0.001	0.006	0.022**	0.039*	-0.012*	-0.007
	(0.007)	(0.018)	(0.004)	(0.011)	(0.020)	(0.007)	(0.017)
	[0.229]	[0.943]	[0.229]	[0.171]	[0.171]	[0.171]	[0.805]
P values for F test:							
temp. × male = temp. × female	0.945	0.978	0.030	0.750	0.855	0.023	0.689
temp.^{2} × male = temp.^{2} × female	0.195	0.588	0.347	0.594	0.756	0.069	0.568
R^2	0.008	0.004	0.009	0.051	0.011	0.059	0.013
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sampling and attrition weights applied.

Table A.5—Labor response differentiated by household land ownership

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature × small	-0.016***	0.030**	0.012	-0.073***	0.021	0.017**	0.013
	(0.006)	(0.015)	(0.010)	(0.014)	(0.013)	(0.008)	(0.012)
	[0.035]	[0.070]	[0.240]	[0.001]	[0.156]	[0.066]	[0.276]
Temperature^2 × small	0.004	-0.009	-0.006	-0.013*	-0.024**	-0.004	0.023***
	(0.003)	(0.008)	(0.005)	(0.007)	(0.012)	(0.004)	(0.006)
	[0.312]	[0.332]	[0.332]	[0.118]	[0.118]	[0.332]	[0.001]
Rain × small	-0.017***	0.006	0.007	-0.034*	-0.006	0.005	0.008
	(0.005)	(0.014)	(0.012)	(0.020)	(0.014)	(0.009)	(0.017)
	[0.006]	[0.696]	[0.696]	[0.295]	[0.696]	[0.696]	[0.696]
Rain^2 × small	-0.002	0.009	-0.009	-0.013	-0.021***	0.008*	0.004
	(0.002)	(0.007)	(0.007)	(0.009)	(0.008)	(0.004)	(0.008)
	[0.520]	[0.300]	[0.300]	[0.300]	[0.041]	[0.177]	[0.628]
Rain × temperature × small	0.011**	0.007	-0.009	0.041**	-0.019	-0.002	-0.011
	(0.004)	(0.011)	(0.012)	(0.016)	(0.013)	(0.008)	(0.016)
	[0.043]	[0.638]	[0.638]	[0.043]	[0.354]	[0.782]	[0.638]
Temperature × large	-0.002	-0.026	0.024*	-0.046***	0.036**	-0.006	0.009
	(0.014)	(0.031)	(0.013)	(0.017)	(0.016)	(0.015)	(0.022)
	[0.895]	[0.698]	[0.163]	[0.040]	[0.095]	[0.821]	[0.821]
Temperature^2 × large	-0.013	0.017	0.004	-0.024*	-0.014	0.003	-0.005
	(0.013)	(0.021)	(0.008)	(0.013)	(0.012)	(0.011)	(0.014)
	[0.681]	[0.751]	[0.806]	[0.480]	[0.681]	[0.806]	[0.806]
Rain × large	0.010	-0.018	0.021	0.012	0.022	-0.017	-0.003
	(0.018)	(0.026)	(0.015)	(0.020)	(0.017)	(0.016)	(0.019)
	[0.680]	[0.680]	[0.673]	[0.680]	[0.673]	[0.673]	[0.878]
Rain^2 × large	-0.006**	-0.035***	-0.006	-0.008	-0.003	-0.003	0.030***
	(0.003)	(0.013)	(0.007)	(0.010)	(0.007)	(0.007)	(0.010)
	[0.085]	[0.024]	[0.602]	[0.602]	[0.659]	[0.659]	[0.024]
Rain × temperature × large	-0.020	-0.006	-0.004	-0.020	-0.017	0.005	0.009
	(0.015)	(0.027)	(0.015)	(0.024)	(0.016)	(0.016)	(0.022)
	[0.839]	[0.839]	[0.839]	[0.839]	[0.839]	[0.839]	[0.839]
P values for F test:							
temp. × small = temp. × large	0.361	0.052	0.483	0.179	0.468	0.157	0.850
temp.^{2} × small = temp.^{2} × large	0.195	0.174	0.356	0.469	0.558	0.567	0.082

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Small and large refer to less or greater than median landholding by country and population density. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sampling and attrition weights applied.

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Table A.5 – continued from previous page

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Rural ×							
Temperature × small	0.012	-0.009	0.001	-0.049***	0.010	0.008	0.004
	(0.008)	(0.012)	(0.006)	(0.010)	(0.011)	(0.006)	(0.008)
	[0.448]	[0.648]	[0.896]	[0.001]	[0.615]	[0.478]	[0.703]
Temperature^2 × small	-0.009	0.025	-0.005	-0.000	0.008	-0.002	-0.012
	(0.006)	(0.015)	(0.005)	(0.010)	(0.009)	(0.004)	(0.013)
	[0.538]	[0.538]	[0.538]	[0.984]	[0.538]	[0.720]	[0.538]
Rain × small	0.003	-0.010	-0.007	0.010	-0.007	-0.003	0.002
	(0.009)	(0.014)	(0.007)	(0.011)	(0.011)	(0.007)	(0.009)
	[0.844]	[0.844]	[0.844]	[0.844]	[0.844]	[0.844]	[0.844]
Rain^2 × small	-0.005	0.021*	0.004	0.007	0.016**	0.002	-0.017*
	(0.006)	(0.012)	(0.004)	(0.007)	(0.007)	(0.006)	(0.009)
	[0.395]	[0.196]	[0.395]	[0.395]	[0.125]	[0.676]	[0.196]
Rain × temperature × small	0.001	0.035	0.008	0.009	0.022	0.002	-0.027
	(0.009)	(0.025)	(0.008)	(0.013)	(0.013)	(0.007)	(0.021)
	[0.929]	[0.482]	[0.538]	[0.698]	[0.482]	[0.929]	[0.482]
Temperature × large	0.015**	-0.002	-0.008	-0.049***	-0.013	0.006	0.001
	(0.007)	(0.008)	(0.005)	(0.008)	(0.014)	(0.005)	(0.005)
	[0.090]	[0.833]	[0.268]	[0.001]	[0.529]	[0.404]	[0.833]
Temperature^2 × large	-0.016**	-0.010	-0.002	-0.001	0.022	-0.001	0.010***
	(0.006)	(0.006)	(0.005)	(0.007)	(0.017)	(0.004)	(0.004)
	[0.037]	[0.271]	[0.916]	[0.916]	[0.356]	[0.916]	[0.037]
Rain × large	0.012	-0.011	-0.014***	-0.006	-0.036**	0.009	0.001
	(0.008)	(0.008)	(0.005)	(0.009)	(0.015)	(0.006)	(0.006)
	[0.249]	[0.249]	[0.057]	[0.554]	[0.057]	[0.243]	[0.933]
Rain^2 × large	-0.005	-0.023***	0.002	-0.001	0.011	-0.004	0.010*
	(0.006)	(0.007)	(0.005)	(0.008)	(0.012)	(0.005)	(0.005)
	[0.631]	[0.013]	[0.833]	[0.892]	[0.631]	[0.631]	[0.268]
Rain × temperature × large	-0.019**	-0.031***	0.006	0.012	0.046*	-0.010	0.020***
	(0.009)	(0.010)	(0.008)	(0.012)	(0.027)	(0.007)	(0.006)
	[0.095]	[0.008]	[0.412]	[0.341]	[0.164]	[0.202]	[0.007]
P values for F test:							
temp. × small = temp. × large	0.820	0.567	0.173	0.958	0.077	0.736	0.722
temp.^{2} × small = temp.^{2} × large	0.400	0.030	0.600	0.961	0.344	0.809	0.103
R^2	0.008	0.006	0.008	0.052	0.012	0.059	0.015
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Small and large refer to less or greater than median landholding by country and population density. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sampling and attrition weights applied.

Table A.6—Predicted participation rates by temperature

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban temperature z-score							
0	0.037	0.509	0.166	0.295	0.116	0.175	0.111
	[0.03–0.04]	[0.50–0.52]	[0.16–0.18]	[0.28–0.31]	[0.11–0.13]	[0.17–0.18]	[0.10–0.12]
1	0.024	0.521	0.179	0.210	0.121	0.183	0.139
	[0.02–0.03]	[0.51–0.54]	[0.17–0.19]	[0.19–0.23]	[0.11–0.14]	[0.17–0.19]	[0.13–0.15]
2	0.014	0.525	0.183	0.099	0.085	0.186	0.205
	[-0.00–0.03]	[0.49–0.56]	[0.16–0.21]	[0.07–0.13]	[0.03–0.14]	[0.17–0.21]	[0.17–0.24]
Rural temperature z-score							
0	0.088	0.840	0.082	0.171	0.115	0.127	0.055
	[0.08–0.10]	[0.83–0.85]	[0.08–0.09]	[0.16–0.18]	[0.10–0.13]	[0.12–0.13]	[0.05–0.06]
1	0.090	0.843	0.074	0.120	0.122	0.133	0.057
	[0.08–0.10]	[0.83–0.86]	[0.07–0.08]	[0.11–0.13]	[0.11–0.14]	[0.13–0.14]	[0.04–0.07]
2	0.067	0.863	0.059	0.069	0.162	0.136	0.054
	[0.04–0.09]	[0.81–0.92]	[0.04–0.08]	[0.03–0.11]	[0.11–0.22]	[0.12–0.15]	[0.01–0.10]

Note: Mean predicted values with 95 percent confidence intervals in brackets, using observed values for all variables except temperature. Sampling and attrition weights applied.

Table A.7—Labor response (no time trend)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	0.007	0.012	0.037***	-0.026**	0.046***	-0.053***	0.009
	(0.004)	(0.016)	(0.007)	(0.012)	(0.010)	(0.007)	(0.010)
	[0.148]	[0.453]	[0.001]	[0.044]	[0.001]	[0.001]	[0.453]
Temperature^2	-0.006*	-0.007	-0.012***	-0.037***	-0.029***	0.024***	0.022***
	(0.003)	(0.010)	(0.004)	(0.006)	(0.010)	(0.004)	(0.005)
	[0.081]	[0.518]	[0.007]	[0.001]	[0.007]	[0.001]	[0.001]
Rain×Temperature	0.001	-0.010	-0.013	0.004	-0.024**	0.015*	0.008
	(0.005)	(0.011)	(0.010)	(0.015)	(0.011)	(0.009)	(0.014)
	[0.790]	[0.699]	[0.382]	[0.790]	[0.214]	[0.250]	[0.790]
Rain	-0.002	0.013	0.022**	0.016	0.014	-0.036***	-0.008
	(0.007)	(0.012)	(0.009)	(0.016)	(0.010)	(0.010)	(0.013)
	[0.766]	[0.466]	[0.078]	[0.466]	[0.426]	[0.002]	[0.646]
Rain^2	-0.000	-0.007	-0.006	0.002	-0.012**	-0.005	0.012
	(0.002)	(0.007)	(0.005)	(0.009)	(0.006)	(0.005)	(0.007)
	[0.817]	[0.489]	[0.489]	[0.817]	[0.220]	[0.489]	[0.351]
Rural ×							
Temperature	0.028***	0.001	0.012***	0.003	0.014	-0.050***	-0.006
	(0.005)	(0.007)	(0.004)	(0.006)	(0.011)	(0.005)	(0.004)
	[0.001]	[0.866]	[0.010]	[0.684]	[0.291]	[0.001]	[0.287]
Temperature^2	-0.018***	0.005	-0.009**	-0.021***	0.010	0.020***	0.002
	(0.005)	(0.010)	(0.004)	(0.007)	(0.012)	(0.004)	(0.007)
	[0.002]	[0.674]	[0.032]	[0.004]	[0.554]	[0.001]	[0.775]
Rain×Temperature	-0.014**	0.007	0.004	0.008	0.032*	0.006	-0.006
	(0.007)	(0.016)	(0.006)	(0.010)	(0.019)	(0.006)	(0.013)
	[0.286]	[0.657]	[0.657]	[0.657]	[0.305]	[0.657]	[0.657]
Rain	0.007	0.002	-0.010**	0.025***	-0.022*	-0.008	-0.010
	(0.006)	(0.009)	(0.005)	(0.007)	(0.012)	(0.006)	(0.006)
	[0.308]	[0.819]	[0.148]	[0.004]	[0.186]	[0.225]	[0.225]
Rain^2	-0.007	0.005	0.002	0.009	0.013*	-0.000	-0.009
	(0.004)	(0.008)	(0.003)	(0.006)	(0.008)	(0.004)	(0.006)
	[0.306]	[0.638]	[0.638]	[0.306]	[0.306]	[0.968]	[0.306]
P values for F test:							
urban × temp = rural × temp	0.003	0.536	0.003	0.024	0.026	0.779	0.185
urban × temp^2 = rural × temp^2	0.036	0.393	0.545	0.062	0.012	0.455	0.030
R^2	0.005	0.000	0.005	0.031	0.009	0.025	0.008
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. No time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sample and attrition weights applied.

Table A.8—Labor response (linear trend)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.002	0.000	0.024***	-0.080***	0.032***	-0.004	0.022**
	(0.005)	(0.016)	(0.008)	(0.012)	(0.010)	(0.007)	(0.011)
	[0.802]	[0.989]	[0.005]	[0.001]	[0.005]	[0.802]	[0.071]
Temperature^2	-0.001	-0.001	-0.006	-0.011*	-0.022**	0.000	0.016***
	(0.003)	(0.010)	(0.004)	(0.006)	(0.010)	(0.004)	(0.006)
	[0.917]	[0.932]	[0.302]	[0.170]	[0.082]	[0.932]	[0.031]
Rain×Temperature	0.005	-0.005	-0.009	0.024	-0.019*	-0.003	0.003
	(0.005)	(0.011)	(0.010)	(0.014)	(0.011)	(0.007)	(0.014)
	[0.624]	[0.828]	[0.624]	[0.351]	[0.351]	[0.828]	[0.828]
Rain	-0.008	0.005	0.013	-0.023	0.004	-0.001	0.001
	(0.006)	(0.012)	(0.010)	(0.016)	(0.011)	(0.008)	(0.013)
	[0.440]	[0.916]	[0.440]	[0.440]	[0.916]	[0.916]	[0.916]
Rain^2	-0.002	-0.009	-0.008	-0.007	-0.014***	0.003	0.014**
	(0.002)	(0.007)	(0.005)	(0.007)	(0.005)	(0.004)	(0.007)
	[0.340]	[0.335]	[0.262]	[0.340]	[0.069]	[0.340]	[0.147]
Rural ×							
Temperature	0.018***	-0.011	-0.001	-0.054***	-0.001	0.001	0.008
	(0.006)	(0.008)	(0.004)	(0.007)	(0.012)	(0.005)	(0.005)
	[0.009]	[0.292]	[0.952]	[0.001]	[0.960]	[0.952]	[0.292]
Temperature^2	-0.014***	0.010	-0.004	0.001	0.016	0.000	-0.003
	(0.005)	(0.010)	(0.004)	(0.007)	(0.012)	(0.003)	(0.008)
	[0.030]	[0.547]	[0.547]	[0.995]	[0.547]	[0.995]	[0.966]
Rain×Temperature	-0.013*	0.009	0.005	0.015	0.034*	-0.000	-0.008
	(0.007)	(0.016)	(0.006)	(0.010)	(0.019)	(0.005)	(0.013)
	[0.239]	[0.688]	[0.598]	[0.343]	[0.239]	[0.987]	[0.688]
Rain	0.004	-0.002	-0.014***	0.005	-0.027**	0.010**	-0.005
	(0.006)	(0.009)	(0.005)	(0.007)	(0.012)	(0.005)	(0.006)
	[0.664]	[0.790]	[0.017]	[0.664]	[0.095]	[0.095]	[0.664]
Rain^2	-0.008*	0.005	0.002	0.006	0.012	0.002	-0.008
	(0.004)	(0.008)	(0.003)	(0.006)	(0.008)	(0.004)	(0.006)
	[0.388]	[0.654]	[0.654]	[0.567]	[0.388]	[0.654]	[0.473]
P values for F test:							
urban × temp = rural × temp	0.003	0.517	0.002	0.034	0.023	0.526	0.196
urban × temp^2 = rural × temp^2	0.023	0.429	0.668	0.177	0.013	0.947	0.038
R^2	0.005	0.001	0.007	0.050	0.010	0.055	0.010
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Linear time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P$<$ 0.1, **P$<$ 0.05, ***P$<$ 0.01. Sample and attrition weights applied.

Table A.9—Labor response (linear trends by population density)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	0.004	0.006	0.024**	-0.078***	0.043***	-0.005	0.024**
	(0.007)	(0.017)	(0.009)	(0.016)	(0.010)	(0.010)	(0.012)
	[0.703]	[0.709]	[0.024]	[0.001]	[0.001]	[0.703]	[0.088]
Temperature^2	-0.004	-0.004	-0.006	-0.012*	-0.028***	0.001	0.015**
	(0.003)	(0.010)	(0.005)	(0.007)	(0.010)	(0.004)	(0.006)
	[0.187]	[0.803]	[0.321]	[0.187]	[0.028]	[0.803]	[0.050]
Rain×Temperature	0.003	-0.007	-0.009	0.023*	-0.023**	-0.002	0.002
	(0.003)	(0.011)	(0.010)	(0.014)	(0.011)	(0.007)	(0.014)
	[0.677]	[0.677]	[0.677]	[0.348]	[0.266]	[0.872]	[0.872]
Rain	-0.004	0.009	0.013	-0.022	0.012	-0.002	0.003
	(0.004)	(0.012)	(0.011)	(0.016)	(0.010)	(0.008)	(0.013)
	[0.554]	[0.614]	[0.554]	[0.554]	[0.554]	[0.823]	[0.823]
Rain^2	-0.001	-0.008	-0.008	-0.007	-0.012**	0.003	0.014**
	(0.002)	(0.007)	(0.005)	(0.007)	(0.006)	(0.004)	(0.007)
	[0.532]	[0.443]	[0.249]	[0.443]	[0.144]	[0.443]	[0.144]
Rural ×							
Temperature	0.017***	-0.013	-0.001	-0.054***	-0.004	0.002	0.007
	(0.006)	(0.008)	(0.004)	(0.008)	(0.012)	(0.004)	(0.005)
	[0.025]	[0.285]	[0.783]	[0.001]	[0.783]	[0.783]	[0.359]
Temperature^2	-0.013***	0.011	-0.004	0.001	0.017	-0.000	-0.003
	(0.005)	(0.010)	(0.004)	(0.007)	(0.012)	(0.003)	(0.008)
	[0.045]	[0.547]	[0.547]	[0.967]	[0.547]	[0.967]	[0.967]
Rain×Temperature	-0.013*	0.009	0.005	0.015	0.034*	-0.000	-0.008
	(0.007)	(0.016)	(0.006)	(0.010)	(0.019)	(0.005)	(0.013)
	[0.226]	[0.677]	[0.601]	[0.340]	[0.226]	[0.978]	[0.677]
Rain	0.003	-0.003	-0.014***	0.005	-0.028**	0.010**	-0.005
	(0.006)	(0.009)	(0.005)	(0.007)	(0.013)	(0.005)	(0.006)
	[0.732]	[0.732]	[0.019]	[0.731]	[0.084]	[0.084]	[0.724]
Rain^2	-0.008*	0.004	0.002	0.006	0.012	0.002	-0.008
	(0.004)	(0.008)	(0.003)	(0.006)	(0.007)	(0.004)	(0.006)
	[0.398]	[0.654]	[0.654]	[0.571]	[0.398]	[0.654]	[0.468]
P values for F test:							
urban × temp = rural × temp	0.157	0.307	0.014	0.181	0.003	0.538	0.200
urban × temp^2 = rural × temp^2	0.089	0.307	0.714	0.196	0.004	0.825	0.073
R^2	0.006	0.001	0.007	0.050	0.011	0.055	0.010
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Distinct linear time trends for urban and rural areas. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sample and attrition weights applied.

Table A.10—Labor response (linear trends by country)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.011**	0.012	0.017**	-0.081***	0.029***	0.005	0.015
	(0.005)	(0.017)	(0.008)	(0.012)	(0.010)	(0.007)	(0.011)
	[0.087]	[0.459]	[0.087]	[0.001]	[0.014]	[0.459]	[0.228]
Temperature^2	0.003	-0.006	-0.002	-0.009	-0.021**	-0.003	0.019***
	(0.003)	(0.010)	(0.004)	(0.006)	(0.010)	(0.004)	(0.006)
	[0.543]	[0.624]	[0.624]	[0.259]	[0.120]	[0.543]	[0.007]
Rain×Temperature	-0.006	0.001	-0.017	0.013	-0.024**	0.002	0.003
	(0.005)	(0.011)	(0.010)	(0.015)	(0.011)	(0.007)	(0.013)
	[0.582]	[0.952]	[0.367]	[0.630]	[0.220]	[0.952]	[0.952]
Rain	-0.006	0.004	0.013	-0.003	0.010	-0.004	-0.002
	(0.006)	(0.012)	(0.010)	(0.016)	(0.011)	(0.008)	(0.013)
	[0.869]	[0.872]	[0.869]	[0.872]	[0.869]	[0.872]	[0.872]
Rain^2	-0.007***	-0.008	-0.011**	-0.021***	-0.019***	0.005	0.017***
	(0.002)	(0.007)	(0.006)	(0.007)	(0.006)	(0.004)	(0.006)
	[0.008]	[0.223]	[0.057]	[0.012]	[0.006]	[0.223]	[0.016]
Rural ×							
Temperature	0.012**	-0.010	-0.007	-0.041***	0.002	0.000	0.005
	(0.006)	(0.008)	(0.004)	(0.008)	(0.012)	(0.005)	(0.005)
	[0.097]	[0.401]	[0.249]	[0.001]	[0.953]	[0.953]	[0.456]
Temperature^2	-0.010**	0.008	-0.000	0.001	0.017	-0.001	-0.002
	(0.005)	(0.009)	(0.003)	(0.008)	(0.012)	(0.003)	(0.007)
	[0.224]	[0.958]	[0.969]	[0.969]	[0.588]	[0.969]	[0.969]
Rain×Temperature	-0.016***	0.008	0.004	0.009	0.032*	-0.000	-0.006
	(0.006)	(0.015)	(0.006)	(0.011)	(0.018)	(0.005)	(0.012)
	[0.068]	[0.746]	[0.746]	[0.746]	[0.282]	[0.947]	[0.746]
Rain	0.008	-0.010	-0.013***	0.030***	-0.018	0.001	-0.005
	(0.006)	(0.009)	(0.005)	(0.009)	(0.012)	(0.005)	(0.006)
	[0.358]	[0.358]	[0.034]	[0.003]	[0.325]	[0.770]	[0.529]
Rain^2	-0.011***	0.003	-0.000	-0.006	0.008	0.002	-0.004
	(0.004)	(0.008)	(0.003)	(0.007)	(0.008)	(0.004)	(0.006)
	[0.059]	[0.831]	[0.930]	[0.831]	[0.831]	[0.831]	[0.831]
P values for F test:							
urban × temp = rural × temp	0.001	0.222	0.006	0.002	0.043	0.509	0.397
urban × temp^2 = rural × temp^2	0.019	0.323	0.708	0.263	0.013	0.693	0.023
R^2	0.014	0.005	0.012	0.058	0.012	0.059	0.011
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Distinct linear time trend for each country. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sample and attrition weights applied.

Table A.11—Labor response (linear trends by country and population density)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.009	0.030	0.017	-0.083***	0.043***	0.005	0.011
	(0.008)	(0.021)	(0.010)	(0.017)	(0.012)	(0.009)	(0.014)
	[0.329]	[0.256]	[0.238]	[0.001]	[0.001]	[0.561]	[0.531]
Temperature^2	0.002	-0.013	-0.002	-0.009	-0.027***	-0.004	0.020***
	(0.004)	(0.012)	(0.005)	(0.007)	(0.010)	(0.005)	(0.007)
	[0.655]	[0.466]	[0.655]	[0.466]	[0.020]	[0.638]	[0.020]
Rain×Temperature	-0.005	-0.004	-0.012	0.004	-0.032***	0.004	0.007
	(0.004)	(0.010)	(0.010)	(0.016)	(0.011)	(0.007)	(0.013)
	[0.625]	[0.785]	[0.625]	[0.785]	[0.038]	[0.785]	[0.785]
Rain	-0.003	0.018	0.008	0.018	0.024**	-0.004	-0.018
	(0.005)	(0.012)	(0.011)	(0.017)	(0.011)	(0.009)	(0.013)
	[0.587]	[0.422]	[0.587]	[0.504]	[0.200]	[0.640]	[0.422]
Rain^2	-0.004*	-0.014**	-0.008	-0.030***	-0.023***	0.006	0.027***
	(0.002)	(0.006)	(0.006)	(0.010)	(0.006)	(0.005)	(0.007)
	[0.107]	[0.055]	[0.193]	[0.007]	[0.001]	[0.224]	[0.001]
Rural ×							
Temperature	0.011*	-0.013	-0.006	-0.047***	-0.003	0.000	0.009
	(0.006)	(0.008)	(0.004)	(0.008)	(0.012)	(0.004)	(0.006)
	[0.212]	[0.212]	[0.212]	[0.001]	[0.954]	[0.954]	[0.212]
Temperature^2	-0.009**	0.008	-0.000	0.002	0.018	-0.001	-0.003
	(0.005)	(0.009)	(0.003)	(0.008)	(0.012)	(0.003)	(0.008)
	[0.348]	[0.843]	[0.985]	[0.924]	[0.503]	[0.924]	[0.924]
Rain×Temperature	-0.017***	0.010	0.003	0.010	0.034*	-0.001	-0.008
	(0.006)	(0.015)	(0.006)	(0.011)	(0.018)	(0.005)	(0.012)
	[0.047]	[0.740]	[0.740]	[0.740]	[0.231]	[0.908]	[0.740]
Rain	0.007	-0.013	-0.011**	0.023***	-0.022*	0.002	0.001
	(0.006)	(0.009)	(0.005)	(0.008)	(0.013)	(0.005)	(0.006)
	[0.371]	[0.235]	[0.079]	[0.048]	[0.216]	[0.873]	[0.873]
Rain^2	-0.012***	0.006	-0.002	-0.003	0.011	0.002	-0.008
	(0.004)	(0.008)	(0.003)	(0.007)	(0.008)	(0.004)	(0.006)
	[0.030]	[0.698]	[0.698]	[0.698]	[0.493]	[0.698]	[0.493]
P values for F test:							
urban × temp = rural × temp	0.041	0.053	0.039	0.053	0.008	0.617	0.900
urban × temp^2 = rural × temp^2	0.059	0.150	0.718	0.298	0.004	0.711	0.029
R^2	0.015	0.005	0.013	0.060	0.012	0.059	0.014
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Distinct linear time trends for rural and urban areas in each country. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sample and attrition weights applied.

Table A.12—Labor response (previous 12-month climate)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.001	0.012	0.020***	-0.068***	0.012	0.008	0.030***
	(0.005)	(0.009)	(0.005)	(0.009)	(0.008)	(0.006)	(0.007)
	[0.814]	[0.248]	[0.001]	[0.001]	[0.195]	[0.195]	[0.001]
Temperature^2	-0.003*	-0.002	-0.000	-0.031***	-0.007	0.001	0.012**
	(0.002)	(0.007)	(0.004)	(0.006)	(0.007)	(0.003)	(0.006)
	[0.135]	[0.933]	[0.961]	[0.001]	[0.600]	[0.933]	[0.105]
Rain	0.002	0.017	0.008	-0.043***	-0.021**	-0.004	0.020
	(0.006)	(0.011)	(0.007)	(0.011)	(0.009)	(0.007)	(0.013)
	[0.677]	[0.223]	[0.314]	[0.002]	[0.098]	[0.630]	[0.223]
Rain^2	-0.004	-0.012**	-0.001	0.014*	0.006	0.005	-0.001
	(0.003)	(0.006)	(0.005)	(0.008)	(0.006)	(0.004)	(0.007)
	[0.290]	[0.244]	[0.882]	[0.244]	[0.462]	[0.430]	[0.882]
Rain × Temperature	-0.005	-0.013	0.006	0.024**	0.018*	0.003	-0.007
	(0.006)	(0.010)	(0.006)	(0.011)	(0.011)	(0.007)	(0.011)
	[0.526]	[0.503]	[0.526]	[0.240]	[0.347]	[0.648]	[0.615]
Rural ×							
Temperature	0.017***	-0.006	0.009**	-0.032***	0.006	-0.001	0.003
	(0.005)	(0.007)	(0.004)	(0.006)	(0.008)	(0.004)	(0.004)
	[0.002]	[0.592]	[0.052]	[0.001]	[0.592]	[0.839]	[0.592]
Temperature^2	0.005	0.001	-0.008**	-0.006	0.006	0.001	0.002
	(0.005)	(0.006)	(0.004)	(0.007)	(0.009)	(0.004)	(0.004)
	[0.823]	[0.857]	[0.211]	[0.823]	[0.841]	[0.841]	[0.841]
Rain	0.005	-0.001	0.002	-0.012*	-0.002	-0.000	-0.001
	(0.005)	(0.007)	(0.004)	(0.007)	(0.009)	(0.004)	(0.005)
	[0.981]	[0.981]	[0.981]	[0.515]	[0.981]	[0.981]	[0.981]
Rain^2	0.009**	0.006	0.006*	-0.003	0.013	0.002	-0.009**
	(0.004)	(0.006)	(0.003)	(0.005)	(0.009)	(0.003)	(0.004)
	[0.121]	[0.454]	[0.121]	[0.563]	[0.248]	[0.563]	[0.121]
Rain × Temperature	0.016**	-0.001	0.004	0.017*	0.019	0.000	-0.003
	(0.008)	(0.011)	(0.006)	(0.010)	(0.017)	(0.006)	(0.007)
	[0.211]	[0.964]	[0.894]	[0.345]	[0.595]	[0.964]	[0.904]
P values for F test:							
urban × temp. = rural × temp.	0.004	0.134	0.079	0.001	0.530	0.171	0.001
urban × temp.^{2} = rural × temp.^{2}	0.133	0.749	0.164	0.006	0.256	0.929	0.127
R^2	0.008	0.003	0.008	0.057	0.010	0.058	0.012
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 12 months. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sampling and attrition weights applied.

Table A.13—Labor response (no attrition weighting)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.014**	0.017	0.016**	-0.070***	0.024**	0.012*	0.010
	(0.006)	(0.017)	(0.008)	(0.012)	(0.011)	(0.007)	(0.011)
	[0.051]	[0.365]	[0.086]	[0.001]	[0.064]	[0.137]	[0.365]
Temperature^2	0.001	-0.004	-0.004	-0.013**	-0.020**	-0.003	0.018***
	(0.003)	(0.011)	(0.004)	(0.006)	(0.010)	(0.004)	(0.006)
	[0.686]	[0.686]	[0.548]	[0.092]	[0.092]	[0.548]	[0.009]
Rain	-0.009	0.007	0.013	-0.021	0.003	0.000	0.000
	(0.006)	(0.012)	(0.010)	(0.016)	(0.011)	(0.008)	(0.013)
	[0.456]	[0.997]	[0.456]	[0.456]	[0.999]	[0.999]	[0.999]
Rain^2	-0.002	-0.008	-0.009*	-0.007	-0.014**	0.003	0.014**
	(0.002)	(0.006)	(0.005)	(0.007)	(0.006)	(0.004)	(0.006)
	[0.355]	[0.316]	[0.186]	[0.385]	[0.105]	[0.400]	[0.105]
Rain × Temperature	0.004	-0.004	-0.010	0.023	-0.019	-0.002	0.003
	(0.005)	(0.011)	(0.009)	(0.014)	(0.011)	(0.008)	(0.013)
	[0.744]	[0.831]	[0.666]	[0.356]	[0.356]	[0.831]	[0.831]
Rural ×							
Temperature	0.014**	-0.005	-0.005	-0.049***	-0.004	0.007	0.003
	(0.005)	(0.008)	(0.004)	(0.007)	(0.012)	(0.004)	(0.005)
	[0.037]	[0.610]	[0.491]	[0.001]	[0.744]	[0.286]	[0.610]
Temperature^2	-0.013***	0.009	-0.003	-0.000	0.017	-0.001	-0.002
	(0.005)	(0.009)	(0.003)	(0.007)	(0.012)	(0.003)	(0.007)
	[0.034]	[0.702]	[0.702]	[0.983]	[0.559]	[0.866]	[0.866]
Rain	0.008	-0.010	-0.011**	0.001	-0.023**	0.004	0.000
	(0.006)	(0.008)	(0.005)	(0.007)	(0.012)	(0.005)	(0.006)
	[0.422]	[0.443]	[0.146]	[0.977]	[0.157]	[0.575]	[0.980]
Rain^2	-0.005	0.001	0.003	0.003	0.014*	-0.001	-0.005
	(0.004)	(0.008)	(0.003)	(0.006)	(0.007)	(0.004)	(0.006)
	[0.671]	[0.924]	[0.671]	[0.814]	[0.459]	[0.823]	[0.671]
Rain × Temperature	-0.010	0.005	0.007	0.011	0.036**	-0.004	-0.005
	(0.006)	(0.015)	(0.006)	(0.010)	(0.018)	(0.005)	(0.012)
	[0.415]	[0.747]	[0.415]	[0.415]	[0.325]	[0.564]	[0.747]
P values for F test:							
urban × temp. = rural × temp.	0.000	0.228	0.014	0.101	0.042	0.496	0.550
urban × temp.^{2} = rural × temp.^{2}	0.011	0.332	0.845	0.147	0.014	0.663	0.023
R^2	0.007	0.004	0.008	0.050	0.011	0.059	0.012
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years including only respondents who report the same residence in each survey round. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sampling weights applied.

Table A.14—Labor response (excluding respondents who change location between survey rounds)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.013**	0.011	0.022***	-0.069***	0.023**	0.010	0.008
	(0.006)	(0.017)	(0.008)	(0.012)	(0.011)	(0.007)	(0.010)
	[0.063]	[0.516]	[0.021]	[0.001]	[0.067]	[0.180]	[0.505]
Temperature^2	0.001	-0.002	-0.006	-0.011*	-0.021**	-0.005	0.021***
	(0.003)	(0.010)	(0.005)	(0.006)	(0.010)	(0.004)	(0.005)
	[0.878]	[0.878]	[0.283]	[0.120]	[0.120]	[0.324]	[0.002]
Rain	-0.009	0.005	0.015	-0.021	0.005	-0.001	-0.002
	(0.006)	(0.012)	(0.010)	(0.016)	(0.011)	(0.008)	(0.013)
	[0.417]	[0.870]	[0.417]	[0.417]	[0.870]	[0.870]	[0.870]
Rain^2	-0.002	-0.013**	-0.010*	-0.010	-0.014**	0.002	0.017***
	(0.002)	(0.006)	(0.005)	(0.007)	(0.006)	(0.004)	(0.006)
	[0.343]	[0.065]	[0.098]	[0.247]	[0.048]	[0.700]	[0.048]
Rain × Temperature	0.004	-0.008	-0.011	0.026*	-0.019*	-0.002	0.004
	(0.005)	(0.010)	(0.009)	(0.015)	(0.012)	(0.008)	(0.014)
	[0.615]	[0.615]	[0.615]	[0.337]	[0.337]	[0.765]	[0.765]
Rural ×							
Temperature	0.015***	-0.006	-0.001	-0.048***	-0.007	0.005	0.003
	(0.006)	(0.008)	(0.004)	(0.007)	(0.012)	(0.004)	(0.005)
	[0.029]	[0.701]	[0.796]	[0.001]	[0.701]	[0.668]	[0.701]
Temperature^2	-0.014***	0.009	-0.003	0.000	0.018	-0.000	-0.004
	(0.005)	(0.009)	(0.003)	(0.007)	(0.012)	(0.003)	(0.008)
	[0.024]	[0.694]	[0.694]	[0.978]	[0.512]	[0.978]	[0.877]
Rain	0.010	-0.009	-0.009*	0.003	-0.025**	0.003	0.001
	(0.006)	(0.008)	(0.004)	(0.008)	(0.012)	(0.005)	(0.006)
	[0.299]	[0.472]	[0.193]	[0.831]	[0.193]	[0.746]	[0.894]
Rain^2	-0.005	0.001	0.002	0.002	0.016**	-0.001	-0.005
	(0.004)	(0.008)	(0.003)	(0.006)	(0.008)	(0.004)	(0.006)
	[0.891]	[0.947]	[0.905]	[0.933]	[0.280]	[0.933]	[0.905]
Rain × Temperature	-0.012*	0.003	0.006	0.012	0.041**	-0.002	-0.005
	(0.007)	(0.015)	(0.005)	(0.010)	(0.019)	(0.005)	(0.012)
	[0.244]	[0.864]	[0.526]	[0.526]	[0.191]	[0.761]	[0.761]
P values for F test:							
urban × temp. = rural × temp.	0.000	0.330	0.005	0.079	0.035	0.425	0.609
urban × temp.^{2} = rural × temp.^{2}	0.013	0.425	0.535	0.173	0.012	0.372	0.008
R^2	0.007	0.005	0.005	0.048	0.011	0.051	0.013
Observations	53,573	53,573	53,573	53,573	53,573	53,573	53,573

Note: Observations are person years including only respondents who report the same residence in each survey round. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sampling and attrition weights applied.

Table A.15—Labor response (raw climate data)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	0.068	-0.487	-0.062	0.526	-0.028	-0.263	-0.502
	(0.172)	(0.351)	(0.224)	(0.393)	(0.275)	(0.207)	(0.377)
	[0.911]	[0.357]	[0.911]	[0.357]	[0.920]	[0.357]	[0.357]
Temperature^2	-0.002	0.010	0.003	-0.018**	-0.000	0.006	0.012*
	(0.003)	(0.006)	(0.004)	(0.007)	(0.005)	(0.004)	(0.007)
	[0.593]	[0.247]	[0.593]	[0.102]	[0.981]	[0.247]	[0.247]
Rain×Temperature	0.002	0.007	-0.007	0.013	0.015	0.006	0.001
	(0.010)	(0.015)	(0.007)	(0.010)	(0.012)	(0.006)	(0.011)
	[0.914]	[0.889]	[0.587]	[0.587]	[0.587]	[0.587]	[0.914]
Rain	-0.035	-0.140	0.226	-0.319	-0.364	-0.203	-0.081
	(0.259)	(0.415)	(0.200)	(0.296)	(0.309)	(0.194)	(0.299)
	[0.892]	[0.892]	[0.519]	[0.519]	[0.519]	[0.519]	[0.892]
Rain^2	-0.001	-0.002	-0.007	-0.002	0.002	0.006	0.007
	(0.007)	(0.011)	(0.005)	(0.009)	(0.007)	(0.007)	(0.008)
	[0.942]	[0.942]	[0.827]	[0.942]	[0.942]	[0.827]	[0.827]
Rural ×							
Temperature	0.289**	0.422	0.179*	-0.043	0.023	0.017	-0.363*
	(0.119)	(0.263)	(0.103)	(0.234)	(0.248)	(0.119)	(0.220)
	[0.108]	[0.192]	[0.192]	[0.925]	[0.925]	[0.925]	[0.192]
Temperature^2	-0.006**	-0.008	-0.004*	-0.002	-0.000	0.000	0.007*
	(0.002)	(0.005)	(0.002)	(0.004)	(0.005)	(0.002)	(0.004)
	[0.140]	[0.186]	[0.171]	[0.954]	[0.981]	[0.981]	[0.171]
Rain×Temperature	-0.006	-0.022**	-0.006*	0.005	0.002	-0.001	0.015
	(0.005)	(0.011)	(0.003)	(0.009)	(0.008)	(0.005)	(0.009)
	[0.329]	[0.214]	[0.214]	[0.798]	[0.798]	[0.798]	[0.244]
Rain	0.188	0.472*	0.147*	-0.036	0.054	0.024	-0.333
	(0.119)	(0.275)	(0.087)	(0.234)	(0.203)	(0.123)	(0.239)
	[0.266]	[0.266]	[0.266]	[0.879]	[0.879]	[0.879]	[0.285]
Rain^2	-0.006*	-0.002	-0.003	-0.008	-0.015**	0.001	0.003
	(0.003)	(0.006)	(0.002)	(0.005)	(0.007)	(0.003)	(0.005)
	[0.229]	[0.739]	[0.280]	[0.280]	[0.156]	[0.739]	[0.739]
P values for F test:							
urban × temp = rural × temp	0.279	0.040	0.322	0.205	0.889	0.239	0.750
urban × temp^2 = rural × temp^2	0.388	0.027	0.146	0.057	0.999	0.208	0.534
R^2	0.007	0.005	0.008	0.054	0.013	0.059	0.013
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall measured in °C and mm. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sampling and attrition weights applied.

Table A.16—Labor response (district-level clustering)

	Dependent variable: Occupational participation dummy						
	Agriculture		Non-agriculture				
	Wage	Self-employed	Wage	Self-employed	Migrate	School	Not employed
Urban ×							
Temperature	-0.014**	0.017	0.016*	-0.070***	0.024**	0.012*	0.010
	(0.006)	(0.014)	(0.009)	(0.012)	(0.012)	(0.006)	(0.009)
	[0.100]	[0.264]	[0.104]	[0.001]	[0.103]	[0.104]	[0.267]
Temperature^2	0.001	-0.005	-0.004	-0.013*	-0.020*	-0.003	0.019***
	(0.003)	(0.007)	(0.004)	(0.007)	(0.011)	(0.004)	(0.006)
	[0.684]	[0.620]	[0.620]	[0.164]	[0.164]	[0.620]	[0.009]
Rain×Temperature	0.004	-0.004	-0.009	0.025	-0.020	-0.002	0.002
	(0.005)	(0.010)	(0.009)	(0.015)	(0.013)	(0.008)	(0.015)
	[0.682]	[0.883]	[0.671]	[0.507]	[0.507]	[0.883]	[0.883]
Rain	-0.009	0.006	0.012	-0.022	0.003	-0.000	0.001
	(0.006)	(0.011)	(0.009)	(0.017)	(0.011)	(0.008)	(0.011)
	[0.425]	[0.988]	[0.425]	[0.425]	[0.988]	[0.988]	[0.988]
Rain^2	-0.002	-0.009	-0.008*	-0.007	-0.014**	0.004	0.014*
	(0.002)	(0.006)	(0.005)	(0.009)	(0.006)	(0.005)	(0.008)
	[0.288]	[0.288]	[0.206]	[0.464]	[0.074]	[0.464]	[0.206]
Rural ×							
Temperature	0.014**	-0.005	-0.004	-0.050***	-0.004	0.007	0.003
	(0.006)	(0.007)	(0.004)	(0.009)	(0.013)	(0.004)	(0.005)
	[0.083]	[0.621]	[0.428]	[0.001]	[0.762]	[0.302]	[0.621]
Temperature^2	-0.013**	0.008	-0.003	0.000	0.017	-0.001	-0.002
	(0.005)	(0.009)	(0.003)	(0.007)	(0.011)	(0.003)	(0.008)
	[0.105]	[0.670]	[0.670]	[0.990]	[0.475]	[0.930]	[0.930]
Rain×Temperature	-0.010	0.004	0.008	0.012	0.037**	-0.004	-0.004
	(0.007)	(0.015)	(0.005)	(0.009)	(0.016)	(0.005)	(0.012)
	[0.329]	[0.800]	[0.329]	[0.329]	[0.189]	[0.475]	[0.800]
Rain	0.008	-0.009	-0.011**	0.001	-0.023**	0.004	-0.000
	(0.007)	(0.008)	(0.004)	(0.008)	(0.011)	(0.005)	(0.006)
	[0.503]	[0.503]	[0.105]	[0.990]	[0.124]	[0.550]	[0.990]
Rain^2	-0.005	0.001	0.004	0.004	0.014**	-0.001	-0.005
	(0.005)	(0.008)	(0.003)	(0.006)	(0.007)	(0.003)	(0.006)
	[0.716]	[0.937]	[0.716]	[0.785]	[0.299]	[0.785]	[0.729]
P values for F test:							
urban × temp = rural × temp	0.000	0.157	0.023	0.079	0.055	0.514	0.451
urban × temp^2 = rural × temp^2	0.016	0.251	0.816	0.117	0.017	0.743	0.026
R^2	0.007	0.003	0.008	0.051	0.011	0.058	0.012
Observations	55,277	55,277	55,277	55,277	55,277	55,277	55,277

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by district. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sample and attrition weights applied.

Table A.17—Labor response conditional on access to agricultural self-employment

Dependent variable: Not employed	
Urban × Access ×	
Temperature	0.002
	(0.026)
	[0.930]
Temperature^2	-0.001
	(0.020)
	[0.974]
Rain×Temperature	-0.003
	(0.022)
	[0.881]
Rain	0.010
	(0.018)
	[0.554]
Rain^2	-0.001
	(0.008)
	[0.936]
Urban × No-access ×	
Temperature	0.023*
	(0.013)
	[0.075]
Temperature^2	0.023***
	(0.007)
	[0.001]
Rain×Temperature	-0.003
	(0.017)
	[0.882]
Rain	-0.002
	(0.019)
	[0.931]
Rain^2	0.013
	(0.008)
	[0.117]
Rural × Access ×	
Temperature	0.008*
	(0.005)
	[0.090]
Temperature^2	-0.010
	(0.008)
	[0.180]
Rain×Temperature	-0.014
	(0.012)
	[0.252]
Rain	0.012**
	(0.006)
	[0.036]
Rain^2	-0.002
	(0.006)
	[0.739]
Rural × No-access ×	
Temperature	0.006
	(0.022)
	[0.787]
Temperature^2	0.031
	(0.019)
	[0.100]
Rain×Temperature	0.014
	(0.024)
	[0.580]
Rain	-0.007
	(0.025)
	[0.768]
Rain^2	-0.021
	(0.014)
	[0.131]

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. No time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: *P< 0.1, **P< 0.05, ***P< 0.01. Sample and attrition weights applied.

Table A.18—Climate impacts on non-agricultural self-employment by agricultural input intensity

Dependent variable:	Occupational participation dummy	
	Agricultural input intensive	Non-agricultural input intensive
Urban ×		
Temperature	0.141***	-0.106***
	(0.046)	(0.041)
	[0.005]	[0.010]
Temperature^2	-0.112***	0.075***
	(0.029)	(0.023)
	[0.001]	[0.002]
Rain×Temperature	-0.003	0.053
	(0.045)	(0.037)
	[0.939]	[0.298]
Rain	-0.021	0.009
	(0.043)	(0.036)
	[0.813]	[0.813]
Rain^2	-0.005	0.013
	(0.018)	(0.014)
	[0.763]	[0.763]
Rural ×		
Temperature	0.149***	-0.120***
	(0.047)	(0.042)
	[0.004]	[0.004]
Temperature^2	-0.116***	0.059*
	(0.039)	(0.034)
	[0.007]	[0.085]
Rain×Temperature	-0.049	0.038
	(0.059)	(0.048)
	[0.431]	[0.431]
Rain	0.017	-0.036
	(0.041)	(0.034)
	[0.680]	[0.575]
Rain^2	-0.007	0.020
	(0.031)	(0.025)
	[0.823]	[0.817]
P values for F test:		
urban × temp = rural × temp	0.865	0.728
urban × temp^2 = rural × temp^2	0.924	0.685
R^2	0.041	0.037
Observations	10,536	10,536

Note: Observations are person years. Temperature and rainfall are z-scores for previous 24 months. Quadratic time trend. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. q-values in brackets. For P-values: $^{*}P< 0.1$, $^{**}P< 0.05$, $^{***}P< 0.01$. Sample and attrition weights applied.