Market distortions and productive responses to extreme heat: evidence from Ugandan farmers

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Abstract

This paper examines whether market distortions affect subsistence farmers' ability to cope with high temperatures. We use a rich dataset from Ugandan farmers that combines household panel data with satellite imagery. Then, we estimate the effects of temperature on farmers' input use allowing for heterogeneous effects by land tenure regime (customary vs. non-customary land rights). We find that farmer responses to extreme heat differ by type of land tenure: increased input use in areas with customary rights, but decrease in areas with non-customary land rights. There are, however, no significant differences on the effect of extreme heat on total output. Our findings suggest that market distortions (such as imperfect property rights) can affect farmers' ability to mitigate weather shocks.

JEL Classification: O13; O12; Q12; Q15; Q51; Q54

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1 Introduction

Market distortions, such as informal property rights or constraints on labor mobility, are pervasive in developing countries and seem to lead to substantial factor misallocation and loss of efficiency (Hsieh and Klenow, 2009, Restuccia and Rogerson, 2013). This issue is especially relevant in the case of agriculture. For instance, several studies suggest that frictions to the reallocation of production factors can explain a sizeable amount of observed differences in agricultural productivity (Adamopoulos and Restuccia, 2014, Caselli, 2005, Restuccia et al., 2008).

The presence of these frictions is particularly worrisome in light of the current predictions of the effect of global warming on agriculture: it is expected that an increase in average temperature of 2°C, as in conservative climate change predictions, would reduce agricultural output by almost 25% (IPCC, 2014). Many of the adjustments needed to attenuate these negative effects, such as migration, occupational change, and changes in land use would require significant reallocation of land and labor (Colmer, 2016, Costinot et al., 2016, Feng et al., 2012). A relevant question is, therefore, to what extent market distortions hinder farmers' ability to mitigate the negative effects of extreme heat

This paper examines this question using the case of Uganda. In particular, we study how farmers' productive responses to extreme temperature (such as changes in input use) varies with the degree of market distortions. Our results provide suggestive evidence that market distortions may hinder farmers' ability to mitigate the negative effects of extreme temperatures.

Our empirical strategy uses a novel panel dataset of Ugandan farmers, and combines detailed agricultural information from household surveys with high-resolution weather data from satellite imagery. Our identification exploits within-farmer variation in weather, and exploits regional variation in in land tenure regimes as our main measure of market distortions.

Land tenure in Uganda broadly falls in two categories: customary and non-customary regimes. Non-customary regimes, such as freehold and leasehold, offer some degree of formal, secure property rights over land. in contrast non-customary regimes are perceived as less secure and, due to lack of formal registries and recognition, may face higher transaction costs. These tenure regimes are geographically concentrated: most of non-customary land is found in the Western and Central regions, while customary land is more prevalent in the Northern and Easter regions.

We start by documenting the effect of temperature on agricultural outcomes. Similar to previous studies, we find a negative effect of extreme heat on land productivity and total output, but a positive effect on land and labor use. This last result is not consistent with the optimal response in the presence of complete markets. However, it can be a coping strategy, albeit an inefficient one, in the presence of incomplete markets. Intuitively, instead of reducing input use as a response to negative productivity shocks, farmers might increase it to attenuate the drop in consumption.

We then examine possible heterogeneous responses exploiting regional variation in land tenure. We find that in areas with better defined property rights (Western and Central regions) farmers respond to extreme heat by weakly decreasing input use, as expected in the case of well functioning markets. In contrast, the effect on input use is positive in areas with more prevalent use of customary land tenures (Northern and Eastern regions). This result is robust to the use of alternative measures of market distortions and several potential confounding factors.

We interpret these findings as suggestive evidence that market distortions, such as customary property rights, hinder farmer' ability to mitigate the negative effects of extreme heat. As a illustration of this phenomenon, we observe that in areas with customary and non-customary land the effect of temperature on output is similar. However, in the latter areas farmers need to use their units more intensively. This result suggests a higher mitigation cost.

Finally, we explore whether regional differences in land tenure reflect meaningful variation in the extent of market distortions. To do so, we apply insights from the factor misallocation literature and examine the relation between farm productivity and farm-level input availability. We find evidence of substantial misallocation in Ugandan agriculture. Contrary to what is expected under an efficient allocation, we observe an almost flat relationship between farmer productivity and farm size, and a strong positive correlation between productivity and yields. Reassuringly, these relations move in the direction of the efficient benchmark in regions where non-customary, better defined, land rights are more prevalent.

Our findings have relevant implications for thinking about the economic effects of climate change. First, they suggest that, in contexts with conditions conducive to factor misallocation (like incomplete land markets), societies would be less able to adjust to increasing weather shocks by reallocating agricultural land and labor. This implies a slowlier, and potentially more costly, process of adaptation to climate change.[1] Second, they suggest a potential channel for climate change to increase world income inequality. Most poor countries are located in the tropics: areas of the world where climate change is expected to occur first and be more intense (Khaliq et al., 2014, Mora et al., 2013). Increasing weather shocks combined with poor institutional frameworks would exacerbate factor misallocation, and the productivity gap between rich and poor countries.

2 Analytical framework

This section presents a simple framework to study how subsistence farmers can mitigate the effects of extreme heat by adjusting their production decisions. This section is based on

[1] This implication echoes findings by Annan and Schlenker (2015) that a policy distortion (i.e. crop insurance subsidies) has reduced incentives of U.S. farmers to adapt to climate change.

Aragón et al. (2020) and standard agricultural producer-consumer household models used in the development literature (Benjamin, 1992, De Janvry et al., 1991, Taylor and Adelman, 2003).

Without loss of generality, let us assume an agricultural production function with a single input. We call this input "land" but it can refer to any other variable input such as labor. The household has an endowment of land, T^e. Land can be used for production or "consumed" in non-productive activities (e.g., leisure). Household's utility is $U(c,t)$, where c is consumption of a market good, while t is the amount of land used in non-productive activities. Households obtain income by renting their land and by producing an agricultural good. Production is defined by function $F(A,T)$, where T is the amount of land used in agriculture, and A is farmer's total factor productivity.

A is a productivity shifter that captures the idea that farmers using identical inputs can have different levels of output due, for instance, to different farming skills, soil quality, or exposure to weather shocks. Consistent with previous studies on the relation between crop yields and temperature, we assume that extreme heat has a detrimental effect on productivity.[2]

Each growing season, the household maximizes utility by choosing the amount of land allocated to productive and non-productive uses. We consider that land is a variable input. This assumption is driven by the observation that, among subsistence farmers, planting is not a one-off activity, but instead it is spread throughout the year. Finally, we assume that both the utility and the production functions are increasing and strictly concave.

Household responses to negative productivity shocks If input markets exist and are well functioning, we can study consumption and production decisions separately (Benjamin, 1992). This separation result is driven by the possibility to trade. Thus, the household's

[2]See for example **?**, Burke and Emerick (2016), Auffhammer et al. (2012), Hsiang (2010), Hsiang (2016), among others.

demand and supply of inputs for production and consumption need not be identical to its endowments. The standard solution is the unconditional input demand $T^*(A, p, w)$. In this context, a farmer's response to negative productivity shock, such as extreme heat, is unequivocal: she will *reduce* the amount of land used in her farm.

This prediction can change in the case of incomplete markets. To illustrate this, consider a case in which there are no input markets. In this simplified setting, the farmer's problem becomes:

$$\begin{aligned} \max_T \quad & U(c, t) \\ \text{s.t.} \quad & c = pF(A, T) \\ & T + t = T^e. \end{aligned}$$

Solving this problem produces an unconditional demand for land that depends not only on prices and productivity, but also on land endowment, $T(A, p, T^e)$. Moreover, if utility is sufficiently concave (for instance if consumption levels are quite low or farmer has high risk aversion), then $\frac{dT}{dA}$ can be negative.[3]

This result suggests that, in context with imperfect input markets, negative weather shocks, such as extreme heat, could result in an *increase* in input use. This occurs because the farmer uses more inputs to attenuate the fall in agricultural output, and reduce the drop in consumption. This response is akin to coping mechanisms to smooth consumption, such as selling disposable assets. The key distinction is that it involves adjustments in productive decisions.

With this framework in mind, our empirical analysis focuses on examining the effect of extreme heat on input use and how this response varies with the extent of market imperfec-

[3] Taking total derivatives to first order condition $pU_cF_T = U_t$, we obtain that:

$$\frac{dT}{dA}(F_T^2 U_{cc} + U_c F_{TT} + U_{tt}) + F_T F_A U_{cc} + U_c F_{TA} = 0.$$

Assuming strictly concave utility and production functions, this expression implies that a necessary and sufficient condition for inputs to increase with a negative productivity shock ($\frac{dT}{dA} < 0$) is $-\frac{U_{cc}}{U_c} > \frac{F_{TA}}{F_T F_A}$. Assuming, a Cobb-Douglas technology $f = AT^\alpha$, this condition simplifies to: $-\frac{U_{cc}}{U_c} > 1$.

tions.

3 Data

3.1 Agricultural and household data

We use data from the Uganda Panel National Survey (UPNS), a household-level panel dataset collected with support from the World Bank, as part of the LSMS-ISA project. This survey is representative at the urban/rural and regional level, and collects agricultural information for cropping seasons happening in either the first or second semester of each year.[4]

We use the five available rounds: 2009-10, 2010-11, 2011-12, 2013-14 and 2015-16. Given that our period of analysis is the cropping season in a given year, we have observations for 10 periods. Our final dataset contains a panel of around 4,500 households that report agricultural activities and which are observed, on average, 4 periods.

The UPNS collects information on agricultural activities for each cropping season. We use this information to obtain measures of agricultural practices, output and input use (land and labor). To measure real agricultural output, we calculate the value of crops using the median national price in 2009. We measure land use by adding up the size of parcels cultivated by the farmer. These parcels include ones owned by the farmer, and also ones over which the farmer has user rights. We construct measures of labor use by adding up the number of person-days employed in the farm. We distinguish between domestic and hired labor, and also construct an indicators of child labor.

Table 1 presents summary statistics for all our sample, and divided by regions. Similar to subsistence farmers in other developing countries, the farmers in our sample have small scale operations (the average farm size is around 3 acres). Their agricultural practices are also

[4]For example, for the 2009-10 wave, the data is collected between May 2009 and April 2010 in two visits: the first one collecting information for the January-June 2009 period and the second, for July-December 2009.

akin to traditional rather than modern farming: high reliance on domestic labor (including child labor), intercropping (i.e, cultivation of several crops in the same plot), and limited use of fertilizers or pesticides.

Table 1: Summary statistics

	All (1)	Western & Central (2)	Northern & Eastern (3)
A. Household characteristics			
HoH age	47.3	47.6	46.9
HoH can read and write (%)	66.3	68.6	64.0
HoH is female (%)	24.4	25.7	23.1
Household size	6.1	6.0	6.1
B. Agricultural characteristics			
Value agricultural output	12,573.9	13,917.0	11,271.3
Area planted (acres)	3.1	2.9	3.2
Labor (no. person-days)	156.6	166.4	147.1
Domestic labor (no. person-days)	141.4	156.0	127.3
Hired labor (no. person-days)	15.2	10.4	19.7
Child labor (%)	53.3	48.6	57.8
% use intercropping	71.1	82.1	60.4
% land with non-customary rights	48.4	86.1	12.4
% fallow land	15.8	8.1	23.3
% use organic fertilizer	11.0	19.5	2.8
% use chemical fertilizer	3.5	4.2	3.0
% use pesticides	10.4	13.0	7.9
C. Weather last growing season			
Degree days (DD)	15.6	14.7	16.6
Harmful degree days (HDD)	0.5	0.2	0.8
Precipitation (mm/month)	136.4	126.1	146.5
No. observations	16,667	8,206	8,461

Notes: Sample restricted to farming households. HoH = Head of household. Non-customary land rights include freehold, leasehold and Mailo. Output measures in thousands of 2009 Ugandan schillings.

3.2 Temperature and precipitation

We use satellite imagery to obtain measures of weather conditions during the growing season. Precipitation data comes from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product (Funk et al., 2015). CHIRPS is a re-analysis gridded dataset that provides estimates of daily precipitation with a resolution of 0.05×0.05 degrees. For temperature, we use the MOD11C1 product provided by NASA. This product provides daily measures of daytime temperature on a grid of 0.05×0.05 degrees, equivalent to 5.6 km squares at the Equator, and is already cleaned of low quality readings and processed for consistency.[5] Note that the satellite data provides estimates of land surface temperature (LST) not of surface air temperature, which is the variable measured by monitoring stations.[6]

We link the weather and household data using households' sub-county location (n=967). Then, we aggregate the daily observations to obtain measures of temperature and precipitation for each farmer during the growing season, i.e. months of the year during which there is active growing of plants.[7] Figure A.1 in the Appendix displays the distribution of daily temperature during the growing season.

To aggregate the daily data, we construct two measures of cumulative exposure to heat: average degree days (DD) and harmful degree days (HDD). DD measures the cumulative exposure to temperatures between a lower bound, usually 8℃, up to an upper threshold τ, while HDD captures exposure to extreme temperatures (above τ). This approach follows the existing literature studying the effects of temperature on agriculture and allows for potentially non-linear effects of extreme heat.[8] Formally, we define the average DD and

[5]The satellite estimates are very precise. Validation studies comparing satellite estimates and ground readings find a discrepancy of only 0.1-0.4℃ (Coll et al., 2005, 2009, Wan and Li, 2008).

[6]LST is usually higher than air temperature, and this difference tends to increase with the roughness of the terrain. However, both indicators are highly correlated (Mutiibwa et al., 2015).

[7]We take into account that the southern part of Uganda has two distinct growing seasons: from February to July and from September to January; while the north of the country has one main growing season from April to October.

[8]See for instance, Aragón et al. (2020), Burke et al. (2015), Carleton and Hsiang (2016), Chen et al. (2016), Deschenes and Greenstone (2007), Lobell et al. (2011), Schlenker et al. (2005, 2006), Zhang et al.

HDD during the growing season as:

$$DD = \frac{1}{n}\sum_{d=1}^{n}(\min(h_d, \tau) - 8)\mathbb{1}(h_d \geq 8)$$
$$HDD = \frac{1}{n}\sum_{d=1}^{n}(h_d - \tau))\mathbb{1}(h_d > \tau),$$

where h_d is the average daytime temperature in day d and n is the total number of days in a growing season with valid temperature data.[9]

We set $\tau = 28$ ℃. We obtain this value by estimating a flexible specification of the yield-temperature relationship,[10] In particular, we regress the log of yields (i.e. output per ha) on a set of variables measuring the proportion of days on which the temperature fell on a two-degree bin (see Figure 1). Then, we identify the temperature at which we observe a statistically significant negative effect.

Consistent with previous studies, Figure 1 shows a non-linear relationship between temperature and yields with extreme temperatures, either too cold (below 15) or too hot (above 28℃), having a detrimental effect on crops. Due to the rare occurrence of low temperatures, in the rest of the paper we focus on farmers' responses to extreme heat.[11]

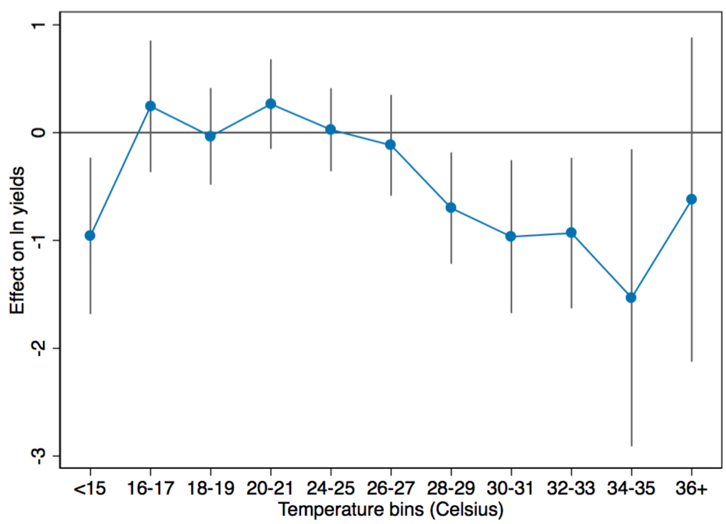
(2017).

[9]Note that we do not calculate total degree days, but instead average degree days. This re-scaling makes interpretation easier and help us address the issue of missing observations due to satellite swath errors.

[10]We obtain similar results using an estimate of total factor productivity (TFP) instead of yields. See Figure A.3 in the Appendix

[11]Temperatures below 15 ℃ occur in around 4% of growing season days, while the probability of daily temperatures above 28 ℃ is around 29%.

Figure 1: Relationship between temperature and yields



Notes: Figure displays estimates of regressing ln(output per ha.) on a set of temperature bins. The omitted category is bin 21-22 ℃. Circles represent points estimates, while lines are 95% confidence intervals. Regression estimated using OLS and includes precipitation and its square, as well as semester, year, and county fixed effects. S.E. clustered at county level.

4 Results

4.1 Effect of extreme heat on agricultural outcomes

We start by examining the average relation between extreme temperature and input use. We estimate a reduce-form unconditional factor demand:

$$\ln Y_{it} = s_i + \eta_t + \delta_1 DD_{it} + \delta_2 HDD_{it} + \phi X_{it} + +\epsilon_{it}, \tag{1}$$

where Y_{it} is a measure of input use (such as area planted or total person-hours used) of household i in period t. DD and HDD are measures of degree days during the growing season as described in the previous section, and X is a set of control variables such as input endowments and monthly precipitation. Regression includes cropping and growing season (η_t) and household (s_i) fixed effects. Standard errors are clustered at household level .

Table 2 presents our main results. We find that extreme temperatures seems to have a positive effect on input use (see columns 1 to 4). For example, an increase of one harmful degree day (HDD) is associated with an increase of around 4 percent in area planted (column 1) and 8 percent in total labor used (column 2). The increase in labor occurs both for hired and domestic labor.

We interpret these findings as evidence that a productive response of farmers to the negative shock of higher temperatures is to increase input use. Similar productive responses have been recently documented by Aragón and Rud (2013) in the context of Peruvian subsistence farmers. The effect on total output is, however, negative. This is consistent with productive responses being unable to completely offset the negative shock of productivity associated with extreme heat.

Table 2: Effect of temperature on land, labor, and output

	Input use				
	Land	Labor			Output
		Total	Hired	Domestic	
	(1)	(2)	(3)	(4)	(5)
Average DD	0.005	0.042***	0.001	0.045***	-0.011
	(0.008)	(0.008)	(0.018)	(0.010)	(0.012)
Average HDD	0.040**	0.082***	0.142***	0.043*	-0.085**
	(0.019)	(0.020)	(0.046)	(0.023)	(0.038)
Endow. control	Yes	Yes	Yes	Yes	No
Household FE	Yes	Yes	Yes	Yes	Yes
Observations	17,689	17,610	7,043	17,610	17,812
R-squared	0.416	0.127	0.064	0.092	0.028

Notes: Standard errors clustered at household level (in parenthesis). Stars indicate statistical significance: *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are in logs. All regressions include household, growing season , and cropping season (first or second semester) fixed effects, DD, HDD, and precipitation and its square. Columns 1 to 5 also include measures of household endowments: log of household size and log of area of available land.

4.2 Farmers' responses and market distortions

We next study whether farmers' responses are affected by the degree of market distortions. Ideally, we would like to have experimental variation in market imperfections such as property rights over land. However, this is not feasible in our study case. Instead, we exploit observational variation in land tenure among Ugandan farmers.

There are four types of land tenure in Uganda: freehold, leasehold, Mailo (form of freehold) and customary land. The first three tenure systems offer some degree of formal, secure, property rights. In contrast, customary systems are perceived as less secure and, due to lack of formal land registries, may face higher transaction costs (Coldham, 2000, Place and Otsuka, 2002).

These tenure systems are spatially concentrated (see Figure 2). Customary land is dominant in the Northern and Eastern regions, where more than 90% of land holdings are under this regime. In contrast, non-customary systems are mostly found in the Western and Central regions. In these regions, less than 7% of land is held under customary systems.

The use of customary land tenure regimes seem to be associated with deeper market distortions. For instance, in regions with more prevalent use of non-customary tenure systems around 47% of land holdings have been traded, i.e., acquired through purchase or rented. In contrast, in regions with more customary land, this figure is much lower, around 27%.

Based on this discussion, we use regional indicators as the main proxies for the degree of market imperfections. In particular, we assume that market imperfections are less severe in regions with more prevalent use of non-customary property rights, such as Western and Central regions. We formally assess the validity of this assumption in Section 4.3. In addition, we check the robustness of our results to using alternative measures, like the share of land under customary tenure at district and farm level, and other indicators of access to markets.

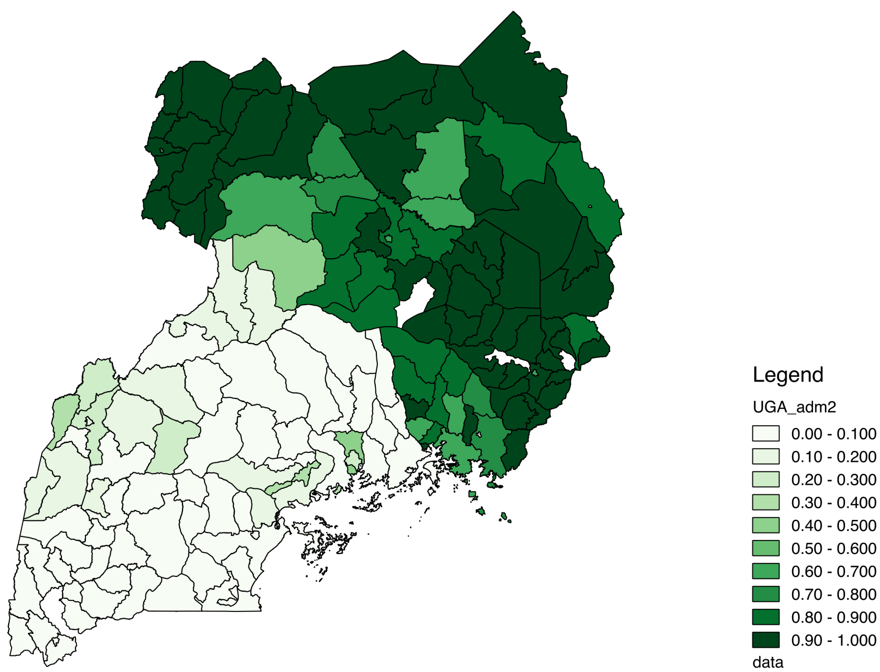
To examine heterogeneous responses by degree of market imperfections, we replicate the results of Table 2 adding an interaction of HDD with an indicator of being in the Western or Central regions, our preferred proxy for the degree of market distortions.

The results, shown in Table 3 suggests qualitatively and statistically significant differences in farmers' responses to extreme heat. The effect of extreme heat on input use (both land and labor) is positive only in the Northern and Eastern regions, where customary land tenure is more prevalent. In contrast, the effects are weakly negative in regions with more prevalent use of non-customary land regimes (i.e., the Western and Central regions). There are, however, no significant differences on the effect on total agricultural output (column 5).[12]

How do we interpret these results? As discussed in Section 2, the response of a farmer

[12]We obtain qualitatively similar results using alternative measures of market distortions, such as an indicator of high prevalence of customary land in a district, share of a farmer's land under customary tenure, and an indicator of a farmer having non-agricultural income (see Table B.1 in the Appendix).

Figure 2: Land tenure systems in Uganda



Notes: Figure depicts the share of customary land holdings by district.

to the negative productivity shock of extreme heat in the case of well functioning markets would be to reduce input use. However, in the presence of market distortions, farmers might respond by increasing input use to mitigate the drop in consumption. This response is constrained optimal from the perspective of a farmer, but inefficient relative to the case of complete markets. Intuitively, without well functioning markets, farmers face a higher cost to mitigate the negative effects of extreme heat on their welfare.

Based on this discussion, we interpret our findings as evidence that market distortions (in the form of customary land tenure) increase farmers' cost to to attenuate the welfare effects of extreme heat. Note, for instance, that in both regions the effect of extreme heat on output is similar, but that in regions with more customary land, this is achieved by using their inputs more intensively.

4.3 Are different input responses driven by market distortions?

We interpret our previous results as evidence that market distortions, such as ill-defined property rights over land, affect farmers' responses to extreme heat. There are, however, several alternative interpretation. In this section, we empirically examine some of them.

Unobserved regional variation A first alternative explanation is that our results are simply reflecting unobserved, time-invariant, regional differences such as climate, crop suitability or agronomic practices. For instance, the Northern and Eastern regions are relatively hotter than Western and Central, and also receive slightly more precipitation (see Table 1, and Figures A.1 and A.2 in the Appendix). Similarly, they could be picking up unobserved economic shocks or policies that also affect farmers' input use. These confounding factors are, however, already accounted for by the use of household and region-by-year fixed effects in our baseline specification.

Table 3: Effect of temperature on land, labor, and output by region

	Input use				
	Land	Labor			Output
		Total	Hired	Domestic	
	(1)	(2)	(3)	(4)	(5)
(A) Average HDD	-0.044	-0.033	-0.060	-0.092	-0.118
Western/Central	(0.050)	(0.050)	(0.121)	(0.058)	(0.092)
(B) Average HDD	0.047**	0.084***	0.166***	0.048**	-0.090**
Northern/Eastern	(0.020)	(0.021)	(0.047)	(0.023)	(0.039)
p-value (A) - (B)	0.065	0.018	0.061	0.015	0.756
Endow. control	Yes	Yes	Yes	Yes	No
Household FE	Yes	Yes	Yes	Yes	Yes
Region-by-GS FE	Yes	Yes	Yes	Yes	Yes
Observations	17,698	17,610	7,043	17,610	17,821
R-squared	0.394	0.073	0.023	0.092	0.013

Notes: Standard errors clustered at household level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All outcome variables are in logs. All regressions include household, region by-growing season, and cropping season (first or second semester) fixed effects, DD, HDD, and precipitation and its square. Columns 1 to 5 also include measures of household endowments: log of household size and log of area of available land. Third row displays p-value of test of equality of coefficients in rows (A) and (B).

Heterogeneous responses due to other farmer characteristics A related concern is that these region-specific characteristics, rather than market distortions, affect farmer's responses to extreme heat. For example, farmers exposed to higher baseline temperatures may be better adapted to extreme heat and thus adjust their input use differently.[13] Similarly, farmers with more productive land or higher disposable income could have access to other coping mechanism besides adjusting input use.

We indirectly assess this possible explanation by adding interactions of HDD with other farmer characteristics. We focus on three variables: average HDD in a district (as a proxy

[13] For instance, several papers interpret the observed heterogeneous effects of temperature on yields in different climatic regions as evidence of adaptation (CITE)

of climatic characteristics), farmer's total income, and a proxy of farm productivity.

To obtain this last measure, we estimate the following Cobb-Douglas production function:

$$y_i = s_i w (T_i^{\alpha} L_i^{1-\alpha})^{\gamma}, \tag{2}$$

where T_i and L_i stand for the amounts of land and labor used by farmer i. In this specification, total factor productivity is equal to $s_i w$, where w is a common productivity shock, such as weather, and s_i is a farm-specific output shifter, such as farming ability or entrepreneurship. Henceforth, we call s_i farm productivity.

We take logs to equation (2) and estimate it by OLS using the household-level dataset. Our specification includes weather controls, time and household fixed effects. We use estimates of the household fixed effects as our measure of the log of farm productivity $\ln s_i$ (see estimates in Table B.2 and Figure A.4 in the Appendix).

Table 4 presents our results for land and total labor gradually adding the interactions of HDD with farmer characteristics. In all cases, the results are qualitatively similar to our baseline findings: increase of input use in regions with widespread use of customary land (Northern and Eastern regions) and no significant change in the rest.

Regional indicators not reflecting market distortions Finally, we examine whether our regional indicators are indeed associated with different levels of market distortions. To do so, we use insights from the factor misallocation literature and assess the relation between farm productivity and input use.[14] The key idea is that, in a complete markets scenario, the marginal productivity of inputs would be equalized across farmers. This condition implies a *positive* correlation between farm productivity (a farmer's specific component of total factor productivity) and input size. Thus, we can use the deviations of the actual relation between

[14]This approach has been used in several studies in the macro and micro economics literature. See for example Banerjee et al. (2003), Hsieh and Klenow (2009), Restuccia and Santaeulalia-Llopis (2017).

Table 4: Effect of temperature on land, labor, and output adding interactions with farmer characteristics

	Land			Labor		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Average HDD	0.026	0.045	0.039	0.059	-0.002	-0.002
Western/Central	(0.054)	(0.056)	(0.057)	(0.053)	(0.066)	(0.066)
(B) Average HDD	0.152***	0.160***	0.160***	0.216***	0.237***	0.236***
Northern/Eastern	(0.029)	(0.035)	(0.035)	(0.032)	(0.038)	(0.038)
p-value (A) - (B)	0.009	0.014	0.010	0.002	0.000	0.000
HDD ×						
Mean district HDD	Yes	Yes	Yes	Yes	Yes	Yes
Farmer income		Yes	Yes		Yes	Yes
Farm productivity			Yes			Yes
Observations	17,698	13,339	13,255	17,610	13,255	13,255
R-squared	0.396	0.339	0.334	0.078	0.046	0.046

Notes: Standard errors clustered at household level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All outcome variables are in logs. All regressions include household, region by-growing season, and cropping season (first or second semester) fixed effects, DD, HDD, and precipitation and its square. Columns 1 to 5 also include measures of household endowments: log of household size and log of area of available land. Third row displays p-value of test of equality of coefficients in rows (A) and (B).

productivity and input size from the efficient benchmark as a measure of the extent of market distortions.

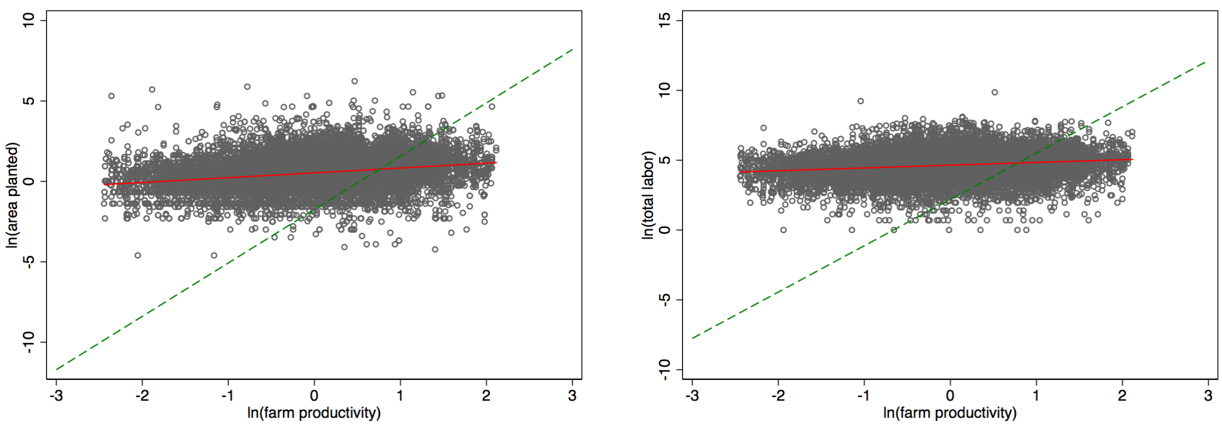
For instance, consider the case of a Cobb-Douglas technology, as in equation (2). Letting $z_i \equiv s_i^{1/(1-\gamma)}$, we can characterize the efficient allocations as::

$$T_i^* = \frac{z_i}{\sum z_i} T^e, \;\; L_i^* = \frac{z_i}{\sum z_i} L^e.$$

where T^e and L^e are the total endowments of land and labor in the economy. Note that in an efficient allocation the correlation between $\ln T_i$ and $\ln s_i$ would be positive and equal to $1/(1-\gamma)$, where $\gamma \in [0,1]$ is the parameter capturing returns to scale.

Figure 3 plots the relation between our estimates of the log of farm productivity ($\ln s_i$) and log of land and labor used by a farm. we also plot the corresponding efficient allocation based on our estimate of $\gamma = 0.694$. We observe a positive correlation between farmer productivity and input use. However, the relationship is quite flat, and much smaller that the one required under an efficient allocation.

Figure 3: Relation between farm productivity and input use



(a) Ln area planted

(b) ln total labor

Notes: Figure displays a scatter plot of our measure of farm productivity (s_i) and input use (both in logs). Solid line represents a linear fit, while dashed line represents the relation if allocation were efficient.

These preliminary results are suggestive of substantial factor misallocation in Ugandan agriculture. This result is similar to the one documented by Restuccia and Santaeulalia-Llopis (2017) and Adamopoulos et al. (2017) in Malawi and China, and echoes other studies reporting severe allocative inefficiency in developing countries (see Restuccia and Rogerson (2013) for a review).

We examine this issue more formally by regressing the log of input use (land and labor) on our measure of farm productivity allowing for heterogeneous effects by regions (see Table 5). This specification includes weather controls as well as growing season, cropping season, and district fixed effects. We use two measures of land allocation: the area planted and also the area of available farm land.

Columns 1 to 3 confirm the patterns shown in Figure 3. There is positive correlation between input allocation and farm productivity. This correlation, however, is much less steep that in the benchmark of perfect markets. Columns 4 to 6 add an interaction of farm productivity with an indicator of being in the Western or Central regions. The interaction term has a positive and statistically significant estimate.

The results suggest significant differences across regions. In the Western and Central regions, the relation between farmer productivity and input availability is stronger. Interestingly, the difference in the relation between farmer productivity and labor are smaller (column 6). This last result may reflect that variation in land tenure (measured with the regional indicators) capture mostly imperfections in land markets.

We interpret these findings as evidence that the regional indicator captures meaningful differences in the extent of factor misallocation, and thus of the severity of market distortion. Reassuringly, these results suggest that in Western and Central regions, areas with more widespread use of non-customary land tenure regimes, these market distortions are less severe. This does not mean, however, that the use of non-customary land rights eliminate factor misallocation: the resulting correlations are still far from the efficient benchmark.[15]

[15] Consistent with the idea that institutional heterogeneity can be associated with improvements in land allocation, A.V. Chari and Wang (2017) show that a reform in China that allow farmers to lease out land increased aggregate productivity.

Table 5: Land tenure and factor misallocation

	Land		Labor	Land		Labor
	ln(area planted)	ln(area available)	ln(total labor)	ln(area planted)	ln(area available)	ln(total labor)
	(1)	(2)	(3)	(4)	(5)	(6)
Farm productivity	0.375***	0.413***	0.276***	0.319***	0.337***	0.250***
($\ln s_i$)	(0.015)	(0.017)	(0.013)	(0.018)	(0.020)	(0.016)
farm productivity ×				0.127***	0.170***	0.058**
Western or Central				(0.028)	(0.031)	(0.023)
Observations	16,527	16,482	16,527	16,527	16,482	16,527
R-squared	0.182	0.238	0.153	0.185	0.243	0.154

Notes: Standard errors clustered at household level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All regressions include growing season, cropping season (first or second semester) and district fixed effects, as well as weather controls: DD, HDD, precipitation and its square.

5 Final remarks

This paper examines farmers responses to extreme heat in the presence of market distortions using variation in property rights and microdata from Uganda, we find that farmers adjust input use as a response to extreme heat. However, this response seems to be affected by the type of property rights: in places with modern property rights they reduce input use, but increase them in areas with customary, informal, rights. The effect of extreme on output in both places is, however, similar.

We interpret these results as evidence that market distortions reduce farmers' ability to relocate their resources to mitigate the damages associated with extreme weather. This insight has important implications for thinking on the expected effects of climate change. In particular, it suggests that places with poorly developed market institutions may face a slowlier, potentially more costly, process of adaptation to climate change.

Our study has, however, still several caveats. The most obvious one is that we only exploit observational variation in property rights. Ideally we would like to have some quasiexperimental variation. In addition, we are limited to study the short-term, response to weather shocks, not the long-term effects of climate change. Addressing these limitations warrants future research.

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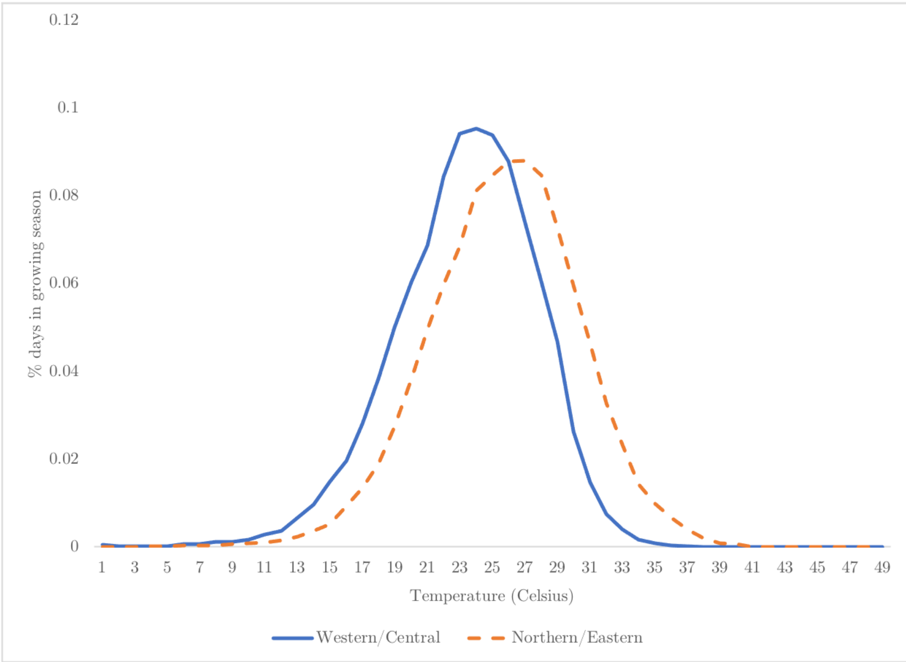
ONLINE APPENDIX - Not for publication

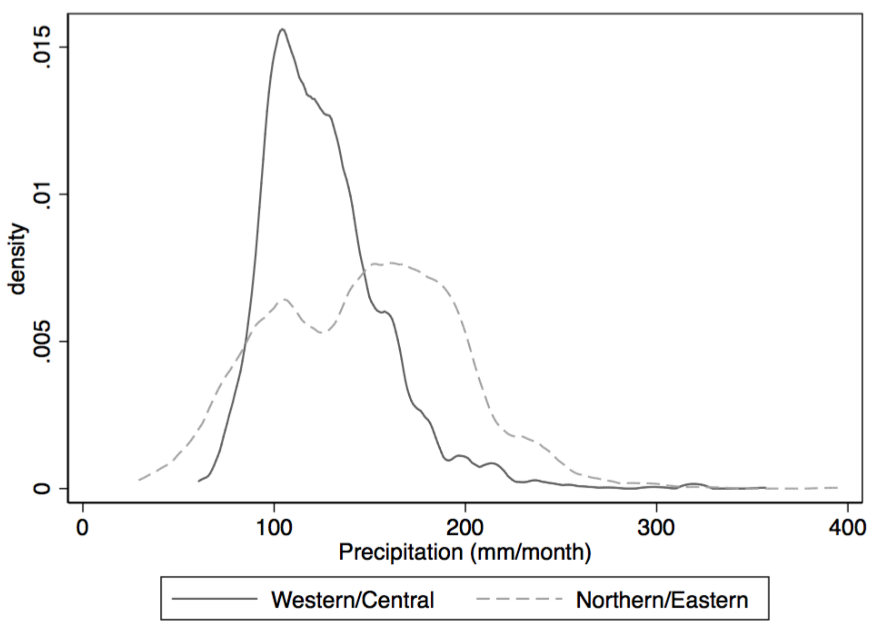
A Additional figures

Figure A.1: Distribution of daily average temperature, by region



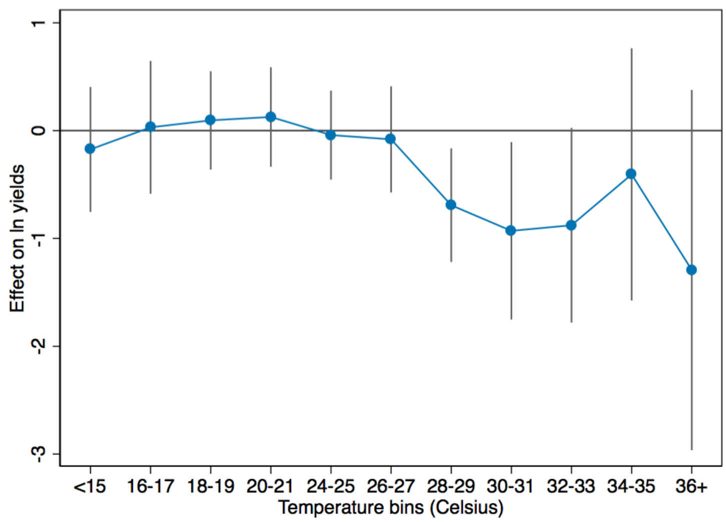
Notes: Figure depicts share of days in each temperature bin during the growing season.

Figure A.2: Distribution of average precipitation, by region



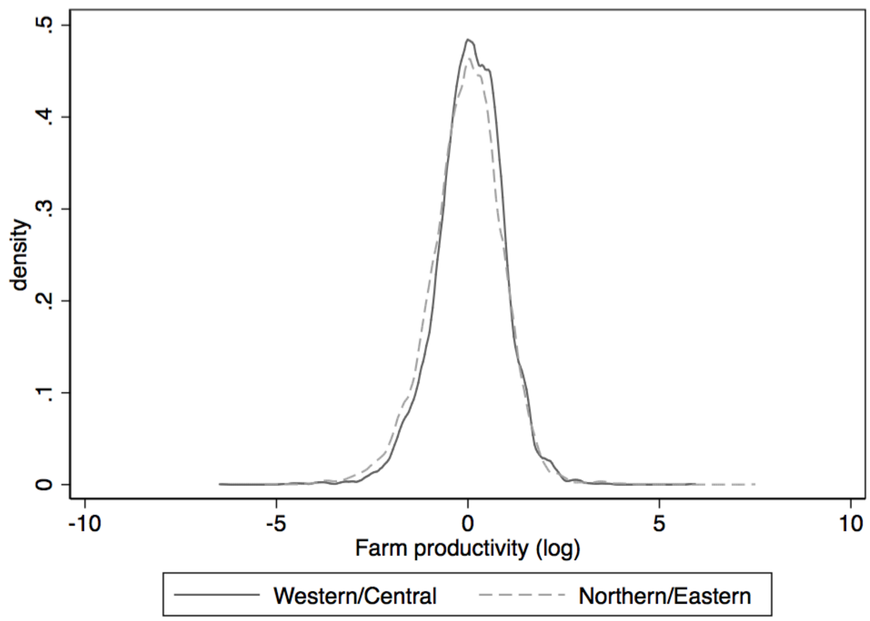
Notes: Figure depicts probability density function of average monthly precipitation during the growing season.

Figure A.3: Relationship between temperature and total factor productivity



Notes: Figure displays estimates of regressing ln(output) on a set of temperature bin controlling for input use (log of area planted and total labor) and household fixed effects. The omitted category is bin 21-22 °C. Circles represent points estimates, while lines are 95% confidence intervals. Regression estimated using OLS and also includes precipitation and its square, as well as semester, and year fixed effects. S.E. clustered at county level.

Figure A.4: Distribution of farm productivity ($\ln s_i$), by region



Notes: Figure depicts probability density function of estimated farm productivity ($\ln s_i$. This last variable corresponds to the household fixed effects of a model regressing log of output on log of land and land, weather controls and year and season fixed effects (see Table B.2).

B Additional tables

Table B.1: Effect of temperature on land, labor, and output by region - robustness checks

	Land			Total labor		
	(1)	(2)	(3)	(4)	(5)	(6)
Average HDD	0.044**	0.054**	0.054**	0.080***	0.101***	0.115***
	(0.019)	(0.021)	(0.027)	(0.021)	(0.022)	(0.027)
Average HDD x proxy market distortion	-0.102	-0.138***	-0.007	-0.048	-0.154***	-0.056**
	(0.069)	(0.041)	(0.026)	(0.058)	(0.045)	(0.028)
Proxy of market distortion	District has high % of non-custom. land	% of non-custom. land	Farmer has non-agric. income	District has high % of non-custom. lLand	% of non-custom. land	Farmer has non-agric. income
Endow. control	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,698	16,242	13,332	17,610	16,163	13,248
R-squared	0.392	0.346	0.319	0.091	0.085	0.068

Notes: Standard errors clustered at household level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All outcome variables are in logs. All regressions include household, growing season , and cropping season (first or second semester) fixed effects, DD, HDD, and precipitation and its square and measures of household endowments: log of household size and log of area of available land. Indicator "District has high % of non–custom. land" is equal to 1 if share of farmland under non-customary tenure in a district is 50% or greater.

Table B.2: Production function estimates

	(1) ln(output)
ln(total person-hours)	0.363***
	(0.017)
ln(area planted)	0.331***
	(0.018)
DD	-0.023*
	(0.012)
HDD	-0.132***
	(0.036)
Precipitation	-0.002**
	(0.001)
Precipitation2	0.000*
	(0.000)
Implied α	0.477
Implied γ	0.694
Observations	17,731
No. households	4,598
R-squared	0.143

Notes: Standard errors clustered at household level (in parenthesis). Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* Regression also includes household, growing season, and cropping season (first or second semester) fixed effects. Estimated household fixed effects are used as our measure of farm productivity $\ln s_i$.