Climate Change and Agriculture: Farmer Responses to Extreme Heat*

Fernando M. Aragón† Francisco Oteiza‡ Juan Pablo Rud§

December 2018

Abstract

This paper examines how farmers respond to extreme heat in the short-run. Using a production function approach and micro-data from Peruvian households, we find that high temperatures reduce productivity and induce farmers to increase the use of land and to change their crop mix during the agricultural season. This reaction attenuates the negative effects of high temperatures on output, but exacerbates the drop in yields. We use our estimates to simulate alternative climate change scenarios and show that accounting for these responses is quantitatively important to estimate the effects of climate change on agricultural production.

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

*We are grateful to Robin Burgess, Andrea Guariso, Maxim Lamare, Anirban Mitra, Matt Neidell, Debraj Ray, Finn Tarp, Marcos Vera and participants in seminars at the RES Annual Conference, the CEPR Workshop in Development (TCD/LSE), Birkbeck University, IDB, IMF, RHUL, NWDW, NEUDC, NCDE, European Development Network, Workshop on Poverty, Inequality and Mobility at QMUL, Navarra Center for International Development, Kent Development Economics workshop, Paris Sorbonne, ZEF-Bonn, EPIC, University of Wisconsin-Madison, University of Manchester, Academia Nacional de Ciencias Económicas Argentina, and Universidad del Pacífico for useful comments and suggestions.

†Department of Economics, Simon Fraser University; email: faragons@sfu.ca

‡Department of Social Science, UCL Institute of Education, email: f.oteiza@ucl.ac.uk

§Department of Economics, Royal Holloway, University of London and Institute of Fiscal Studies; email: juan.rud@rhul.ac.uk

1 Introduction

A growing body of evidence suggests that extreme temperatures have negative effects on crop yields.[1] Based on these findings, current estimates suggest that climate change will bring dramatic shifts in agriculture: a global warming of 2℃, as in conservative predictions, would reduce agricultural output by almost 25% (IPCC, 2014). Among those exposed to this shock, the rural poor in developing countries are probably most vulnerable. They are located in tropical areas, where the changes in climate will occur faster and be more intense, and their livelihoods are more dependent on agriculture.

Given these potentially disruptive effects, it is extremely important to understand possible adaptation strategies and the scope for mitigation. Some studies suggest that a possible response to climate change would be re-allocation of economic activity, in the form of migration, changes in trade patterns or sectoral employment (Colmer, 2018, Costinot et al., 2016, Feng et al., 2012). Other studies, based on farmers' self-stated adaptive strategies, emphasize changes in consumption and savings as potential temporary responses (Akpalu et al., 2008, Di Falco et al., 2011, Gbetibouo, 2009, Hisali et al., 2011).

Less is know, however, about productive adaptations, i.e., changes in production decisions to attenuate the negative effects of extreme temperatures. Existing studies from the U.S. and India find that farmers do not seem to change crop mix or agricultural practices in response to rising temperatures, even though crop yields are negatively affected by both short-term weather shocks and long-term changes in climate patterns (Burke and Emerick, 2016, Guiteras et al., 2015). This finding has been interpreted as evidence that farmers do not engage in long-run productive adaptation.

This paper examines how farmers respond to extreme heat in the context of a developing country. Our main contribution is to show that an important mitigation response is to increase the use land and to change the crop mix. This response to a negative productivity shock, can be rationalized in a context of traditional subsistence farming characterized by thin input markets and limited outside opportunities. To the best of our knowledge, this margin of adjustment to extreme temperatures has not been documented before. It has, however, relevant implications for the quantification of predicted economic losses due to climate change, and for understanding the potential long-term effects of weather shocks.

To separate the effects of temperature on agricultural productivity, output, and productive decisions, we use a production function approach combined with a novel dataset. We match micro-data from Peruvian farming households for 2007-2015 with high-frequency temperature data obtained from satellite imagery. The granularity of our data allows us to estimate the relationship between temperature and agricultural outcomes –such as total factor productivity (TFP), yields, output

[1] See for instance, 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. (2017a).

and input use– using observations at the farm level.[2]

Our approach has several advantages over existing studies examining the effect of temperature on agriculture using crop yields. First, crop yields capture both biological and human responses, such as changes in labor and other inputs. However, by construction, they cannot reflect changes in land use, missing a potentially important margin of adjustment. Second, most of the existing evidence comes from farmers in the U.S. These farmers engage in mostly intensive, monocropping agriculture and have access to ex-ante risk coping mechanisms, such as crop insurance. These features may reduce incentives to adapt to climate change (Annan and Schlenker, 2015). Hence, their responses may not be informative of farmers' adaptation in other contexts. Finally, household and satellite data like the ones used in this paper are publicly available for most developing countries. Thus, our analysis can be replicated in contexts that lack rich weather station data.

We find that farmers respond to extreme temperature by *increasing* use of land and by increasing their share of tubers in total production, at the expense of cereals. This occurs despite extreme temperatures reducing agricultural productivity. The magnitude is economically significant and partially offsets the drop in total output. One standard deviation increase in our measure of extreme heat is associated with a 7.4% increase in land use and a 2.9% increase in the share of tubers, at the expense of cereals. These results are robust to a variety of specification checks and are not driven by changes in agricultural prices. We provide suggestive evidence that farmers engage in this productive responses throughout the year.

This is a surprising finding: in standard production models lower productivity would weakly reduce input use. However, it is consistent with decisions of consumer-producers facing incomplete markets as in agricultural household models (De Janvry et al., 1991, Taylor and Adelman, 2003). In this view, subsistence farmers may use their inputs more intensively to attenuate drops in output and consumption. With this framework in mind, we interpret our results as evidence of productive adaptation, i.e., changes in production decisions to reduce the negative effects of extreme temperature.

We also examine several ex-post coping mechanisms previously identified in the literature on consumption smoothing, such as migration, off-farm labor, and disposal of livestock (Bandara et al., 2015, Beegle et al., 2006, Kochar, 1999, Munshi, 2003, Rosenzweig and Wolpin, 1993, Rosenzweig and Stark, 1989). Consistent with previous studies, we find that households reduce their holdings of livestock after a negative weather shock and seem to increase hours working off the farm. Interestingly, the increase in land as a response to extreme heat occurs even among farmers who have alternative risk-coping instruments at hand.

Our findings have important implications for the quantification of the potential economic costs of climate change, especially for developing countries. Most current predictions rely on estimates of the effect on crop yields from studies in developed countries or performed in controlled conditions.

[2]A similar approach has been used for manufacturing plants in China in Zhang et al. (2017b).

These estimates fail to take into account changes in land use, and thus may overestimate the effects of climate change on agricultural output.

To illustrate this point, we use our estimates to predict the potential effect on yields and output of evenly distributed increments in average daily temperatures, derived from climate change projections of scenarios RCP4.5 and RCP8.5 of the 4th IPCC Assessment Report. We conduct this analysis separately for the two main climatic regions of Peru, i.e., coast and highlands. We obtain two important results. First, the effects of increased temperature are heterogeneous. The coast, with an arid semi-tropical climate, would suffer large losses (between 17-30% of total output). In contrast, the highlands, with a cooler and wetter climate, would benefit slightly from the warmer temperatures. Similar heterogeneous effects have been document for U.S. agriculture (Deschenes and Greenstone, 2007, Mendelsohn et al., 1994, Schlenker et al., 2006) but not for a developing country. Second, accounting for farmer responses is relevant to quantify output losses. In the case of the coast, failing to account for adaptive behavior would overestimate the estimated losses up to 16%.

The rest of this paper is organized as follows. Section 2 discusses the data and the empirical strategy. Section 3 presents the main results on productive effects and responses and other coping mechanisms, while Section 4 explores in more detail changes in land use. Section 5 presents simulations of climate change scenarios. Section 6 concludes.

2 Data and Methods

2.1 Data

Our empirical analysis focuses on subsistence farming households in two climatic regions of rural Peru: the coast and the highlands (see Figure 1 for a location map).[3] The two regions exhibit a rich variety of climatic, socioeconomic and agronomic characteristics. We argue that these features make the Peruvian case an ideal testing ground of the effect of extreme heat on agriculture. By providing a snapshot of the effects on different climates and subsistence farmers, it can be informative of potential effects in other developing countries.

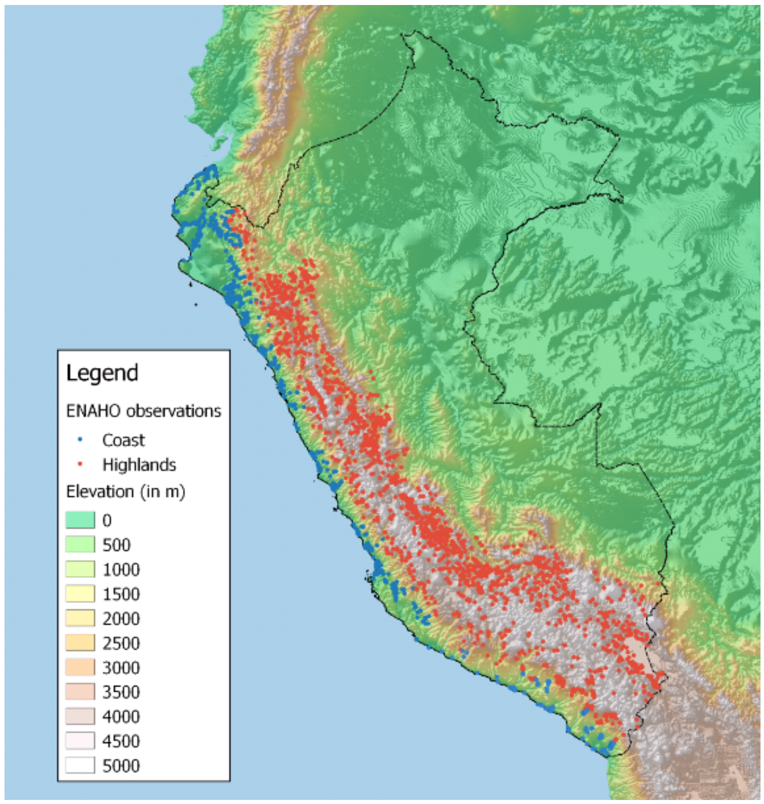
The small-scale farmers we study use traditional technologies and have little market interactions (i.e. they produce using mostly household land and labor only). Despite the fact that most rural households engage in these type of farming, the analysis of their productive decisions in a warming environment has been overlooked in the climate change literature. Similar to other countries, these household farms coexist with modern farming (usually capital intensive and export-oriented), but

[3]Peru has three main climatic regions: the coast to the west, the Andean highlands, and the Amazon jungle to the east. The coast is the region from 0 to 500 meters above sea level (masl) on the west range of the Andes. Highlands range from 500 to almost 7,000 masl, while the jungle is the region of low lands (below 1000 masl) to the east of the Andes. We drop the jungle due to small sample size and poor quality of satellite data: many observations are missing due to cloud coverage.

have little interactions or technological transfers.

We combine household surveys with satellite imagery to construct a comprehensive dataset with information on agricultural, socio-demographic, and weather variables at the farm level. The dataset includes more than 53,000 households and spans from 2007 to 2015.[4]

Figure 1: ENAHO observations 2007-2015



Notes: Location of the ENAHO observations used in this study by climatic region.

2.1.1 Agricultural and socio-demographic data

We use repeated cross sections of the Peruvian Living Standards Survey (ENAHO), an annual household survey collected by the National Statistics Office (INEI). This survey is collected in a continuous, rolling, basis. This guarantees that the sample is evenly distributed over the course of the calendar year. Importantly, the ENAHO includes geographical coordinates of each primary sampling unit or survey block.[5] In rural areas, this corresponds to a village or cluster of dwellings.

[4]We restrict the sample to households with some agricultural activity in each survey year. We drop 282 farmers reporting land holdings larger than 100 hectares and around 500 farmers reporting less than 0.03 hectares. We also drop observations from the jungle due to small sample size and poor quality of satellite data due to cloud cover.

[5]There are more than 3,400 unique coordinate points.

We use this information to link the household data to satellite imagery. Figure 1 depicts the location of the observations used in this study.

The ENAHO contains rich information on agricultural activities in the 12 months prior to the interview. We use this information to obtain measures of agricultural output and input use. To measure real agricultural output, we construct a Laspeyres index with quantity produced of each crop and local prices.[6] Land use is obtained by adding the size of parcels dedicated to seasonal and permanent crops. We observe the size and use of each parcel, but not which specific crops are cultivated in each one. Since most farmers cultivate several crops, this prevents us from calculating crop-specific yields.

We use self-reported wage bill paid to external workers as a measure of hired labor use. Labor information on household members is available for the week prior to the interview.[7] Using this information we calculate the number of household members working in agriculture and build an indicator of child labor.[8] These variables serve as proxies for domestic labor.

We complement the household survey with data on soil quality from the Harmonized World Soil Database (Fischer et al., 2008). This dataset provides information on several soil characteristics relevant for crop production on a 9 km square grid.[9]

2.1.2 Temperature and precipitation

A main limitation in Peru, and other developing countries, is the lack of high resolution weather data: in the period of analysis there were just 14 stations in the whole country. This lack of data also introduces a significant measurement error in gridded products, such as reanalysis datasets, which use weather station data as their main input.[10]

To overcome these limitations, we use satellite imagery. For temperature, we use the MOD11C1 product provided by NASA. This product is constructed using readings taken by the MODIS tool aboard the Terra satellite. These readings are processed to obtain 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.[11]

[6] As weights, we use the median price of each crop in a given department in 2007.

[7] Given that interviews can occur after the growing season, these measures of domestic labor may not reflect actual input use during the period of interest. We address this concern in the analysis of input use by using only observations interviewed during the growing season.

[8] Child labor is defined as an indicator equal to one if a child living in the household aged 6-14 reports doing any activity to obtain some income. This includes helping in the family farm, selling services or goods, or helping relatives, but excludes household chores.

[9] The soil qualities include nutrient availability and retention, rooting conditions, oxygen availability, excess salts, toxicity and workability.

[10] Two commonly used examples are published by the European Center for Medium-Range Weather Forecasting (ECMWF) and the National Center for Environmental Prediction (NCEP). These products rely on weather station data and interpolate it on a global grid using general circulation models.

[11] MODIS validation studies comparing remotely sensed land surface temperature estimates and ground, *in situ*, air temperature readings found discrepancies within the 0.1-0.4°C range (Coll et al., 2005, 2009, Wan and Li, 2008).

The satellite data provides estimates of land surface temperature (LST) not of surface air temperature, which is the variable measured by monitoring stations. For that reason, the reader should be careful when comparing the results of this paper to other studies using re-analysis data or station readings. 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).

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 combines satellite imagery with monitoring station data. It provides estimates of daily precipitation with a resolution of 0.05×0.05 degrees.

We combine the weather data with household's location to obtain daily measures of temperature and precipitation for each farmer during the last completed growing season.[12] Following the Peruvian agricultural calendar, we define the growing season to span from October through March. This period corresponds to the southern hemisphere's Spring and Summer. The distribution of temperatures in the relevant locations over each growing season are shown in Figure 2.

Climate change projections - We consider two possible climate change scenarios developed by the IPCC's Fifth Assessment Report (AR5), released in 2014. These scenarios, or representative concentration pathways (RCPs), represent two different sets of assumptions about the future trajectory of global greenhouse gas emissions over the following century. We use the model output produced by the Hadley Centre Global Environment Model version 2 (HadGEM2), used in the IPCC AR5, for scenarios RCP85 and RCP45. RCP85 is a 'business as usual' framework, where no additional greenhouse gas emission mitigation policies are introduced. It is comparable to A1FI emission scenario from previous IPCC reports and it forecasts an increase of 4.9°C in global temperatures by the end of the century. The RCP45 scenario assumes increased efforts to curb emissions at a global scale, forecasts an average 2.4°C increase in global temperatures and is comparable to the earlier B1 emissions scenario.

These projections provide monthly average temperatures for the year 2099. In a similar way as we do for actual temperature and precipitation readings, we extract the projected temperature for each month of the growing season at the household level. Before incorporating them into our analysis, though, a correction has to be performed to this data to account for systematic model error and the fact that our historical data is measured as land surface temperature instead of air temperature. In the spirit of Deschenes and Greenstone (2011), we first calculate, for each location, month of the year and RCP scenario, the difference between the forecasted temperature and the historical temperature from the HadGEM2 experiment for the year 2005.[13] This provides

[12] We assign the outcomes for growing season t (October $t = 1$ through March t), to any household interviewed as of April t and up to March $t + 1$. We believe this approach is conservative since it only assigns weather outcomes to households once the growing seasons has finished.

[13] This is the latest year for which historical HadGEM2 data exists, and the only one for which there is overlap

us with an internally consistent projection of the temperature anomaly expected for each location and month of the year, for the year 2099, since the start of our study period. Then we add this projected difference to the historical daily temperatures from the MODIS satellite product for each location, averaged at the calendar day level over the 2005-2015 period. In other words, we add the projected month-by-location temperature anomaly expected by the end of the century, to the average daily temperatures recorded over the study period in each location.

2.1.3 Summary Statistics

Table 1 present some summary statistics for our sample of farming households. There are several relevant observations for the empirical analysis. First, most farmers are poor and depend on agriculture as their main economic activity. The incidence of poverty in our sample of farmers is around 50%. For comparison purposes, a similar methodology shows that poverty over the whole of Peru during the period of analysis was 21.6%. Poverty and reliance in agriculture as the primary economic activity are higher in the highlands than in the coast. Second, farmers have small scale operations (the average farm size is around 2 ha), and use practices akin to traditional rather than industrial farming: they rely on domestic labor including child labor, cultivate a variety of crops instead of monocropping, and leave some land uncultivated. This feature is consistent with fallowing and crop rotation.

Finally, climatic conditions are drastically different in both regions in the sample. The coast has a sub-tropical climate with mild to hot temperatures and very little rainfall. Not surprisingly, most of the agriculture in this region occurs in irrigated lands.[14] In contrast, the highlands have cooler temperatures and more rain during the growing season. These differences do not entail substantially different results in the key components of our analysis, but have important implications when thinking in terms of the potential effects of greater temperatures due to climate change.

2.2 Analytical framework

The aim of the empirical analysis is to examine how traditional farmers in a developing country adjust their production decisions as a response to extreme heat. To this end, we follow standard agricultural household models in the development literature (Aragón and Rud, 2016, Benjamin, 1992, De Janvry et al., 1991, Taylor and Adelman, 2003) where households make simultaneous, potentially interrelated, consumption and production decisions. Households maximize utility (a function of consumption c and leisure l) subject to a budget constraint, where income is derived from an agricultural production function $F(A, L, T)$ that uses land T and labor L and is subject to a productivity shifter A. The latter term implies that farmers using identical inputs can have

with our study period.

[14] Given the potential importance of irrigation as a method to counteract the damage from high temperatures, a branch of the literature decides to exclude areas with high irrigation coverage, see for instance Schlenker and Roberts (2009). We keep these observations but control for the share of irrigated land.

different levels of output, among other reasons, because they are better managers or are exposed to some location-specific characteristics or shocks, such as weather events.

If input markets work well, farmers can also derive income from renting some of their land or supplying off-farm labor. As shown in Benjamin (1992), this implies that farmers can make productive decisions independently of their consumption decisions. Namely, they can choose their optimal levels of land and labor separately from their labor supply decisions that affect their consumption and leisure.

However, the environment under which these households farms operate in rural Peru (and other parts of the developing world) may be substantially different. First, outside opportunities for land and labor may be limited. For example, Table 1 shows that, on average, more than 50% of household members of the household work in the farm and only 47% of households have a member with a job off the farm. Similarly, only around 9% of farmers use rented land and the share of uncultivated land is large, on average. While this may reflect a productive decision, almost 50% of farmers that have uncultivated land do not use any of it for fallowing. An important implication of these features of agricultural production is that input use is constrained by household endowments (such as household size and owned land).

Second, farmers tend to show little specialization and engage in multi-cropping and crop rotation. Additionally, while some months in the year are more suited for and intensive in planting, these farmers cultivate land all throughout the year (see Figure 5 in Section 4). This, combined with the availability of uncultivated land, implies that both inputs and outputs are flexible throughout the season.

Finally, as shown in Table 1, a large share of households are poor, and many more are chronically around the poverty line. This suggests that shocks to production may be very costly for these households as they have little outside options and farming is their main source of livelihood.

Taking all these elements together, what can we expect from farmers exposed to extreme temperatures that reduce productivity A in a given agricultural season? In a frictionless world, farmers would use smaller quantities of inputs in production. Separately, they would choose their labor supply according to the wage in labor markets and their preferences for leisure. Things would be different in a more constrained environment, where farmers are close to subsistence, there are limited outside opportunities for labor and endowments are an important determinant of input use, output and, ultimately, consumption. In this setting, a negative productivity shock to the main source of livelihood would require mitigating actions, to reduce the impact on output and consumption. As discussed above, farmers have at least two instruments at hand to buffer the shock to output. First, they can increase their input intensity by drawing from the unused land and increasing their labor efforts. Second, they can change the pattern of production, moving to crops that may be more resistant to heat, or provide relatively cheaper calories.

2.3 Empirical Strategy

In this section we discuss how we explore empirically the link between extreme heat and both input use and agricultural output. These outcomes can be modelled as reduced form functions of productivity A and a set of relevant parameters such as local prices or household endowments. Assuming that A is a function of local weather and other factors, such as household and district characteristics, we can approximate these reduced forms using the following log-linear regression model:

$$\ln y_{ijt} = g(\gamma, \omega_{it}) + \phi Z_i + \rho_j + \psi_t + \epsilon_{ijt}, \tag{1}$$

where the unit of observation is farmer i in district j during growing season t, and y is an outcome such as agricultural output, or quantity of input used. $g(\gamma, \omega_{it})$ is a non-linear function of local weather conditions (ω_{it}), to be specified later. Z_i is a set of household or household head characteristics, and ρ_j and ψ_t are district and year fixed effects.[15]

In this baseline specification, we are interested in γ: the reduced-form estimate of the effect of weather on agricultural outcomes. At the core of our analysis is the assumption that extreme heat affects productivity. We examine this assumption in two ways. First, we estimate regression (1) using as dependent variable total output per hectare (Y/T), a proxy for agricultural yields. This approach is similar to previous studies in the literature which use crop yields.[16] A main limitation of this approach is that yields is a measure of partial productivity which captures both changes in TFP *and* the relative use of (endogenous) inputs. If inputs were fixed, for instance as in lab conditions, the standard approach would be informative of effects on TFP. However, in our context, it can obscure the effect of temperature shocks on agricultural productivity from input and output responses such as crop mix. For that reason, we complement our results by estimating a production function. Assuming a Cobb-Douglas production function $Y_{ijt} = A_{ijt} T_{it}^{\alpha} L_{it}^{\beta}$, applying logarithms, and using the functional form assumption of A, we obtain the following regression model:

$$\ln Y_{ijt} = \alpha \ln T_{it} + \beta \ln L_{it} + g(\gamma, \omega_{it}) + \phi Z_i + \rho_j + \psi_t + \epsilon_{ijt}, \tag{2}$$

where Y is agricultural output, and T and L are quantities of land and labor. This model is similar to equation (1), however, by controlling for input use, γ can now be interpreted as the effect of weather on TFP.

A potential concern with this specification is that ϵ does not simply reflect unanticipated shocks but unobserved determinants of farmer's productivity. Since output and input use are both affected by productivity, this would lead to a problem of omitted variables. To address this concern, we estimate (2) using both OLS and IV models. OLS estimates would be consistent if our household

[15] A district is the smallest administrative jurisdiction in Peru and approximately half the size of the average U.S. county. Our sample includes 1,320 districts out of a total of 1,854.

[16] Due to data limitations we are unable to calculate crop-specific yields, except for a small share of farmers.

controls (e.g. age and education of head), our farm controls (land quality), and our time and regional fixed effects capture all productivity differences between household farms. The IV specification intends to address issues of unobserved heterogeneity by using endowments (i.e., household size and area of of land owned) as instruments for input use, under the presumption that unobserved contemporaneous productivity shocks do not affect them. The motivation to use these instrument comes from the observation that, in the absence of input markets, the quantity used of land and domestic labor would be determined by the land owned and the household size.[17] The validity of these instruments would rely on the assumption that endowments affect output only through its effect on input use, i.e., endowments should not be conditionally correlated to other unobserved contemporaneous shocks, ϵ_{ijt}.[18]

Finally, in our analysis of inputs demand functions, we also control for household endowments, namely household size and land owned, as discussed in section 2.2. In these specifications, any change in input use associated to the exposure to extreme temperatures will be conditional on household resources available to farmers.[19] In all specifications, we cluster the standard errors at district level to account for spatial and serial correlation in the error term.[20].

2.3.1 Modeling the relation between weather and productivity $g(\gamma, \omega_{it})$

Following previous economic and agronomic findings, we model the relation between weather and agricultural productivity as a function of the farm's cumulative exposure to heat and water.[21] This approach is based on the assumption of time separability, i.e., weather outcomes have the same impact on output per hectare whenever they occur within a given growing season. Similar to Schlenker et al. (2006), we construct two measures of cumulative exposure to heat during the growing seasons: degree days (DD) and harmful degree days (HDD). DD measures the cumulative exposure to temperatures between a lower bound, usually 8°C up to an upper threshold τ_{high}, while HDD captures exposure to extreme temperature (above τ_{high}), The inclusion of HDD allows for potentially different, non-linear, effects of extreme heat.

Formally, we define $DD = \frac{1}{n}\sum_d g^{DD}(h_d)$, with

$$g^{DD}(h) = \begin{cases} 0 & \text{if } h \leq 8 \\ h - \tau_{low} & \text{if } 8 < h \leq \tau_{high} \\ \tau_{high} - 8 & \text{if } \tau_{high} < h, \end{cases}$$

[17]With perfect input markets, we would obtain the standard result of separability of consumption and production decisions and there would be no correlation between endowments and input use (Benjamin, 1992). Empirically, this would create a problem of weak instruments.

[18]The interpretation of this IV strategy would be as a local average treatment effect, since the coefficients would be identified from farmers subject to input market imperfections.

[19]All our results hold if we do not add these controls.

[20]Results are robust to clustering standard errors at provincial level (see Table 5)

[21]See, for example Schlenker and Roberts (2006).

h_d is the average daytime temperature in day d and n is the total number of days in a growing season. Similarly, $HDD = \frac{1}{n}\sum_d g^{HDD}(h_d)$, with

$$g^{HDD}(h) = \begin{cases} 0 & \text{if } h \leq \tau_{high} \\ h - \tau_{high} & \text{if } \tau_{high} < h \end{cases}$$

After calculating total degree days, we estimate the average degree days by day over the entire growing season, by dividing over the number of days with non-missing temperature data, for consistency. This re-scaling makes interpretation easier and does not affect the results. Similarly, we measure exposure to precipitation using the average daily precipitation (PP) during the growing season and its square.[22] With these definitions in mind, we parametrize the function relating weather to productivity $g(\gamma, \omega_{it})$ as:

$$g(\gamma, \omega_{it}) = \gamma_0 DD_{it} + \gamma_1 HDD_{it} + \gamma_2 PP_{it} + \gamma_3 PP_{it}^2. \tag{3}$$

A key remaining issue is to define the value of the upper threshold above which temperature has a negative effect (τ_{high}) on agricultural yields. Previous studies in U.S. set this value between 29-32°C (Deschenes and Greenstone, 2007, Schlenker and Roberts, 2006). These estimates, however, are likely to be crop and context dependent and hence might not be transferable to our case.[23] For that reason, we prefer to use a data-driven approach.

To do so, we estimate a flexible version of (1) using log of output per hectare as outcome variable and replacing DD and HDD with a vector of variables measuring the proportion of days in a growing season on which the temperature fell in a given temperature bin.[24] Based on the distribution of temperatures in the Peruvian case, we define fourteen bins: $<$ 6°C, 42 =<°C, and twelve 3°C-wide bins in between. Our omitted category is the temperature bin 30-33°C.

Figure 3 displays the estimated coefficients and their 95% confidence interval. The effect is negative and statistically significant at the 5% level from temperature bin 33-36°C.

In Figure 4 we perform an iterative regression method as proposed by Schlenker and Roberts (2009). In this exercise, the upper threshold is determined by running Equation 1 for all possible thresholds of HDD in Equation 3 and choosing the one with the largest R^2. Figure 4 shows the results. Based on both set of results, we use a value of τ_{high} equal to 33°C for the whole sample.[25]

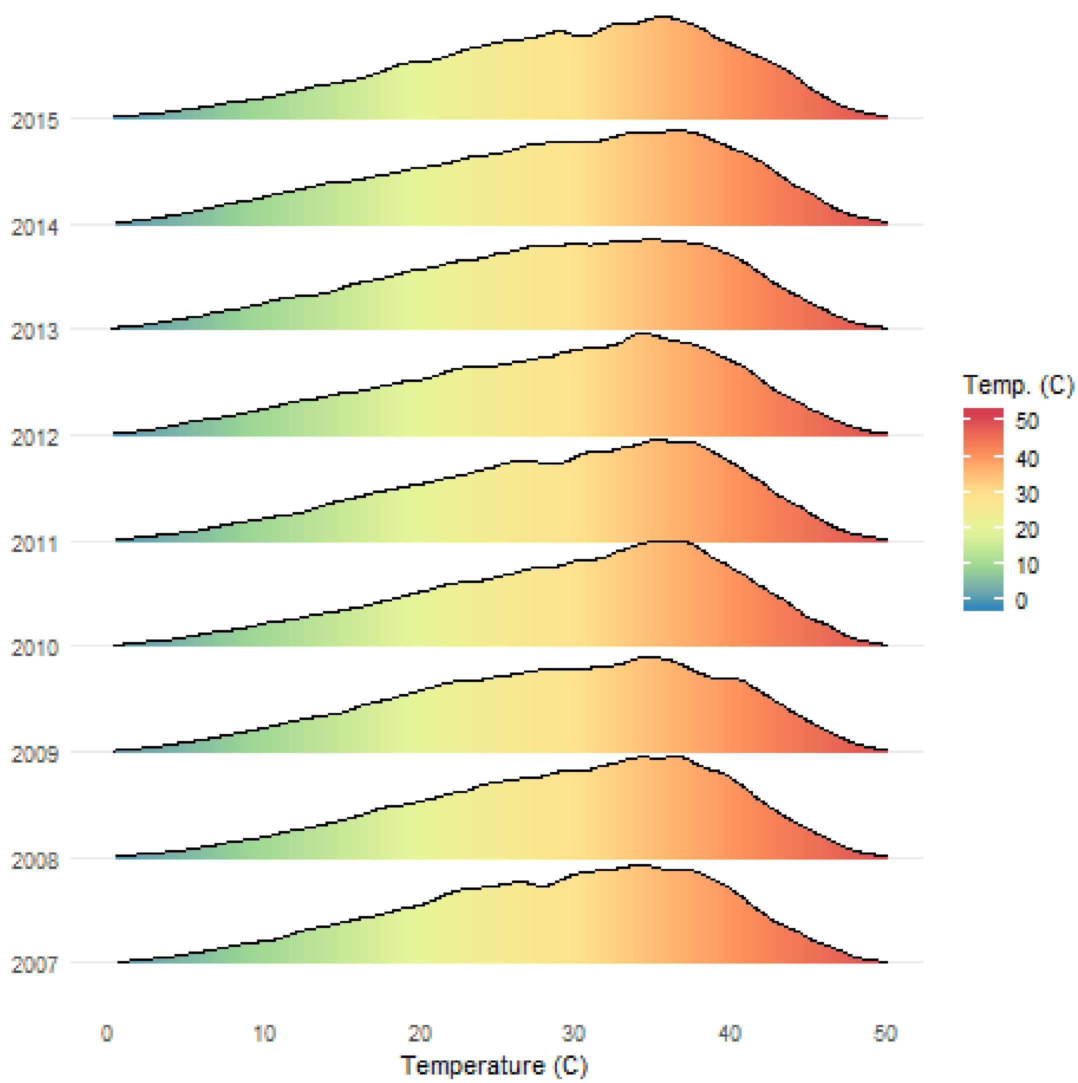
[22] Precipitation and temperature are likely to be correlated, so it is important to include this regressor.

[23] In addition to differences in crop mix and agricultural technology, we use a different measure of temperature (i.e. land surface temperature). These factors make previous estimates not applicable to our case study.

[24] This specification is similar to the one used by Burgess et al. (2017) to study the effect of weather on mortality.

[25] In Section 3.3 we verify the robustness of our main results to other thresholds.

Figure 2: Distribution of daily average temperature



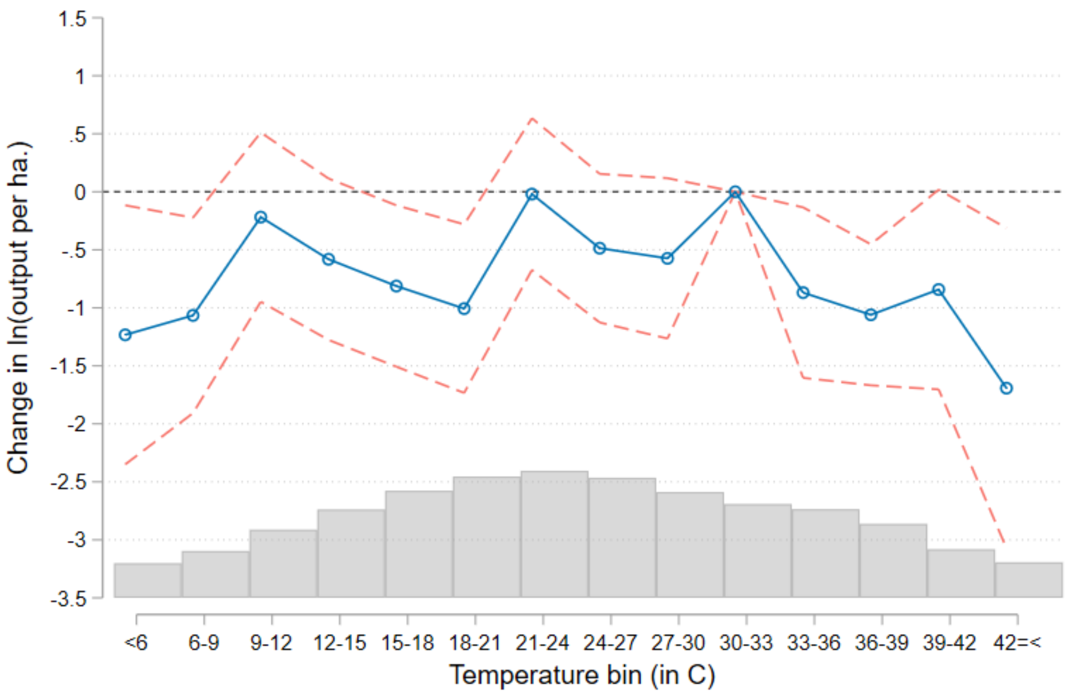
Notes: Figure depicts the share of days spent in each temperature bin by the farmers in our sample, during the 2007-2015 growing seasons.

Table 1: Summary statistics (ENAHO 2007-2015)

	(1) All	(2) Coast	(3) Highlands
A. Household characteristics			
Poor (%)	51.15	26.59	55.09
Household size	4.34	4.41	4.33
Primary education completed by HH head (%)	50.93	58.47	49.72
Child works (%)	21.83	9.65	23.80
At least 1 HH member has off-farm job (%)	47.55	56.48	46.11
B. Agricultural characteristics			
Value of agric. output (Y), 2007 USD	1050.77	3269.75	693.86
Output per ha. (Y/T), 2007 USD	1048.92	1868.49	917.09
Land used (T), in ha.	1.99	2.42	1.93
No. HH members work on-farm	2.31	2.21	2.33
Hire workers (%)	48.89	57.16	47.56
Uncultivated land (% of land holding)	40.16	11.51	44.77
Irrigated land (% land holding)	36.06	81.98	28.67
Fruits (% total output)	7.41	31.59	3.52
Tubers (% total output)	31.36	5.55	35.52
Cereals (% total output)	31.31	30.46	31.45
Own livestock (%)	77.61	55.91	81.10
Value of livestock, 2007 USD	681.23	459.57	716.88
C. Weather during the last growing season			
Average temperature (C)	22.84	33.07	21.20
Average DD	14.27	22.39	12.97
Average HDD	0.73	2.69	0.42
% days with HDD	0.17	0.53	0.11
Precipitation (mm/day)	3.16	0.93	3.51
Observations	53,493	7,412	46,081

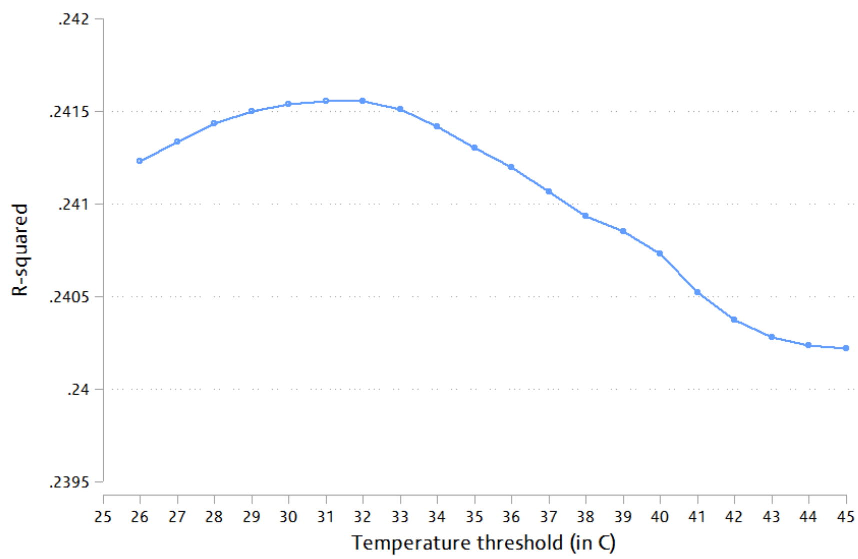
Notes: Sample restricted to farming households from the coast and highlands. Other sources of household agricultural income include garden crops, legumes, forage, and other unspecified agriculture-based goods.

Figure 3: Non-linear relationship between temperature and agricultural yields



Notes: Points represent coefficient estimates of the effect of increasing the share of days in the growing season in each of the temperature bins, relative to the 30-33°C bin, on log of output per ha. Bin labels denote the lower (included) and upper (excluded) bounds. For example, bin 30-33 measures the fraction of the growing season spent on days with temperatures above or equal to 30°C and lower than 33°C. Dashed lines show the 95% confidence interval.

Figure 4: Model fit (R^2) of weather regressions with different temperature thresholds



Notes: Figure plots the model fit (R^2) for regressions of Equation 1 using the weather specification 3 for all possible different values of τ_{high}, the thresholds to split between DD and HDD, for the whole sample. Controls include household head's characteristics (age, age^2, gender and education attainment), precipitation, its square, indicators of soil quality, and district and growing season fixed effects.

3 Results

This section presents our empirical results on farmers' responses to extreme heat. We begin by documenting the non-linear effect of temperature on agricultural productivity. Then we examine productive adaptations, such as changes in input use and crop mix. Finally, we evaluate other coping strategies identified in the consumption smoothing literature.

3.1 Temperature and agricultural productivity

Figure 3 sets the scene for our empirical analysis. It provides prima facie evidence of a non-linear relationship between temperature and agricultural productivity: at moderate levels, temperature increases output per hectare, but at higher levels, the effect is negative.

Table 2 corroborates this finding using our preferred specification, which includes degree day measures of cumulative exposure to temperature: DD and HDD. Column 1 uses agricultural yields (Y/T) as a proxy for productivity. As mentioned above, this approach may not accurately measure the impact of weather outcomes on productivity, since it confounds impacts on both TFP and input use. For that reason, in columns 2 and 3 we estimate a production function, i.e, output conditional on input use, using an OLS and IV strategy, where input use is instrumented with household endowments. By controlling for input use, these latter estimates can be interpreted as the effect of temperature on TFP.

Our estimates suggest that extreme heat has a negative effect on agricultural productivity.The magnitude of the effect is economically significant: the most conservative estimate suggests that an increase of 1℃ in the average growing season temperature above the optimal level would decrease agricultural productivity by around 7%. To put this figure in further context, note that climate change scenarios discussed in Section 5 envisage that, by the end of this century, the average number of harmful degree days over the growing season could increase between 0.64 and 1.32 degrees, with the already hot Coast observing changes of between 3 and 5 additional HDDs. Negative effects of extreme heat on crop-specific yields of similar magnitudes have been documented in agronomic field trials and using aggregated data in U.S., India, and Sub Saharan Africa, among others.[26]

What happens with total output? Consistent with a drop in productivity, we find that extreme heat reduces agricultural output (column 4). However, the magnitude of this effect is smaller than for TFP or yields and loses significance. This is suggestive that farmers implement productive adaptations (i.e., changes in production decisions) to attenuate the negative effect of extreme heat on total output. We examine this hypothesis in detail next.

[26]See, for example, Auffhammer et al. (2012), Guiteras et al. (2015), Burgess et al. (2017), Burke et al. (2015), Burke and Emerick (2016), Schlenker and Roberts (2009), Lobell et al. (2011).

Table 2: Impacts of DD and HDD on agricultural productivity and output

	Y/T	TFP		Y
	(1)	(2)	(3)	(4)
Dep var:	ln(output/ha)	ln(output)	ln(output)	ln(output)
Average DDs	0.020*	0.013*	0.014*	0.011
	(0.011)	(0.007)	(0.008)	(0.009)
Average HDDs	-0.116***	-0.066*	-0.071**	-0.043
	(0.040)	(0.034)	(0.034)	(0.041)
Input controls	No	Yes	Yes	No
Method	OLS	OLS	IV	OLS
N	53,493	53,487	53,487	53,493
R2	0.334	0.548	0.359	0.348

Notes: Standard errors (in parenthesis) are clustered at the district level. Stars indicate statistical significance: **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and control for household head characteristics (age, age^2, gender, and level of education); indicators of soil quality from Fischer et al. (2008) (nutrient availability, nutrient retention, rooting conditions, oxygen availability, salinity, toxicity and workability) and the share of irrigated land. Input controls: log of number of household members working in agriculture, total land used, and amount spent on hiring labor. Instruments for domestic labor and land used: household size and land owned. First stage joint significance F-test is 462.72.

3.2 Productive adaptations: input use and crop mix

Table 3 presents our main results on productive adaptation. We start by examining changes in input use as a response to extreme heat. We focus on three key agricultural inputs: land, household labor, and hired labor.

We find that extreme heat during the growing season significantly *increases* the use of land. As discussed in Section 2.2, in a standard production model, we could expect negative productivity shocks to reduce the use of variable inputs. This finding, however, is consistent with the response of subsistence farmers in a context of incomplete markets. In that scenario, farmers exposed to a negative shock and limited off-farm opportunities may need to resort to a more intensive use of non-traded inputs to avoid undesirable drops in output and consumption.[27]

In terms of household labor, as well as the probability of child labor slightly increase with HDD, even though only the latter effect is significantly different from zero.[28], we do observe that the quantity of household labor used in the farm (measured both as number of individuals or number of hours) This last result is consistent with findings in the literature on child labor (Bandara et

[27]Indeed, do not find evidence of a drop in measures of consumption, income and poverty due to extreme heat. See Table B.2 in the Appendix.

[28]Due to data limitations, we cannot say whether this effect captures lower hours hired or lower hourly wages paid.

al., 2015, Beegle et al., 2006) that show that poor households may resort to employing children in productive activities when subject to negative income shocks, in line with the luxury axiom proposed initially by Basu and Pham (1998). On the contrary, the coefficient of HHD on expenditure in hired labor is negative, albeit also insignificant. This suggests a slight tendency of farms to use more intensively household labor in hot seasons.

The use of additional land to mitigate a drop in productivity may be particularly relevant for farmers in less developed countries that are increasingly exposed to higher temperatures. This margin of adjustment may have been missed in existing studies of the effect of temperature on agriculture due to their focus on farmers in developed countries. In that context, better access to markets, crop insurance and other coping mechanism may make changes in land use a less relevant response.

Our findings have two important implications. First, it suggests a potential dynamic link between weather shocks and long-run outcomes. There is an obvious limitation to increasing land as a way to mitigate above-average temperatures in a growing season. Also, for some farmers leaving land unused may be a dynamic productive decision. In our sample, around 50% of farmer have some land fallowing, a common practice in traditional agriculture to avoid depleting soil nutrients, recover soil biomass, and restore land productivity (Goldstein and Udry, 2008). Thus, using these inputs more intensively, as a response to hotter temperatures, may not be sustainable.

Second, this adaptive response may affect estimations of the effect of climate change on agricultural production. These estimates are usually based on the effect of temperature on crop yields (Y/T). This is a correct approach if land use is fixed. In that case, changes in crop yields are the same as changes in output. However, using crop yields may be less informative in contexts in which farmers adapt to weather shocks by changing land use. As we show in Section 5, taking into account this adaptive response reduces, in a non-trivial magnitude, the predicted effects on total output.

Changes in crop mix Recent studies have emphasized the possible role of changes in crop mix as an adaptive response to climate change (Burke and Emerick, 2016, Colmer, 2018). A relevant question is how important is this margin of adjustment in our context.

In Table 4 we explore this issue by looking at the effect of temperature on quantities and value shares of three main crop types: cereals (mostly rice in the Coast and corn in the Highlands), tubers (i.e., potatoes) and legumes. These crops represent more than 70% of agricultural production and are widely widespread. Note, however, that farmers in our context practice multi-cropping: the average farmers grows almost six different crops.[29] This is a commonplace practice among subsistence farmers across the developing world, and is in stark contrast with the modern agricultural practices of the U.S. and other developed countries, which mostly practice mono-cropping.

[29] In our sample, less than 10% of farmers report growing only one crop.

Table 3: Impacts of DD and HDD on input use

	Land	Household Labour			Hired Labor
	(1)	(2)	(3)	(4)	(5)
Dep var:	ln(land used)	HH members in farm	HH hours in farm	Child labor	ln(wage bill)
Average DDs	-0.006	-0.009**	-0.025***	-0.016***	0.021
	(0.009)	(0.004)	(0.007)	(0.005)	(0.016)
Average HDDs	0.057***	0.020	0.031	0.026**	-0.070
	(0.018)	(0.012)	(0.019)	(0.012)	(0.056)
Owned Land (logs)	0.180***	0.006***	0.019***	0.005***	0.138***
	(0.006)	(0.001)	(0.003)	(0.002)	(0.006)
Household Size (logs)	0.195***	0.495***	0.479***	0.119***	-0.002
	(0.013)	(0.007)	(0.013)	(0.014)	(0.028)
N	53,493	26,668	26,670	14,335	53,492
R2	0.443	0.499	0.326	0.307	0.243

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns (3) to (5) include only information for households interviewed during the growing season as well as month of interview fixed effects.

We find that extreme heat reduces the quantity (in absolute and relative terms) of cereals, but increases the production of tubers. We interpret these results as suggestive evidence that farmers change crop mix as an adaptive response to extreme heat. In the Peruvian context, tubers (potatoes) may be used as a risk-coping strategy: they have a more flexible planting calendar and may more resilient to extreme temperatures, so they can be used as a way to reduce the drop in income when other crops are failing. Additionally, they provide cheaper calories. Dercon (1996) documents a similar strategy using sweet potato among Tanzanian farmers with no liquid assets in the form of livestock.

Our analysis has two important limitations. First, we cannot distinguish between farmer's actively changing crop mix from crops' heterogeneous response to heat: our results could be similar if potatoes thrive in extreme heat even if farmers do not change crop mix at all. Second, we only observe short-run responses, within a growing season, so our results are not informative of long-run adaptation. Despite these caveats, these results do suggest a role for changes in crop mix as a coping strategy in the short-run.

3.3 Alternative specifications

In Table 5 we present results for a number of alternative specifications. We start by looking into additional controls, such as region-growing season fixed effects and month of interview fixed effects

Table 4: Impacts of DD and HDD on crop mix

Dep var:	ln(output)			Share of total output		
	(1)	(2)	(3)	(4)	(5)	(6)
Crop group:	Cereals	Tubers	Legumes	Cereals	Tubers	Legumes
Average DDs	0.048***	-0.086***	0.019**	0.012***	-0.029***	0.003*
	(0.010)	(0.016)	(0.009)	(0.002)	(0.004)	(0.001)
Average HDDs	-0.099***	0.107***	0.014	-0.018**	0.022***	0.004
	(0.037)	(0.036)	(0.038)	(0.007)	(0.005)	(0.005)
N	42,845	39,711	34,068	53,493	53,493	53,493
R2	0.458	0.392	0.319	0.384	0.523	0.241

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns (3) to (5) include only information for households interviewed during the growing season as well as month of interview fixed effects.

(to account for recall bias if the agricultural season is far in the past). This is a very demanding specification that flexibly accounts for department-specific trends in agricultural productivity. Row 1 shows that saturating the regression with these indicators does not substantially change our estimates. Similarly, results hold when we cluster standard error at a higher level of aggregation, allowing for shocks to be correlated within provinces (Row 2).

In Rows 3 and 4 we find that the main set of results do not hinge on the choice of threshold obtained from Section 2.3.1, whether by using 30°Cor by calculating different thresholds per region. Similarly, the results hold in Row 5, when using the share of days with temperatures above 33°Cin the growing season as an alternative measure of exposure to hot temperatures.

Finally, in Panel C we run the same specification separately for each region and find that the effects are qualitatively similar, even though the effect on land and yields is somewhat stronger in the Highlands. This is consistent with the idea that land availability matters, as the share of unused land in this region is substantially higher (see Table 1).

Table 5: Robustness checks

	Y/T	TFP	Y	T
	(1)	(2)	(3)	(4)
Dep var:	ln(output/ha)	ln(output)	ln(output)	ln(land used)
Panel A: Fixed effects and uncertainty				
1. Month of interview and state-GS FE	-0.108***	-0.059*	-0.032	0.062***
	(0.039)	(0.034)	(0.041)	(0.020)
2. Clustering s.e. by province (n=159)	-0.116***	-0.066**	-0.043	0.057***
	(0.037)	(0.031)	(0.041)	(0.020)
Panel B: Temperature specifications				
3. Common HDD threshold at 30C	-0.086***	-0.048*	-0.029	0.048***
	(0.028)	(0.025)	(0.031)	(0.014)
4. Region-specific HDD threshold (33C and 36C)	-0.115***	-0.071*	-0.055	0.048***
	(0.044)	(0.038)	(0.045)	(0.018)
5. Number of HDD days during the GS (>33C)	-0.548**	-0.306*	-0.163	0.317**
	(0.217)	(0.183)	(0.228)	(0.126)
Panel D: By climatic region				
6. Coast, 33C threshold (N=7,412)	-0.127***	-0.078**	-0.071	0.040**
	(0.044)	(0.037)	(0.043)	(0.019)
7. Highlands, 36C threshold (N=46,081)	-0.231**	-0.097	-0.019	0.154*
	(0.102)	(0.065)	(0.076)	(0.089)

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include the same controls as baseline regression in Table 2. Rows 2 to 7 include district and climatic region-by-growing season fixed effects. **Input controls:** number of household members working in agriculture, total land used and amount spent on hiring labor, all in logarithms. Each row presents the estimates using a different specification.

4 Understanding changes in land use and crop mix

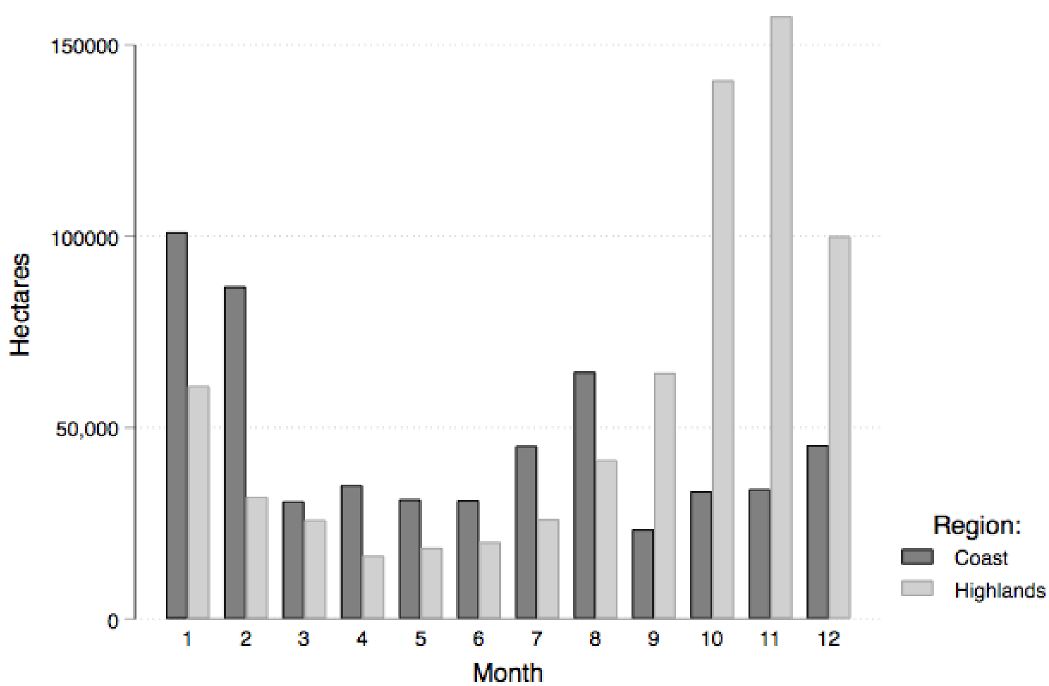
In this section we explore more carefully the nature of the changes in land use as a mitigating response to high temperatures. We focus on the increase in land use as an important adaptation mechanism for at least three reasons. First, land is an important agricultural input which, due to factors such as ill-defined property rights, is usually subject to severe market imperfections. Second, since unused land can be part of a dynamic productive decision (such as fallowing), adjustments in land to attenuate current weather shocks may impose productivity losses in the future. Finally, by focusing on crop yields, the current literature on climate change and agriculture, has neglected this margin of adjustment. This coping mechanism has also been overlooked by the literature examining ex-post consumption smoothing.

4.1 The timing of decisions

The ability to adapt to weather shocks may vary during the growing season. For instance, there may be technical constraints to adjust the use of land during the growing season (e.g., related to climate, crop suitability or labor availability). Alternatively, we may be observing a delayed response from farmers to extreme temperatures in previous agricultural seasons instead of a within-season response. In this section we investigate further the timing of land adjustments to extreme heat.

We start by noting that planting happens throughout the year in both regions of Peru. Evidence in Figure 5 shows that, despite some seasonal patterns, farmers take decisions about how much land to cultivate every month.

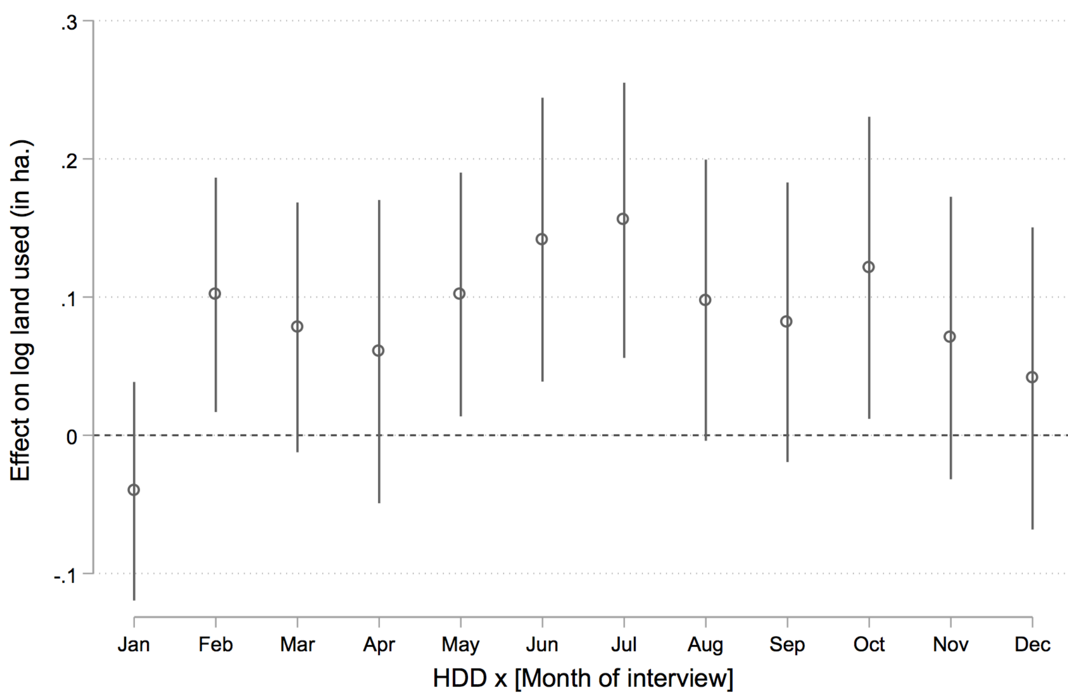
Figure 5: Hectares planted by calendar month and climatic region



Notes: Total hectares planted by calendar month, for the crops harvested during the 2017 growing season. Planting period goes from January 2015 to May 2017. *Source:* National Agricultural Survey of Peru, 2017.

The question in the household survey asks farmers whether each of their parcels was used for agricultural production in the previous 12 months. This suggests that the timing of the interview may matter, as farmers may be either in the middle of the planting or growing season and they have to recall planting decisions made almost a year before. To look into this, we estimate the effect of HDD by month of interview, by running our main land specification and interacting HDD and month of interview. Results in Figure 6 shows that, with the exception of January interviews, the rest of the effects seems to be quite similar regardless of the month where the survey was implemented. However, the effects seem to be stronger between April and September, after the standard growing season has ended and most of the harvesting happens.

Figure 6: Effects of HDD on land use according to month of interview



Notes: Same specification as in column 1 in Table 3, but interacting HHD with month of interview.

In Table 6 we look at different time-frames to measure HDD, focusing only on farmers interviewed after the main growing season has ended, i.e. between April and September. Whether we use the last growing season, the previous six months or the previous twelve months, the effects on land and crop mix are positive and significant. These different time frames suggest that the adjustments in land and crops likely happen all year round, as different temperature occurrences are associated with productive responses, even if they fall outside the main growing season.

Finally, we construct separate measures of DD and HDD according to whether the temperature shock happened in different quarters of the calendar year, to capture the first (October to December), or the second half (January to March) of the growing season or earlier. Note again, that these farmers were interviewed between April and September, so that the lags include up to 5 quarters previous. In Table 7, columns 1 and 4 we find that farmers, on average, seem to respond more to heat that happens early in the growing season, namely between October and December. However,

Table 6: Different time-frames for impacts on land and crop mix

	ln(land used)			Share of Tubers (%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Average HDD (Growing Season)	0.081***			0.020***		
	(0.026)			(0.006)		
Average HDD (Last 6 Months)		0.054**			0.024***	
		(0.024)			(0.006)	
Average HDD (Last 12 Months)			0.126***			0.037***
			(0.039)			(0.011)
N	26,799	26,799	26,799	26,799	26,799	26,799
R2	0.458	0.455	0.458	0.531	0.530	0.531

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. **Input controls:** number of household members working in agriculture and total land used.

this average response hides heterogeneous responses in the Coast and the Highlands, that are consistent with the intensity of planting during the calendar year observed in Figure 5. Heat seems to affect more in key planting moments of the agricultural season in each region. In the Coast, the responses seem to be very similar to hot temperatures across the growing season and the previous quarter. These results look consistent with the more homogeneous plantation pattern observed in Figure 5. In the Highlands, the responses on land are stronger when the hotter temperatures occur during the growing season. In all the regressions, earlier occurrences of HDD do not seem to explain adjustments in land or crop mix.

Taken together, these results point towards productive adjustments to hot temperatures happening consistently during the agricultural year.

4.2 Productive adjustments and consumption smoothing

4.2.1 Other coping mechanisms

The literature on consumption smoothing has identified several mechanisms used by rural households to adjust to income, and weather, shocks. For example, individuals in affected households can seek employment off the farm (Colmer, 2018, Kochar, 1999, Rosenzweig and Stark, 1989), migrate (Kleemans and Magruder, 2017, Munshi, 2003, Feng and Schlenker, 2015) or sell assets, such as cattle (Rosenzweig and Wolpin, 1993).

Table 7: Impacts of lagged HDD on farmer land and crop mix

	ln(land used)			Share of Tubers (%)		
	(1) All	(2) Coast	(3) Highlands	(4) All	(5) Coast	(6) Highlands
Average HDD (Jan-Mar)	0.033	0.017	0.167*	0.007	0.002	-0.008
	(0.025)	(0.024)	(0.101)	(0.004)	(0.004)	(0.021)
Average HDD (Oct-Dec)	0.072**	0.035	0.086*	0.020***	0.001	0.028***
	(0.033)	(0.027)	(0.050)	(0.005)	(0.009)	(0.008)
Average HDD (Jul-Sep)	0.030	0.107*	-0.025	-0.007	0.010	0.020
	(0.087)	(0.058)	(0.156)	(0.014)	(0.016)	(0.021)
Average HDD (Apr-Jun)	-0.081	-0.099*	0.167	0.004	-0.017	0.119
	(0.063)	(0.051)	(0.458)	(0.012)	(0.011)	(0.111)
N	26,778	3,629	23,149	26,778	3,629	23,149
R2	0.460	0.398	0.461	0.534	0.199	0.491

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2.

Table 8 explores these mechanisms. Columns 1 and 2 examine whether households adjust to extreme heat by increasing off-farm employment. We use an indicator of a household member having a non-agricultural job, as well as the total number of hours worked off-farm.[30] These outcomes capture supply of off-farm employment in the extensive and intensive margin. In the extensive margin, the effect is positive, but very small and insignificant. However, we do find evidence of an increase in the number of hours worked off the farm among those with an off-farm job.

In columns 3 to 5 we look for evidence of migration. Due to data limitations, we cannot measure migration directly. Instead, we use proxy variables such as an indicator of whether any member has been away from home for more than 30 days, household size, and an indicator of whether the household receives remittances. None of these variables seems to be affected by extreme weather and two of the point estimates, albeit small and insignificant, show the opposite sign of what we would expect if migration was a coping mechanism.

These results should be interpreted with caution. Our analysis focuses on a short time period (within a year) and these adjustments may happen over a longer time frame. In addition, our measures of labor and migration may be noisy proxies of actual behavior. These factors likely

[30]These variables are only reported for the week previous to the interview. As in Table 3, we restrict the sample to households interviewed during the growing season. However, results do not change if we include observations for the whole year.

reduce the power of our statistical analysis and could explain the insignificant results.

Finally, we examine cattle sales as a possible coping mechanism (columns 6-8). Consistent with previous findings, such as Rosenzweig and Wolpin (1993), our results show that households reduce their holding of livestock.[31] The effect of a reduced value (column 6) seems to come from households selling, rather than consuming their livestock (columns 7 and 8).

Table 8 shows evidence that households engage in consumption smoothing mechanisms when exposed to extreme temperatures. We have also seen that reductions in agricultural output are also mitigated thanks to productive responses in land and crop mix. Table B.2 in the Appendix, suggests that these strategies as we find no evidence of significantly lower income or consumption among farming households exposed to extreme heat.

[31]This includes cattle, sheep, horses, llamas and pigs.

Table 8: Other adjustments to DD and HDD

	Off-farm work		Migration			Livestock buffer		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep var:	HH member has off-farm job	Hours worked off-farm	HH member away 30+ days	HH size	Receives private transfers	Decrease in livestock value	Sold livestock	Consumed livestock
Average DDs	0.009**	0.025***	0.003**	-0.003	0.005**	-0.008***	-0.013***	-0.013***
	(0.004)	(0.009)	(0.001)	(0.014)	(0.002)	(0.002)	(0.002)	(0.003)
Average HDDs	0.006	0.059**	-0.002	0.014	0.002	0.022***	0.017*	0.007
	(0.011)	(0.027)	(0.003)	(0.031)	(0.006)	(0.007)	(0.010)	(0.009)
Mean outcome	0.464	57.532	0.085	4.340	0.195	0.332	0.517	0.476
N	26,670	12,356	53,493	53,493	53,493	48,052	48,052	48,052
R2	0.217	0.171	0.058	0.245	0.149	0.077	0.147	0.240

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p* <0.10, ** *p* <0.05, *** *p* <0.01. All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2. Columns 1 and 2 include only information for households interviewed during the growing season as well as month of interview fixed effect. Livestock value from Columns (6) and (9) are measured in 2007 USD.

4.2.2 Complementary or substitute strategies?

We found that farmers also engaged in behaviour identified in the literature as ex-post consumption smoothing. In this part, we study the interplay between consumption smoothing and productive adaptation to understand which types of farmers adjust their land use and output. In particular, we are interested in understanding whether farmers use the consumption mechanisms to complement changes in land use or crop mix or whether these strategies are substitutes instead.

To examine these potentially heterogeneous responses, we run our baseline regressions interacting HDD with an indicator of whether farmers had livestock before the start of the growing season or not. The choice of this interaction term is driven by our previous finding (see Table 8) that selling cattle seems to be among the set of relevant consumption smoothing mechanism. We also examine interactions with indicators of availability of off-farm work.

Our results in Table 9 suggest that the increase in land use and the move towards tubers is similar across types of farmers, regardless of whether they had livestock or not before the start of the growing season (columns 1 and 2). We observe similar pattern when comparing households where at least one member has an off-farm job (columns 3 and 4).

In brief, farmers engage in productive mitigation strategies irrespective of whether the can resort to other instruments to cope with levels of extreme heat that affects their productivity. While some farmers may look to alternative ways of smoothing consumption, this does not prevent them from adapting their production strategies to buffer the shock and avoid bigger losses.

Table 9: Temperature impacts on land use and TFP, by type of farmer

	Livestock		Only Farmer	
	(1)	(2)	(3)	(4)
Dep var:	ln(land used)	Share of Tubers (%)	ln(land used)	Share of Tubers (%)
Average HDD x Owns livestock	0.079***	0.021***		
	(0.029)	(0.005)		
Average HDD x No livestock	0.066**	0.016**		
	(0.028)	(0.006)		
Average HDD x Only Farmers			0.079***	0.017***
			(0.027)	(0.006)
Average HDD x Other activity			0.082***	0.022***
			(0.026)	(0.006)
N	26,799	26,799	26,799	26,799
R2	0.467	0.532	0.459	0.531

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): *$p<0.10$, ** $p<0.05$, *** $p<0.01$. All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2.

4.3 A response to weather or to prices?

We interpret the increase in land use as a strategy to attenuate the negative effects of extreme heat. An alternative explanation is that areas subject to extreme temperature experience a decrease in the supply of agricultural products. To the extent that there is a positive price effect, then farmers may be induced to increase production and thus, also the quantity of inputs. If that is the case, our result may be interpreted as a purely profit-driven decision rather than as an adaptive response.

Formally, by failing to account for output prices, our previous results would suffer from omitted variable bias. This issue would be less of a concern if prices are set in national markets. In that case, their influence would be picked up by the set of growing season fixed effects. The problem would persist, though, if agricultural markets were geographically smaller.[32]

In Table 10, we examine this possibility in two ways. First, column 1 and 3 include region-growing season fixed effects (i.e., a set of around 200 dummies that account for 20 regions in 10 agricultural years). If agricultural markets were indeed regional, then this approach would control for prices. Columns 2 and 4 go a step further by controlling for the median log prices of cereals and tubers, calculated at the district level. In both cases, the relationship between HDD and land remains positive and significant. The magnitude of the effect of extreme temperatures on land use and on crop mix is also similar to the baseline results in Table 2.

Second, we examine the effect of temperature on prices of cereals and tubers at the district level. In columns 5 and 6, we find no significant effects. Taken together, these results suggest that changes in prices are unlikely to fully explain the expansion in land use.

[32]For instance Aragón and Rud (2013) find evidence that in the northern highlands of Peru prices of agricultural products are determined locally.

Table 10: Temperature impacts on regional and local prices

Dep var:	ln(land used)		Share Tubers		ln(local price)	
	(1)	(2)	(3)	(4)	(5) Grains	(6) Tubers
Average DD	-0.020	-0.005	-0.031***	-0.024***	0.001	-0.006*
	(0.014)	(0.012)	(0.005)	(0.004)	(0.003)	(0.003)
Average HDD	0.107***	0.086***	0.019***	0.023***	-0.011	0.009
	(0.032)	(0.033)	(0.007)	(0.006)	(0.008)	(0.011)
Province-Year FE	Yes	No	Yes	No	No	No
Control for local prices	No	Yes	No	Yes	No	No
N	26,761	25,094	26,761	25,094	25,991	25,685
R2	0.513	0.458	0.572	0.488	0.780	0.689

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2.

5 Predicting the effect of climate change

In this section, we use our previous estimates to predict the damages to yields and agricultural output associated with higher temperatures predicted in climate change scenarios. Importantly, we show that these predictions are over-estimated when failing to account for productive adaptations, such as changes in land use.

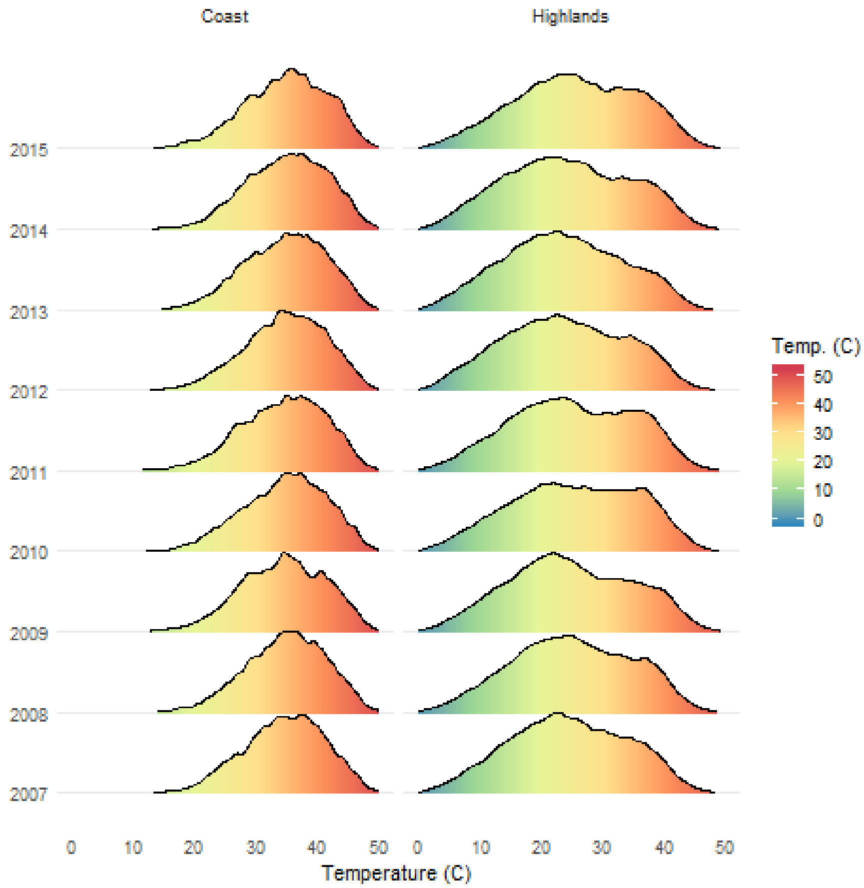
5.1 Peru's climatic regions

As discussed in relation to Table 1, our sample has two distinct climatic and agricultural regions. On average, the coast is hotter and dryer, and farmers there are exposed to more harmful degree days over the course of a growing season. These climatic differences are apparent when observing the distribution of daily temperature in these two regions (see Figure 7).

The two regions also differ in their agricultural practices. Coastal farmers are, on average, substantially better off, as seen in Table 1. They are more productive, more educated and more likely to have access to irrigation. Compared to highland farmers, coastal farmers are also more likely to specialize on fruits, are less likely to own livestock, and crucially, they use a much greater proportion of their land.

A natural question to ask is therefore whether our results vary by region. Table 11 shows the results of reproducing our main analysis of the impact of weather on agricultural output and yields, separately for each region. In spite of their climatic and productive differences, we can see that the marginal impact of each additional harmful degree day is very similar. Harmful degree days reduce

Figure 7: Daily average temperatures by growing season



Notes: This figure plots the density of daily temperatures by growing season and climatic region. Temperatures are in degrees Celsius and recorded by the MODIS Terra instrument.

yields and have no detectable impact on output, as a result of the adaptive responses documented in the previous sections. As shown in columns 3 and 6, where we run a single regression interacting weather variables with a region indicator, the small differences observed in the coefficients of each region are not statistically significant.

5.2 Climate change scenarios

The purpose of this exercise is to highlight two important issues: (1) the heterogeneity of impacts within a country according to their climatic regions and, (2) the importance of accounting for farmers' response when estimating the impact of climate change scenarios. Our exercise does not account for a multitude of factors that might affect agricultural outcomes and thus should be

Table 11: No differential impact of HDD on output and yields by region

Dep var:	ln(output per ha)			ln(output)		
	(1)	(2)	(3)	(4)	(5)	(6)
Region:	Coast	Highlands	All	Coast	Highlands	All
Average DD	0.062*	0.018		0.044	0.005	
	(0.034)	(0.011)		(0.037)	(0.009)	
Average HDD	-0.127***	-0.148***	-0.115**	-0.071	0.009	-0.064
	(0.044)	(0.057)	(0.049)	(0.043)	(0.043)	(0.046)
Difference in HDD impact Highlands-Coast			-0.030			0.078
			(0.076)			(0.065)
N	7,412	46,081	53,493	7,412	46,081	53,493
R2	0.302	0.326	0.335	0.296	0.308	0.349

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include household controls (age, age squared, gender, and level of education of the household head); soil quality controls (nutrient availability, nutrient retention, rooting conditions, oxygen availability, salinity, toxicity and workability; each indicating severe, moderate or no constraints to plant growth, from Fischer et al. (2008)); and controls for the share of irrigated land owned by the household.

interpreted with caution.[33]

As mentioned in the Section 2.1, we consider two scenarios from the IPCC's Fifth Assessment Report (IPCC, 2014). RCP45, our more optimistic scenario, assumes a reduction of greenhouse emissions due to the adoption of green technologies. RCP85 is a 'business as usual' scenario with no large scale adoption of new technologies for emission mitigation. For each scenario j and location k, we calculate DD_k^j and HDD_k^j using the projected daily temperatures described in Section 2.1. We assume the same optimal temperature threshold as discussed in the previous section, 33°C. In both scenarios, average precipitation is predicted to stay within one standard deviation of its natural internal variability, so we do not assume any change in this respect (IPCC, 2014).

We are interested in the estimating the loss in agricultural output and yields associated with each climate change scenario, as a result of the increase in DD and HDD. Using data from 2005-2015, we calculate the average historical DD and HDD in each location ($\bar{DD}_k$ and $H\bar{D}D_k$). Finally define the change in HDD as $\Delta HDD_k^j = HDD_k^j - H\bar{D}D_k$. We follow a similar procedure to obtain ΔDD_k^j. With these predicted changes in DD and HDD, we proceed to estimate agricultural losses in each scenario, by region. We will also assess the importance of taking into account farmer's responses when estimating the impacts of climate change on output and yields. Specifically, we

[33] An important omitted factor is the increased concentration of CO_2 in the atmosphere and its interaction with changing weather conditions. While lab experiments suggest that higher levels of CO_2 could help plant growth, there is significant uncertainty regarding its interaction with other weather variables and its impact on global agricultural yields remains hard to predict (Gosling et al., 2011). We also do not consider any impacts from increased flooding and reduced water access due to glacial melting, nor potential changes of relative food prices.

define the predicted effect on yields (output per ha) and output as follows:

$$\Delta y_i = \hat{\beta}_1 \Delta DD_k^j + \hat{\beta}_2 \Delta HDD_k^j$$

Here, y are yields for farmer i in location k. $\hat{\beta}_1$ and $\hat{\beta}_2$ correspond to the estimates for the two regions taken from Table 11.

Table 12 presents our predictions for the whole sample and each natural region (coast and highlands). Row A shows that, in terms of growing degree days (DD), the coast and the highlands will experience a similar increase in terms of DDs under scenario RCP45, but that the highland will experience almost twice as many DDs under RCP85. DD have little bearing on yields and output in our context, so the more significant findings are in Row B. The increase in temperature will create substantially more harmful temperatures in the coast than in the highlands. While the coast is expected to experience 3-5 additional harmful degrees a day during growing season months, the highlands are expected to experience up to 0.7 HDD a day, in the most pessimistic scenario. These results are a natural consequence of the current distribution of temperatures in both regions, as presented in Figure 7. The coast is already quite warm and has a larger proportion of days already close to the HDD threshold. Hence, the shift of the distribution due to higher average temperature has a greater impact on HDD in this region than in the highlands. Additionally, in the highlands, we can expect the negative impact on yields accruing from these additional HDDs to be partially offset by the positive impact of the large expected increase in DD.

Table 12: Heterogeneous effects of increased temperatures by region

CC scenario:	RCP45			RCP85		
Sample:	All (1)	Coast (2)	Highlands (3)	All (4)	Coast (5)	Highlands (6)
Effect on temperature over the growing season						
A. Average DD	1.131	1.235	1.114	3.401	1.792	3.667
B. Average HDD	0.638	3.031	0.244	1.322	4.925	0.728
Effect on agricultural productivity and output						
C. Change in productivity (ln(Y/T))	-0.050	-0.271	-0.014	-0.093	-0.451	-0.035
D. Change in output (ln(Y))	-0.019	-0.173	0.006	-0.024	-0.290	0.020
Over-estimation of effect in Y (|D-C|)	0.031	0.098	0.020	0.069	0.161	0.055

Notes: Coefficients to estimate effects are from Table 11.

The result of these uneven warming patterns are strongly heterogeneous impacts on agricultural production: while the coast will experience sizable losses in terms of yields and agricultural output, the effect on the highlands will be significantly smaller, particularly under the most optimistic scenario RCP45 (rows C and D). In fact, our projections show that the highlands might even experience small increases in output, in either scenario. This is consistent with other studies finding stronger negative impacts of climate change in low-lying areas (Auffhammer and Schlenker, 2014) and strong regional differences (Deschenes and Greenstone, 2007).

Finally, we ask what the implications of our findings regarding land use are, for future calculations of the costs of climate change? The answer is that despite the fact that the magnitude of the observed effects on land use is not large (i.e. around 4 percentage points increase), taking into account farmers' responses is important. In the coast, ignoring this adaptive response would mean that the negative effect of high temperatures on agricultural output would be overestimated by 5.6 and 9.3 percentage points, according to the RCP45 and RCP85 scenarios, respectively. In colder highlands this error would be smaller, 0.6 and 1.7 percentage points. However, when considered as a proportion of the effects on yields (row C), these errors are much greater in the highlands, due to the fact that farmers manage to attenuate the drop in output more here than in the coast, thanks to a greater use of land. Highland farmers will experience additional HDD, but would at the same time benefit from a) higher temperatures, and their associated increase in beneficial DDs, and b) because they engage in more adaptive behavior.

This finding is important for the estimation of the economic costs of climate change in developing countries. It suggest that extrapolating estimates of the effect of extreme heat on crop yields from samples of farmers in developed countries or from controlled agronomic studies may significantly bias forecasts of climate change impacts in areas where traditional agriculture is the norm. As previously noted, the more intensive use of land in the short term might reduce productivity in the long-run. Due to data limitations, our analysis abstracts from this potential negative effect of climate change in our analysis. The medium to long-term costs of short term adaptations are an important avenue for further research.

6 Conclusion

How do poor farmers mitigate the impact of extreme temperature events? We show evidence that farmers change productive decisions in a way that allows them to minimize the shock to production and to buffer the shock to productivity. We document robust increases in land use and changes to crop intensity when farms are exposed to hot temperatures during the growing season.

Some households engage in other activities that would allow them to cope with a bad agricultural season, such as working more hours off the farm or selling livestock. However, the effects on land use and crop choice are very similar for households who do have alternative sources of consumption or income smoothing and those who do not.

Taken together, our results have important implications for the analysis of climate change in the context of traditional subsistence farming in developing countries. First, as vulnerable households adapt their production in seasons with extreme temperatures, they successfully offset part of the negative impact on agricultural output. This questions the usefulness of estimates of the link between hot temperatures and yields obtained from other contexts where these short-run responses are not available or unlikely (such as studies from developed countries or from controlled experiments). Second, while in the short run farmers can attenuate shocks by using more land, it is less clear whether this practice is sustainable in the long run, as extreme events become more regular and land is not allowed to fallow as needed. Third, an appraisal of potential effects of climate change in developing countries should allow for regional variation, as warmer temperatures may benefit some regions while harm others. Fourth, our results suggest that instruments such as index-insurance that are linked to the measurement of hot days during the growing season could potentially benefit households engaged in traditional farming.

Some important questions raised in this paper remained unanswered, and may be relevant in terms of understanding the links between short-run adaptation to weather shocks, climate change and welfare. Temporary migration, changes in agricultural practices and methods, and the exact timing of the responses we observe could not be fully addressed due to data constraints, and are likely to play a significant role. Similarly, medium to long run costs of current adaptation in terms of land productivity or other unobserved private costs (e.g. on health, education or well-being) also deserve further attention as well as more appropriate data. Finally, while satellite data provides a good fix for the lack of reliable high frequency data in rural areas in developing countries, improvements in measurement of temperature are necessary to make progress in the understanding of the effects of a changing climate in areas and populations that will likely be the most affected.

References

Akpalu, Wisdom, Rashid M Hassan, and Claudia Ringler, "Climate variability and maize yield in South Africa," *IFPRI Discussion Paper*, December 2008, (00843).

Annan, Francis and Wolfram Schlenker, "Federal crop insurance and the disincentive to adapt to extreme heat," *American Economic Review*, 2015, *105* (5), 262–66.

Aragón, Fernando M. and Juan Pablo Rud, "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine," *American Economic Journal: Economic Policy*, May 2013, *5* (2), 1–25.

_ and _ , "Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana," *The Economic Journal*, 2016, *126* (597), 1980–2011.

Auffhammer, Maximilian and Wolfram Schlenker, "Empirical studies on agricultural impacts and adaptation," *Energy Economics*, 2014, *46*, 555–561.

_ , Veerabhadran Ramanathan, and Jeffrey R Vincent, "Climate change, the monsoon, and rice yield in India," *Climatic Change*, 2012, *111* (2), 411–424.

Bandara, Amarakoon, Rajeev Dehejia, and Shaheen Lavie-Rouse, "The Impact of Income and Non-Income Shocks on Child Labor: Evidence from a Panel Survey of Tanzania," *World Development*, 2015, *67* (Supplement C), 218 – 237.

Basu, Kaushik and Van Pham, "The Economics of Child Labor," *American Economic Review*, 1998, *88* (3), 412–27.

Beegle, Kathleen, Rajeev H. Dehejia, and Roberta Gatti, "Child labor and agricultural shocks," *Journal of Development Economics*, 2006, *81* (1), 80 – 96.

Benjamin, Dwayne, "Household Composition, Labor Markets, and Labor Demand: Testing for Separation in Agricultural Household Models," *Econometrica*, 1992, *60* (2), 287–322.

Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone, "Weather, Climate Change and Death in India," 2017.

Burke, Marshall and Kyle Emerick, "Adaptation to Climate Change: Evidence from US Agriculture," *American Economic Journal: Economic Policy*, August 2016, *8* (3), 106–40.

_ , Solomon M Hsiang, and Edward Miguel, "Global non-linear effect of temperature on economic production," *Nature*, 2015.

Carleton, Tamma A and Solomon M Hsiang, "Social and economic impacts of climate," *Science*, 2016, *353* (6304), aad9837.

Chen, Shuai, Xiaoguang Chen, and Jintao Xu, "Impacts of climate change on agriculture: Evidence from China," *Journal of Environmental Economics and Management*, 2016, *76*, 105–124.

Coll, Cesar, Vicente Caselles, Joan M. Galve, Enric Valor, Raquel Niclos, Juan M. Sanchez, and Raul Rivas, "Ground measurements for the validation of land surface temperatures derived from AASTR and MODIS data," *Remote Sensing of Environment*, 2005, *97* (3), 288 – 300.

_ , Zhengming Wan, and Joan M. Galve, "Temperature-based and radiance-based validations of the V5 MODIS land surface temperature product," *Journal of Geophysical Research: Atmospheres*, 2009, *114* (D20), n/a–n/a. D20102.

Colmer, Jonathan, "Weather, Labour Reallocation, and Industrial Production: Evidence from India," *CEP Discussion Papers*, 2018, (1544).

Costinot, Arnaud, Dave Donaldson, and Cory Smith, "Evolving Comparative Advantage and the Impact of Climate Change on Agricultural Markets: Evidence from 1.7 million Fields Around the World," *Journal of Political Economy*, 2016, *124* (1).

Dercon, Stefan, "Risk, Crop Choice, and Savings: Evidence from Tanzania," *Economic Development and Cultural Change*, 1996, *44* (3), 485–513.

Deschenes, Olivier and Michael Greenstone, "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, 2007, *97* (1), 354–385.

_ and _ , "Climate Change, Mortality and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, 2011, *3* (4), 152–185.

Falco, Salvatore Di, Marcella Veronesi, and Mahmud Yesuf, "Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia," *American Journal of Agricultural Economics*, 2011, *93* (3), 829–846.

Feng, Shuaizhang, Michael Oppenheimer, and Wolfram Schlenker, "Climate change, crop yields, and internal migration in the United States," Technical Report, National Bureau of Economic Research 2012.

Fischer, G., F. Nachtergaele, S. Prieler, H.T. van Velthuizen, L. Verelst, and D. Wiberg, "Global Agro-ecological Zones Assessment for Agriculture," Technical Report, IIASA 2008.

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura Harrison, Andrew Hoell, and Joel Michaelsen, "The climate hazards infrared precipitation with stations: a new environmental record for monitoring extremes," *Scientific Data*, 2015, *2.*

Gbetibouo, Glwadys Aymone, *Understanding farmers' perceptions and adaptations to climate change and variability: The case of the Limpopo Basin, South Africa*, Vol. 849, International Food Policy Research Institute, 2009.

Goldstein, Markus and Christopher Udry, "The profits of power: Land rights and agricultural investment in Ghana," *Journal of political Economy*, 2008, *116* (6), 981–1022.

Gosling, Simon N, Robert Dunn, Fiona Carrol, Nikos Christidis, John Fullwood, Diogo de Gusmao, Nicola Golding, Lizzie Good, Trish Hall, Lizzie Kendon et al., "Climate: Observations, projections and impacts," *Climate: Observations, projections and impacts*, 2011.

Guiteras, Raymond, Amir Jina, A Mushfiq Mobarak et al., "Satellites, Self-Reports, and Submersion: Exposure to Floods in Bangladesh," *American Economic Review*, 2015, *105* (5), 232–36.

Hisali, Eria, Patrick Birungi, and Faisal Buyinza, "Adaptation to climate change in Uganda: evidence from micro level data," *Global Environmental Change*, 2011, *21* (4), 1245–1261.

IPCC, "Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change," Technical Report, IPCC, Geneva, Switzerland 2014. [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)].

Janvry, Alain De, Marcel Fafchamps, and Elisabeth Sadoulet, "Peasant household behaviour with missing markets: some paradoxes explained," *The Economic Journal*, 1991, *101* (409), 1400–1417.

Kleemans, Marieke and Jeremy Magruder, "Labour Market Responses To Immigration: Evidence From Internal Migration Driven By Weather Shocks," *mimeo*, 2017.

Kochar, Anjini, "Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India," *The Review of Economics and Statistics*, 1999, *81* (1), 50–61.

Lobell, David B., Marianne Banziger, Cosmos Magorokosho, and Bindiganavile Vivek, "Nonlinear heat effects on African maize as evidenced by historical yield trials," *Nature Clim. Change*, 2011, *1* (1), 42 – 45.

Mendelsohn, Robert, William D Nordhaus, and Daigee Shaw, "The impact of global warming on agriculture: a Ricardian analysis," *The American economic review*, 1994, pp. 753–771.

Munshi, Kaivan, "Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market," *The Quarterly Journal of Economics*, 2003, *118* (2), 549–599.

Mutiibwa, Denis, Scotty Strachan, and Thomas Albright, "Land surface temperature and surface air temperature in complex terrain," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2015, *8* (10), 4762–4774.

Rosenzweig, Mark R. and Kenneth I. Wolpin, "Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Bullocks in India," *Journal of Political Economy*, 1993, *101* (2), 223–244.

_ **and Oded Stark**, "Consumption Smoothing, Migration, and Marriage: Evidence from Rural India," *Journal of Political Economy*, 1989, *97* (4), 905–926.

Schlenker, Wolfram and Michael J. Roberts, "Nonlinear Effects of Weather on Corn Yields," *Review of Agricultural Economics*, 2006, *28* (3), 391–398.

_ **and** _ , "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 2009, *106* (37), 15594–15598.

_ **, W Michael Hanemann, and Anthony C Fisher**, "Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach," *The American Economic Review*, 2005, *95* (1), 395–406.

_ **,** _ **, and** _ , "The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions," *Review of Economics and Statistics*, 2006, *88* (1), 113–125.

Shuaizhang, Michael Oppenheimer Feng and Wolfram Schlenker, "Weather Anomalies, Crop Yields, and Migration in the US Corn Belt," *mimeo*, 2015.

Taylor, J Edward and Irma Adelman, "Agricultural household models: genesis, evolution, and extensions," *Review of Economics of the Household*, 2003, *1* (1), 33–58.

Wan, Z. and Z. Li, "Radiance based validation of the V5 MODIS land surface temperature product," *International Journal of Remote Sensing*, 2008, *29* (17-18), 5373–5395.

Zhang, Peng, Junjie Zhang, and Minpeng Chen, "Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation," *Journal of Environmental Economics and Management*, 2017, *83*, 8–31.

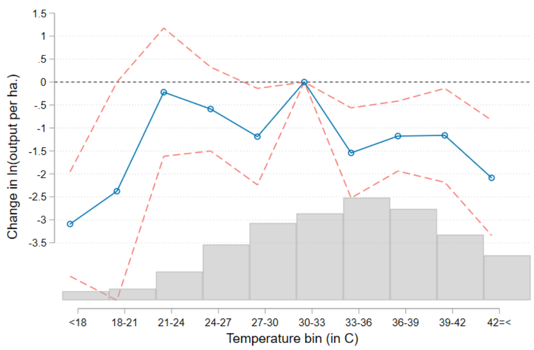
— , **Olivier Deschenes, Kyle Meng, and Junjie Zhang**, "Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants," *Journal of Environmental Economics and Management*, 2017, pp. 1–17.

ONLINE APPENDIX - NOT FOR PUBLICATION

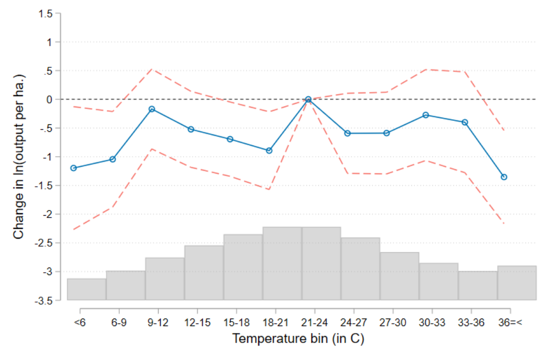
A Additional Figures

A.1 Optimal temperature thresholds by Region

Figure A.1: Non-linear relationship between temperature and agricultural yields by region



(a) Coast



(b) Highlands

B Additional tables

Table B.1: Effect of HDD on other farm inputs

	Fertilizers		Pesticides		Tractor	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Yes	Exp.	Yes	Exp.	Yes	Land(%)
Average DD	-0.004	-0.022	0.001	0.002	0.000	0.000
	(0.003)	(0.022)	(0.004)	(0.018)	(0.000)	(0.000)
Average HDD	0.003	0.003	0.006	0.029	-0.000	-0.000***
	(0.010)	(0.052)	(0.008)	(0.042)	(0.000)	(0.000)
N	53,493	53,492	53,493	53,492	53,493	53,454
R2	0.272	0.375	0.244	0.353	1.000	1.000

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01*. All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 3.

Table B.2: Effect of temperature on household income, consumption and poverty rates

	ln(income pc)			ln(consumption pc)			Poor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep var:	All	Coast	Highlands	All	Coast	Highlands	All	Coast	Highlands
Average DD	0.023***	0.008	0.024***	0.021***	0.012	0.021***	-0.013***	-0.008	-0.013***
	(0.004)	(0.013)	(0.004)	(0.004)	(0.014)	(0.004)	(0.003)	(0.012)	(0.003)
Average HDD	-0.019	-0.018	-0.009	-0.015	-0.017	0.000	0.004	0.009	-0.007
	(0.013)	(0.013)	(0.022)	(0.010)	(0.011)	(0.018)	(0.007)	(0.008)	(0.015)
N	53,493	7,412	46,081	53,493	7,412	46,081	53,493	7,412	46,081
R2	0.380	0.386	0.334	0.451	0.446	0.415	0.263	0.275	0.243

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01*. All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 2.

Table B.3: Effect of temperature on farm labor inputs, by type of farmer

	Household Labor			Hired Labor
	(1)	(2)	(3)	(4)
Dep var:	HH members in farm	HH hours in farm	Child labor	ln(wage bill)
Average HDD x Owns livestock	0.020*	0.031*	0.022*	-0.099
	(0.012)	(0.019)	(0.013)	(0.061)
Average HDD x No livestock	0.014	0.015	0.030**	-0.041
	(0.013)	(0.025)	(0.014)	(0.055)
N	26,668	26,670	14,335	53,492
R2	0.512	0.360	0.311	0.247

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 3.

Table B.4: Effect of temperature on off-farm work and migration, by type of farmer

	Off-farm work		Migration	
	(1)	(2)	(3)	(4)
Dep var:	HH member has off-farm job	Hours worked off-farm	HH member away 30+ days	Receives private transfers
Average HDD x Owns livestock	-0.008	-0.037	-0.001	0.011
	(0.015)	(0.056)	(0.004)	(0.010)
Average HDD x No livestock	0.009	0.033	0.003	0.010
	(0.012)	(0.052)	(0.005)	(0.013)
N	26,799	26,799	26,799	26,799
R2	0.258	0.302	0.102	0.162

Notes: Standard errors clustered at the district level (in parenthesis). Stars indicate statistical significance (assuming district-level clustering): **p <0.10, ** p <0.05, *** p <0.01.* All specifications include district, and climatic region-by-growing season fixed effects, and the same controls as baseline regression in Table 3.