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Do Shocks and Environmental Factors Shape Personality Traits? Evidence from the Ultra-Poor in Uganda

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ABSTRACT *Personality characteristics and non-cognitive skills are key determinants of decision-making and economic outcomes. While personality is commonly believed to be stable after age 30, evidence suggests that significant changes in occupational or social roles, or exposure to family or health shocks, can have effects on personality traits. In this paper, we study the short-term effects of two kinds of shocks on measured personality traits among young adults from ultra-poor households in Uganda. In particular, we examine the short-term impacts of (i) a randomized anti-poverty program and (ii) environmental changes—exposure to drought, high temperatures, and wind—on personality traits. We find significant differences in measured personality traits across these factors, in particular among food insecure individuals. These results suggest that economic shocks and environmental factors may have an effect on the non-cognitive skills among young ultra-poor adults. On the other hand, our results also suggest that caution is warranted when using these tools used to measure personality traits in such rural, low-income settings.*

KEYWORDS: Personality; non-cognitive skills; ultra-poor; drought; climate; Uganda

JEL CLASSIFICATION CODES: D01; D10; J24; O15; Q54

1. Introduction

A growing literature explores how cognitive and non-cognitive abilities shape economic outcomes. Non-cognitive abilities, such as personality traits are shown to be important determinants of outcomes that include schooling, earnings, and participation in crime (Borghans, Duckworth, Heckman, & Ter Weel, 2008; Heckman, Stixrud, & Urzua, 2006; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). Moreover, there is increasing evidence that psychological factors, such as poor mental health, diminished intellectual and emotional abilities, including cognitive and executive function, self-control, and hope are highly correlated with poverty and may create internal constraints on capabilities (Alloush, 2022; Kaur, Kremer, & Mullainathan, 2015; Lybbert & Wydick, 2017; Mani, Mullainathan, Shafir, & Zhao, 2013).

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At the same time, evidence suggests that personality traits can be shaped by economic outcomes. Poverty during early life affects adult personality traits, often generating negative consequences later in life (Akee, Copeland, Costello, & Simeonova, 2018; Almond & Currie, 2011). Still, the literature is inconclusive about the mechanisms and time frames by which economic conditions affect these traits. Specifically, little is known about the short-term stability of personality traits and the effect of different shocks on these non-cognitive skills, especially among poor and hard-to-reach populations. Causal identification of such effects encounters econometric challenges, despite intuition and evidence that these skills and economic outcomes interact in a myriad of important ways. Moreover, Laajaj et al. (2019) show that stability in the measurement of personality traits depends on a few factors, such as administration method, interviewee incentives, and acquiescence bias. Overcoming these challenges to better understand the causal relationship between economic conditions and personality traits could have important implications for well-being, for promoting pro-social behavior, and more generally for the design of the optimal poverty-alleviation policy.

Our paper contributes to the literature by providing experimental and quasi-experimental evidence on how measured non-cognitive skills vary in a sample of individuals from ultra-poor households in Uganda.[1] We look at the short-term effects of two types of shocks on the observed personality traits of extremely poor individuals in rural, agricultural areas of Uganda. The first shock is random assignment into an intensive poverty graduation program designed and implemented by BRAC Uganda.[2] The second plausibly exogenous shock is recent experience with drought conditions and other factors, such as high temperatures and wind speed. By conducting a personality survey based on the Big Five construct (John & Srivastava, 1999; McCrae & Costa, 1997) and matching with the baseline survey of the graduation program and data from the African Flood and Drought Monitoring System (PrincetonClimateAnalytics, 2018), we are able to estimate the short-term differences in measured personality traits across shocks and environmental factors providing novel evidence on non-cognitive skills among a sample of rural ultra-poor young adults.

Our estimates show that within two to four weeks after the asset transfer and training, individuals exposed to the program had a statistically significant shift in personality measures related to socialization and stability, that is, Agreeableness and Conscientiousness. However, the experience of droughts of different lengths appears to undo much of these effects. We do not find statistically significant effects on the combined measure of personality traits that measure personal growth and plasticity. We also find that temperature and wind speeds on interview days have statistically significant predictive value on some measures of personality traits. Lastly, we find that these estimated effects are larger for food-insecure individuals.

These findings suggest that personality traits (or at least their measures) in our ultra-poor setting are notably malleable over time horizons shorter than previously seen in the literature. Several implications follow: first, whether personality traits fluctuate in this way has critical implications for program design and implementation; our findings suggest that a carefully designed welfare program may improve socialization and emotional stability. Thus, welfare programs designed to reinforce and develop personality traits and non-cognitive skills could prove a fruitful approach, especially among extremely vulnerable individuals. At the same time, because such programs typically work with such vulnerable populations who frequently experience negative shocks, for example, poor farmers in drought-prone areas, these negative shocks can, when occurring close enough in time to the intervention, undermine other valuable improvements of non-cognitive skills induced by the program. This warrants attention by program managers so key gains are not undermined, when possible, by external events.

Second, our results raise an important methodological consideration in psychological measurement, in particular in developing country settings, supporting some of the conclusions of Laajaj et al. (2019). Measurement of personality traits, and perhaps other non-cognitive traits or certain attitudes, might be more sensitive to environmental, social, and idiosyncratic contexts than was previously appreciated. Especially in non-WEIRD (Western, Educated, Industrialized, Rich, and

Democratic) settings,[3] these tools should be used with caution and awareness about their potential lack of validity and stability.

2. Non-cognitive skills: personality traits

In this section, we provide a brief summary of personality traits and their use in the relevant economic literature. In Section 2.1, we present the main personality trait measurement tools, and in Section 2.2 we discuss determinants of personality, while in Section 2.3, we highlight the economic importance of personality. In Section 2.4, we highlight studies that focus on how climate, weather, and personality traits interact.

2.1. *Trait measurement*

Wei et al. (2017) describe personality as 'the interactive aggregate of personal characteristics that influence an individual's response to the environment'. The most widely used personality measurement tool stemming from psychology is the Big Five personality inventory (John & Srivastava, 1999; McCrae & Costa, 1997). Through factor analysis of hundreds of personality traits, this Big Five inventory divides traits into five broad dimensions: Openness to experience (related to creativity and curiosity), Conscientiousness (organization/efficiency), Extroversion (outgoing/risk-taking), Agreeableness (friendly/compassionate), and Neuroticism (related to emotional stability).[4] A voluminous literature spanning nearly three decades studies features of the model itself as well as uses it to study personality.

One branch of this literature explores the extent to which the Big Five personality factors can be further grouped into two higher-order factors: Alpha and Beta factors (DeYoung, 2006; Digman, 1997). Alpha includes Agreeableness, Conscientiousness, and Emotional Stability (the obverse of Neuroticism), and represents stability and socialization. These constructs are related to characteristics that help in social interactions and increase emotional stability. Digman (1997) suggests that Alpha traits are correlated with impulse restraint, increased conscientiousness, reduction of hostility, aggression, and neurotic defense. The Beta factor includes Openness representing risk aversion and Extroversion representing plasticity and personal growth (Digman, 1997).

Given that most research on personality uses populations in richer countries, which are commonly literate and predominantly urban (commonly referred to as WEIRD settings, an acronym standing for White Educated Industrialized Rich Democratic), an additional issue that arises with personality research relates to the validity of these models among individuals who are poor, rural, and have low levels of education. Existing research on samples of mostly illiterate and poor individuals suggests that their personality traits are similar in distribution to those of more urban and educated populations (Gurven, Von Rueden, Massenkoff, Kaplan, & Lero Vie, 2013). Further, there is wide support for the universality of the Big Five traits across cultures (Benet-Martinez & John, 1998; McCrae & Terracciano, 2005; Piedmont, Bain, McCrae, & Costa, 2002). However, there is also some concern over the stability of measurement tools in non-WEIRD contexts: for example, Laajaj et al. (2019) find that the stability of measured traits among non-WEIRD populations depends on factors, such as administration methodology, acquiescence biases, and the quality of language translation. In this paper, we find evidence that suggests the validity of the Big Five structure in this population; however, we also find that daily fluctuations in temperatures and wind affect the measured outcomes, which lends some support to the conclusions of Laajaj et al. (2019).

2.2. *Personality development*

An individual's personality is the result of numerous, diverse factors, including evolutionary instincts, genetics, biological processes, environmental factors, and socioeconomic life events

(Briley & Tucker-Drob, 2014; Costa, McCrae, & Löckenhoff, 2019; Riccelli, Toschi, Nigro, Terracciano, & Passamonti, 2017; Roberts & Nickel, 2017). Studies show that the stability of personality traits increases with age, peaking near age 50, and then begins to decline again (Roberts & DelVecchio, 2000; Specht, Egloff, & Schmukle, 2011). These broad trends are explained through personality maturation theory, that is, the idea that individuals tend to become more agreeable, more conscientious, and less neurotic from early to middle adulthood (Bleidorn et al., 2013; Costa et al., 2019).

The literature that examines the effects of socioeconomic events, such as occupational role transitions, health or family shocks, and change in economic status is limited. Studies find that reporting a large number of adverse health shocks and other stressful life events is associated with small decreases in emotional stability and conscientiousness (Cobb-Clark & Schurer, 2012; Riese et al., 2014). Major shifts in social and occupational roles (such as getting a job for the first time or becoming a parent) are also shown to have significant and lasting effects on personality traits (Clausen & Gilens, 1990; Gottschalk, 2005; Roberts & Chapman, 2000; Roberts, Helson, & Klohnen, 2002). An empirical weakness of many of these observational studies is that reverse causality is difficult to rule out: it is unclear whether observed changes in personality contributed to the change in employment or social status or vice versa. One exception, however, is Gottschalk (2005), which provides quasi-experimental evidence that identifies a causal effect of employment changes on personality traits.

There is an increasing focus on measuring non-cognitive skills in less-developed countries and among poorer populations. Specifically, several studies view personality traits as important outcomes that are possibly affected by behavioral interventions (Blattman, Jamison, & Sheridan, 2017; Campos et al., 2017). By relying on experimental and quasi-experimental variation in economic shocks and estimating the short-run impacts on measured personality traits, our study contributes to this literature on the stability and measurement of personality traits.

2.3. *Traits and outcomes*

Personality traits are shown to be strong predictors of economic outcomes. Prior research finds strong associations between non-cognitive skills and economic behavior and outcomes (Heckman et al., 2006; Lee & Ohtake, 2012; Silles, 2010; Störmer & Fahr, 2013). For example, conscientiousness is conceptually related to risk aversion, preference for leisure, and discounting over time, while a range of studies in the psychology literature shows that self-control, perseverance, and other aspects of conscientiousness are major predictors of academic and professional success (Chamorro-Premuzic & Furnham, 2003; Dilchert, Ones, Davis, & Rostow, 2007; Duckworth & Seligman, 2005; Noftle & Robins, 2007; Paunonen & Ashton, 2001). Emotional stability predicts earnings and job performance (Nyhus & Pons, 2005; Salgado, 1997); where, for example, Störmer and Fahr (2013) find this specific personality trait to be highly predictive of work attendance. Childhood agreeableness, conscientiousness, and openness to experience are shown to influence adult health status indirectly through educational attainment, healthy eating habits, and smoking (Hampson, Goldberg, Vogt, & Dubanoski, 2007). Moreover, Chiteji (2010) presents evidence that non-cognitive skills are associated with health-related behaviors.[5]

Though much of the evidence just cited focuses on the developed country context, some studies have used the Big Five personality measures in developing countries as well to show inter alia: (i) personality traits predict job and economic performance (Calderon, Iacovone, & Juarez, 2017; Groh, McKenzie, & Vishwanath, 2015); (ii) there is the heterogeneity of treatment effects by personality traits (Donato, Miller, Mohanan, Truskinovsky, & Vera-Hernandez, 2017; Ibañez & Riener, 2018); and (iii) personality traits can be used as a tool to improve information frictions in credit markets (Arráiz, Bruhn, & Stucchi, 2016).

2.4. Climate, behavior, and personality

A growing literature at the intersection of climate and social science shows that climatic factors significantly affect human behavior (Graff Zivin & Neidell, 2013). For example, deviations from normal precipitation and higher temperatures systematically increase the risk of violence, often substantially (Hsiang, Burke, & Miguel, 2013). Higher temperatures are associated with increased aggression toward others; there is a positive and increasing relationship between temperature and aggravated crime (Gamble & Hess, 2012). In addition, there is a relationship between temperatures and violence toward oneself: higher temperatures are associated with higher suicide rates in the US and Canada (Burke et al., 2018) as well as in India (Carleton, 2017). Other studies have found evidence of climate effects in decreasing productivity (Hsiang, 2010), affecting cognitive performance (Graff Zivin, Hsiang, & Neidell, 2018), and even altering how much one cares for one's local environment (Tambet & Stopnitzky, 2019).

Personality traits could serve as a mediating mechanism for many of these outcomes, but the literature on such roles is sparse. One recent contribution, which is closely related to this study, focuses on the relationship between ambient temperature and measured personality traits and argues that more clement temperatures (those closer to 22 °C) are associated with higher levels of socialization, stability, personal growth, and plasticity in samples both of Chinese and US citizens (Wei et al., 2017). This study focuses on a static geography of personality in cross-sectional data; while this is suggestive of an influence of climate on personality, it does convincingly identify effects of climate variability on personality. Our study's use of individual exposure to drought, high temperatures, and wind—and how these affect the measured personality traits—adds to this literature.

3. Ultra-poor graduation program and data

This study uses data from a broader impact evaluation of a poverty graduation program implemented by BRAC in rural Uganda.[6] These programs have been implemented in many different contexts around the world and have generally shown high levels of success with sustained long-term positive impacts (Banerjee et al., 2015; Banerjee, Duflo, & Sharma, 2021). The primary goal of such poverty graduation programs is to provide households with an income-generating asset while also addressing the multitude of stresses and constraints that the ultra-poor experience. The income-generating asset transfer is usually accompanied by asset management training, financial skills training, short-term income support, and life coaching/counseling during recurrent household visits.

This program was implemented across five sub-districts with high poverty rates.[7] A door-to-door survey conducted by BRAC identified the poorest individuals eligible for participation in the program: 2,200 individuals in 348 villages were selected based on age eligibility and a constructed poverty score. This sample of ultra-poor, able-bodied young adults was randomized into a treatment and control groups at the village level with a 2:1 ratio resulting in treatment and control groups with 1295 and 905 individuals, respectively. The assets–primarily livestock–that were distributed to individuals in the treatment group are meant to serve as a new source of long-term income.[8] Moreover, the beneficiaries underwent an asset management training focused on the best management practices. The personality surveys we use in this analysis were conducted in the month right after the initial distribution of assets and related training. The other components of the program, such as financial literacy training, life skills coaching, and short-term income support began after personality surveys. More details on the timeline of the program are available in Appendix A.

3.1. Data

Our data come from three sources: the baseline survey, the personality survey, and the African Floor and Drought Monitoring System. We describe these below.

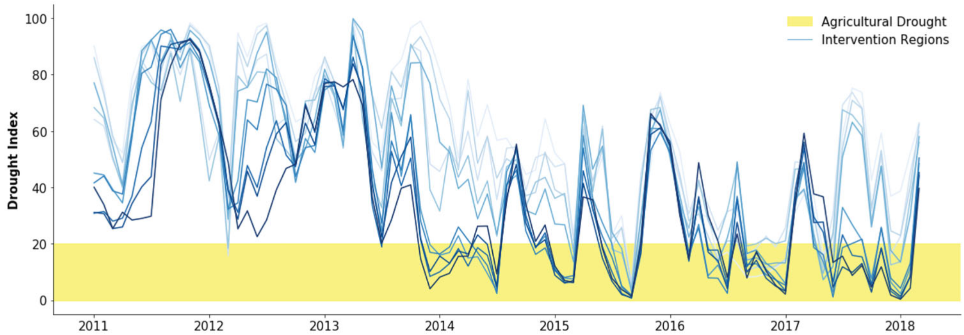

Figure 1. Drought: each line represents the value for a 0.25*0.25° region in the years leading up to the intervention. The regions depicted in the graph have at least one treatment or control village.

Baseline surveys were conducted two months before the start of the program. The data contain an array of socioeconomic information on potential program participants (working-age adults) and their households.

Personality surveys were conducted three to four weeks after the start of the program at which time the initial asset distribution and asset management training sessions occurred among individuals in the treatment group. As opposed to other 10-item personality surveys that have been shown to perform badly in contexts like ours (Laajaj et al., 2019; Ludeke & Larsen, 2017; Rammstedt & John, 2007), we use a 44-item survey instrument to measure the Big Five traits (John & Srivastava, 1999). The survey was translated into three local languages—Luganda, Baruli, and Kiswahili. To avoid discrepancy in the translation, we dropped seven questions that were deemed redundant after translation resulting in a 37-item questionnaire.[9] The long-form survey instrument also alleviated the concern around using the shorter 10-item survey (Rammstedt & John, 2007) to measure Big Five traits (Laajaj et al., 2019; Ludeke & Larsen, 2017).[10]

Due to budget constraints, the personality surveys were conducted among a smaller sample (nearly half) on the phone. We randomly selected 650 and 450 individuals from the treatment and control groups, respectively. The phone surveys were conducted over two-week period. We were able to survey 89 per cent of (650) treatment and 93 per cent of (450) control group participants selected for phone surveys.[11] We find no detectable differences in baseline survey data between our final sample, the non-surveyed sample, or those who were unable to be reached. Our sample size allows for a minimum detectable effect of ~0.1 standard deviations.

We rely on the *African Flood and Drought Monitoring System* (AFDM) for data on climatic conditions experienced by individuals in the days leading up to the intervention and personality survey (PrincetonClimateAnalytics, 2018). The climatic conditions experienced are based on an individual's GPS location from the baseline survey.

Droughts and lower than average rainfall cycles have become more frequent across Uganda in recent years (Nsubuga & Rautenbach, 2018). Climate models have predicted that these shocks are likely to worsen in severity and become more frequent in the coming decades (Dai, 2013). We find similar patterns across the districts in our study (Figure 1). Between 2011 and 2013, only one of the regions in our study experienced a drought. However, between 2014 and early 2018, there have been at least six different instances when a majority of the regions experienced drought. Some regions experienced drought-like conditions in months leading up to training sessions, asset distribution, and personality surveys. More than half of the villages in our sample population experienced drought conditions for at least one month right before the personality survey and nearly a quarter experienced drought conditions for at least two months before the personality survey. This gives short-term variation that allows us to estimate the effect of a very recent drought on measured personality traits. The methodology we use to construct the drought exposure variables used in our analysis is discussed in Appendix A.4.[12] In addition to drought, we also evaluate the effect of daily differences in maximum temperatures and wind levels on measured personality traits. In most WEIRD contexts, personality surveys are conducted in controlled environments, such as, for example, air-conditioned offices or university classrooms. In this rural and poor context, the inability to limit one's exposure to heat and other elements may play a role in how these personality surveys are answered. To study these environmental influences, we use geo-located daily temperatures and wind speeds as measured two meters above the surface, which are available through AFDM.

3.2. Sample characteristics

The study sample consists of 981 individuals across 215 villages in five districts in Uganda. Table 1 presents descriptive statistics at the individual and household level, as well as balance tests for differences across treatment status. Participants are generally young, with an average

Table 1. Descriptive statistics and balance

	Control	Treatment	Difference	p-Value
Graduation program				
Sample size	905	1295	−300	
Personality surveys				
Sample size	450	650	−200	
Characteristics of personality surveyed population				
Individual level				
Age	24.700	23.794	0.906***	0.003
	(0.238)	(0.195)	(0.308)	
Years of education	8.397	8.03	0.367	0.101
	(0.170)	(0.143)	(0.224)	
Female	44.9%	45%	−0.1	0.966
	(0.025)	(0.020)	(0.032)	
Married	56.04%	52.12%	3.92	0.229
	(0.025)	(0.021)	(0.033)	
Literate	77.9%	78.5%	−0.6	0.835
	(0.021)	(0.017)	(0.027)	
Experienced a long drought	21.3%	31.3%	−10.0***	0.001
	(0.021)	(0.019)	(0.029)	
Interview day wind speed (mph)	2.59	2.48	0.11***	0.000
	(0.022)	(0.009)	(0.022)	
Interview day max temperature (°C)	33.04	33.55	−0.50***	0.000
	(0.063)	(0.052)	(0.082)	
Household level				
Household size	5.790	6.469	−0.679***	0.000
	(0.155)	(0.1195)	(0.193)	
Meals per day	2.085	2.069	0.015	0.700
	(0.031)	(0.025)	(0.040)	
At least one employed member in household	57.2%	59.6%	−2.4	0.526
	(0.025)	(0.020)	(0.032)	
Taken a loan in the past year	14.9%	19.3%	−4.4*	0.075
	(0.18)	(0.016)	(0.025)	
Have some savings	37.2%	35.5%	1.6	0.600
	(0.025)	(0.020)	(0.031)	
Worried about food in last month	74.6%	73.1%	−6.7	0.597
	(0.022)	(0.018)	(0.029)	
Head unemployed	41%	47.7%	−6.7**	0.039
	(0.025)	(0.021)	(0.032)	

Summary statistics of our sample by treatment and control status. Our sample is on average young with eight years of education and a small majority are male. There are some observed differences across environmental factors which are controlled for in our regressions.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

age of 24, and 55 per cent are male. Just under half of the participants are married and 78 per cent are literate. Household size is approximately six on average and households are considerably food insecure: nearly 75 per cent of them worried about being able to secure enough food every day.

The table shows that the control and treatment groups are fairly balanced. There are statistically significant differences between the two groups with respect to household size, participant age, the unemployed status of the household head, and drought experience. Individuals in the control group come from smaller households: 5.7 individuals on average. In addition, the control group is about one year older on average than the treatment group and comes from households where the household head is six percentage points less likely to be employed. An individual in the control group is also 10 percentage points less likely to have faced a recent drought, as well as more likely to have experienced slightly higher wind speeds and lower temperatures. Given these differences, we include these variables as controls in our regressions.

4. Results

To estimate the short-run effect of the graduation program and different environmental factors we estimate variations of the following basic specification:

$$\begin{aligned} PT_i = \beta_0 + \beta_1 Treated_i + \beta_2 Drought_i + \beta_3 LongDrought_i \\ + \beta_4 TQuartile_i + \beta_5 WSQuartile_i + \mathbf{X}_i' \delta + e_i \end{aligned}$$

where PT_i is a principal component factor of a personality trait (one of the Big Five traits) or the Alpha or Beta measure. $Treatment_i$ is a dummy variable indicating program treatment status (being part of the graduation program). $Drought_i$ and $LongDrought_i$ are dummy variables indicating a month and two-month long drought experience, respectively. $TQuartile_i$ and $WSQuartile_i$ control for short-term environmental conditions: $TQuartile_i$ is a flexible approach for controlling for the maximum temperature on the day of the personality interview – we include quartile dummy variables with the first quartile as the reference group. Similarly, $WSQuartile_i$ is a set of dummy variables for the quartile of average wind speed (in miles per hour) on the day of the interview.[13]

X_i is a vector of individual and household characteristics that include age, gender, number of members in the household, marital status, literacy, education level, sub-district level fixed effects, and enumerator fixed effects.[14] Literacy level is a dummy variable indicating if an individual can read and write, while education level is the number of completed years of schooling. Although literacy, education, and marital status can depend on the personality and could be endogenous, we include these variables as controls and assume that they have not been affected by treatment, drought, or very short-term environmental factors, such as temperature and wind speed. e_i is the unobserved, idiosyncratic error term allowed to be arbitrarily correlated across individuals within village clusters.[15]

Sections 4.1 and 4.2 present the primary results for treatment, varying levels of drought, and short-term environmental factors on Alpha, Beta, and each of the Big Five personality traits. In Section 4.3 provides evidence of the heterogeneity. Robustness checks are provided in the Supplemental Material.

4.1. Alpha

Column 1 of Table 2 presents the coefficient estimates of our primary explanatory variable on the Alpha trait. Columns 2 through 4 decompose this effect into each of the three main traits that comprise Alpha—Agreeableness, Conscientiousness, and Neuroticism. Being in the treated group has a positive short-term effect on the measured Alpha personality traits, which is

Table 2. Effects of treatment and environmental factors on personality traits

	Alpha				Beta		
	Combined (1)	Agreeableness (2)	Conscientiousness (3)	Neuroticism (4)	Combined (5)	Openness (6)	Extroversion (7)
Treatment	0.212***	0.306***	0.195***	−0.022	0.043	−0.000	−0.181*
	(0.038)	(0.036)	(0.053)	(0.057)	(0.042)	(0.046)	(0.093)
Drought	−0.280*	−0.139	−0.308*	0.328*	0.008	0.073	0.060
	(0.155)	(0.234)	(0.156)	(0.179)	(0.156)	(0.127)	(0.154)
Long drought	−0.239***	−0.257**	−0.235**	0.107	−0.133	−0.098	−0.040
	(0.079)	(0.122)	(0.098)	(0.077)	(0.079)	(0.085)	(0.068)
Temperature quartile (2)	0.222***	0.275**	0.201**	−0.069	0.273**	0.319***	0.105**
	(0.077)	(0.105)	(0.078)	(0.063)	(0.109)	(0.085)	(0.047)
Temperature quartile (3)	0.362***	0.365***	0.317***	−0.224	0.328***	0.376***	0.041
	(0.104)	(0.124)	(0.114)	(0.132)	(0.100)	(0.083)	(0.152)
Temperature quartile (4)	0.409**	0.563***	0.406***	0.103	0.343	0.478***	−0.347
	(0.157)	(0.161)	(0.137)	(0.269)	(0.203)	(0.170)	(0.214)
Wind speed quartile (2)	0.210***	0.218**	0.196**	−0.092	0.154***	0.180***	0.063
	(0.074)	(0.093)	(0.090)	(0.073)	(0.052)	(0.049)	(0.063)
Wind speed quartile (3)	0.233***	0.216***	0.164	−0.269*	0.041	0.075***	−0.042
	(0.082)	(0.056)	(0.107)	(0.140)	(0.040)	(0.027)	(0.125)
Wind speed quartile (4)	0.400***	0.464***	0.335**	−0.265*	0.123*	0.160**	0.005
	(0.095)	(0.077)	(0.131)	(0.133)	(0.067)	(0.066)	(0.126)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	978	978	978	978	978	978	978

Cluster robust standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Dependent variable is the principal component factor of a trait. Treatment is a binary indicator for whether the individual was randomly assigned to treatment. Drought and Long Drought are binary indicators of a month long or two month long drought experience, respectively. Temperature and Wind Quartiles are dummy variables controlling for maximum temperature and wind speed on the day of the personality interview with the first quartile as the reference group. Controls include age, gender, household size, marital status, literacy, and education level. Controls also include enumerator and sub-district level fixed effects. Standard error clustered over village level clusters formed with a threshold of 3 km. Number of clusters: 31.

consistent with the program's activities that foster pro-social cooperation. An increase in Alpha and its sub-traits signify increases in the stability and socialization factor of personality (Digman, 1997). It suggests that the treatment caused movement towards more social behavior through increased conscientiousness and reduced aggression. We find an increase in the overall measured Alpha traits as well as Agreeableness and Conscientiousness. Those in the treatment group have measures that are more than 0.21 standard deviations higher. The magnitude of this short-term effect of being in the treatment group on Agreeableness and Conscientiousness is similar to those estimated in Akee et al. (2018) who estimate the effect of cash transfers on the personality traits of Native American adolescents in the United States. Emotional stability, however, does not consistently show differences across treatment groups.

Our personality surveys were conducted three to four weeks after the asset distribution and training; this time lag was not enough for an individual to experience a significant income gain from the treatment. These changes in personality could potentially be attributed to psychological aspects, such as an increase in aspirations and hope or an expected change in occupational and social roles. This is consistent with existing literature which shows that participants experience positive changes to their measured hope and aspirations due to selection into treatment, even if returns to the treatment are not expected anytime soon (Glewwe, Ross, & Wydick, 2018). It is also consistent with the literature that suggests that changes in occupational and social roles, especially among young adults, can affect their personality (Clausen & Gilens, 1990; Gottschalk, 2005; Roberts & Chapman, 2000; Roberts et al., 2002).

The coefficient estimates on the two drought variables suggest that drought has negative effects on Alpha and its sub-traits; the estimates for longer drought are similar in magnitude to that of drought, however, they are more consistently statistically significant. The results suggest drought decreases the socialization and stability factors of personality. The drought was likely too recent to have a significant difference in an individual's income as harvesting has not yet begun. These observed changes in personality traits could potentially be due to uncertainty about future economic status which is posited by recent literature (Coêlho, Adair, & Mocellin, 2004; Jones, 2018; O'Brien, Berry, Coleman, & Hanigan, 2014).

Finally, the last six rows show the estimated coefficients on dummy variables for daily maximum temperatures and wind speed quartiles. These are very short-term effects: different maximum temperatures and wind speeds on the day of the interview result in differences in measured Alpha and Beta traits. Higher temperatures and higher wind speeds are associated with higher scores on agreeableness and conscientiousness. To our knowledge, there is no previous work that studies the effects of environmental factors on the Big Five traits in a non-WEIRD context. Our results are consistent with studies in non-WEIRD settings that show that feeling physically warm can affect both reported agreeableness and induce some acquiescence in interviewees (Fetterman, Wilkowski, & Robinson, 2018; Steinmetz & Posten, 2017; Williams & Bargh, 2008). Short-term differences in weather seem to affect the measurement of personality traits in this context and with both wind and temperature, we can see consistent increasing coefficients with higher quartiles. The evidence strongly suggests that external environmental factors affect respondents' answers to personality questionnaires, a pattern that is robust to alternative specifications and definitions of these weather variables (Results are shown in Section S.2 of the Supplemental Material).

4.2. Beta

Column 5 of Table 2 presents the coefficient estimates of our main explanatory variables on the Beta personality trait, which represents personal growth and plasticity (Digman, 1997). Columns 6 and 7 decompose this effect into each of the two main traits that comprise Beta—Openness and Extroversion.

For the principal component of Beta, we do not find that those in the treatment group experienced a statistically significant change in this overall trait. However, we find a difference when we look at the components of the two sub-traits individually: extroversion is lower among the treated and this difference is statistically significant at the 10 per cent level.

While not statistically significant, the results also hint at small negative effects of longer drought experiences on Beta traits. An existing literature shows that decreases in Beta are associated to (i) increase in risk aversion, (ii) reduction in openness to new experiences, and (iii) reduction in the openness to the use of intellect. Our results thus align with research suggesting that individuals are more risk averse after a natural disaster (Balgah & Buchenrieder, 2011; Cameron & Shah, 2015).

Finally, the results show statistically significant differences in measured Openness based on temperature and wind quartiles, which highlights the potential noisiness of these measures in these contexts. Our results align with studies done in WEIRD contexts where temperature and wind are shown to affect all Big-5 traits—with more consistent changes in Alpha compared to Beta traits (Fetterman et al., 2018; Wei et al., 2017).

These findings suggest that personality traits (or at least their measures) among an ultra-poor sample are notably malleable over time horizons shorter than previously seen in the literature. Factors that seem to influence the measurement of personality traits are (i) being enrolled in a welfare program, (ii) very recent shocks, such as drought, and/or (iii) short-term changes in weather. It is plausible that enrollment in the graduation program may be providing a psychological boost to these working-age poor individuals such that it is causing a short-term change in personality traits. Another possible explanation is the observed short-term changes illustrate the noisiness of personality traits measured by Big Five in a non-WEIRD context, as argued in Laajaj et al. (2019), even though our study design and methodology attempt to mitigate against this.

4.3. Heterogeneity

The mechanisms through which these effects take place are unclear, though in this section we conduct sub-group analyses that shed some light on the interaction of external circumstances and measured personality. For example, it is possible that those with the most to gain or lose from these shocks are affected the most by them. To explore possible mechanisms, we investigate the heterogeneity of these impacts across two important variables: household food security and participant gender.

The individuals in this sample are extremely poor by global standards, with food insecurity affecting nearly 74 per cent of households in the month preceding the household survey. We split the sample and run regressions separately for participants who experienced food insecurity during this time window. Column 1 of Table 3 shows the effects of the treatment and drought on the Alpha and Beta personality traits among individuals in the household who do not report food insecurity in the months leading up to the household surveys. Column 2 shows results for individuals whose households reported food insecurity. When it comes to Alpha personality traits, a comparison of the two suggests rather strongly that average effects of treatment and drought are driven mainly by those who in the baseline who were living under more dire economic circumstances. On the other hand, the differences across temperature and wind quartiles are evident among both groups. This is suggestive that the treatment and drought are likely acting at least partially through an expected economic well-being mechanism, while the short-term environmental factors are adding noise to the measurement.

The average effects on Beta personality characteristics were not statistically significant in Table 2. However, in Table 3, we can see individuals in households that report food insecurity show positive effects on their Beta personality traits due to the program. We find a similar distinction in the coefficients on drought and long drought, which suggests that the average

Table 3. Heterogeneity of treatment and environmental effects

	Food insecure		Female	
	= 0 (1)	= 1 (2)	= 0 (3)	= 1 (4)
Alpha				
Treatment	0.137*	0.233***	0.247***	0.192***
	(0.068)	(0.058)	(0.047)	(0.049)
Drought	0.403	−0.468**	−0.508*	−0.128
	(0.423)	(0.175)	(0.272)	(0.213)
Long drought	0.134	−0.308***	−0.187	−0.328***
	(0.300)	(0.089)	(0.125)	(0.076)
Temperature quartile (2)	0.256***	0.179*	0.142	0.395***
	(0.084)	(0.099)	(0.121)	(0.038)
Temperature quartile (3)	0.430***	0.372***	0.239	0.495***
	(0.134)	(0.122)	(0.142)	(0.066)
Temperature quartile (4)	0.787***	0.339*	0.190	0.576***
	(0.182)	(0.170)	(0.184)	(0.121)
Wind speed quartile (2)	0.120	0.221**	0.247***	0.094
	(0.107)	(0.095)	(0.075)	(0.112)
Wind speed quartile (3)	0.246**	0.221**	0.316***	0.108
	(0.097)	(0.106)	(0.110)	(0.083)
Wind speed quartile (4)	0.377***	0.385***	0.465***	0.259***
	(0.105)	(0.123)	(0.110)	(0.090)
Beta				
Treatment	−0.215	0.108**	0.083	0.005
	(0.124)	(0.033)	(0.046)	(0.107)
Drought	0.585	−0.167	−0.005	−0.043
	(0.473)	(0.206)	(0.147)	(0.350)
Long drought	−0.013	−0.163*	−0.066	−0.322
	(0.179)	(0.080)	(0.112)	(0.166)
Temperature quartile (2)	0.593***	0.204	0.249	0.350**
	(0.098)	(0.135)	(0.139)	(0.099)
Temperature quartile (3)	0.754***	0.132	0.279*	0.332*
	(0.141)	(0.148)	(0.136)	(0.147)
Temperature quartile (4)	0.895*	0.088	0.321	0.350
	(0.404)	(0.270)	(0.195)	(0.350)
Wind speed quartile (2)	0.198	0.141*	0.264***	0.012
	(0.108)	(0.055)	(0.044)	(0.129)
Wind speed quartile (3)	0.035	0.061*	0.230***	−0.269**
	(0.141)	(0.029)	(0.040)	(0.074)
Wind speed quartile (4)	0.094	0.112	0.120	0.035
	(0.155)	(0.091)	(0.069)	(0.105)
Controls	Yes	Yes	Yes	Yes
Sample size	257	721	540	438

Cluster robust standard errors in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$. Dependent variable is a principal component factor of a trait. Treatment is a binary indicator for whether the subject was randomly assigned to treatment. Drought and Long Drought are binary indicators of a month long or two month long drought experience, respectively. Temperature and Wind Quartiles are dummy variables controlling for maximum temperature and wind speed on the day of the personality interview with the first quartile as the reference group. Controls refer to age, gender, household size, marital status, literacy, and education level. Controls also include enumerator and sub-district level fixed effects. Standard error clustered over village level clusters formed with a threshold of 3 km. Number of clusters: 31.

coefficient is driven by those with food insecurity. On the other hand, the coefficient on the temperature quartiles is statistically significant only among those who do not report food insecurity; the opposite is true for the wind speed quartile. This again suggests that these differences in short-term environmental factors add noise to the measurement.

Columns 3 and 4 of Table 3 show the effects of treatment and drought on the Alpha and Beta personality traits of women and men separately. The estimated effects for both men and women are similar to the primary results in Table 2 with some statistically insignificant differences. Moreover, the temperature and wind quartiles show some statistically significant coefficients that differ across men and women, though with no consistent pattern.

5. Conclusion

Personality characteristics are among the core factors that dictate an individual's behavior. However, the short-term effect of shocks on measured personality traits is not well-studied. Moreover, most of the existing personality data come from urban and educated samples in developed countries. In this study, we fill a gap in the literature by studying the short-term changes in personality traits due to economic shocks and environmental factors for a sample of ultra-poor individuals living in a rural setting in a developing country.

We study the impact of two types of shocks – enrollment in an ultra-poor graduation program and exposure to environmental fluctuations, such as drought, high temperatures, and wind. The study design provides us with experimental and quasi-experimental evidence on the short-term effects of these shocks on measured personality traits. The study design also takes into account various findings of Laajaj et al. (2019) to increase the validity of personality traits in our non-WEIRD context.

We find that individuals in the treatment group exhibited higher scores on traits that represent socialization and stability. In contrast, those experiencing drought showed decreased scores on these Alpha traits and their related sub-traits. In addition, we show that differences in daily temperature and wind speed also have statistically significant associations with some of the measured traits. It is important to note that these findings document short-term differences across the groups; future research should study the extent to which longer-term outcomes are affected by these economic and environmental influences. An additional caveat applies as well: although the personality data in our study had higher validity than past studies in similar contexts (Piedmont et al., 2002), some of our harder-to-interpret findings align with the conclusions of Laajaj et al. (2019) suggesting certain weaknesses in how these personality measures apply in this non-WEIRD context.

Several other important but tentative conclusions are also suggested by these results. We present them cautiously here because additional research is needed to clearly identify causal mechanisms linking personality changes to economic outcomes. First, development programs may have short-term effects on personality in measurable ways, as we have shown here. Therefore, interventions can in principle be designed such that personality changes could themselves be leveraged to enhance program effectiveness and improve outcomes. Doing so would require additional research into mechanisms by which specific traits are altered, of course, but this paper suggests the relevance of this consideration. At the same time, recent negative shocks may also impact personality and can do so in ways that undermine development interventions. To cite one hypothetical example, decreased socialization post-drought (a pattern we show in this study) might degrade communal interactions and perhaps disrupt informal risk-sharing networks in the process. While this particular mechanism is speculative it highlights how personality changes might affect other economic processes of known importance. Third, the literature suggests a role of negative climate shocks, such as drought in fueling conflict (Hsiang et al., 2013). Our results add to this work and suggest an additional mechanism – possible changes in impulse restraint, conscientiousness, and hostility – by which climate shocks might affect drivers of conflict. Finally, additional research on measurement tools for personality traits in Non-WEIRD contexts is vital for researchers and policymakers to better understand the role of non-cognitive skills in rural low-income settings, such as this one.

Notes

1. The ultra-poor are defined by as those living on <50 cents a day (in 2007) by the International Food Policy Research Institute.
2. BRAC, originally established in Bangladesh, implements poverty graduation programs in countries around the world. These anti-poverty programs are multi-faceted and aim to address the multitude of stresses faced in poverty with the goal of achieving self-sufficiency with productive assets (Banerjee et al., 2015).
3. Most studies on non-cognitive skills are done among individuals living in Western, Educated, Industrialized, Rich, and Democratic (WEIRD) places in controlled settings.
4. In this order, the first letters spell OCEAN. These factors represent personality broadly and are each formed from a number of distinct and specific personality characteristics (Digman, 1990; Goldberg, 1990; McCrae & John, 1992). Most of the variables used to assess personality in the psychology literature can be mapped into one or more of the factors of the Big Five.
5. Heckman et al. (2006) and Judge and Hurst (2007) show, using data from the 1979 cohort of the National Longitudinal Survey of Youth, that individuals who report positive self-evaluations when measured in young adulthood have higher incomes in mid-life. Further, these positive self-evaluations during youth further enhance the benefits of family socioeconomic status and academic achievement on mid-life income. The authors also show that non-cognitive skills play a role in predicting risky behavior such as crime and drug/alcohol consumption.
6. Impacts of the program on poverty and other economic outcomes are being studied separately as part of a larger, pre-registered evaluation.
7. Poverty rate was determined based on the 2004 census.
8. Beneficiaries were given a choice between receiving chickens, pigs, or goats. Their choice set took into account their capacity in terms of land available for grazing and the amount of time the beneficiary would be able to commit to their livestock. Additionally, beneficiaries were given two bags of potato vines to smooth their food consumption until income from their newly acquired assets was generated.
9. Translators were unable to adequately differentiate the questions from each other in the local languages. The 37 questions are shown in Appendix A.3. Figure S.1 in the Supplemental Material shows distribution of scores across our sample.
10. The longer questionnaire reduces acquiescence bias as there are more reverse and non-reverse framed questions.
11. The protocol for reaching individuals included attempting to call individuals twice a day—morning and evening—for two consecutive days.
12. Our results are robust to alternative drought specifications as shown in Table B.1 in the Supplemental Material.
13. The variation in the short-term environmental factors such as temperature and wind comes from two sources, (i) being in different locations, that is, comparing individuals in drought affected and non-drought affected regions, (ii) being interviewed on different days—two individuals from the same village could have experienced different temperature and wind conditions if they were interviewed on different dates.
14. There was a day-long enumerator training to go through survey methodology and communication protocols, however, phone surveys can be sensitive to enumerator's clarity in communication, level of patience and pacing of the conversation at the time of survey. There is also evidence that administrating surveys via enumerators adds variance in personality scores (Laajaj et al., 2019). We add enumerator fixed effects to control for any such variation.
15. Personality may be similar among individuals living in same geographical region. Hence, villages are clustered together using Ward's Hierarchical Clustering with a threshold distance of 3 km. Results are also evaluated with other thresholds for robustness with similar results (Results provided in Section S.2: Table S.6 in the Supplemental Material).

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Code availability statement

The code to reproduce the findings of this study is available here.

Data availability statement

Drought, temperature, and wind speed data is publicly available via the *African Flood and Drought Monitoring System* (AFDM) (PrincetonClimateAnalytics, 2018). Survey data is proprietary information belonging to BRAC Uganda, and cannot be publicly released. Upon request, we will provide information to researchers on how to request the survey data from BRAC Uganda.

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Appendix A. Uganda Ultra-Poor graduation program

A.1. Selection

The program was implemented across five sub-districts with a high poverty rate based on the 2004 census. A door-to-door pre-baseline survey was conducted by BRAC across rural regions of these districts to identify poor households. The survey collected data on the personal and household assets of about 10,000 young adults living in rural regions of these five districts. Next, survey data was used to calculate a poverty score for everyone. The poorest 2,200 individuals based on poverty score were selected for participation in the program. These individuals were categorized as 'poorest of the poor' or 'ultra-poor' (in BRAC's terminology). The selected sample was randomized into treatment and control groups. Randomization was done at the village level such that treatment to control village count was in a 2:1 ratio. Consequently, the treatment and control groups had 1295 and 905 members.

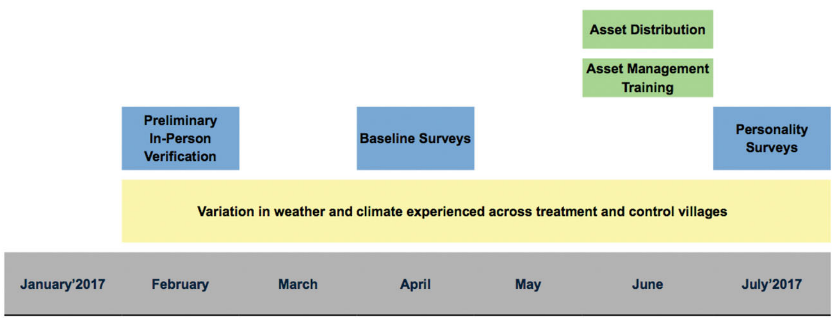

Figure A.1. Timeline of intervention.

A.2. Intervention timeline

Baseline surveys were conducted in April 2017. It involved collecting information about individual and household characteristics, such as assets, employment, health, well-being, geographical location, and contact information. Income generating asset distribution and asset management training were held in June 2017. The assets–primarily livestock–distributed to individuals in the treatment group were supposed to serve as a new source of long-term income. Moreover, the beneficiaries underwent an asset management training focused on the best management practices. It involved discussing where and how to create a space for livestock within household; when and what to feed it; how to know when it's sick; and other related best practices. The personality surveys we use in this analysis were conducted in the month right after the initial distribution of assets and related training.

The other components of the program, such as financial literacy training, life skills coaching, and short-term income support began after personality surveys. However, this paper only uses baseline and personality surveys along with climate data in the months leading up to the personality survey. Hence, we do not discuss any trainings (except asset management training) or events that took place post-personality survey.

A.3. Big five personality survey

Big Five personality questionnaire consists of the following 44 questions. Questions marked with asterisk (*) were skipped in our surveys.

Please enter a number next to each question to indicate the extent to which you agree or disagree with that statement.

1—Disagree Strongly
2—Disagree
3—Neither Agree or Disagree
4—Agree
5—Strongly Disagree

I see myself as someone who …

Q1 _____ is talkative
Q2 _____ tends to find fault with others
Q3 _____ does a thorough job
Q4 _____ is depressed, blue
Q5 _____ is original, comes up with new ideas
Q6 _____ is reserved
Q7 _____ is helpful and unselfish with others
Q8 _____ can be somewhat careless
Q9 _____ is relaxed, handles stress well
Q10 _____ is curious about many different things
Q11 _____ is full of energy
Q12 _____ starts quarrels with others
Q13 _____ is a reliable worker
Q14 _____ can be tense
Q15 _____ is ingenious, a deep thinker
*Q16 _____ generates a lot of enthusiasm
Q17 _____ has a forgiving nature
Q18 _____ tends to be disorganized
Q19 _____ worries a lot
*Q20 _____ has an active imagination
Q21 _____ tend to be quiet
Q22 _____ is generally trusting
Q23 _____ tends to be lazy
Q24 _____ is emotionally stable, not easily upset
*Q25 _____ is inventive
Q26 _____ has an assertive personality
Q27 _____ can be cold and aloof
Q28 _____ perseveres until the task is finished
Q29 _____ can be moody

*Q30 _____ values artistic, aesthetic experiences
Q31 _____ is sometimes shy, inhibited
Q32 _____ is considerate and kind to almost everyone
*Q33 _____ does things efficiently
*Q34 _____ remains calm in tense situations
Q35 _____ prefers work that is routine
Q36 _____ is outgoing, sociable
Q37 _____ is sometimes rude to others
Q38 _____ makes plans and follows through with them
Q39 _____ gets nervous easily
*Q40 _____ likes to reflect, play with ideas
Q41 _____ has a few artistic interests
Q42 _____ likes to cooperate with others
Q43 _____ is easily distracted
Q44 _____ is sophisticated in art, music, or literature

A.4. Drought indicator

We use data from the African Flood and Drought Monitoring System (AFDM), a system developed by the Princeton Climate Analytics group (PrincetonClimateAnalytics, 2018). AFDM has data on Sub-Saharan Africa for various climatic conditions. It provides indices that measure meteorological, hydrological, and agricultural droughts. Meteorological drought represent a dry weather pattern in a given area. Hydrological drought usually occurs after several months of meteorological drought when low water supply becomes evident in streams, reservoirs, and groundwater levels. Agricultural drought represent conditions when soil moisture is insufficient and results in the lack of crop growth and production. An agricultural drought indicates an instance of meteorological and hydrological drought in recent past. In this study, we use a drought index representing agricultural drought.

AFDM's agricultural drought index is a soil moisture-based drought index developed using the Variable Infiltration Capacity (VIC) model. ADM obtains a multi-decadal reconstruction of the terrestrial water cycle by combining the VIC land surface hydrological model with a reanalysis observation dataset (Liang, Wood, & Lettenmaier, 1996). This historical data forms the climatic conditions against which current conditions are compared. Data for current conditions comes from a real-time monitoring system (2009–present) driven by remotely sensed precipitation and atmospheric analysis data that track drought conditions. The index is calculated by determining the percentile of the daily average of relative soil moisture in each 0.25 by 0.25° grid cell with respect to its cumulative probability distribution function provided by the historical simulations (1950–2008).

The data is available as daily drought index values for each 0.25*0.25° region. As a percentile, the drought index holds a value between 0 and 100. We create a 30-day-average from these daily averages for each individual based on his GPS location from the baseline survey. The 30 days are counted from the day the personality interview was conducted. We also calculate averages for the second-last month. The two averages – last month and second last month – tell us the length of drought experienced by each individual. Finally, we convert these averages into respective dummy variables which indicate an experience of drought by an individual. As suggested by the research group behind AFDM, we use a threshold value of 20 or lower as an indication of agriculture drought (Sheffield et al., 2014). Our results are robust to different specifications for drought as shown in Table S.5 in the Supplemental Material.