Negative Rainfall Shocks Increase Levels of the Stress Hormone Cortisol Among Poor Farmers in Kenya*

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Abstract

Does poverty lead to stress? Despite several studies showing correlations between socioeconomic status and levels of the stress hormone cortisol, it remains unknown whether this relationship is causal. We used random weather shocks in Kenya to address this question. Our identification strategy exploits the fact that rainfall is an important input for farmers, but not for non-farmers such as urban artisans. We obtained salivary cortisol samples from poor rural farmers in Kianyaga district, Kenya, and informal metal workers in Nairobi, Kenya, together with GPS coordinates for household location and high-resolution infrared satellite imagery measuring rainfall. We show that, the absence of rain constitutes a random negative income shock for farmers, but not for non-farmers. We find that low levels of rain in the preceding year increase cortisol levels among farmers, but not non-farmers. Similarly, farmers but not non-farmers exhibit higher levels of self-reported stress when the preceding year had high compared to low levels of rain. In addition, the effect of rain on cortisol is larger in farmers who depend solely on agriculture for their income than among those who also have other sources of income. Together, these findings suggest a causal effect of negative shocks on stress levels.

JEL Codes: C93, D03, D87, O12

Keywords: weather shocks, rainfall, cortisol, stress, worries

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1 Introduction

Does poverty have psychological and potentially neurobiological consequences? In recent years, a small literature has emerged that asks this question. For instance, recent work in the psychology and economics of happiness has documented a robust relationship between income and happiness, both within and across countries: poor people are less happy and satisfied with their lives than rich people in the same country; in addition, people in richer countries are, on average, happier than people in poorer countries (Stevenson and Wolfers 2008). Conversely, the prevalence of depression is higher among the poor than among the wealthy: in a meta-analysis of 115 studies on the relationship between mental health and poverty in low- and middle-income countries, Lund et al. (2010) find a negative association between poverty indicators and good mental health outcomes in 79% of studies.[1] Whether this relationship also holds across countries remains unclear; Bromet et al. (2011) find no cross-country association between national income and scores on a standardized WHO instrument (CIDI), but their study uses a small sample of 18 countries.

This burgeoning literature suffers from two shortcomings. First, the direction of causality (if any) remains unclear: does poverty cause depression and unhappiness, or vice-versa? Second, if poverty causally affects these variables, what are the channels through which it does so? Regarding the second question, a number of authors have argued that low-income environments may be characterized by both greater exposure to stressful events, and the absence of resources to deal with such stress (Baum et al. 1999; Steptoe et al. 2002; Brunner 1997; Kristenson et al. 2004). Indeed, several studies find significant correlations between socio-economic status (SES), self-reported stress, and the stress hormone cortisol (Cohen et al. 2006a; 2006b; Evans and Kim 2007; Evans and English 2002; Li et al. 2007; Lupien et al. 2000; Arnetz et al. 1991; see Dowd et al. 2009 for a review). Stress is a significant factor in the etiology of depression: 80% of all patients with depression have histories of chronic stress or stressful life events (Hammen 2005), and depression is marked by dysregulation of the hypothalamic-pituitary-adrenal (HPA) axis, which controls the release of cortisol (Holsboer 2000). Together, these strands of literature suggest that poverty may be characterized by increased levels of stress, and in particular the stress hormone cortisol. However, these findings are correlational and therefore do not indicate whether poverty causes stress, or vice-versa.

The present paper aims to fill this gap by using rainfall shocks as an exogenous source of variation in the incomes of Kenyan farmers, and measuring their levels of perceived stress

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and cortisol after years with high vs. low levels of rainfall. To this end, we study two groups of people in Kenya: rural farmers in Kianyaga, an agricultural region 100 km north of Nairiobi, who mainly depend on farming for income; and self-employed workers in the informal metal industry in Nairobi. We first document that incomes are highly dependent on past annual rainfall among farmers, but not among non-farmers. We then show that annual levels of rainfall strongly affect levels of the stress hormone cortisol in farmers, but not non-farmers: among farmers, low levels of rainfall in the preceding year lead to higher levels of cortisol; this relationship does not hold in non-farmers, and the difference between the two groups is statistically significant. Furthermore, when focusing on responses to a standard psychological survey instrument for stress, Cohen's Perceived Stress Scale (Cohen et al. 1983), we find the same pattern of responses: lower annual rainfall increases self-reports of stress in farmers, but not non-farmers. These results are robust to different types of spatial clustering and the inclusion of control variables.

We then divide the sample of farmers into those for whom farming is the sole source of income, and those who also receive income from other activities. Again we find that low past annual rainfall leads to increased levels of cortisol, and this effect is significantly larger in respondents for whom farming is the sole source of income. Together, these findings suggest that weather-induced shocks to income among farmer households raises levels of perceived stress and of the stress hormone cortisol, thus establishing a causal link between increases in poverty and increases in stress levels.

In providing evidence for a causal effect of poverty on stress, our study complements two recent studies that measured the impacts of development programs on stress levels. Fernald & Gunnar (2009) measured cortisol levels in children who had been exposed to the Mexican Progresa program, the comprehensive conditional cash transfer program with a focus on health and education. The authors found that children who had been exposed to the program exhibited lower baseline cortisol levels than those children who had not been in the program. Note, however, that this study assesses only a treatment-on-the-treated (TOT) effect, and thus endogeneous determination of program participation remains a concern. In another study, Fernald et al. (2008) investigated responses to stress and depression questionnaires in a sample of South-African respondents after they were randomly assigned to receive a loan. Those who had received loans showed lower levels of depressive symptoms than the control group; interestingly, however, questionnaire-assessed stress levels were higher after receiving a loan than in the control group, possibly due to the stress induced by having to pay back the loan at a high interest rate (200% p.a.). Our study contributes by showing a significant causal effect of exogenous income shocks on stress and cortisol levels among adult rural farmers.

2 Methods

2.1 Sample

The study relies on two main subsamples. The main focus is a group of 280 households in (rural) Kianyaga district in Central Kenya who mainly depend on farming for income. Of these households, 203 solely depend on farming for their income; another 77 neighboring households also receive non-farm income in addition to farming income. These Kianyaga households were interviewed from January–December 2010.[2] Respondents were chosen randomly from a previous 2007 survey of 2940 households in the area. Because the 2010 survey did not collect information about agricultural income, we use the 2007 survey of 2940 households when studying the effect of rainfall on income.

The second subsample takes advantage of the baseline information for a separate evaluation study on micro insurance, and consists of 897 urban informal workers (93 women), all working in one industrial location called Kamukunji Jua Kali in Nairobi, which is reserved for the informal metal industry. Respondents were interviewed between March–December 2011.

2.2 Data

Questionnaire Data

Data were collected by trained enumerators in one-on-one field interviews at the respondents' homestead or workplace. Interviews were conducted in Kikuyu in the Kianyaga sample, and in Swahili in the Nairobi sample. The order of the interviews was randomized.[3]

We administered a standard socioeconomic questionnaire that elicited information about household structure, income, education, health, and self-reported levels of stress. The questionnaire was administered for separate micro-insurance projects run by the authors. The crucial questionnaire data for the purpose of this paper are a) respondents' income levels, b) respondents' self-reported levels of stress on Cohen's Perceived Stress Scale (PSS; Cohen et al. 1983).

[2]Each participant gave written consent; illiterate participants gave consent by fingerprint. The study was approved by the ethics commissions at the University of Zurich, McGill University, Innovations for Poverty Action Kenya (IPAK), and the Kenya Medical Research Institute (KEMRI). Participants received KES 200 (USD 1.20) for participation; in addition, they could earn money in the economic games that were part of the questionnaire. Respondents were paid after completing the interview.

[3]To ensure accurate translations of the questionnaire, it was translated into Kikuyu and Swahili by four different translators, and then back-translated into English by another four translators. The four back-translated versions were then compared to the English originals, and the team of 8 translators plus one supervisor agreed on a final translation. At the beginning of the interview, the consent script was read and consent was obtained by signature or thumbprint.

Incomes were recorded by asking respondents how much money they earned from each income-generating activity they were engaged in over the past year. For the Nairobi sample, this data was also available for the past week. Because the 2010 survey in Kianyaga did not record incomes, the analyses relating past rainfall to income are conducted on the 2007 data for the Kianyaga subsample.

To measure self-reported levels of stress, we used the 10-item version of the PSS, translated into Kikuyu for the Kianyaga sample, and into Swahili for the Nairobi sample. This instrument asks respondents if, in the past month, they felt (1) upset because of an unexpected event, (2) unable to control their life, (3) nervous and stressed, (4) confident to handle problems, (5) things were going their way, (6) unable to cope with things, (7) able to control irritations, (8) on top of things, (9) angered because things were outside their control, and (10) difficulties were piling up. Responses are recorded on a scale from 0 (never) to 4 (very often). Items 4, 5, 7, and 8 are reverse-coded during analysis, and a total stress score is formed by summing the responses to the individual items. High scores indicate higher levels of perceived stress.

Cortisol Levels

Cortisol is the body's major stress hormone, synthesized by the hypothalamic-pituitary adrenal (HPA) axis: in response to external stressors, the hypothalamus in the midbrain secretes corticotrophin-releasing hormone (CRH), which in turn controls the release of adreno-corticotropic hormone (ACTH) from the pituitary gland; ACTH then causes the release of cortisol from the adrenal gland.

Cortisol is released in response to both psychological and physiological strain on the organism. In the physical domain, it increases following bodily injuries, physical exertion, illness, and extreme temperatures. In the psychological domain, cortisol increases in response to social stressors such as having to give a speech in front of a panel of judges, performing mental arithmetic, or enduring physically unpleasant situations like immersion of one's hand in cold water (Kirschbaum et al. 1993; Ferracuti et al. 1994). Cortisol increases blood sugar to levels that prepare the organism to deal with stress. Moreover, cortisol exerts a direct and broadly suppressive effect on the immune system; in particular, it suppresses pro-inflammatory cytokines such as interleukin-6 and interleukin-1 (Straub 2006; Wilckens 1995). Chronic elevations of cortisol, however, appear to have the opposite effect, leading to permanent mild elevations of cytokine levels (Kiecolt-Glaser et al. 2003). These cytokine elevations then contribute directly to disease onset and progression, e.g. in atherosclerosis and cancer (Steptoe et al. 2001; 2002; Aggarwal et al. 2006; Coussens and Werb 2002; Ross 1999). Thus, while transient cortisol elevations are adaptive and protective, permanently high cortisol is physiologically damaging, quite apart from the psychological effects.

To measure cortisol levels, trained interviewers obtained salivary samples using Salivette sampling devices (Sarstedt, Nümbrecht, Germany) once before and once after questionnaire administration. Salivary samples were stored at room temperature for at most 10 days before being transported to Nairobi where they were stored at -20° C until further analysis.[4] An enzyme-linked immunosorbent assay (ELISA) was used to determine free cortisol levels. Free cortisol is the physiologically active component of cortisol, and is closely related to the rate of cortisol secretion by the adrenal gland (Kirschbaum and Hellhammer 1989; Aardal and Holm 1995; Aardal-Eriksson et al. 1998). During analysis, the two samples were averaged to obtain more stable estimates of cortisol levels.

GPS Information

The GPS coordinates of the households in Kianyaga were collected using a handheld GPS device and recorded in degrees of latitude and longitude, at a resolution of 1/1000th of an arcminute, which corresponds to 0.18 meters at this proximity to the equator. In Nairobi, all respondents were located within a 0.5×0.5 km area, and thus the same GPS location was used for all households in this location; the identification comes from temporal variation.

Rainfall Data

Rainfall data were obtained from the Famine Early Warning Systems Network, FEWSNET.[5] The data cover the years 2000-2011, and the temporal resolution is daily. The spatial resolution is 0.1°, which corresponds to 11 km at this proximity to the equator. To obtain household-specific rainfall data, we identified the four closest grid points in the rainfall data based on the GPS location of each household, and then used bilinear interpolation to compute a weighted rainfall average for that household relative to the date of the survey for that household. This yielded a rainfall estimate that was unique to each household, both in space and in time.

[4]The analysis was done at Lancet Pathologists, Nairobi. In a blinded test of this laboratory with duplicate samples, the correlation across sample pairs was r = 0.995 (N=60).

[5]www.fews.net. The data were originally downloaded in ArcGIS format, and then transferred into Stata format using a custom-written FORTRAN program. The data are provide a rainfall estimate based on high-resolution Meteosat infrared data, rain gauge reports from the global telecommunications system, and microwave satellite observations.

3 Agricultural Income and Sensitivity to Rain

3.1 Overview

Agricultural production in Kenya is heavily reliant on rainfall due to low irrigation (UoN and ICRISAT and KMD 2007; Kabubo-Mariara and Karanja 2007[6]). The amount and variability in rainfall have the highest influence on the outcome of any agricultural investment and management practices. To establish a causal link between poverty and stress, we first need to establish whether sampled farmers depend importantly on rainfall for their agricultural output and household income. For this, we rely on information on detailed farming outputs collected in the original survey of 2940 farmers conducted between May and August 2007 (but not collected in the 2010 follow-up survey), and rainfall data during the year preceding these interviews. As shown in Table 1, sampled farmers own on average 1.87 acres of land. With only 15% of the land irrigated, much of it is rainfed agriculture. Average monthly income per capita is 2630 KES, which translates into approximately 1.15 USD per capita per day.

Farmers in this community plant three types of crops: perennial, crops rainy season crops, and dry season crops, according to a precise timeline illustrated in Figure 1. The major cash crops are tea and coffee, while the major food crops are beans and maize.

3.2 Perennial Crops

The most important source of agricultural income for Kianyaga farmers is perennial crops such as coffee, tea, banana, sugar cane, passion fruit, mango, papaya, avocado, and macadamias: 99% of the Kianyaga sample is engaged in the production of such crops, which are harvested continually.[7] These plants require well-distributed rainfall throughout the year (Jaetzold and Schmidt 1983).[8] In the year prior to the survey, average rainfall across the

[6]In this latter paper, the authors follow a very similar methodology to ours to study the efect of rainfall on agricultural output. However, the sampling procedure was purposely designed to target at least four households from each agro-ecological zone. The authors then compare in a cross section income per acre of different farmers. The problem with such an analysis is that results may be driven by unobservables across agro-ecological zones. In contrast, in our paper, all farmers come from the same agro-ecological zone. Our results are thus unlikely to be driven by unobservables specific to agro-ecological zones.

[7]Except for coffee for the months of February to May, when farmers tend to plants. This involves weeding, applying fertilizers and spraying. In this period, a dry spell of 1.5 to 2.5 months is generally regarded as beneficial because it hardens the wood and gets the tree in a cycle of flowering and bearing (Wieringen 1988).

[8]Crop water requirements have been estimated by Jaetzold and Schmidt (1983). They use the water requirements curves of crops from the FAO (Doorenbos and Pruitt 1977; Doorenbos and Kassam 1979), and recalculated for the Kenyan varieties and agro-ecological zone.

sampled farmers was 775 mm, well below the water requirement of any perennial crops.[9] Lack of rainfall was therefore likely a major constraint for these crops.

3.3 Rainy Season Crops

Kianyaga, like much of Kenya, has two rain seasons: the long rains, approximately April to June, with some drizzling in June to mid-August, and the short rains from approximately October to December. The main rainy season food crops are beans and maize. Sampled farmers also plant sweet potatoes, tomatoes, green peppers, pili pili, onions, and pumpkins. Beans take three months to mature. On the other hand, maize takes five months to mature.[10] These crops are dependent on the amount of rainfall during the rainy seasons (Jaetzold and Schmidt 1983). Average rainfall in the last rainy season was 320 mm, well below the water requirement of all rainy season crops.[11] Lack of rainfall was therefore likely a major constraint for these crops. Farmers that were interviewed after July 2007 experienced a harvest of beans, sweet potatoes, tomatoes, green peppers, pili pili, onions, pumpkins following the long rains of 2007. To measure the impact of the 2007 long rains on these crops, we therefore restrict our sample to people interviewed after July 2007.

3.4 Dry Season Crops

Some crops cannot do well in very heavy rains. Crops like kales, French beans, cabbage and green pepper need a controlled amount of water[12] and since rain cannot be controlled, farmers end up not growing them during rainy seasons. Some farmers instead use irrigation because they can decide when and how to water them. Moreover, since irrigation is time consuming and access to water is limited, farmers use irrigation to grow commercial crops, such as export crop French beans, and not maize and beans that can be grown during normal rainy seasons. The most common irrigation method is fallow irrigation where a section of the river is diverted into a manmade stream that passes through the farm until crops are sufficiently watered. Because of this dependence on irrigation, we would expect dry season crops to be less affected by rainfall than rainy season or perennial crops.

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[9] From Jaetzold and Schmidt (1983): coffee: >1150 mm, tea: 1250-1800 mm, banana: 1000 mm, sugar cane: 1250-1800 mm, mango: 650-1500 mm, papaya: 1000-1500 mm, avocado: 1000-1500 mm, macademia: 750-1200 mm.

[10] Maize benefits from the drizzling from June to mid August as it is the flowering period and water is necessary.

[11] From Jaetzold and Schmidt (1983): maize: 600-900 mm (long growing period), beans: 250-450 mm (short to medium growing period), sweet potatoes: 500-900 mm, onions: 500-700 mm, tomatoes: 350-600 mm.

[12] From Jaetzold and Schmidt (1983): French beans: 350-680 mm, cabbages: 500 mm

3.5 Methodology: Rainfall and Income

While the 2010 interviews of the Kianyaga farmers did not include detailed agricultural output/income information, the 2007 survey – which interviewed 2940 households from which the 2010 sample was randomly selected – did include this detailed information. For this reason, we focus on the sample of 2940 small-scale farmers that were interviewed in 2007, and perform the following estimations:

$$\text{Income}_{it} = \beta_0 + \beta_1 R_{it-1} + \boldsymbol{\gamma}\mathbf{X}_i + \alpha_s + \theta_t + \varepsilon_{it} \tag{1}$$

where i indexes the household and t the time of interview. The dependent variable is monthly per capita income from perennial, rainy season, or dry season crops.[13] R_{it-1} is the household-specific total rainfall in the time period preceding time t. This time period is one year in the case of perennial crops, the preceding rainy season in the case of rainy-season crops, and the preceding dry season in the case of dry season crops.[14] $\mathbf{X}_i$ is a vector of controls and includes variables likely to affect agricultural production, i.e., household size, acres of land, fraction of land irrigated, land inputs (animal manure purchased, chemical fertilizer, seeds, pesticides, mechanical inputs (e.g. pump etc.), and other non-labor farm inputs (in KES per month), total days of work on plot (per month, by household head, spouse household head, children of household head, parents (and in-law) of household head, siblings (and in-law) of household head, other family of household head, non-family hired labor, and other), and a dichotomous variable equal to one when the household head is the owner of plot. α_s and θ_t are sublocation and month fixed effects, respectively. Standards errors are robust and clustered at the sublocation level.

To evaluate the impact of rainfall on income for Nairobi metal workers, we perform the following regression on the sample of nearly 900 Nairobi metal workers:

$$\text{Income}_{it} = \beta_0 + \beta_1 R_{it-1} + \boldsymbol{\gamma}\mathbf{X}_i + \theta_t + \varepsilon_{it} \tag{2}$$

The measure of income for individual i is either average weekly income over the past

[13] For each crop, we collect data on household production sold at market, the average price fetched at the market for this production, household production sold to broker, the average price fetched from the broker for this production, and household production for home consumption. As most farmers sell to brokers, we use the price fetched from the broker for this crop by this household to evaluate the monetary value of household production for home consumption. When this price is not available, we use the median price fetched from brokers by other farmers for this crop. Total income from a crop is then the sum of the monetary value of household production sold at market, sold to brokers, and for home consumption.

[14] To be precise, in the days 31 to 396 before time t. We exclude the last month since the minimum recall period for crop income is one month. Rain in the last month is thus unlikely to affect income from crops in that same month.

year, or weekly income in the past week. In addition to the annual measure of rainfall (same as above), we also explore recent rainfall as measured by rainfall in the past 10-20 days, the dekad preceding the weekly income measure. The vector $\mathbf{X}_i$ includes controls for female, age, years of education, and dummies whether the respondent is married with the spouse in Nairobi, or married with the spouse not in Nairobi.

Recall that each individual is observed only once. Although it is a priori not clear whether the cortisol level error terms ε_{it} and ε_{jt} of two different individuals i and j should be correlated – especially after conditioning on the fixed effects and the individual background and rain values –, we assume that ε_{it} and ε_{jt} may be correlated for different individuals in the same sublocation within the same month t but that ε_{it} and $\varepsilon_{jt\prime}$ for $t \neq t\prime$ are not correlated.

Because the number of sublocations in the Kianyaga sample is small, we estimate not only naïve standard errors, but additionally perform Cameron et al.'s (2008; 2010; 2011; hereafter, CGM) wild cluster boostrap correction to account for the small number of clusters. In addition, we further further relax the assumption of uncorrelated errors across sublocations by estimating the same regression assuming errors are correlated across people in different geographic clusters regardless of when the cortisol measure was taken, but that the correlation between any two individuals declines linearly as a function of the geographic distance between them following the approach of the approach of Conley (1999).

3.6 Results: Rainfall and Income

Among Kianyaga farmers, income from perennial crops was affected by past year rainfall. Columns (1) and (2) of Table 2 show that one extra mm of rain in the past year increased monthly per capita income from perennial crops by 18.7 KES, or 1.1% of average monthly income per capita from perennial crops (at 1572 KES).

Income from rainy season crops was weakly affected by rainfall during the rainy season. Columns (3) and (4) show that one extra mm of rain in the last rainy season increased income per capita from rainy season crops by 3.2 KES, or 0.9% of average monthly income per capita from rainy season crops (at 354 KES). Rain thus had an equivalent effect on perennial and rainy season crops. However, this effect was significant only at the 10% level, and insignificant when using wild clustered boostrap p-values or Conley standard errors.

Dry season crops were not affected by rain in the last dry season. Columns (5) and (6) of Table 2 shows that rain in the last dry season has no effect on income per capita from dry season crops. This is expected considering dry season crops rely on irrigation, not rain.

Among Nairobi metal workers, average weekly income over the past year was KES 5927, while average weekly income in the past week was KES 4407, which is equivalent to approximately KES 5700-7700 per (Nairobi) household member per month. Table 3 shows that annual rainfall and rainfall in the past 10-20 days had no impact on either weekly income over the past year or weekly income over the past one week.

4 Stress and Sensitivity to Rain

4.1 Methodology: Stress and Rainfall

The analysis of rain and income showed that past annual rainfall had a strong effect on income, while rainfall during the rainy season only weakly affected income, and rainfall during the dry season did not affect income. We therefore focus on past annual rainfall in the following analyses. We note first that, comparing cortisol levels among these 3 groups, average levels of cortisol are highest among Kianyaga households solely dependent on farm income: 39.6 $nmol/l$. Among their neighbors who also have access to non-farm income, average levels are lower: 24.9 $nmol/l$. Nairobi metal workers have the lowest average levels: 14.5 $nmol/l$. Median levels also differ, although not nearly as much: 14.0, 10.6, and 8.5 $nmol/l$ respectively, indicating that the differences in means are driven by outliers. Because cortisol levels are usually skewed in this fashion, it is customary to use the natural log of cortisol for analysis; we adopt this approach here. The first main question of this paper is whether past annual rainfall affects cortisol levels among farmers, but not among non-farmer, such that low levels of rainfall lead to high cortisol levels.

First, to assess the impact of annual rainfall on the Kianyaga sample relative to the Nairobi sample, we estimate the following equation:

$$\ln(cort)_{it} = \beta_0 + \beta_1 R_{it-1} \times K_i + \beta_2 R_{it-1} + \beta_3 K_i + \boldsymbol{\gamma}\mathbf{X}_{it} + \alpha_s + \theta_t + \varepsilon_{it} \tag{3}$$

where R_{it-1} is annual past rainfall for individual i, K_i is a dummy variable indicating whether individual i is a Kianyaga respondent (=1) or not, and $\mathbf{X}_{it}$ is a set of individual characteristics that affect cortisol levels. Salivary cortisol levels are subject to a number of confounds; in particular, eating, drinking coffee, tea, or alcohol, consuming miraa (khat), and engaging in strenuous physical activity can bias cortisol levels; we therefore control for these variables in each of the estimations. To this end, participants answered whether they engaged in any of these activities earlier on the day of the interview, and a dummy variable was created for each activity. Further, α_s captures sublocation fixed effects and θ_t captures month fixed effects.

Second, to assess whether among Kianyaga farmers, those whose income solely depends on rainfall show a greater effect of rainfall on cortisol levels, we estimate a modified version of equation (3):

$$\ln(cort)_{it} = \beta_0 + \beta_1 R_{it-1} \times F_i + \beta_2 R_{it-1} + \beta_3 F_i + \boldsymbol{\gamma}\mathbf{X}_{it} + \alpha_s + \theta_t + \varepsilon_{it} \tag{4}$$

This specification is identical to equation (3), except that the sample is restricted to Kianyaga respondents, and the dummy variable F_i indicates respondents who depend solely on farming for their income.

Third, we ask whether rainfall affected not only levels of cortisol, but also self-reported levels of stress on Cohen's Perceived Stress Scale (PSS). To this end, we estimate equations (3) and (4) using not the log of cortisol, but the composite score of the PSS as the outcome variable. Cortisol control variables are omitted in these regressions.

4.2 Results: Stress and Annual Rainfall

Table 4 reports results from estimating equation (3) with cortisol as the outcome variable; columns (1) and (2) report naïve and CGM p-values, while columns (3) and (4) report Conley standard errors with spatial cutoffs of 0.1 and 1 degree, respectively. In columns (2) and (4), farmer control variables are included. In all specifications, the coefficient of interest is that on the interaction term between being a Kianyaga respondent (and thus dependent on rain for income) and past annual rainfall. This coefficient is significantly negative in all models, indicating that decreases in past annual rainfall lead to increases in cortisol levels among Kianyaga respondents, but not Nairobi respondents. The magnitude of the effect is on the order of -0.9% for an extra mm of annual rainfall. Concretely, this means that as a result of differences in annual rainfall between the 25th percentile (561 mm) and the 75th percentile (578 mm) of Kianyaga farmers, the former have 15.3% higher levels of cortisol.

We next ask whether the relationship between rainfall and cortisol is stronger among those farmers in Kianyaga who depend solely on agriculture for their income. To this end, we estimate equation (4) with cortisol as the outcome variable; in this model, the sample is restricted to Kianyaga respondents, and the indicator variable F identifies respondents whose only income comes from farming. The coefficient of interest is the interaction between rainfall in the past year and the indicator variable for depending solely on agriculture for income. The results are reported in Table 5. Again this coefficient is significantly negative in all specifications, i.e. both in terms of naïve and CGM p-values as well as Conley standard errors, and whether or not farmer controls are included. The magnitude of the coefficient suggests that an extra mm of rainfall is associated with a 0.7% decrease in cortisol levels. Thus, levels of past annual rainfall affect cortisol levels more for Kianyaga respondents than Nairobi respondents, and more for those respondents in Kianyaga whose only income comes from farming.

To see if the relation between cortisol and rain for farmers is also reflected in the same way in qualitative psychometric responses of well-being, Table 6 next repeats the same estimation as in Table 4, replacing the (log of) cortisol levels with responses to psychological measures capturing 10 different dimensions of feelings of stress over the past month as captured by the PSS10 questionnaire. Thus, this analysis tests whether rainfall affects self-reported stress more among Kinayaga than Nairobi respondents. The interaction of interest is again significantly negative in all specifications, indicating that lower levels of rainfall lead to higher levels of self-reported stress among Kianyaga respondents, and this effect is larger than in Nairobi respondents. Note, however, that the CGM-adjusted p-values do not reach significance in this analysis, while the coefficients are significant when naïve and Conley standard errors are used.

Finally, Table 7 reports results from the same estimation as in Table 5, replacing cortisol levels with PSS scores, but now comparing Kianyaga respondents who depend solely on farming for their income to other Kianyaga respondents who also have income from other sources. In these regressions, the interaction between past annual rainfall and having farming as the only source of income is not significant; instead, there is a highly significant negative coefficient on the main effect of past annual rainfall on PSS responses. This result suggests that lower levels of annual rainfall increase levels of self-reported stress among Kianyaga respondents irrespective of whether they depend entirely or partly on agriculture for their income. This result contrasts with the finding that cortisol levels are affected by past annual rainfall in the Kianyaga sample only for respondents whose only source of income is agriculture; thus, this discrepancy suggests that spillovers from respondents whose sole income source is farming to those who also have other sources of income may be larger for self-reported stress than for cortisol.

A potential concern with our finding that annual rainfall impact stress among rural households strictly dependent on farming is that annual rainfall impacts work intensity on the farm, which in turn may impact cortisol levels; respondents who experienced a lack of rain may have to perform more strenuous physical activity to make up for the adverse climatic conditions, and our cortisol results could reflect this physical strain as opposed to psychological stress. However, we deem this account unlikely for three reasons. First, the estimations control for whether the respondent performed strenuous physical activity prior to the interview. When we leave this variable out of the estimations, the findings remain the same. Second, the effect would be predicted to go in the opposite direction: farmers in this region need to work harder when it rains compared to when it does not rain, thus increasing work related stress levels. And, third, the self-reported psychological stress findings are consistent the cortisol findings. If the effects of rain were purely related to work intensity, one would not expect to the link with mental stress measures.

4.3 Magnitude

Columns (1) and (2) of Table 2 showed that one extra mm of rain in the past year increased monthly per capita income from perennial crops by 18.7 Ksh, while one extra mm of rain raises cortisol levels by 0.9% among Kianyaga farmers. At the mean value of 35.6 nmol/l of cortisol among this group, this increase corresponds to an increase of 0.32 $nmol/l$ per mm of rain.

Under the assumption that the full measured effect of annual rainfall on stress is through its effect on agricultural income, we can use the relation between annual rainfall and agricultural income and the relation between annual rainfall and stress to estimate the relation between agricultural income and stress: a monthly per capita increase in income by 18.7 Ksh translates into a decrease in cortisol of 0.32 $nmol/l$. Taken at face value, this result suggests that if a monthly transfer of Ksh 1500 (USD 18) were given to a Kianyaga respondent, her cortisol levels would fall from an elevated average of 35.6 $nmol/l$ to a normal range of below 10 $nmol/l$. Of course it is questionable whether this result could actually be obtained in practice, but the example serves to illustrate that the effect is economically meaningful.

5 Conclusion

In this paper we asked whether changes in income levels among the poor lead to increases in levels of the stress hormone cortisol and levels of self-reported stress. The study relies on three subsamples: a group of 203 households in (rural) Kianyaga district in Central Kenya who solely depend on farming for income, (2) 77 neighboring households from the same area who in addition to receiving farm income also receive non-farm income, and (3) 897 urban informal workers all working in one industrial location called Kamukunji Jua Kali in Nairobi. For each of these households we combine measures of the hormone cortisol measures with high-resolution satellite rainfall data using household-level GPS data.

We first find that that only agricultural incomes in our sample are impacted by rain, and only annual past rain, not recent rainfall. Next, we find that one extra mm of rain raises cortisol levels by 0.9% among Kianyaga farmers, suggesting that the measured impact of annual rainfall on stress is caused by its impact on income. We further find that this effect is significantly larger for Kianyaga respondents who depend solely on agriculture for their income compared to those who also have other sources of income. In addition, we find that the pattern of annual rainfall dependent responses to self-reported measures of stress by Kianyaga respondents is consistent with the cortisol hormone response.

These results contribute to the emerging literature on the relationship between stress and income/socioeconomic status by showing that this relationship is causal. A growing number of studies have documented that poor and otherwise disadvantaged people show increased levels of cortisol (Cohen et al. 2006a; 2006b; Evans and Kim 2007; Evans and English 2002; Li et al. 2007; Lupien et al. 2000; Arnetz et al. 1991; Dowd et al. 2009); however, to date this relationship has been identified through correlation, leaving it unclear in which direction causality runs. One could easily imagine it going in both directions: the idea that poverty can cause stress is uncontroversial; conversely, however, it is also possible that stressed individuals are more likely to end up in poverty, e.g. through impaired job performance due to stress. The contribution of this study is to provide causal evidence for the first channel, i.e. the effect of poverty – as measured by exogenous income shocks among a poor population – on levels of the stress hormone cortisol and self-reported stress.

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Figure 1: Timeline of crops

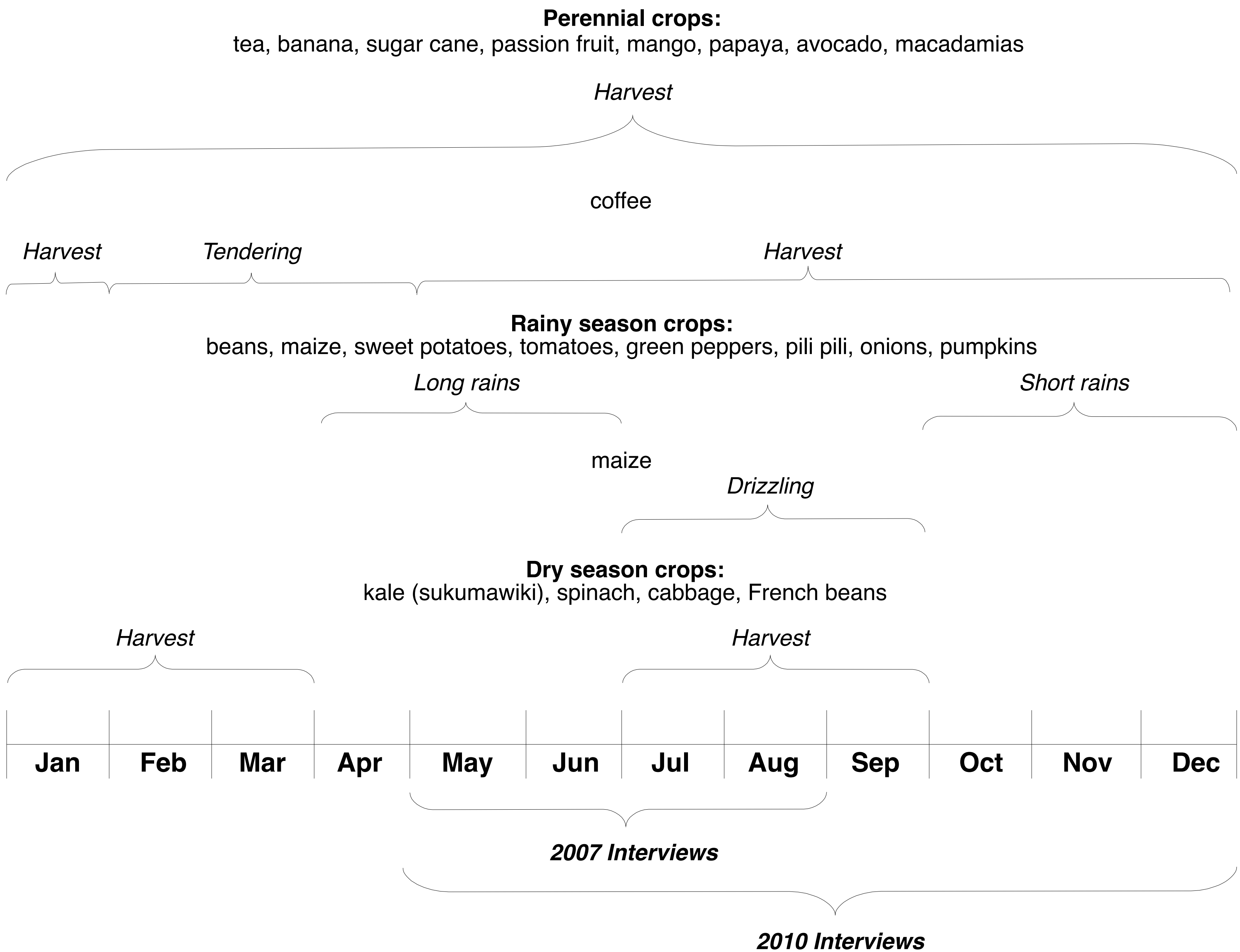

Table 1: Summary statistics

	(1) Kianyaga 2007		(2) Kianyaga 2010		(3) Nairobi	
	Mean	SD	Mean	SD	Mean	SD
Household size	3.63	(1.54)				
Acres of land	1.87	(2.00)				
Fraction of land irrigated	0.15	(0.34)				
Land inputs (Ksh per month)	1201.55	(2136.44)				
Total days of work on plot (per month)	34.86	(39.07)				
Household head owner of plot (1=Yes, 0=No)	0.82	(0.38)				
Per capita income	2630.48	(15206.16)				
Perennial crop earner (1=Yes, 0=No)	0.99	(0.11)				
Per capita income from perennial crops	1571.55	(13839.46)				
Rainy season crop earner (1=Yes, 0=No)	0.93	(0.26)				
Per capita income from rainy season crops	354.28	(1316.63)				
Dry season crop earner (1=Yes, 0=No)	0.49	(0.50)				
Per capita income from dry season crops	637.21	(2735.11)				
Past annual rainfall (mm)	774.48	(37.20)				
beans	320.24	(135.23)				
kale	75.62	(6.83)				
Female			0.40	(0.49)	0.10	(0.30)
Past annual rainfall (mm)			566.66	(32.21)	500.89	(34.95)
Cortisol			35.58	(58.31)	14.46	(26.04)
Cortisol (farm is only income)			39.63	(64.00)		
Cortisol (farm is not only income)			24.91	(37.90)		
Farm is only income			0.72	(0.45)		
Years of education					10.73	(2.66)
Years in Nairobi					14.67	(9.92)
Per capita income (monthly)					5938.89	(7527.10)

Notes: Descriptive statistics. Column (1) reports the means and standard deviations of household characteristics, agricultural income, and rainfall in the Kianayga survey of 2007. Column (2) reports past annual rainfall and cortisol levels for respondents in Kianyaga from the survey of 2010, separately for respondents for whom farming is the sole source of income and those who also have an alternative source of income. Column (3) reports levels of income, past annual rainfall, and cortisol in the Nairobi sample.

Table 2: Effect of past rainfall on income, Kianyaga sample

	Perennial crops		Rainy season crops		Dry season crops	
	(1)	(2)	(3)	(4)	(5)	(6)
Past annual rainfall (mm)	18.65**	18.65***				
	(5.027)	(5.985)				
Rainfall in past rainy season (mm)			3.187*	3.187		
			(1.482)	(6.356)		
Rainfall in past dry season (mm)					0.412	0.412
					(27.56)	(20.34)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sublocation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2940	2940	1388	1388	1457	1457
Cluster level	Sublocation	Conley	Sublocation	Conley	Sublocation	Conley
No. clusters / Conley cutoff	6	.1 deg	6	.1 deg	6	.1 deg
Wild cluster bootstrap p-value	0.149		0.694		0.994	

Notes: OLS estimates of effect of rainfall on income in Kianyaga. Robust standard errors in parentheses, clustered at the level of sublocation. * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable is per capita income from perennial crops (coffee, tea, banana (Kampala, Sweet, Train, Israel, Kiganda, Kikuyu, Kisagara, Nyoro, Muraru), sugar cane, passion fruit, mango, papaya, avocado, macadamias). The main explanatory variable of interest is the household-specific total rainfall in the past year in columns (1) and (2), rainfall in the past rainy season in columns (3) and (4), and rainfall in the preceding dry season in columns (5) and (6). The control variables are household size, acres of land, fraction of land irrigated, land inputs (KES), days of work on plot, household head owner of plot (1=Yes). Month fixed effects and sublocation fixed effects are always included. The sample is restricted to perennial crop earners in columns (1) and (2), rainy season crop earners interviewed after July 2007 in columns (3) and (4), and dry season crop earners in columns (5) and (6). Because the specifications in columns (1) and (2) have a small number of clusters, we computed wild bootstrap clustered p-values following Cameron et al. (2008), using 1000 iterations for each p-value. These p-values are shown in the last row of the table for these specifications. In columns (3)-(4), we instead compute Conley spatial standard errors to account for spatial correlation in the data; column (3) uses a cutoff of .1 deg, which at this distance from the equator corresponds to 11 km; column (4) uses 1 degrees or 110 km.

Table 3: Effect of past rainfall on income, Nairobi sample

	Income last year		Income last week	
	(1)	(2)	(3)	(4)
Past annual rainfall (mm)	−74.37 (95.62)		0.600 (18.10)	
Past dekad rainfall (mm)		−44.68 (45.35)		−7.103 (15.94)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	864	864	879	879

Notes: OLS estimates of effect of rainfall on income in Nairobi. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. In columns (1) and (2), the dependent variable is per capita income in the past year. In columns (3) and (4), the dependent variable is per capita income in the past week. Since the Nairobi sample is composed of metal workers, this income stems mainly form producing and selling metal produts. The explanatory variables of interest are total rainfall in the past year (columns (1) and (3)) and rainfall in the preceding 10-20 days (columns (2) and (4)). The control variables are gender, age, years of education, years spent living in Nairobi, an indicator variable for marrier respondents whose spouse lives in Naiorbi, and an indicator variable for married respondents whose spouse does not live in Nairobi. Month fixed effects are always included.

Table 4: Effect of past annual rainfall on cortisol levels: Kianyaga & Nairobi samples

	Naive & CGM p-values		Conley p-values	
	(1)	(2)	(3)	(4)
Past annual rainfall x Kianyaga	-0.008^{**}	-0.009^{**}	-0.009^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.003)	(0.001)
Past annual rainfall (mm)	0.002	0.002	0.002^{**}	0.002^{**}
	(0.002)	(0.002)	(0.001)	(0.001)
Cortisol controls	No	Yes	Yes	Yes
Farmer controls	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sublocation FE	Yes	Yes	Yes	Yes
Observations	1176	1172	1172	1172
Cluster level	Sublocation	Sublocation	Conley	Conley
No. of clusters or Conley cutoff	6	6	.1 deg	1 deg
Wild cluster bootstrap p-value	0.055	0.072		

Notes: OLS estimates of effect of rainfall on cortisol levels in Kianyaga and Nairobi. * significant at 10%; ** significant at 5%; *** significant at 1%. In all columns, the dependent variable is the natural log of cortisol levels (in nmol/l), taken at a random time of day. Cortisol controls include dummies for recent eating, smoking, drinking coffee or tea, performing intense physical activity, taking medication, chewing miraa earlier on the same day, and time since waking. Farmer control variables are: household size, acres of land, fraction of land irrigated, land inputs (KES), days of work on plot, household head owner of plot (1=Yes). Month fixed effects and sublocation fixed effects are always included. In columns (1) and (2), standard errors are heteroskedasticity-robust and clustered at the sublocation level; the Nairobi sample is considered a single sublocation. Because the specifications in columns (1) and (2) have a small number of clusters, we computed wild bootstrap clustered p-values following Cameron et al. (2008), using 1000 iterations for each p-value. These p-values are shown in the last row of the table for these specifications. In columns (3)-(4), we instead compute Conley spatial standard errors to account for spatial correlation in the data; column (3) uses a cutoff of .1 deg, which at this distance from the equator corresponds to 11 km; column (4) uses 1 degree or 110 km.

Table 5: Effect of past annual rainfall on cortisol levels: Kianyaga sample only

	Naive & CGM p-values		Conley p-values	
	(1)	(2)	(3)	(4)
Past annual rainfall x Farm is only income	-0.006^{***}	-0.007^{***}	-0.007^{***}	-0.007^{***}
	(0.001)	(0.001)	(0.001)	(0.000)
Past annual rainfall (mm)	-0.003	-0.003	-0.003	-0.003^{***}
	(0.003)	(0.003)	(0.003)	(0.001)
Farm is only income	3.836^{***}	4.308^{***}	4.308^{***}	4.308^{***}
	(0.394)	(0.456)	(0.747)	(0.254)
Cortisol controls	Yes	Yes	Yes	Yes
Farmer controls	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sublocation FE	Yes	Yes	Yes	Yes
Observations	280	280	280	280
Cluster level	Sublocation	Sublocation	Conley	Conley
No. of clusters or Conley cutoff	5	5	.1 deg	1 deg
Wild cluster bootstrap p-value	0.052	0.080		

Notes: OLS estimates of effect of rainfall on cortisol levels among farmers and non-farmers in Kianyaga. * significant at 10%; ** significant at 5%; *** significant at 1%. In all columns, the dependent variable is the natural log of cortisol levels (in nmol/l), taken at a random time of day. Cortisol controls include dummies for recent eating, smoking, drinking coffee or tea, performing intense physical activity, taking medication, chewing miraa earlier on the same day, and time since awakening. Farmer control variables are: household size, acres of land, fraction of land irrigated, land inputs (KES), days of work on plot, household head owner of plot (1=Yes). "Farm is only income" is a dichotomous variable equal to 1 if the household's income only comes from farming, and 0 if some other income is earned from business, formal sector work, casual work not related to agriculture. Month fixed effects and sublocation fixed effects are always included. In columns (1) and (2), standard errors are heteroskedasticity-robust and clustered at the sublocation level. Because these specifications have a small number of clusters, we computed wild bootstrap clustered p-values following Cameron et al. (2008), using 1000 iterations for each p-value. These p-values are shown in the last row of the table for these specifications. In columns (3)-(4), we instead compute Conley spatial standard errors to account for spatial correlation in the data; column (3) uses a cutoff of .1 deg, which at this distance from the equator corresponds to 11 km; column (4) uses 1 degree or 110 km.

Table 6: Effect of past annual rainfall on stress levels: Kianyaga & Nairobi samples

	Naive & CGM p-values		Conley p-values	
	(1)	(2)	(3)	(4)
Past annual rainfall x Kianyaga	-0.058^{***}	-0.055^{***}	-0.055^{***}	-0.055^{***}
	(0.013)	(0.012)	(0.012)	(0.004)
Past annual rainfall (mm)	-0.005	-0.005	-0.005	-0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Farmer controls	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sublocation FE	Yes	Yes	Yes	Yes
Observations	1203	1203	1203	1203
Cluster level	Sublocation	Sublocation	Conley	Conley
No. of clusters or Conley cutoff	6	6	.1 deg	1 deg
Wild cluster bootstrap p-value	0.183	0.202		

Notes: OLS estimates of effect of rainfall on stress levels in Kianyaga and Nairobi. * significant at 10%; ** significant at 5%; *** significant at 1%. In all columns, the dependent variable is the total score on Cohen's Perceived Stress Scale (PSS), where higher values indicate greater levels of perceived stress. Farmer control variables are: household size, acres of land, fraction of land irrigated, land inputs (KES), days of work on plot, household head owner of plot (1=Yes). Month fixed effects and sublocation fixed effects are always included. In columns (1) and (2), standard errors are heteroskedasticity-robust and clustered at the sublocation level; the Nairobi sample is considered a single sublocation. Because the specifications in columns (1) and (2) have a small number of clusters, we computed wild bootstrap clustered p-values following Cameron et al. (2008), using 1000 iterations for each p-value. These p-values are shown in the last row of the table for these specifications. In columns (3)-(4), we instead compute Conley spatial standard errors to account for spatial correlation in the data; column (3) uses a cutoff of .1 deg, which at this distance from the equator corresponds to 11 km; column (4) uses 1 degree or 110 km.

Table 7: Effect of past annual rainfall on stress levels: Kianyaga sample only

	Naive & CGM p-values		Conley p-values	
	(1)	(2)	(3)	(4)
Past annual rainfall x Farm is only income	0.004	−0.000	−0.000	−0.000
	(0.008)	(0.006)	(0.004)	(0.001)
Past annual rainfall (mm)	−0.067**	−0.063**	−0.063***	−0.063***
	(0.019)	(0.020)	(0.019)	(0.006)
Farm is only income	−1.455	1.374	1.374	1.374**
	(4.592)	(3.228)	(2.082)	(0.683)
Farmer controls	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sublocation FE	Yes	Yes	Yes	Yes
Observations	304	304	304	304
Cluster level	Sublocation	Sublocation	Conley	Conley
No. of clusters or Conley cutoff	5	5	.1 deg	1 deg
Wild cluster bootstrap p-value	0.696	0.963		

Notes: OLS estimates of effect of rainfall on cortisol levels among farmers and non-farmers in Kianyaga. * significant at 10%; ** significant at 5%; *** significant at 1%. In all columns, the dependent variable is the total score on Cohen's Perceived Stress Scale (PSS), where higher values indicate greater levels of perceived stress. Farmer control variables are: household size, acres of land, fraction of land irrigated, land inputs (KES), days of work on plot, household head owner of plot (1=Yes). "Farm is only income" is a dichotomous variable equal to 1 if the household's income only comes from farming, and 0 if some other income is earned from business, formal sector work, casual work not related to agriculture. Month fixed effects and sublocation fixed effects are always included. In columns (1) and (2), standard errors are heteroskedasticity-robust and clustered at the sublocation level. Because these specifications have a small number of clusters, we computed wild bootstrap clustered p-values following Cameron et al. (2008), using 1000 iterations for each p-value. These p-values are shown in the last row of the table for these specifications. In columns (3)-(4), we instead compute Conley spatial standard errors to account for spatial correlation in the data; column (3) uses a cutoff of .1 deg, which at this distance from the equator corresponds to 11 km; column (4) uses 1 degrees or 110 km.