Environmental Factors Shape Risk Preferences

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Abstract

Risk preferences differ across individuals and change over time, but little is still known on what determines them. We present incentivized panel data from Ethiopia, and pair them with rainfall data to address this question. We find rainfall shocks to decrease risk tolerance for the same individuals over time. Once we purify preferences of the effect of shocks and aggregate them over time, we are able to explain over 60% of the cross-sectional variation in idiosyncratic preferences using environmental characteristics. The results highlight the importance of environmental factors in shaping preferences, which are found to adapt to the environment.

Keywords: risk preferences; development; panel data; shocks

JEL-classification: C93; D03; D80; O12

> *A great deal can be learned about rational decision making by taking into account* [...] *the limitations upon the capacities and complexity of the organism, and by taking account of the fact that the environments to which it must adapt possess properties that permit further simplication* [sic] *of its choice mechanisms.*
>
> Herbert A. Simon (1956), p. 129

1 Introduction

Preferences over risk and uncertainty play a key role for economic decision making. They contribute not only to the determination of investment behavior, but also to labor market choices, investments into education, and marriage and fertility decisions. As drivers of entrepreneurship, they contribute to shaping the development and growth perspectives of entire countries. It thus appears desirable to understand what shapes preferences. Notwithstanding recent advances documenting correlates of risk preferences in general populations (Tanaka, Camerer and Nguyen, 2010; Dohmen, Falk, Huffman, Sunde, Schupp and Wagner, 2011; von Gaudecker, van Soest and Wengström, 2011; Choi, Kariv, Müller and Silverman, 2014; Noussair, Trautmann and van de Kuilen, 2014; Falk, Becker, Dohmen, Enke, Huffman and Sunde, 2018), relatively little is still known on what causally determines preferences. We aim to contribute to this topic by systematically documenting the role of environmental factors in shaping preferences.

A consensus has started to emerge that preferences are changeable (Bowles, 1998; Voors, Nillesen, Verwimp, Bulte, Lensink and Van Soest, 2012; Cohn, Engelmann, Fehr and Maréchal, 2015; Schildberg-Hörisch, 2018). Our ability to explain the variation in preferences over time and across individuals, however, remains limited. Two stylized facts emerge from the recent literature: 1) investigations of the effects of different types of 'shocks' on preferences have arrived at highly contradictory conclusions, with an aggregate effect that is most likely null (Chuang and Schechter, 2015); and 2) while preferences vary considerably across individuals, we are typically able to explain only a relatively small proportion of this variation based on observable characteristics of the decision makers (von Gaudecker et al., 2011; L'Haridon and Vieider, 2019). The causal determinants of heterogeneity in preferences thus remain poorly understood.

We present the results of a panel study conducted with subsistence farmers scattered across the Ethiopian highlands—the first of its kind. We obtained detailed, incentivized measures of the risk preferences of close to 1000 respondents. We then linked the preference measures to a historical database of rainfall constructed by combining infrared satellite imagery with data from rain gauges on the ground. This provides an ideal testbed to study the causal determinants of preferences. In particular, the high environmental variability found in the Ethiopian highlands both over time and across space ensures that environmental effects, if indeed present, should have a large impact. Given the dependence of local livelihoods on rain-fed agriculture (Dercon and Christiaensen, 2011; Dercon and Porter, 2014), we can use exogenous variation in rainfall to study how preferences change within subjects over time. Having data collected in incentivized experiments based on known-probability prospects allows us to study changes in risk *preferences*, rather than risk *taking* as measured in survey questions, which may capture elements of probabilistic beliefs and cash availability in addition to pure preferences.

We use these data to systematically document the effect of the environment on risk preferences. Our results thus contribute to a recent theoretical and empirical literature investigating the causal determinants of endogenously changing risk preferences. On the theoretical side, Galor and Michalopoulos (2012) modeled the global distribution of risk preferences as endogenously shaped by historical growth processes and fertility decisions. Doepke and Zilibotti (2014) emphasized the importance of conscious education decisions by parents preparing children for the economic environment they will face as adults (see also Doepke and Zilibotti, 2008; 2017). Kőszegi and Rabin (2007) and Netzer (2009) presented models in which preferences can be determined by expectations about outcomes and by beliefs about the environment, respectively.

On the empirical side, Malmendier and Nagel (2011) documented how exposure to an economic depression can reduce subsequent financial risk taking. Cohn et al. (2015) showed that financial professionals become more risk averse after being primed with a recession scenario. Cesarini, Dawes, Johannesson, Lichtenstein and Wallace (2009) documented the genetic heritability of risk taking traits using data on Swedish twins. Bouchouicha and Vieider (2019) used a globally representative database on risk taking to test the predictions of Galor and Michalopoulos (2012) and Doepke and Zilibotti (2014), and found them to be largely supported in the data. In a rare panel investigation using hypothetical lottery responses from a large sample in Japan, Hanaoka, Shigeoka and Watanabe (2018) documented the effects on risk aversion of being exposed to an earthquake. They did, however, find effects that were not coherent across demographic groups, and null in the aggregate data.[1] Falk, Kosse, Pinger, Schildberg-Hörisch and Deckers (2019) map the preferences of children from families with high and low socio-economic status, and empirically document the role of parental investment.

We make three main contributions to this literature. We start by presenting a theoretical model that allows us to make predictions on how preferences change following shocks. The model is based on a biological framework first proposed by Robson (2001a), and further developed by Netzer (2009), and inspired by neurological evidence of how dopamine receptors actually register rewards in the brain (Tobler, Fiorillo and Schultz, 2005). While highly stylized, the model allows us to derive predictions for our context, which constitutes an added value over a literature that has thus far been purely empirical.

[1] While several other panel datasets exist, they are often ill-suited for investigating causal effects on preferences. In the relatively homogenous Western populations where the collection of panel data is relatively more frequent, environmental differences tend to be small and unsystematic, and exogenous shocks are observed less often. The presence of insurance and social safety nets means that the consequences also tend to be less dramatic. Survey questions—though having contributed significantly to our understanding of risk taking behavior—are less suited to detect changes in risk *preferences*, since they may capture additional elements such as probabilistic beliefs and liquidity constraints.

Second, we show that rainfall shocks reduce risk tolerance within subjects over time. The combination of high-impact exogenous shocks with the panel dimension and fixed effects estimators allows for clean causal identification. We further document how the between effects go in the opposite direction of the within effects in our data. This shows the added value of our findings over a literature that is prevalently cross-sectional.[2] Our findings cannot be interpreted as simple movements along a utility function, but constitute genuine shifts in preferences. Measuring utility over significant stake ranges, we unequivocally find the utility function to be characterized by increasing relative risk aversion and constant absolute risk aversion. Given that we find relative risk aversion to *increase* following shocks, however, accounting for our effects through movements along the utility function would require a function characterized by *decreasing* relative risk aversion—the opposite pattern of what we find, and a form which has not received any empirical support (see Wakker, 2010, section 3.5, for a review).

Finally, we show that environmental factors—beyond driving changes in preferences over time—also explain a large part of the variation in risk preferences across space. Purifying individual preferences of the effects of shocks and aggregating them over time, we obtain measures of what we refer to as *idiosyncratic risk preferences*. Regressing idiosyncratic risk preferences on historical rainfall and geographical characteristics, we are able to explain about 60% of the cross-sectional variation—an order of magnitude more than than the variance typically explained by previous studies.[3] We thereby explain mostly variation in preferences across different environments. Variation of preferences within any given environment can only be explained to a small extent using demographic and economic characteristics—a finding that is highly consistent with conclusions reached based on data from more homogenous environments and subject populations (von Gaudecker et al., 2011; L'Haridon and Vieider, 2019). Overall, these results paint a highly coherent

[2]Our shocks are 'exogenous' in the sense that they cannot be influenced by respondents, thus excluding reverse causality. In cross-sectional analysis, however, these shocks may still be correlated with the error term, thus not meeting the bar of exogenity according to the econometric definition of the term. This is indeed what drives the difference between the within and between estimators we document.

[3]An exact figure of the variance explained in previous studies is difficult to come by because of the wide variety in techniques used and the inconsistent reporting of variance metrics. von Gaudecker et al. (2011) state that the variation associated with demographic chracteristics, "is small compared to the variance ascribed to unobserved heterogeneity" (p. 666). Sutter, Kocher, Glätzle-Rützler and Trautmann (2013) explain about 4% of the variance in risk preferences in their sample of school children. Noussair et al. (2014) can explain at most 6% of the variance in their estimated risk aversion parameter using a wide array of demographic and economic characteristics. Vieider, Lefebvre, Bouchouicha, Chmura, Hakimov, Krawczyk and Martinsson (2015) report R^2 measures between 0.01 annd 0.07 for their incentivized measures of risk tolerance. At the higher end of the spectrum, Cesarini et al. (2009) attribute 16% of the variance in risk preferences to genetic factors in a sample of Swedish twins.

picture of how the environment shapes individual preferences.

This paper proceeds as follows. Section 2 presents our model. Section 3 describes the data we use. Section 4 presents our empirical approach, and section 5 describes the results. Section 6 concludes the paper.

2 Model and predictions

We start by sketching a model that accounts for the central features of our data and allows us to derive predictions relevant for our context. This model allows us to reconcile several findings that may otherwise be seen as contradictory—high overall levels of risk tolerance in our study region as compared to typical Western subject populations, and a decrease of risk tolerance with rainfall shocks—while at the same time bringing some rigor to a topic of investigation that has thus far been entirely empirical. The model builds on the insights presented by Robson (2001a) as further developed by Netzer (2009). It allows us to derive predictions on how utility adapts to the local environment—or in other words, on how the environment *shapes* risk preferences.

The starting point is that cognitive processing capacity is limited—there is a finite number of neurones that can register rewards in the brain—while the number of potential outcomes is infinite. It will thus be evolutionarily optimal for an organism to allocate the finite number of perceptual thresholds at its disposal where they matter most. Tobler et al. (2005) provide direct neurological evidence that dopamine receptors in the brain register reward magnitudes relative to expected magnitudes. Over a ten-fold range in reward values, the level of activation of the reward receptors for different relative amounts was thereby found to be constant.

This suggests that utility is recorded on a constant scale, with differences between successive perceptual thresholds being recorded as equally spaced jumps in utility. One can thus characterize successive jumps in utility as *just noticeable differences* in utility (*JNDs*; Robson and Whitehead, 2017). By definition of 'just noticeable', each successive step will result in a constant increase in utility. The neurological account thus suggests modeling utility as a step function, with the steps corresponding to constant increases in utility. The thresholds at which the jumps in utility take place will optimally be allocated in such a way as to maximize evolutionary fitness (Robson, 2001a; Netzer, 2009). Hedonic utility can then be conceived of as a vehicle for the organism to ensure the survival of its genes. These insights produce testable predictions for economic behavior.

Formally, utility V is defined over outcomes $x \in \mathcal{X}$, indicating evolutionary fitness. However, given the infrequency with which evolutionary outcomes are observed, it is optimal from an evolutionary point of view to define utility over intermediate outcomes that are observed with higher frequency, such as consumption (Robson, 2001b). This can readily be taken into account by making fitness a function of consumption, $x = \phi(c)$. A utility function U can thus be defined directly over consumption levels $c \in \mathcal{C}$, where $U = V \circ \phi$. Since only JNDs in utility can be distinguished, utility takes the form of a step function with N equally spaced utility steps, where N corresponds to the number of JNDs. Without loss of generality, we assume that each step results in a utility increment of $1/N$, confining the utility interval to $[0, 1]$.

The utility function U is then determined by optimally allocating the N perceptual thresholds, $\{\hat{c}_1, ..., \hat{c}_N\}$, in the set of outcomes $\mathcal{C}$. Any outcomes that fall between two contiguous thresholds will be indistinguishable in terms of utility, resulting in potential mistakes due to random choice. That is, if $\hat{c}_n \leq c_i, c_j \leq \hat{c}_{n+1}$, then $U(c_i) = U(c_j)$, such that the choice probability π of choosing either outcome will be the same, $\pi(c_i) = \pi(c_j) = 1/2$. Given constant utility steps $1/N$, the utility of a given outcome c will simply equal the number of steps allocated below c, that is for any $\hat{c}_n \leq c_n \leq \hat{c}_{n+1}$ utility is $U(c_n) = \frac{n}{N}$. It follows that many thresholds should be allocated to regions where decisions need to be taken frequently, in order to minimize the probability of mistakes. Furthermore, thresholds should be allocated paying heed to the size of mistakes—measured in terms of evolutionary fitness and captured by the function ϕ—as well. This means that utility will increase slowly in regions where decisions are taken infrequently and probabilities of mistakes are low, and where the mistakes are not important. It will increase quickly in regions where the frequency of outcomes is high, and the consequences of mistakes in terms of lost fitness are large. Curvature of utility is then an indicator of changes in attention across different outcome ranges (Netzer, 2009).

The setup just discussed allows us to make predictions for our context. Let us start from the effect of rainfall shocks during the main growing season, which will translate into shocks to consumption. Let $g(c)$ be the density function of consumption levels, with a cumulative distribution function $G(c)$. This can be interpreted as a distribution of consumption levels that is known from experience. The decision maker will try and approximate g with a series of threshold levels $\{\hat{c}_1, ..., \hat{c}_N\}$. Utility U over consumption should thus reflect the features of G, e.g. resulting in reduced risk tolerance in geographical areas where consumption is low due to low average farm productivity, or in regions where outcomes are distributed over wider ranges because of high rainfall variability.[4]

Following Robson and Whitehead (2017), we furthermore allow the consumption thresholds to be time-dependent and to follow a simple updating rule:

$$\hat{c}_n^{t+1} = \hat{c}_n^t + \psi_s[g_s^{t+1}(c) - g_s^t(c)], \tag{1}$$

where ψ is a function governing the extent to which the thresholds react to shifts in the density of consumption. The subscript s indicates that both the adjustments and the perceptions of the density function may be subjective. To the extent that the consumption distribution g^{t+1} is lower than g^t, i.e. there is a negative shift in the density function resulting from a rainfall shock, the consumption thresholds will adapt to this by shifting downward. This shift is likely to be strongest in the middle region, where thresholds are particularly densely allocated, so as to shift the attention to where the action is likely to occur. The greater the threat to evolutionary fitness deriving from a shock, the greater the adjustment.[5] Any downward adjustment of the thresholds, in turn, will result in a more concave utility function.

The model thus predicts that preferences will change over time, with rainfall shocks decreasing risk tolerance. Notice how these changes are indeed predicted based on shifts in the utility function, not mere movements along a pre-existing function—see Netzer (2009), section III, for a discussion of this point. The model also predicts that respondents living in regions with low average rainfall levels—as well as other features that may reduce consumption prospects—will be less risk tolerant than respondents in regions with more favourable environmental characteristics. The same holds true, *ceteris paribus*, for respondents living in regions where historical rainfall variability is high. Indeed, high

[4] Robson (2001a) shows this formally using the criterion of minimizing the probability of mistakes, showing that the optimal allocation is equally spaced in terms of probability. In the limit as $N \to \infty$, minimizing the probability of mistakes thus yields $U(c) = G(c)$. Netzer (2009) solved the optimization problem for the more appropriate criterion of minimizing losses in fitness. Under the criterion of minimizing losses of fitness, for which the size of mistakes also count, the resulting utility is a less extreme projection of the underlying density function. Importantly, under the maximization of fitness criterion the shape of the function ϕ mapping consumption into evolutionary outcomes also contributes to the shape of utility.

[5] Since what utimately matters is evolutionary fitness, reactions will be determined both by the perceived shift in the distribution function over consumption opportunities, and by the extent to which these shifts map into evolutionary fitness through the function ϕ. Netzer (2009), section I.C, formally characterizes the relative influence of theses two elements on utility. For our purpose, the intuition that both will matter in such comparisons is sufficient.

historical variability can be thought of as a succession of shocks, which will make it difficult to optimally adapt to a given set of environmental conditions. High variability thus ought to result in a utility function that is geared towards avoiding mistakes where they are most costly, i.e. toward avoiding catastrophically low consumption outcomes.

We are further able to account for the documented cross-country differences in risk tolerance. In particular, we expect risk tolerance to be very high in our study region relative to typical levels in the West, based on comparative studies showing high risk tolerance especially in Africa (Vieider et al., 2015; Falk et al., 2018; Vieider, Beyene, Bluffstone, Dissanayake, Gebreegziabher, Martinsson and Mekonnen, 2018; Bouchouicha and Vieider, 2019). In rich countries, important decisions are relatively rare—choose your field and level of education; take a job; change your job if a better one becomes available. Most decisions are taken over small to moderate amounts. Furthermore, the function ϕ mapping consumption outcomes into fitness levels is relatively flat, given that evolutionary fitness is largely dissociated from income. We may thus expect the utility function to rise steeply initially, and then to level off gradually up to very high outcomes, resulting in a highly concave function.

The situation is exactly the opposite in developing countries. Important decisions need to be taken frequently, following the agricultural cycle. With consumption close to the subsistence level, such decisions are of vital importance, and mistakes can be very costly indeed. Furthermore, fitness reacts strongly to economic outcomes. A substantial literature in economic history points to the number of surviving offspring increasing in income levels in Malthusian economies (Lee, 1987; Clark and Hamilton, 2006; Clark, 2007; Goodman, Koupil and Lawson, 2012). Although no longer truly Malthusian, many modern-day developing countries inherit some Malthusian characteristics, including child mortality rates that are inversely linked to income and education (Gakidou, Cowling, Lozano and Murray, 2010; O'Hare, Makuta, Chiwaula and Bar-Zeev, 2013).

Our model predicts variation between environments, but is less suited to capture variation within environments. We remain largely agnostic as to what may be driving the latter. Possibilities include mis-perceptions of consumption opportunities and biased beliefs (Tversky and Kahneman, 1974; Barber and Odean, 2001; Abdellaoui, L'Haridon and Paraschiv, 2011b), educational choices of parents (Doepke and Zilibotti, 2014; 2017), idiosyncratic experiences, and genetic factors (Cesarini et al., 2009). These elements are beyond the scope of the present paper, which focuses on shared environmental factors.

3 Data

3.1 Sampling Framework and Descriptives

Sampling. The sampling area comprises the mountainous Ethiopian heartland. Lower-lying regions in the south and east of the country were excluded from the sampling frame because they have different geographical features and farming practices, and because of security concerns. Observations inside these regions derive from 20 different *Woredas* (administrative districts). Figure 1 shows the geographical distribution of sampled households. The sampling area measures 7.5 degrees latitude times 5.2 degrees longitude, corresponding to 581 by 714 kilometers.

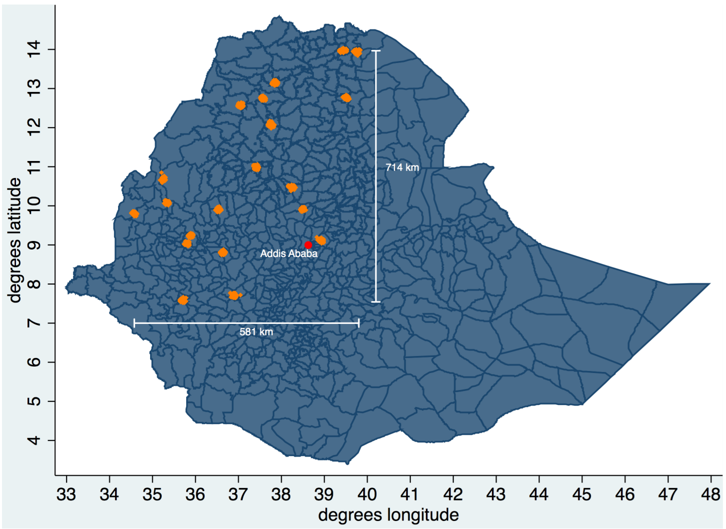


Figure 1: Geographical location of samples in Ethiopia

The sampling frame was developed to ensure representation at the Woreda level of rainfall patterns in terms of both annual total and variation; the four classes of traditionally defined agro-ecological zones found in the wider Nile basin; the vulnerability of food production systems; and irrigation prevalence. The 20 Woredas were selected to match as closely as possible the proportions for each class (see S6 for further details). From each Woreda, 50 households were randomly selected from municipal rosters across 147 Gots (villages). Upon our first visit in 2013, 930 households from the original 1000 could be identified. Some households were absent and could not be reached after several attempts, leaving us with a sample of 918 in the first round of the experiment (2013). In the second round (2015), this number was reduced to 910 households, with some households lost due to issues in identifiers that impeded matching and because of attrition.

In the third round (2017), this sample was further reduced to 861 household. The risk experiment and survey was run with the household head in individual interviews.

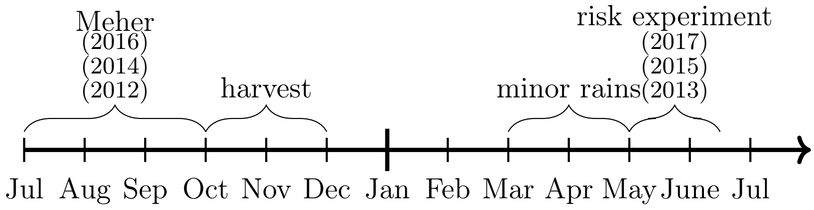


Figure 2: Time line of data collection

Timeline. We use rainfall levels during the main agricultural season, or *Meher*, as our main independent variable. This rainfall season allows the main staple crops, such as teff, maize, and wheat, to be grown. The main rainfalls tend to start in late June and continue through September. Harvest takes place from October to November (figure 2). There further is a small rainy season in March to early May, used mostly for small vegetable crops. We conducted all risk measurements in May and early June—an idle period during which no farming activities take place.

3.2 Rainfall data

We obtained our rainfall data from the Climate Hazards Group, using the Climate Hazards Infra-Red Precipitation with Station data (Funk, Peterson, Landsfeld, Pedreros, Verdin, Shukla, Husak, Rowland, Harrison, Hoell et al., 2015). The data combine satellite imagery with station data to produce a grid of rainfall data with a $0.05° \times 0.05°$ resolution (3×3 nautical miles close to the equator). This gives us 343 distinct observations about historical rainfall levels. We refer to these separate locations as *areas*. The data comprise rainfall levels from 1981 to the present. Our main measure of interest is the total rainfall occurring during the main rainy season, or *Meher*, by area. In addition, we use the total rainfall during the minor rainy season, or *Belg*, as a placebo.

We assemble measures of historical means and standard deviations by area from 1981 to 2010. We then define shocks as absolute deviations from the long term means:

$$d_{at} = |\ell_{at} - \mu_a|\,, \tag{2}$$

where d_{at} indicates the absolute deviation in a given year t in a determined area a,

ℓ_{at} indicates the local rainfall level in that year, and μ_a is the local average historical rainfall from 1981 to 2010. This definition emerges naturally from our model, capturing the informative value of the rainfall realization. The assumption underlying the use of this measure is that agricultural practices are adapted to local circumstances.

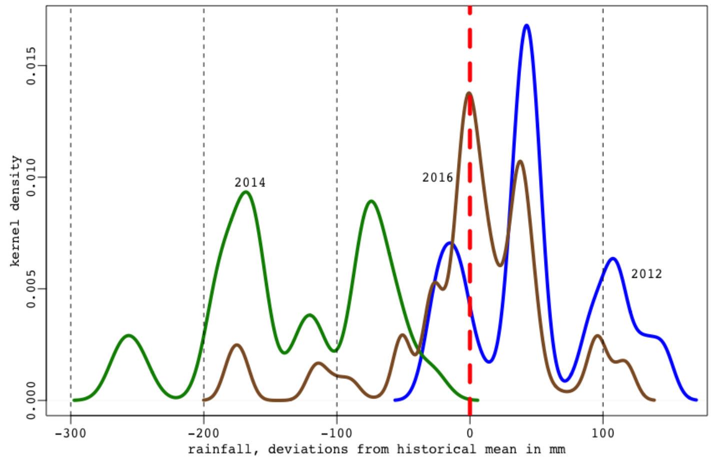


Figure 3: Rainfall deviations from historical average

Rainfall variability across geographic areas as well as year-on-year within each area is large. Historically, we observe most of the variation in rainfall across Woredas, which account for fully 76% of the variation. The variation across areas within a given Woreda, on the other hand, is relatively small at 5% of the total. The remaining 19% of the overall variation takes place within any given area over time. Figure 3 shows the rainfall deviations for the Meher seasons immediately preceding our preference measurements (the deviations lagged once and twice are shown in figures S2 and S3). In 2012 we observe some excess rainfall, although few households experience rainfall that falls above 100mm in excess of the historical average. In 2014 we observe extensive droughts, with a large majority of the sample experiencing shortfalls in rain, some of them up to 300mm below the historical average. This constitutes one of the worst droughts in recent memory, on a par with the one of 1982, which triggered extensive famines.[6] Finally, in 2016 we observe largely regular rainfalls, with a minority of respondents experiencing severe droughts. Overall, we thus observe considerable droughts during our study period but only moderate excess rainfall. As a consequence, we expect any effects of shortfalls in

[6]While the drought was comparable to the one in 1982, its consequences were not. The consequences of the 1982 drought, with over a million lifes lost over the following years, were so disastrous bacause of the combination with civil war which made the access for help organizations all but impossible (Dercon and Porter, 2014).

rain to be clearly identified, while any effects of excess rainfall will likely be more tricky to detect due to the weak 'treatment'. In addition to the variation over time, we also observe large geographical variation in rainfall patterns in each season. Figure S1 shows maps of our 20 Woredas indicating average rainfall levels for the Meher immediately preceding our risk experiments. By comparing the maps to each other, one can see that the Woredas affected by rain shortfalls and excesses change over time.

3.3 Risk preference data

Elicitation procedure

We elicited a total of 14 certainty equivalents (CEs) for each respondent per round.[7] CEs are well suited for experiments in developing countries, because they are amongst the simplest tasks to measure risk preferences. Physical representations of the choice problems are straightforward. Only monetary amounts vary within a given choice list, while probabilities stay fixed. This makes it easy to lay out money on a table and represent probabilities physically, which is a great advantage given people's familiarity with money. Furthermore, they are easy to manipulate and to use in the construction of nonparametric indices, as well as in the identification of the parameters of preference models, thus explaining their popularity (Bruhin, Fehr-Duda and Epper, 2010; Abdellaoui, Baillon, Placido and Wakker, 2011a; Dohmen et al., 2011; Sutter et al., 2013).

The 14 prospects differed both in terms of probabilities of obtaining the high amount or *prize*, and in terms of the amounts themselves. The design follows the one used by Vieider et al. (2015), but only used the gain part of that experiment and known probabilities. We presented prospects with 50-50 probabilities first, namely Birr $\{(30, 0); (60, 0); (120, 0); (180, 0); (180, 60); (180, 120)\}$. These prospects were followed by prospects in order of ascending probability, with $p = i/8, i = 1, ..., 7$, offering either Birr 120 or else 0.[8] The expected earnings for a risk-neutral participant were around €18 (USD 24) in PPP, with the highest prize reaching €30 PPP. These are significant amounts for rural Ethiopian households, a majority of whom live on less than $2 PPP per day. Tasks were kept in a

[7] In 2017, we elicited a total of 17 CEs. The three additional CEs were a repetition of CEs already included in the 14 initial ones, and were added to obtain an indicator of the test-retest reliability of our measures. By adding them to the end of the experiment, after the 14 regular measures had been obtained, we avoided tinkering with the main design features of the panel.

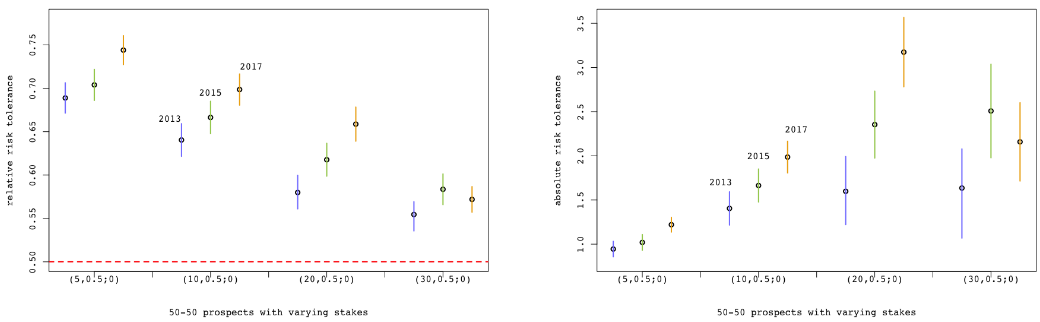
[8] Given that all choices were presented physically to the subjects, many of whom were illiterate, we did not have experimental instructions in the traditional sense. We did, however, have instructions that were meant as a reference for the enumerators. These instructions are included in section S5.

fixed order to facilitate the physical representation of the prospects using colored balls and money, since only either probabilities or outcomes would typically change from one task to the next. A large test of order effects conducted with students in Vietnam showed that such a fixed ordering facilitated the task, while not producing different results from a random order (results available upon request). A previous experiment in rural Ethiopia also showed no order effects (Vieider et al., 2018). Importantly, the lists are balanced on average, so that the expected value switching point falls into the middle of the choice list, serving to avoid systematic noise deriving from the administration of unbalanced choice lists (Andersson, Tyran, Wengström and Holm, 2016; Vieider, 2018).

Subjects were asked to choose repeatedly between a prospect and a list of sure amounts ranging between the high and the low amount of the prospect and changing in steps of 3 Birr. Since they have to choose between this invariant lottery and different sure amounts, it is straightforward to find the amount at which subjects want to switch from choosing the prospect to choosing the sure amount. The CE of the prospect is then simply encoded as the average sure amount around the switching point (using an interval regression between the two bounding values does not affect our results in any way). In an initial example, subjects were first offered a choice between a given prospect or zero. They were then offered a choice between that same prospect and the highest outcome of the prospect. This procedure served to test the understanding of the tasks, and to nudge subjects towards switching from the lottery to the sure amount at some point in the list. If this procedure showed that a subject had not understood the task, enumerators were instructed to explain the task again. Single switching was not enforced after this in the elicitation process. However, only in very few instances did subjects want to switch back to the lottery after they had switched to the sure amount. We dropped the five observations were this happened from the data. At the end of the experiment, one choice task was chosen at random to count for real pay—the standard procedure in this kind of elicitation. Subjects also obtained a participation fee of 30 Birr, to compensate them for their time and ensure that nobody left empty-handed.

Descriptive insights on risk tolerance

Figure 4 shows risk tolerance for 50-50 prospects offering a prize of x or else 0. (Figure S10 depicts risk tolerance across probability levels, and indicates the typical pattern of risk tolerance declining in probability; see L'Haridon and Vieider, 2019). The measure of relative risk tolerance depicted in panel 4(a), shows a clear pattern of decreasing relative risk tolerance, or equivalently, increasing relative risk aversion (IRRA). This is highly significant, with each subsequent measure as stakes increase resulting in lower levels of relative risk tolerance, and it is indeed the typical pattern found in the literature. Panel 4(b) shows a measure of *absolute* risk tolerance for the same prospects. The pattern here is less clear. While there appears to be a tendency toward increasing absolute risk tolerance, or equivalently, decreasing absolute risk aversion (DARA), when passing from the smallest prize to the next larger one, this pattern subsides as prizes increase further. Fitting a parametric model to the data, we indeed find that an exponential utility function, incorporating IRRA and CARA, fits the data significantly better than a logarithmic function (Scholten and Read, 2014), combining IRRA with DARA (WAIC of 238,664.5 versus 238,740.2 in favour of the exponential function, giving it a weight of 1;[9] this holds both in an expected utility framework, and in generalizations thereof allowing for nonlinear probability weighting—see section S2 for details).



(a) Relative risk tolerance

(b) Absolute risk tolerance

Figure 4: Risk tolerance in 50-50 prospects

The figure shows non-parametric indices of risk tolerance for 50-50 prospects offering a prize x or else 0. Relative risk tolerance is defined as $\frac{ce}{x}$, constituting an index of risk tolerance *relative* to the outcome range. The dashed horizontal line in panel (a) indicates risk neutrality. Absolute risk tolerance is defined as $ce - ev$, where ev designates the expected value of the prospect. The pattern we find is one of increasing relative risk aversion (IRRA) and constant absolute risk aversion (CARA).

Variance decomposition and correlations

Some interesting insights can be obtained from a variance decomposition of our measures. The highest levels of variance registers at the residual level, with $E(\sigma_r^2) = 0.055$,

[9] *WAIC* stands for Watanabe-Akaike Information Criterion; see e.g. Gelman, Hwang and Vehtari (2014a) or McElreath (2016), chapter 6, for a discussion. The weight attributed to a model can be intuitively interpreted as a probability that the specific model is the best amongst the tested models.

closely followed by variance over time, with $E(\sigma_t^2) = 0.042$. Variance across subjects and Woredas is considerably lower at $E(\sigma_s^2) = 0.007$ and $E(\sigma_w^2) = 0.010$, respectively.

To garner an understanding of the significance of these results, it is more fruitful to examine the intraclass-correlation coefficient (ICC) across the different levels.[10] An intuitive interpretation of the ICC is that it captures the correlation between randomly drawn observations from that group (Snijders and Bosker, 2012). At the level of measurements in a single time period, we find an ICC of $\rho(t) = 0.48$, indicating that two random measurements taken for the same individual in a given year show a correlation of 0.48 on average. This is indeed consistent with the large variation of preferences across prospects we have documented above. To try and separate prospect-dependent preferences from pure noise, we can take a look at the test-retest reliability—the correlation between two measures for identical tasks administered in the same session. At 0.66-0.71, this measure falls close to but somewhat below typical measures observed on Western data collected with students.[11] This suggests that the true correlation between any two tasks, after controlling for attenuation, is about 0.7.

There are two further measures we want to look at. The first is the ICC at the individual level, ie. aggregating across individuals and Woredas while assuming the residual variance to be equal to 0, $\rho(s, w|\sigma_r^2 = 0)$. We can interpret this as a correlation of the means for the same individuals over time, which we quantify at $\rho(s, w|\sigma_r^2 = 0) = 0.288$ (put a different way, 71% of the total variation between aggregated measurements takes place across time). This figure is in line with previous findings on the inter-temporal correlation of preferences in the literature (see Chuang and Schechter, 2015, for a review). Once we control for attenuation, this figure increases to 0.41—still rather low. The upshot of this finding is that it should come as no surprise that cross-sectional analysis performs poorly at identifying correlates of risk tolerance—cross-sections measured in different years will be very different from each other.

The final comparison we are interested in concerns the similarity of individuals within the same Woreda. It is most meaningful to examine this measure while setting the

[10]The ICC is defined as the proportion of total variance captured at a given level of analysis. For instance, the ICC across time is defined in our context as $\rho(t) = \frac{\sigma_t^2}{\sigma_r^2+\sigma_t^2+\sigma_s^2+\sigma_w^2}$.

[11]E.g., Brooks, Peters and Zank (2013) report that about 70% of repeated choices matched the initial choices, with this proportion increasing to 73% if they focus on gains only as we do here. They also provide a short list of papers in the literature which report similar figures. Abdellaoui, Kemel, Panin and Vieider (2019) report somewhat higher figures of correlations between 0.75 and 0.8 in an experiment using very high stakes with Western students.

inter-temporal variance to 0, $\sigma_t^2 = 0$. What is left are then the risk preferences across individuals once inter-temporal fluctuations are averaged out, which we will refer to as *idiosyncratic preferences*. Under this assumption we find an ICC of $\rho(w|\sigma_r = 0, \sigma_t = 0) = 0.568$. In other words, the idiosyncratic risk tolerance of two random individuals from a random Woreda shows a correlation of 0.568 after accounting for variation over time. This suggests that the environment of a respondent indeed plays a major role in the determination of her risk preferences.

4 Econometric Analysis

We analyse our data using a random effects panel model including Woreda fixed effects. We use fixed effects to guard against the possibility of bias arising from time-changing predictors that are correlated with the error terms. Since our predictors overwhelmingly vary across Woredas rather than individuals, fixed effects at this level are sufficient—a fact to which we will return below. The nesting of individual-level effects in the Woreda fixed effects ensures that our errors are clustered at the level of treatment stratification. Relative to individual-level fixed effects this setup stabilizes the estimation of the residuals, while explicitly dealing with noise in the data—a factor that is important, given our interest in the cross-sectional as well as the time-varying effects.

We start by sketching our general model. We explicitly model heterogeneity between prospects, i, for a given subject, s, sampled from a district or Woreda, w, in a given year, t. The general model we estimate models risk tolerance, r, as follows:

$$r_{wsti} = \alpha_t + S_{st}\beta + X_{st}\zeta + w + \nu_{ws} + \eta_{wst} + \epsilon_{wsti}, \tag{3}$$

where α_t is a global intercept including time fixed effects, and the matrix S_{st} contains measures of rainfall shocks, so that the coefficient vector β captures the effects of shocks on risk tolerance. The matrix X_{st} contains additional time-changing controls, as well as interaction terms between time-changing characteristics and fixed characteristics of the respondents, and ζ the relative coefficients. The term $w + \nu_{ws} + \eta_{wst} + \epsilon_{wsti}$ is a composite error term. The part $\nu_{ws} + \eta_{wst}$ represents a classic random-effects panel data model, with $\eta_{wst} \sim \mathcal{N}(0, \sigma_t^2)$ and $\nu_{ws} \sim \mathcal{N}(0, \sigma_s^2)$. We augment this random effects model with two additional terms. First, the Woreda fixed effects w guard against issues arising from potential correlations of the error term with the treatment variables, and cluster the errors at the Woreda level.[12] The term $\epsilon_{wsti} \sim \mathcal{N}(0, \sigma_r^2)$ represents residuals at the level of the measurement, i, allowing us to use all individual measurements, rather than averaging over measurements and thus discarding potentially useful information.

To account for heterogeneity in the propensity of choice errors, we explicitly allow for heteroscedasticity in the residual error term. That is, we let $\sigma_r^2 = \sigma_{r0}^2 + \sigma_{rw}^2 + \sigma_{rs}^2$, whereby the residual variance may differ across individuals and Woredas. We find such a model to fit our data significantly better than a homoscedastic specification (WAIC of -15182.7 versus -9483.1, giving it a weight of 1).

The model above allows us to identify the time-changing effects *within* individuals. In addition, we are interested in what determines individual-level risk tolerance, or *idiosyncratic risk tolerance*, captured by $\delta_s = \alpha + w + \nu_{ws}$. That is, we obtain the individual-level residuals after all time-changing characteristics are controlled for. We then analyze the correlates of idiosyncratic preferences in a second stage, by regressing the preferences on a set of predictors while accounting for the measurement error in the individual preference measures (Gelman, Carlin, Stern, Dunson, Vehtari and Rubin, 2014b; McElreath, 2016). That is achieved using the following system of equations:

$$\delta_s \sim \mathcal{N}\left(\frac{\theta_s}{se_s^2}\right) \tag{4}$$

$$\theta_s = k + Z_s\gamma + \xi_s, \tag{5}$$

where δ_s and se_s are the mean and standard error of the idiosyncratic risk preference measures, and θ_s is an estimated parameter of the mean to be regressed on a matrix of predictors Z containing characteristics of the environment and the individual, with an intercept k and a residual ξ_s. This method thus allows us to take the measurement uncertainty in idiosyncratic risk tolerance into account in the second stage regressions.

We estimate our model using Bayesian routines, which is natural in a hierarchical setup (Gelman and Hill, 2006; McElreath, 2016). Since most priors are estimated endogenously within our model, we only need to specify the highest-level priors—typically referred to as *hyperpriors*—for our aggregate parameters. We follow best practice by

[12]The clustering derives from the fact that the random intercepts at the individual level, ν_{ws}, are distributed with mean w. This explicitly takes the interdependence of individual measurements in one and the same Woreda into account, thus delivering a conservative estimate of the effects of independent variables intervening at the Woreda level.

giving the priors for the model parameters a normal distribution, with a standard deviation chosen in such a way as to be one order of magnitude larger than the estimates we expect based on the scale of the data. For scale parameters we use similarly vague Cauchy distributions truncated at zero (Gelman, 2006). Given the quantity of data, the results we present are not sensitive to changes in these priors. All estimations were run in *Stan* using Hamiltonian-Monte-Carlo simulations (Carpenter, Gelman, Hoffman, Lee, Goodrich, Betancourt, Brubaker, Guo, Li and Riddell, 2017), and launched from *R* using *RStan* (Stan Development Team, 2017). Convergence was checked by making sure that no divergent iterations occurred, by visually examining the trace plots, and by inspecting the Gelman-Rubin $\hat{R}$ statistic (Gelman, Rubin et al., 1992).

5 Results

We subdivide the results into three subsections. We start by showing that the inferences derived from our model emulate those based on a model with individual-level fixed effects. We then examine the effects of shocks on risk tolerance over time. Subsequently we turn to idiosyncratic risk preferences, and try to explain them based on observable characteristics of the environment and the decision maker.

5.1 Woreda fixed-effects, within, and between estimators

We pursue two aims in this section. The first is to show that our model with Woreda fixed-effects results in conclusions on the effects of time-varying variables that are indistinguishable from those obtained using individual fixed effects. The second is to show that this is not trivially true, in the sense that our data show a strong correlation between the predictors and the residuals that would result in spurious inferences from a cross-sectional analysis of our data.

We start from the model comparison. The main comparison of interest is with individual fixed effects, to probe the suitability of our model for the identification of time-varying effects. Lest one think that the comparison trivially produces the same result, e.g. because inferences from the cross-sectional data and panel data result in identical conclusions, we juxtapose these with the *between* results. We obtain both within and between results from a specification following a variation on Mundlak (1978):

$$r_{sti} = \alpha_t + (S_{st} - \overline{S}_s)\beta_1 + \overline{S}_s\beta_2 + \nu_s + \eta_{st} + \epsilon_{sti}, \tag{6}$$

where $\overline{S}_s = \frac{1}{T}\sum_{t=1}^{T}(S_{st})$, β_1 is the vector of within coefficients, and β_2 the vector of between coefficients. Under the condition $\beta_1 = \beta_2$, the within estimator and the between estimator would result in the same conclusions (Allison, 2009; Wooldridge, 2010).

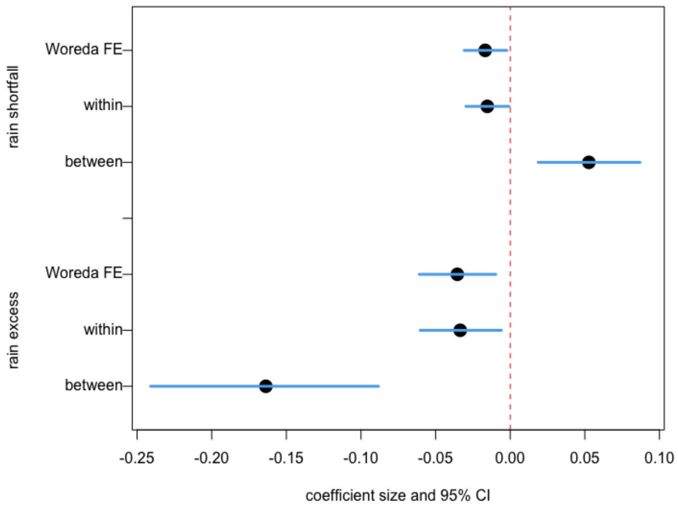


Figure 5: Comparison of estimators: hierarchical, within, between

Figure 5 depicts the regression coefficients together with their 95% credibility intervals (*CIs*, the Bayesian equivalent of confidence intervals) separately for rain shortfalls and excesses. Two clear sets of results emerge from the figure. One, the coefficients estimated using our favourite model and the within estimator are virtually identical. Two, this result is not trivial. Indeed, the between estimator is significantly different from the within estimator for both rain shortfalls and excesses.

A major implication of the differences in the within and between estimators is that cross-sectional analysis of our data would necessarily result in biased conclusions. This is indeed also the case if we include Woreda fixed effects, which results in an estimate of no effect of the rainfall shocks since they vary at the district level, while in reality we observe risk tolerance to decline with shocks. This insight acquires special significance in our context, since the great majority of previous studies investigating the effect of shocks on preferences have used cross-sectional data. That literature is indeed highly split, with several studies concluding that shocks increase risk tolerance (Voors et al., 2012; Page, Savage and Torgler, 2014),[13] while others reached the opposite conclusion (Kim and Lee, 2014; Cameron and Shah, 2015; Jakiela and Ozier, 2018). Reviewing this literature in more detail than we can afford here, Chuang and Schechter (2015) concluded that the effect is null on average. While the solidity of individual findings in that literature will depend on the identification strategy and the level at which the shock occurs, a detailed re-examination of the literature based on these criteria is beyond the scope of this paper.

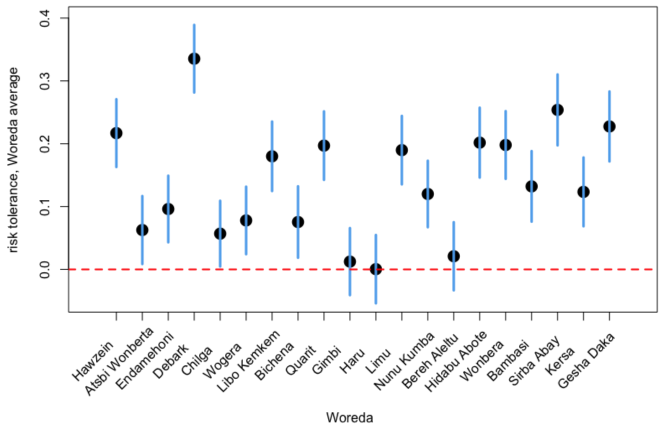


Figure 6: Geograhical cumulation of risk preferences by Woreda

To see why the within and between estimator may differ, it is useful to recall that preferences are highly geographically aggregated in our sample (recall the high ICC at the Woreda level). This high cumulation at the level of the Woreda is the main culprit for the spurious associations detected in cross-sectional analyses of our data. Figure 6 shows the average level of idiosyncratic risk tolerance by Woreda. There exist large and highly significant differences between Woredas. Far from disappearing once rainfall shocks are controlled for, we will see below that in our study period they actually increase after controlling for shocks. Spurious inferences may then result even though our shocks are exogenous and random *ex ante*. Potential confusion may arise from different usages of the term 'exogenous'. Applied researchers often take the term 'exogenous' to indicate that the predictor of interest is unaffected by any actions the study participants may undertake. Our measures unambiguously fulfil that criterion. In econometrics,

[13] Callen, Isaqzadeh, Long and Sprenger (2014) reached similar, albeit more complex, conclusions. They reported that the interaction of exposure to violence and fear priming increased risk tolerance in two separate lists, but to different degrees across the lists, which they organized by postulating a 'preference for certainty'. However, Vieider (2018) showed that behaviour in both lists was driven by noise, casting doubt on their measurements and thus also on the conclusions reached based on those measures.

on the other hand, the term 'exogenous' is used to signify 'uncorrelated with the error term'. Exogeneity of the first type is thus not sufficient to guarantee exogeneity of the econometric type. The positive between estimator for rainfall shortfalls shown above then just indicates that these shocks by chance prevalently hit relatively risk tolerant districts during our study period (and vice versa for excess rainfall).

To see why this issue may arise, consider this highly stylized example. Assume a country is divided into risk seekers, living in the south, and risk averters, living in the north. Further assume that shocks truly have no effect on risk preferences. If the particular shocks we observe hit prevalently in the south, we may conclude from cross-sectional analysis that shocks *increase* risk tolerance. If, on the other hand, the shocks we observe hit prevalently in the north, we might be tempted to conclude that shocks *decrease* risk tolerance. Even if exogeneity and randomness hold for our shock measures, the conclusions drawn would be false in both cases, since preferences were not uniformly distributed across regions ex ante. Unless we observe and correctly measure differences in preferences pre-existing the shocks themselves, these differences will be subsumed in an error term that is now correlated with the predictor variables. Given the 'exogenous'—in the applied rather than econometric usage of the term—nature of rainfall, it is all too easy to mistake such spurious correlations for causal effects.

5.2 Rainfall shocks reduce risk tolerance

We now describe the effect of shocks on risk tolerance over time. Table 1 shows the regressions of risk-tolerance on rainfall deviations (placebo regressions using the minor rains can be found in section S4). Notice that we only present reduced form regressions, regressing risk tolerance directly on rainfall deviations and not including any economic controls. There are two reasons for this. One, our model clearly predicts that the effects should pass through economic effects on consumption, so that adding economic variables as controls would be conceptually misguided. And two, our economic variables measured in the surveys—notwithstanding considerable effort dedicated to obtaining plot-wise data on crop type and production levels—are extremely noisy, and do not yield any sensible insights. This is indeed not unique to our data, with several recent studies showing severe and systematic distortions in survey measurements of consumption and income for smallholder farmers (Abay, Abate, Barrett and Bernard, 2018; Lobell, Azzari, Burke, Gourlay, Jin, Kilic and Murray, 2018).

Table 1: Regression of risk-tolerance on rainfall shocks

dep. var.: risk-tolerance	(1)	(2)	(3)	(4)	(5)
rain shortfall	-0.111	-0.111	-0.168	-0.271	-0.331
	(0.026)	(0.029)	(0.038)	(0.048)	(0.052)
rain shortfall sq.	0.042	0.046	0.056	0.091	0.123
	(0.011)	(0.013)	(0.013)	(0.018)	(0.018)
rain excess	-0.234	-0.212	-19.3	-0.174	-0.380
	(0.050)	(0.053)	(0.051)	(0.059)	(0.067)
rain excess sq.	0.156	0.148	0.138	0.146	0.284
	(0.040)	(0.041)	(0.042)	(0.046)	(0.052)
rain shortfall lag 1		-0.060	-0.072	-0.065	-0.115
		(0.024)	(0.029)	(0.032)	(0.033)
rain shortfall lag 1 sq.		0.012	0.029	0.021	0.036
		(0.010)	(0.011)	(0.012)	(0.012)
rain excess lag 1		0.047	-0.004	0.010	0.026
		(0.044)	(0.025)	(0.045)	(0.049)
rain excess lag 1 sq.		-0.003	0.003	0.012	0.018
		(0.029)	(0.019)	(0.030)	(0.032)
altitude*shortfall					-0.099
					(0.021)
altitude*excess					0.083
					(0.047)
skewness*shortfall					-0.063
					(0.026)
skewness*excess					0.029
					(0.068)
animals*shortfall					0.024
					(0.017)
animals*excess					0.071
					(0.027)
year fixed effects	NO	NO	YES	YES	YES
rain deviations lag 2	NO	NO	NO	YES	YES
Var over time: σ_t^2	0.041	0.041	0.041	0.040	0.038
Var across subjects: σ_s^2	0.007	0.007	0.007	0.008	0.008

SDs of posterior samples reported in parentheses, corresponding to SEs of the mean estimates (see Train, 2009, chapter 12). The shorthand 'sq.' indicates the square of the deviations. Equation (1) includes the measures of positive and negative rainfall deviations, and their squares. Subsequent regressions add the same rainfall variables lagged once (2), year fixed effects (3), and the lag 2 rainfall variables (4). Equation (5) includes interaction effects of the rainfall measures with altitude (mean-centered), the skewness of the historical rainfall distribution, and a dummy indicating whether a household holds animals.

While statistically significant for the most part, the effects shown in table 1 are difficult to interpret due to the polynomial expressions. To overcome this shortcoming, figure 7 shows the total effect of rainfall shortfalls. The grey lines represent the total sampling uncertainty surrounding the mean parameter estimates. To highlight the economic effects of the shock, the scale on the vertical axis represents a change in the certainty equivalent for an average prospect offering either €20 PPP or else nothing. CEs can be seen to decline rapidly in rainfall shortfalls. For a rainfall shortfall of 100mm, the

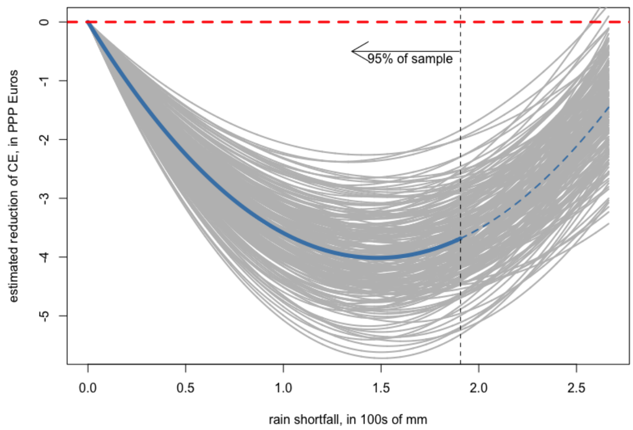


Figure 7: The effect of rainfall shocks, coefficients
Graph of overall effect of rainfall shortfalls ('droughts') on calculated certainty equivalents. The solid blue line represents the mean effect of the polynomial. The grey lines represent the full sampling uncertainty, based on 200 random draws of the parameter pairs from the Bayesian posterior. Estimates beyond 191mm, indicated by the dashed vertical line, are based on less than 5% of the sample, and should thus be interpreted with caution.

mean estimate of the CE declines by €3.59—an economically sizeable effect. Although there is some uncertainty surrounding the exact estimate of the effect, all estimates fall clearly below zero up to 200mm shortfalls relative to the historical means, and beyond. However, effects beyond 191mm, indicated by the dashed vertical line, are based on less than 5% of the treated sample, and should thus be interpreted with caution.

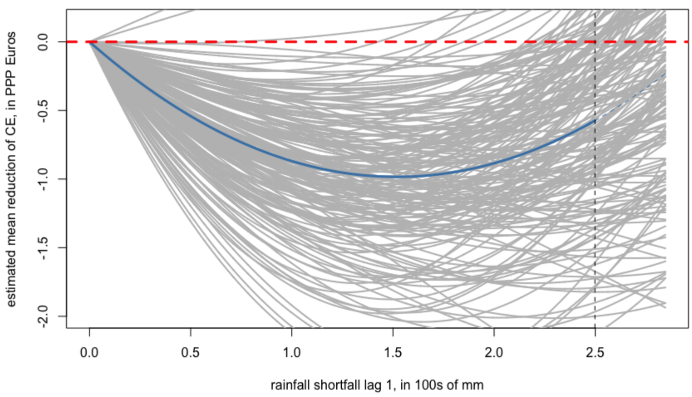


Figure 8: The effect of rainfall shocks, coefficients
Graph of overall effect of rainfall shortfalls lagged by one year on calculated certainty equivalents. The solid blue line represents the mean effect of the polynomial. The grey lines represent the full sampling uncertainty, based on 200 random draws of the parameter pairs from the Bayesian posterior. Estimates beyond 250mm, indicated by the dashed vertical line, are based on less than 5% of the treated sample, and should thus be interpreted with caution.

Figure 8 shows the effects of rain shortfalls lagged by one year. The effects are clearly weaker than for the agricultural season immediately preceding the risk measurement.

There is also some estimation imprecision, although the effects can generally be seen to be significant at conventional levels for most of the relevant range comprising 95% of the treated individuals (i.e., those who have actually experienced a shortfall). One can thus conclude that rainfall shocks have a lasting effect, with preferences partially reverting to their long-term values if no further shock is observed (or rather, in the spirit of our model, when rainfall levels are consistent with the historical distributions). Notice also that the different shocks may be cumulative. That is, if a subject is affected by two rainfall shocks in two subsequent seasons, then the economic effects may add up.

Figure 9 shows the equivalent effects for excess rainfall. Two main differences stand out. One, the effect shows a much more pronounced U-shape than for shortfalls. Two, there is considerably more uncertainty surrounding the estimates. These differences can be traced partially to the fact that we simply observe much less excess rainfall than shortfalls during our study period. This phenomenon registers both at the extensive margin—we observe an excess of more than 123mm for less than 5% of the treated sample—and at the intensive margin, with fewer subjects being affected by excess rainfall (see rainfall descriptives above and figures S4 and S5). An additional issue is that excess rainfall may affect people very differently depending on where and how it occurs. For instance, some additional rainfall may be beneficial if it occurs in places with low average rainfall. Furthermore, a given amount of additional rainfall distributed evenly over the Meher may have very different effects from the same rainfall occurring in one or two days during critical phases of the planting period. We thus argue that excess rainfall is inherently different—and more complex—than shortfalls.

The treatment effects differ by household and environmental characteristics, as highlighted by the interaction effects in regression (5). In particular, rain shortfalls have a stronger negative impact at high altitude, while excess rainfall has less of a negative impact at high altitude (significant at 10%). Households with animal holdings tend to generally react less to rainfall shocks, which is consistent with animal herding reacting less strongly to rainfall variations, and especially to excess rainfall. Finally, we find that in places having a positive skewness in historical rainfall a shortfall in rain has a considerably larger impact than in places with negative skewness in historical rain (the opposite holds true for excess rainfall, but it is very imprecisely estimated). This supports the intuition emerging from our model that what counts is the informational value of a given rainfall realization relatively to the historical distribution.

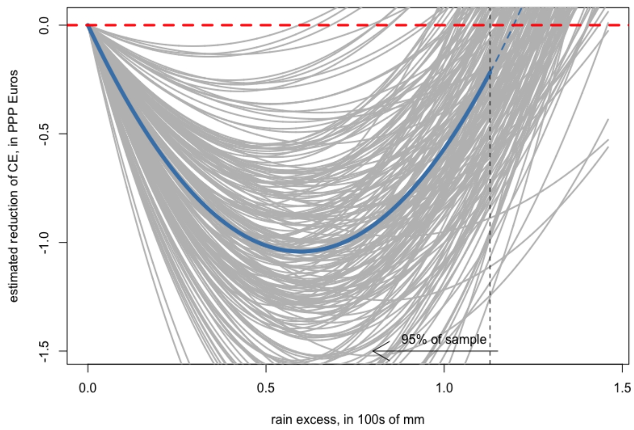


Figure 9: The effect of rainfall shocks, coefficients
Graph of overall effect of rainfall excesses ('floods') on calculated certainty equivalents. The solid blue line represents the mean effect of the polynomial. The grey lines represent the full sampling uncertainty, based on 200 random draws of the parameter pairs from the Bayesian posterior. Estimates beyond 114mm, indicated by the dashed vertical line, are based on less than 5% of the sample, and should thus be interpreted with caution.

Before concluding this section, we examine the amount of inter-temporal variance explained by our model. Regression (4) in table 1 explains about 4% of the inter-temporal variance. Adding the heterogenous treatment effects in regression (5) brings this figure to 9%. Much of the variation in preferences over time remains unexplained. The variance in idiosyncratic preferences, defined as the total preference variation across individuals, actually increases when controlling for rainfall deviations (the adjusted R^2 measure we use indicates a change of minus 15%). This reflects the observation made above that the rainfall deviations mainly affect relatively risk-tolerant households during our study period, which is indeed what drives the difference in the within and between effects.

5.3 Environmental determinants of idiosyncratic risk tolerance

We now proceed to examining correlates of idiosyncratic risk tolerance. We start by showing the raw correlations between idiosyncratic risk tolerance and features of the environment that we expect to impact consumption and hence preferences, following the predictions emerging from our model. We encode idiosyncratic risk tolerance as the means of the individual-level intercepts, as estimated in the model with time-varying characteristics just described. This means that we capture individual-level preferences purified of the effects of shocks as captured in our model, and averaged over time.

Figure 10 shows the correlation between average historical rainfall levels and idiosyn-

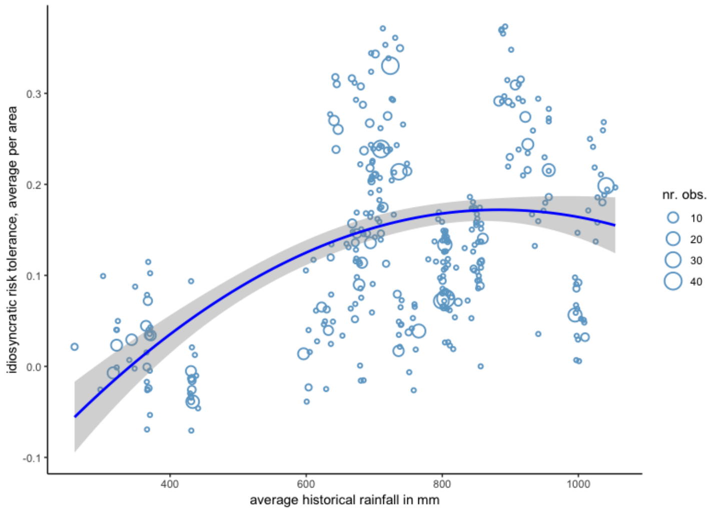


Figure 10: Correlations between historical rainfall average and idiosyncratic risk tolerance
Graph of idiosyncratic risk tolerance against the mean in historical rainfall per area. Since historical rainfall data do not differ at the individual level but rather by rainfall area, we show idiosyncratic risk tolerance aggregated by area and weighed by the number of observations contained in each point.

cratic risk tolerance. We observe a clear pattern of risk tolerance increasing in average historical rainfall, at a decreasing rate. Rainfall levels of 700-900mm during the Meher appear to constitute a goldilocks zone, although the decreasing trend at the highest rainfall levels is not precisely estimated. Figure 11 shows the correlation between the standard deviation in historical rainfall and idiosyncratic risk tolerance. Risk tolerance decreases strongly in rainfall SD, once again at a decreasing rate. Notice how these two effects are highly consistent with the predictions of our model—higher average levels of rainfall and lower levels of variability both increase risk tolerance.

In addition to rainfall levels, geographical features may also impact consumption levels. Given the mountainous geography of Ethiopia, one would expect that the altitude at which a farm is located will impact productivity, since temperatures decline quickly with altitude, and because higher altitudes create vulnerability because of exposure to wind, quick draining of soils, difficulty in ploughing due to the steepness of fields, etc. (Diamond, 2005). Figure 12 shows the correlation between idiosyncratic risk tolerance and altitude. Risk tolerance steeply declines with altitude, as expected. Finally, figure 13 shows the correlation between idiosyncratic risk tolerance and geodesic distance to the capital, Addis Ababa. The latter serves as a proxy for access to markets, and risk tolerance can be seen to decline steeply with this distance measure as well.

Clearly, these are simple correlations, and the effects may well be driven by collinearity between the different measures (see figures S6 to S8). We thus enter all of these

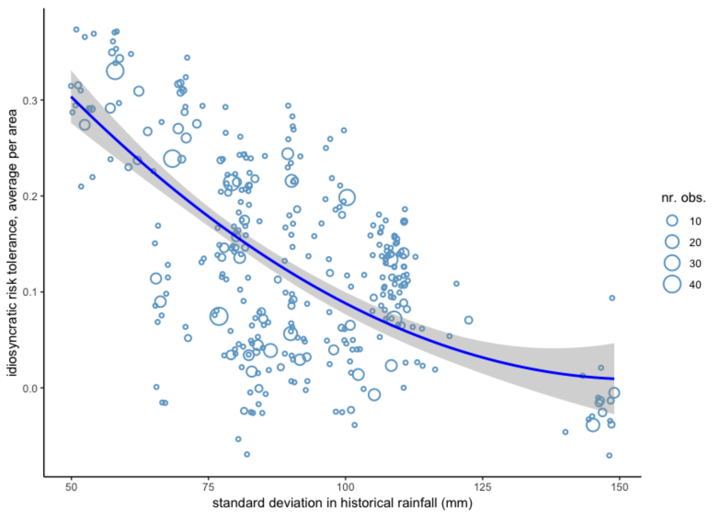


Figure 11: Correlations between historical rainfall SD and idiosyncratic risk tolerance
Graph of idiosyncratic risk tolerance against the standard deviation (SD) in historical rainfall. Since historical rainfall data do not differ at the individual level but rather by rainfall area, we show idiosyncratic risk tolerance aggregated by area and weighed by the number of observations contained in each point.

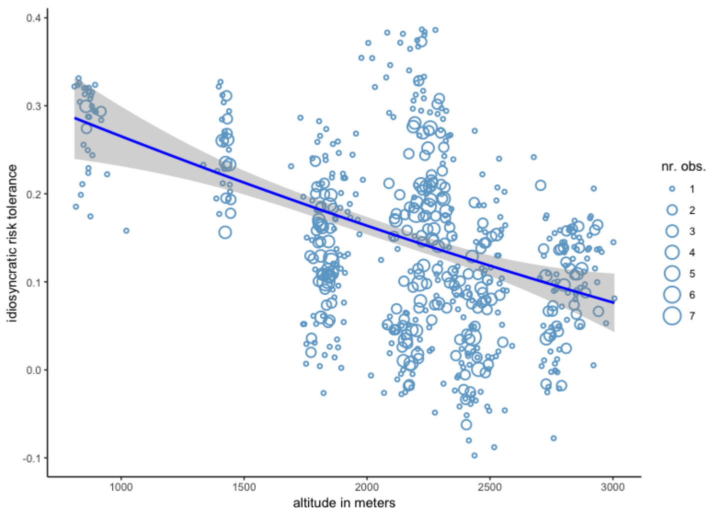


Figure 12: Correlations between altitude and idiosyncratic risk tolerance
Graph of idiosyncratic risk tolerance against altitude as measured by the GPS coordinates. Idiosyncratic risk preferences is aggregated by the independent observations at exactly the same altitude, and weighted by the number of observations.

measures jointly into a regression framework. The regressions are shown in table 2. The variables shown above remain significant when entered jointly into the regression. In addition to the variables depicted previously, we further find that risk tolerance decreases in age, and increases in the logarithm of the land holdings. According to the R^2 measures, calculated following the conservative approach proposed for weighted regression models by Willett and Singer (1988) and adjusted for the number of predictors, models (4) and (5) explain over 60% of the variance in idiosyncratic risk tolerance. This figure is an

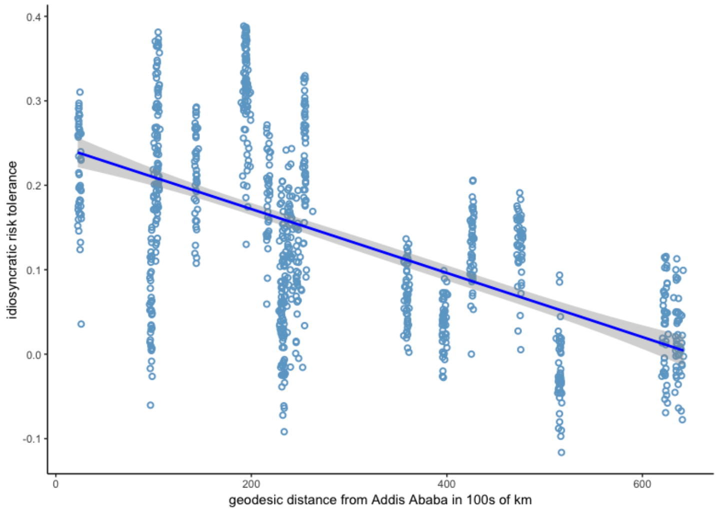


Figure 13: Correlations between distance to capital and idiosyncratic risk tolerance

Graph of idiosyncratic risk tolerance against geodesic distance from Addis Ababa.

order of magnitude larger than what has been reported in the cross-sectional literature, where typical figures are 1-7%, and figures above 10% appear to be rare.

Table 2: Regression of idiosyncratic risk-tolerance on environmental variables

	(1)	(2)	(3)	(4)	(5)
mean rain (100s of mm)	0.102		0.025	0.135	0.138
	(0.010)		(0.010)	(0.023)	(0.024)
mean rain sq.	-0.006		0.000	-0.008	-0.009
	(0.001)		(0.001)	(0.002)	(0.002)
SD rain (100s of mm)		-0.816	-1.105	-1.010	-0.961
		(0.087)	(0.092)	(0.094)	(0.099)
SD rain sq.		0.262	0.431	0.421	0.402
		(0.044)	(0.046)	(0.047)	(0.049)
altitude (1000s of m)			-0.369	-0.391	-0.364
			(0.041)	(0.041)	(0.043)
altitude sq.			0.088	0.094	0.088
			(0.010)	(0.010)	(0.011)
distance Addis (100s of km)				-0.103	-0.111
				(0.014)	(0.015)
distance Addis sq.				0.014	0.015
				(0.002)	(0.002)
age (in decades)					-0.004
					(0.002)
log hectares land					0.015
					(0.003)
male					0.003
					(0.010)
Nr. respondents	906	906	906	906	906
adjusted R^2	0.223	0.336	0.564	0.615	0.618

Standard errors reported in parentheses below coefficients. The shorthand 'sq.' indicates the square of the variable. Distances to Addis Ababa, the capital, is calculated using geodesic distance. The R^2 parameter is calculated by the conservative equation for weighted regression analysis proposed by Willett and Singer (1988) and adjusted for the number of predictors.

Figure 14 plots the distribution of idiosyncratic risk tolerance across unobservable characteristics against the distributions of risk tolerance predicted by various models based on observable characteristics. There is hardly any difference between the predictions generated by model (4), including only environmental characteristics, and those generated by model (5), including individual characteristics of the respondents as well. Both, however, predict a wide distribution of preferences that gets close to the actual distribution observed, while falling short towards the extremes of the highest levels of risk seeking and risk aversion we observe. The graph furthermore shows a benchmark obtained by predicting the distribution of risk tolerance based purely on Woreda fixed effects. The predictions based on models (4) and (5) get very close to this distribution, showing that we manage to explain most of the variance between Woredas. The biggest differences occur at the lower end, where our predictions somewhat underestimate risk aversion, and in the middle of the distribution, where our predictions overestimate—while the Woreda fixed effects underestimate—the true frequency of risk tolerance patterns.

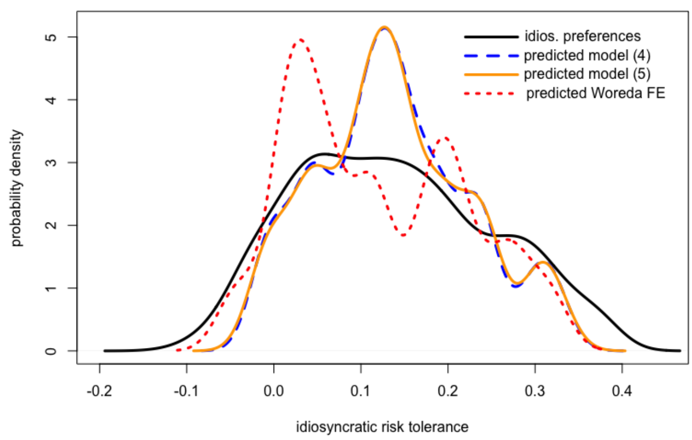
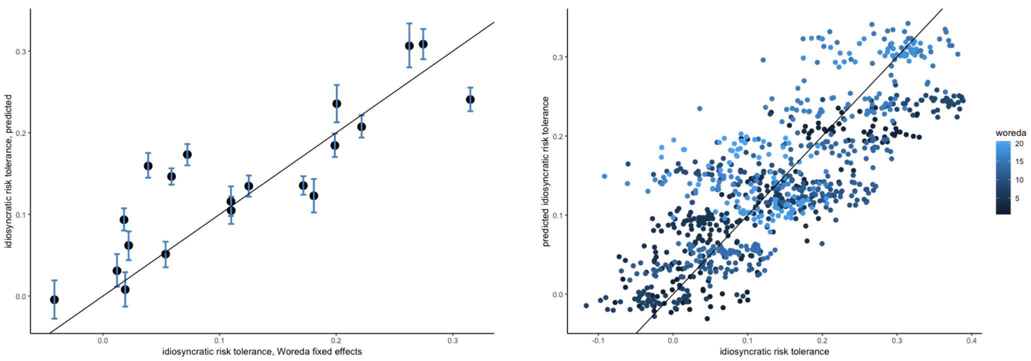


Figure 14: Estimated versus predicted idiosyncratic risk tolerance
Graph of the overall distribution in idiosyncratic risk tolerance compared to the distribution predicted by different models. The models refer to table 2, with model (4) generating predictions based on the mean and SD of rainfall, altitude, and distance to Addis Ababa (plus their squares), whereas model (5) generates predictions based on those same variables plus the individual measures. The additional curve shows the benchmark obtained by predicting idiosyncratic risk tolerance based on Woreda fixed effects only.

Ultimately, we thus do well in explaining variation between different environments, here proxied by the Woreda fixed effects (recall that most variation in the environment occurs between Woredas). We do much less well in explaining variation between individuals within the same environments, doing only slightly better than the model with

Woreda fixed effects. This is further illustrated in figure 15. The predictions at the Woreda level, shown in panel 15(a), quite closely trace the actually observed values. For about 40% of Woredas the predictions are indeed undistinguishable from the actual values, while the differences in the other cases are mostly small. Panel 15(b) shows the predictions at the individual level. Here our model performs less well, with many observations falling to both sides of the 45 degree line. This is indeed as expected. We are able to account for differences in preferences across environments, but not differences within environments, which could be driven by a variety of other factors that we do not measure. There may further be individual-level shocks unrelated to the environmental characteristics we observe, and which could account for some of the variation in preferences amongst individuals in the same environment.



(a) Predictions Woreda

(b) Predictions individual

Figure 15: Observed versus predicted idiosyncratic risk tolerance

The graphs plot the observed idiosyncratic preferences, on the horizontal axis, against the predicted preferences on the vertical axis. Panel (a) uses preferences estimated by means of Woreda fixed effects on the horizontal axis, and the predictions emerging from model (4) on the vertical axis. Panel (b) shows the idiosyncratic preferences on the horizontal axis, against the predictions emerging from model (5) on the vertical axis. The closer the points fall to the 45 degree line traced in the graphs, the better the predictions.

We are inclined to interpret the environmental effects causally. This interpretation is based on logic and plausibility, for the following reasons:

1. The effects accord with those predicted by our model, which makes causal predictions on environmental circumstances determining preferences. In this sense, the causality emerges from the theory, which is in turn supported by the data.

2. The effects of the historical rainfall measures are fully consistent with the changes over time documented above, for which a causal interpretation is beyond reasonable doubt. Especially the effect of the SD in historical rainfall closely traces the

decaying lags effect of past rainfall shocks in the time dimension of the analysis.

3. Rural to rural migration is virtually non-existent in Ethiopia, given the interdiction on selling and purchasing land. The Ethiopian constitution mandates that land belongs exclusively to the state. Committees allocate use rights to households. A key condition for the allocation of land is that the household members remain residents of the same *Kebele*, an administrative level subordinated to the Woreda (Rahmato, 2008). This allocation system creates a disincentive for migration, which is consistent with recent empirical evidence on economic migration in Ethiopia (De Brauw and Mueller, 2012).[14]

4. Accounts based on selection preceding the current land distribution, several decades or even centuries ago, and subsequent transmission of preferences through the generations are also difficult to reconcile with the evidence we present. For one, the strong impact of shocks shown in the fixed effects regressions makes such high persistence in preferences very unlikely. Furthermore, the selection hypothesis would suggest that the most risk averse respondents have selected themselves into the areas with the highest variation in rainfall and the lowest rainfall means—exactly the opposite type of selection that one might expect.

6 Conclusion

We presented unique incentivized panel data on risk preferences from Ethiopia, and paired those data with detailed historical data on rainfall levels. This allowed us to investigate the effects of rainfall shocks on risk preferences. Using a fixed effects model, we found rainfall deviations to reduce risk-tolerance. We also showed how an analysis of cross-sectional data would have led to the exact opposite conclusion, showing our contribution over a literature that has used mainly cross-sectional data. Further regressing idiosyncratic risk preferences—individual-level intercepts obtained after filtering out the effect of shocks and aggregating across years—on a variety of environmental characteristics, we uncovered effects that are highly consistent with the time-changing ones.

[14]While rural to urban migration *does* exist, the scale is too small to be able to account for our findings. Given the differences between the most risk tolerant and most risk averse Woredas, accountig for these differences by migration would imply that the large majority of people in the most risk averse Woredas would have migrated—a pattern that does simply not add up with the urbanization rates in Ethiopia. We also observe little or no evidence of migration during the timeframe of our study.

In particular, we found idiosyncratic risk tolerance to increase in the average historical rainfall, and to decrease in the standard deviation of historical rainfall, in altitude, and in distance to markets.

The effects we presented cannot be explained by mere movements along a fixed utility function. Assume for a moment that we only observe wealth or income effects (i.e. movements along a pre-existing utility function). Since we use a measure of relative risk tolerance to analyze our results, we find shocks—presumably resulting in a decrease in wealth—to increase relative risk aversion. This means that movements along the utility require a function characterized by *decreasing* relative risk aversion in order to account for our findings. Measuring utility over considerable stakes, we found utility to be characterized by *increasing relative risk aversion*—the exact opposite pattern, and the prevalent finding in the empirical literature (Fehr-Duda, Bruhin, Epper and Schubert, 2010; Wakker, 2010; Bouchouicha and Vieider, 2017). This results in a contradiction. We further find no support for decreasing absolute risk aversion, on which arguments about wealth effects must rest. We thus conclude that moves along a pre-determined utility function cannot organize our results.

We find that up to 60% of the variation in risk tolerance in our sample is explained by environmental factors. This high figure needs to be put into perspective. One of the reasons for the high value is that the preferences of individuals are highly correlated geographically in our data, with 56% of the overall variance between individuals occurring between environments, rather than between individuals within one and the same environment. Cesarini et al. (2009) documented the genetic heritability of risk taking traits using data on Swedish twins. They explain about 16% of the variation in risk taking—one of the highest proportions in the literature to our knowledge. It should, however, be clear that the relative role of genetic and environmental factors will itself not be constant across environments. Indeed, we would expect environmental variations to play less of a role in relatively more homogenous Western populations (see Ridley, 2003, for a book-length discussion). This was indeed one of the reasons for carrying out the experiment in Ethiopia—to maximize our chance to detect environmental influences.

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SUPPLEMENTARY MATERIALS (For online publication)

Environmental Forces Shape Risk Preferences

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S1 Additional descriptives rainfall data

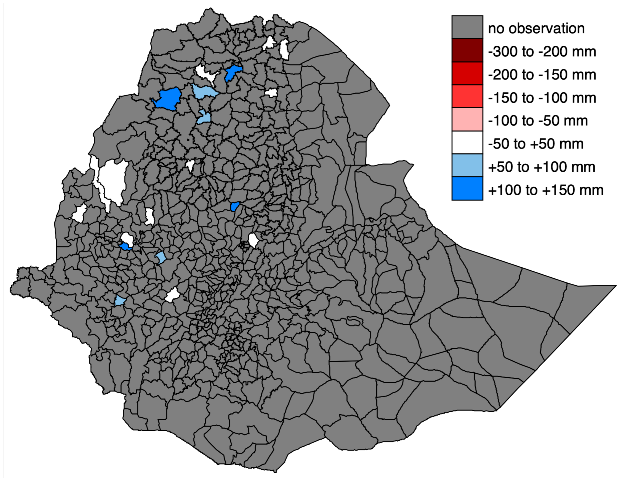
Figure S1 shows the geographical distribution of shocks during the three Meher seasons immediately preceding our risk measurements.

Figure S2 displays the rainfall deviations from the historical means, lagged by one year (i.e. for 2011, 2013, and 2015). 2011 was a largely regular year, with some relatively large outliers in terms of both excess and shortfalls in rain. 2013 was marked by a very wide distribution, with regular rainfall, excess and shortfalls all important for parts of our sample. 2015 follows in the footsteps of the very dry 2014, being characterized by large shortfalls in rain for a large part of our sample.

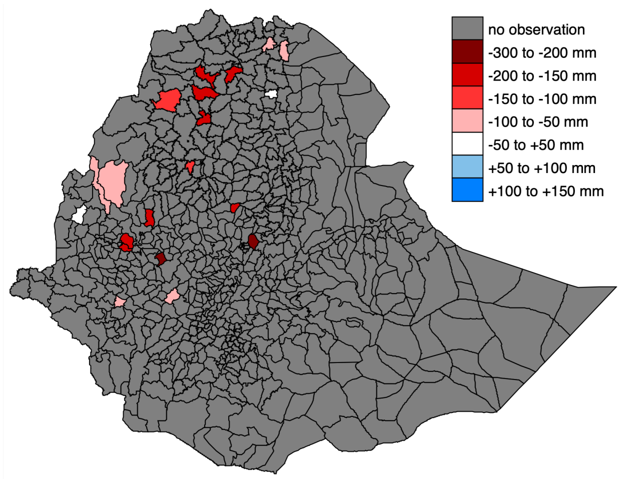
Figure S3 shows the equivalent figure for the measures lagged by 2 years, i.e. for 2010, 2012, and 2014. We have already discussed 2012 and 2014 in the main text, with 2010 thus providing the only new information. The rains in 2010 almost entirely fall into the region of ± 100 mm of the historical mean. Overall, this picture tells us that lag 2 will be poorly identified in our regressions, given how 2012 and 2014 are already included in the unlagged predictors, and 2010 does not contain large outliers in rainfall.

Figure S4 shows the rainfall deviations averaged over the three years preceding our risk preferences measurements, 2012, 2014, and 2016. All households were affected by rain shortfalls to some extent, some severely and repeatedly, as implied by means of over 150 mm. Excess rainfall, on the other hand, was much less frequent. Furthermore, the large density peak at 0 indicates that many households were entirely unaffected by excess rainfall over the main study period. This, in turn, means that the coefficients capturing the effects of excess rainfall would not be well-identified.

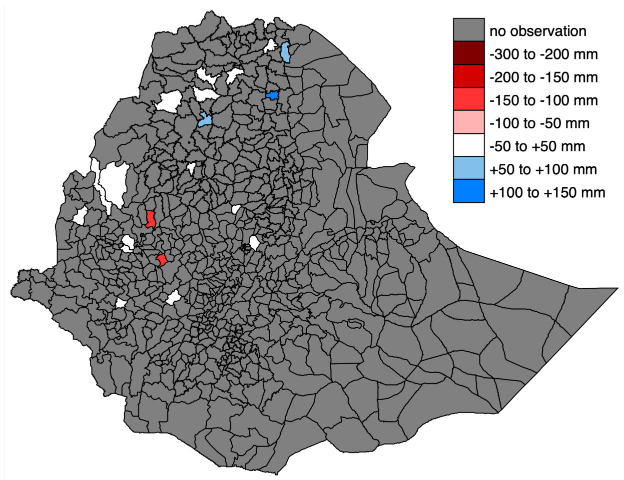
Arguably, an even more important indicator for whether a household was affected by a rainfall shock is the *meximum* deviation experienced during our observation time.



(a) 2012



(b) 2014



(c) 2016

Figure S1: Maps of geographical distribution of rainfall, deviation from historical trends, 2012-2016

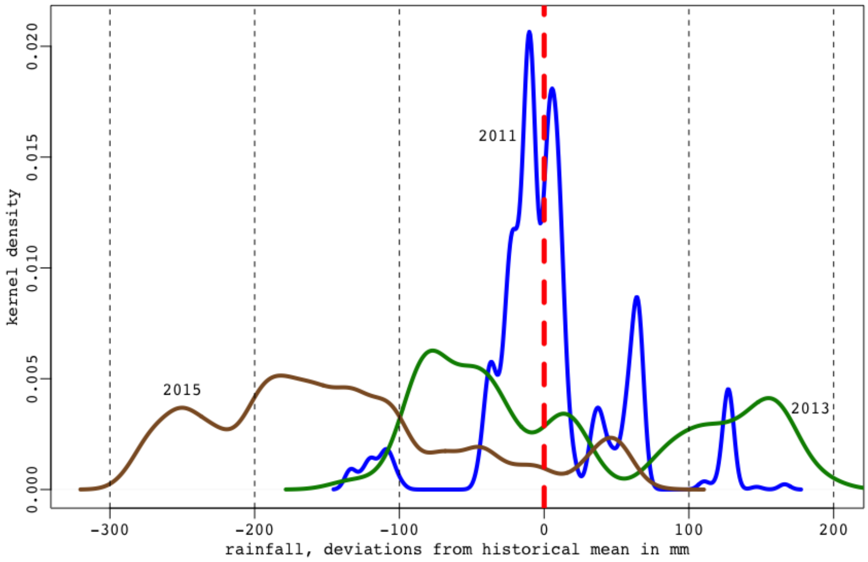


Figure S2: Average absolute rainfall deviations

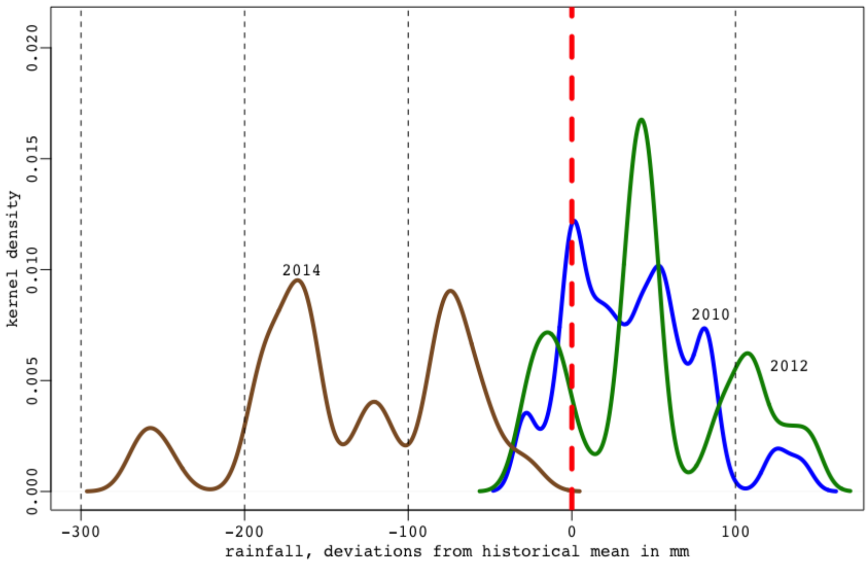


Figure S3: Average absolute rainfall deviations

This is displayed in figure S5 for our unlagged rain variable. Once again, quite a few subjects can be seen not to have experienced any positive rainfall deviation during the study period. Amongst those who have experienced excess rainfall, the modal pattern is around 50 mm—arguably not a very large shock. Few individuals have experienced more than 150 mm over the historical average. Now contrast this with shortfalls in rainfall. Nobody appears to be completely unaffected, and very few households have seen less than 50 mm. The modal drought is around 150 mm of rain below the historical average,

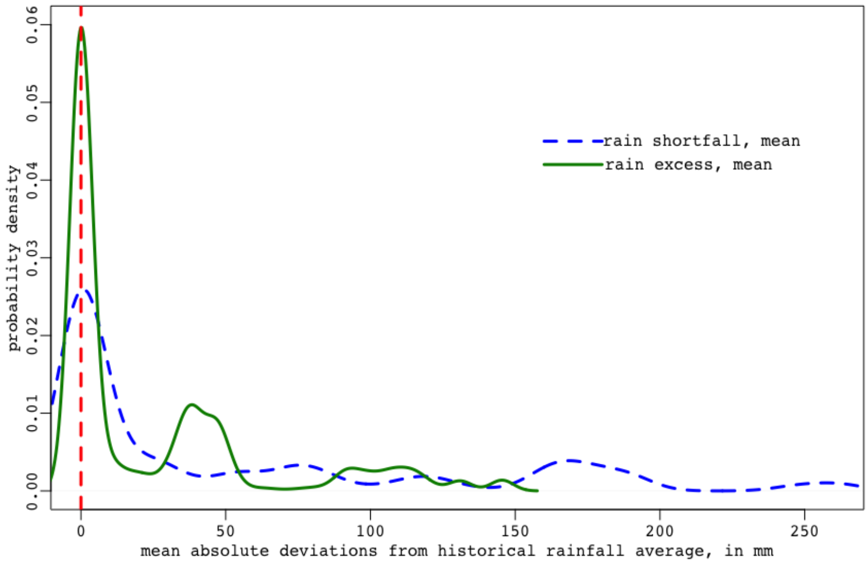


Figure S4: Average absolute rainfall deviations

with a significant number of households experiencing even more extreme droughts up to 300 mm and above.

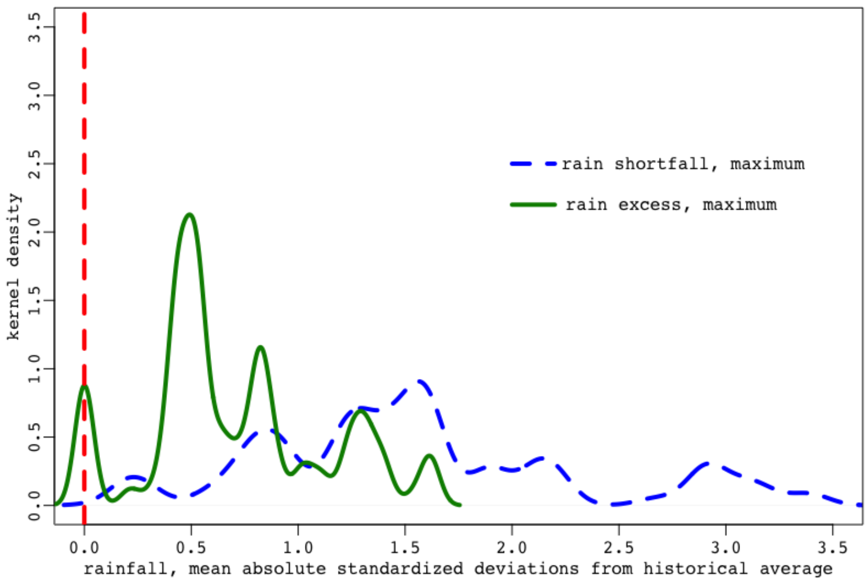


Figure S5: Maximum absolute rainfall deviation

To get a better idea of the key characteristics of the historical trends, it is useful to use summary measures such as historical means and SDs. Figure S6 plots historical standard deviations in rainfall per area against the historical mean rainfall during the Meher season for the same areas. Areas with small and large historical averages tend to be characterized by higher standard deviations. However, there is quite some variation in SDs at intermediate levels of average rainfall as well as for low levels of rainfall. This introduces orthogonality between the means and SDs that will aid our econometric identification of the effects.

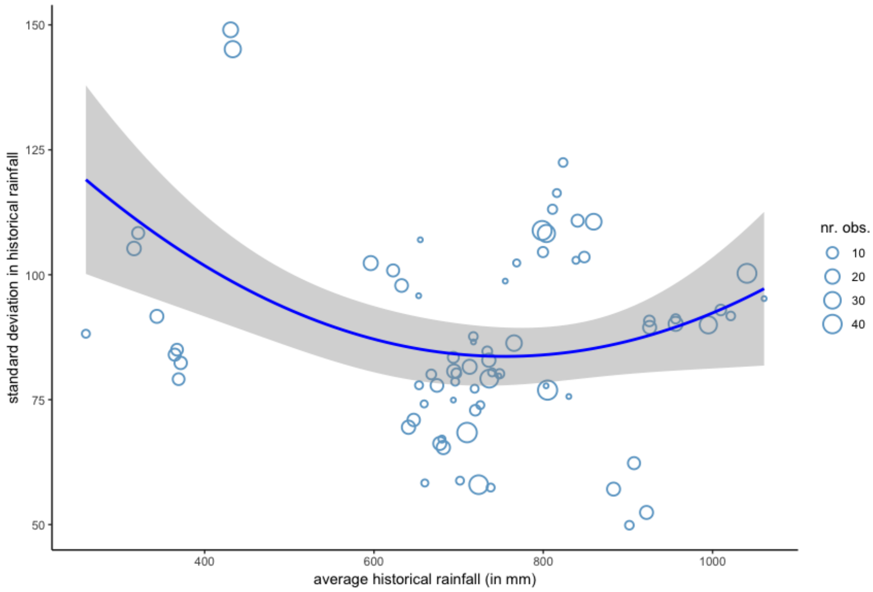


Figure S6: Historical SDs in rains against historical averages, up to 2010

Figures S7 and S8 plot the historical average and SDs respectively against altitude, measured in meters. The data are aggregated at the level of the histrorical rainfall areas. While this masks significant heterogeneity in altitude, which is averaged within any given area (in reality we have 818 distinct altitude measures), aggregating the data at this level enhances the readability of the graphs.

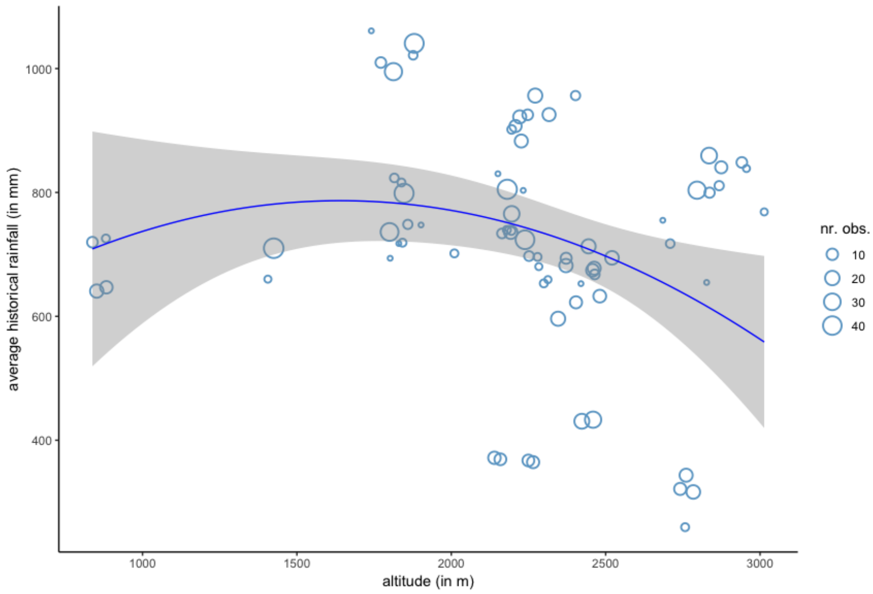


Figure S7: Historical averages against altitude, up to 2010

Rainfall averages seem to be initially increasing in altitude, up to about 1700 meters, though with little confidence given the few observations at low altitudes. Afterwards, they sharply decline in altitudes. Nevertheless, there is considerable variation in historical averages that is orthogonal to the altitude measure. Historical SDs clearly increase in altitude, reinforcing the idea of altitude creating 'vulnerability'. Again, there is enough orthogonal variation to give us confidence in the econometric estimates.

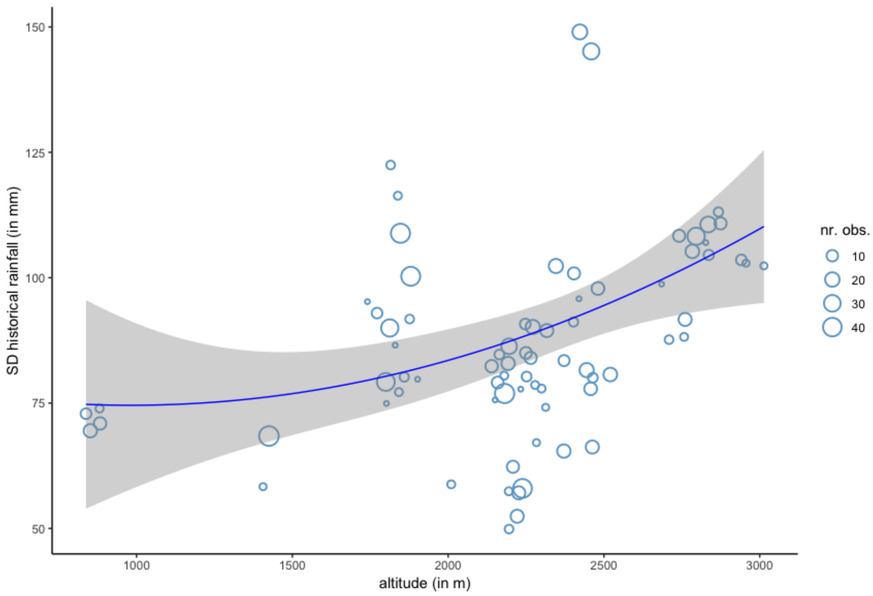


Figure S8: Historical SDs against altitude, up to 2010

Figure S9 displays the probability density functions of historical rainfall across three Woredas. The densities include variation within Woredas, as well as over time. One can see that the Woredas are clearly different in terms of means. Furthermore, the distribution of Wonbera can easily be seen to be narrower than in the other two Woredas. Whereas Haru has a roughly symmetric distribution, Atsbi Wonberta has a distribution with positive skew.

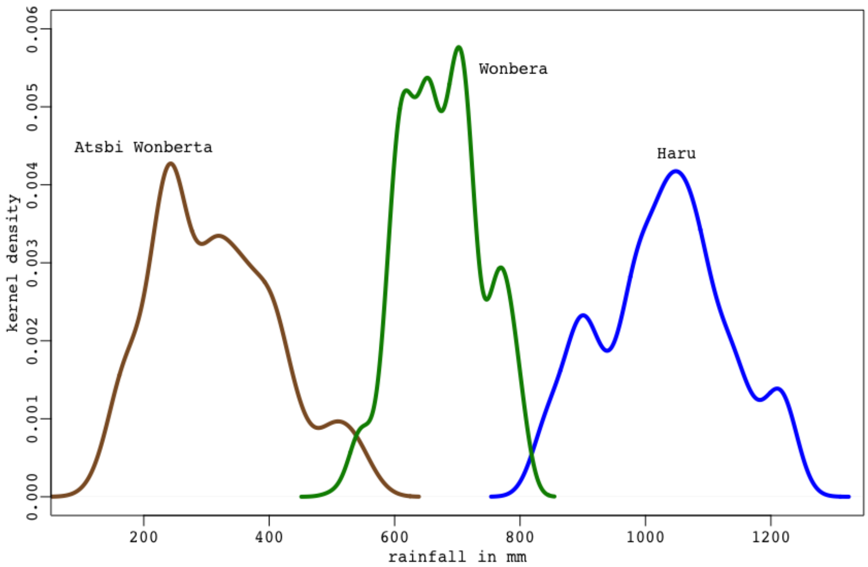


Figure S9: PDF of historical rainfall across select woredas

S2 Utility fit to risk data

Figure S10 shows how relative risk tolerance changes across the probability range. Two findings stand out. One, we again find very high levels of risk tolerance. Indeed, we find significant risk seeking for all probability levels but the highest two, and only for the highest probability level do we find significant risk aversion. Two, the pattern is clearly one of likelihood-insensitivity. Both these findings line up perfectly with the comparative evidence for students across 30 countries presented by L'Haridon and Vieider (2019), who document that i) risk tolerance systematically decreases in GDP, i.e. developing countries tend to be much more risk tolerant than developed countries; and ii) likelihood insensitivity for gains is universal. This makes it clear that any model ought to capture changes in preferences over outcomes as well as over stakes.

In order to discriminate between decreasing absolute risk aversion and constant ab-

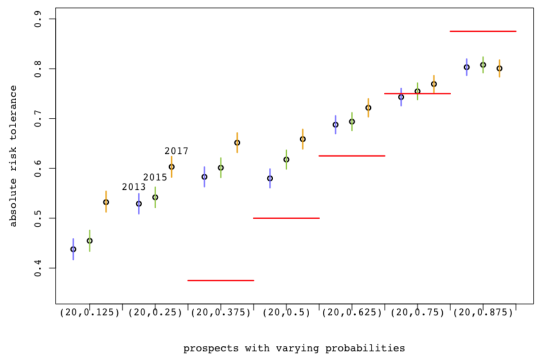


Figure S10: Relative risk tolerance across probabilities

solute risk aversion, we determine the best-fitting utility function to our data. Taking the most general approach, we can describe the indifference between a certain amount and a prospect as follows:

$$u(ce) = w(p)u(x) + (1 - w(p))u(y), \tag{7}$$

where u is a utility function and w a probability weighting function with the typical characteristics. We then estimate the relationship by using techniques akin to those used by L'Haridon and Vieider (2019) by either setting $w(p) = p$, thus assuming an expected utility framework, or by giving $w(p)$ a functional form. We always use a two-parameter formulation, and using either the 2-parameter version of Prelec (1998) of a neo-additive utility function (Abdellaoui et al., 2011a) fits the data equally well in combination with either utility function we test.

The utility function is the main part of interest. In particular, we pitch an exponential utility function, reflecting IRRA and CARA, against a logarithmic utility function, reflecting IRRA and DARA. The two functions take the following form:

$$u(x) = \frac{1 - exp(-\rho x)}{\rho} \tag{8}$$

$$u(x) = \frac{ln(1 + \rho x)}{\rho}, \tag{9}$$

where ρ is the coefficient of risk aversion. The exponential function fits the data significantly better under RDU (WAIC of 238,663 vs. 238,740, weight equal to 1; results under EUT are very similar).

S3 Raw correlations of risk measurements

We next look at correlations between our measures. Table S1 shows the correlations between the average measures of risk tolerance per year. The correlations hover around 0.3, with the correlation between 2015 and 2017 falling somewhat below that value. Correlations between 2013 and 2017 are lower at 0.21. These correlations, while certainly not large, fall towards the upper quartile of the inter-temporal correlations discussed by Chuang and Schechter (2015).

Table S1: Correlations of risk-tolerance over time

	2013	2015	2017
2013	1		
2015	0.306	1	
	($p < 0.001$)		
2017	0.213	0.265	1
	($p < 0.001$)	($p < 0.001$)	

Correlation coefficieints indicate Spearman rank order correlations between means of risk-tolerance per year.

The test-retest reliability allows us to correct the raw correlations described above for attenuation. Denote the raw correlation by $\rho(x, y)$, where x and y can designate different measurements, either using the same task at different periods in time, or using different tasks within the same session. Let x' and y' indicate re-tests—measurements using an identical tasks within the same session. The correlation coefficient corrected for attenuation will now be:

$$\hat{\rho}(x, y) = \frac{\rho(x, y)}{\sqrt{\rho(x, x')\rho(y, y')}} \tag{10}$$

We can calculate this for correlations between different tasks in 2017. While the average raw correlation between different tasks is 0.48, the corrected correlation coefficient will be 0.69. For the inter-temporal means, we need to look at individual tasks (rather than means), and we need to assume that the test-retest reliability does not change across the years (since we only measure this for 2017). Under these assumptions, the average inter-temporal correlation rises from the raw 0.28 to a corrected figure of 0.41.

S4 Placebo regression using minor rains (Belg)

Table S2 shows the placebo regressions, using the total rainfall measured over the minor rainy season, or *Belg*. Regression (1) regresses risk tolerance on the negative and positive deviations plus their squares in the Belg season only. Regression (2) adds the same measures for the Meher. Regression (3) includes rainfall during the Belg lagged once. And regression (4) once again adds the rainfall measures for the main rainy season. A clear picture emerges. The measures for the minor rainy season are generally not significant, while the measures for the major rainy season show the same significance levels as reported in the main text.

Table S2: Regression of risk-tolerance on rainfall: Placebo regressions

dep. var.: risk-tolerance	(1)	(2)	(3)	(4)
rain shortfall Belg	0.028	-0.019	-0.062	-0.114
	(0.066)	(0.070)	(0.066)	(0.087)
rain shortfall sq. Belg	-0.092	-0.100	-0.028	0.008
	(0.102)	(0.101)	(0.105)	(0.122)
rain excess Belg	0.002	-0.057	0.003	-0.060
	(0.024)	(0.029)	(0.025)	(0.029)
rain excess sq. Belg	0.018	0.045	0.004	0.035
	(0.020)	(0.021)	(0.020)	(0.022)
rain shortfall lag 1 Belg			-0.320	-0.355
			(0.084)	(0.096)
rain shortfall lag 1 sq. Belg			0.467	0.499
			(0.114)	(0.124)
rain excess lag 1 Belg			0.073	0.118
			(0.056)	(0.068)
rain excess lag 1 sq. Belg			-0.025	-0.069
			(0.042)	(0.054)
rain shortfall Meher		-0.134		-0.123
		(0.029)		(0.033)
rain shortfall sq. Meher		0.051		0.061
		(0.013)		(0.014)
rain excess Meher		-0.265		-0.236
		(0.051)		(0.058)
rain excess sq. Meher		0.181		0.193
		(0.040)		(0.046)
rain shortfall lag 1 Meher				-0.009
				(0.029)
rain shortfall lag 1 sq. Meher				0.012
				(0.012)
rain excess lag 1 Meher				0.040
				(0.048)
rain excess lag 1 sq. Meher				-0.004
				(0.032)
Var over time: σ_t^2	0.041	0.041	0.041	0.040
Var across subjects: σ_s^2	0.007	0.007	0.007	0.008

SDs of posterior samples reported in parentheses, corresponding to SEs of the mean estimates (see Train, 2009, chapter 12). The shorthand 'sq.' indicates the square of the deviations. Belg refers to the minor rains, used as a Placebo. Meher indicates the main rains.

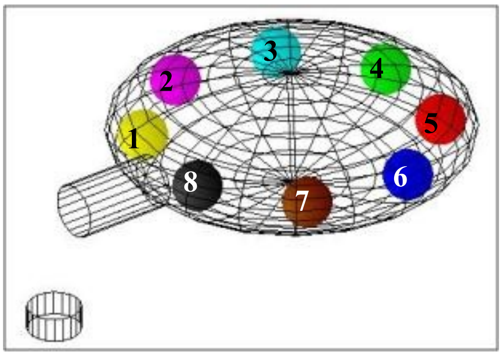
S5 Instructions for enumerators

INSTRUCTIONS

In the present experiment, you will be asked to choose repeatedly between a fixed amount of money and a lottery. The lottery will always give you a chance to win one of two amounts of money. Figure 1 shows a typical choice task. You are asked repeatedly to choose between playing the lottery and obtaining a sure amount of money. **For each row**, you are asked to indicate whether you would prefer to play the lottery or to obtain the sure amount of money by ticking the preferred option.

The urn indicated in the figure contains eight numbered balls. One ball will be extracted from the urn to determine your payoffs in case you should play the lottery. In the lottery displayed, if ball 1 , 2 , 3, or 4 is extracted, you obtain 60 Birr; if ball 5 , 6 , 7 , 8 is extracted, you obtain nothing. Please pay close attention to the amounts to be won as well as the number of balls associated with each outcome, since they change across decisions.

Fig. 1: Example of a typical decision task



Win **60 Birr** if one of the following balls is extracted:

1 2 3 4

Win **0 Birr** if one of the following balls is extracted:

5 6 7 8

Lottery	Sure amount	
O	O	0 Birr for sure
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure

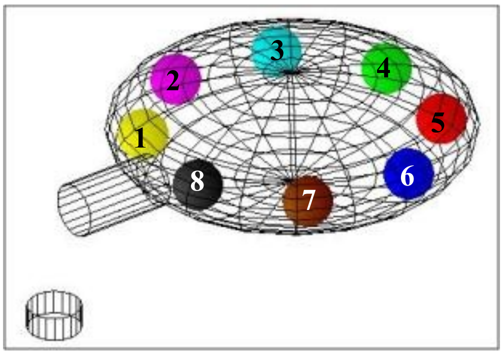
We are interested in the amount for which you will switch from preferring the lottery to preferring the sure amount. Most likely, you will prefer the lottery over a sure amount of 0, and at a certain point switch to the sure amount as the latter increases. Most likely, you would also prefer the sure amount of 60 Birr over the lottery giving you at most 60 Birr, but with a chance of obtaining 0. If you do not want the lottery at all when a positive sure amount is available, you can choose to get the sure amount in the first row and then continue with the sure amount for all choices. Where you will switch from the lottery to the sure amount depends entirely on your preferences—there are no right or wrong answers.

You will be asked to take 17 decisions, for each one of which you will need to decide between a lottery and a series of sure amounts as exemplified in figure 1 above. **Please pay close attention to the amounts to be won as well as the number of balls associated with each outcome!** Indeed, both the higher and lower amount, as well as the number of balls associated to the higher outcome, change between decision problems. Since your final payoff depends on these decisions, it is crucial for you to pay close attention to these features.

Payoff determination
After you have taken all the decisions, one of your decisions will be randomly drawn for real pay, i.e. **the amounts indicated in the decision problem will be paid out for real**. First, one of the 17 decision tasks is drawn at random, using a chance device with equal probability for each decision task to be extracted. For the extracted decision task, one of your decisions, corresponding to one row for which you had to indicate your preference between the sure amount and the lottery, will then be drawn at random with **equal probability for each row**. If for the row that is drawn you have indicated that you prefer the sure amount of money, you will simply be paid that amount.

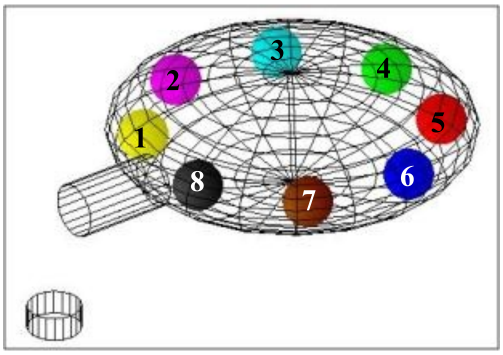
In case you have chosen the lottery for the randomly determined row, then that lottery will be played according to the probabilities indicated. You will then be paid the outcome corresponding to the ball you drew.

Decision 1



	Lottery	Sure	
	O	O	3 Birr for sure
	O	O	6 Birr for sure
	O	O	9 Birr for sure
	O	O	12 Birr for sure
	O	O	15 Birr for sure
	O	O	18 Birr for sure
	O	O	21 Birr for sure
	O	O	24 Birr for sure
Win **30 Birr** if one of the following balls is extracted:	O	O	27 Birr for sure
Win **0 Birr** if one of the following balls is extracted:			
5 6 7 8			

Decision 2



Win **60 Birr** if one of the following balls is extracted:

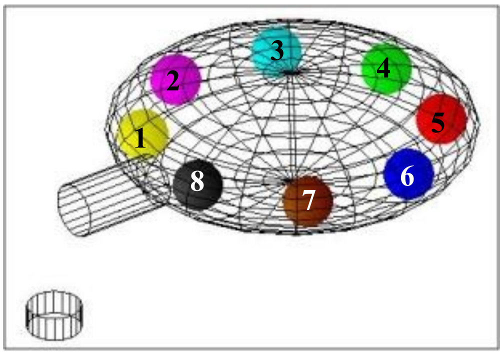
1 2 3 4

Win **0 Birr** if one of the following balls is extracted:

5 6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure

Decision 3



Win **120 Birr** if one of the following balls is extracted:

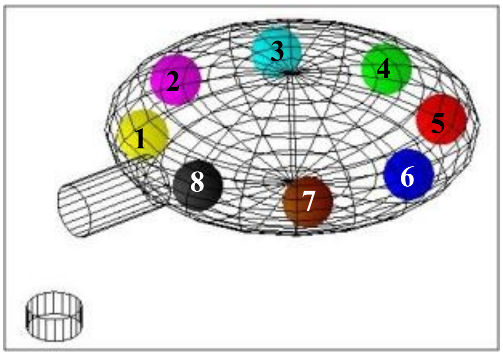
1 2 3 4

Win **0 Birr** if one of the following balls is extracted:

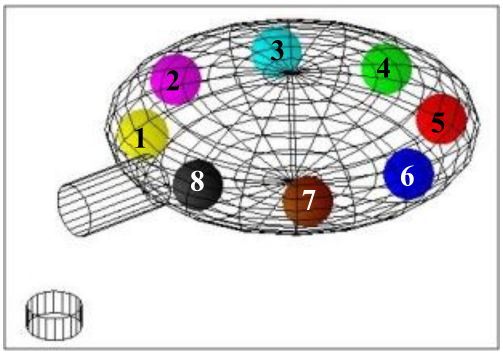
5 6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 4

	Lottery	Sure	
	O	O	30 Birr for sure
	O	O	33 Birr for sure
	O	O	36 Birr for sure
	O	O	39 Birr for sure
	O	O	42 Birr for sure
	O	O	45 Birr for sure
	O	O	48 Birr for sure
	O	O	51 Birr for sure
	O	O	54 Birr for sure
	O	O	57 Birr for sure
	O	O	60 Birr for sure
	O	O	63 Birr for sure
	O	O	66 Birr for sure
	O	O	69 Birr for sure
Win **180 Birr** if one of the following balls is extracted:	O	O	72 Birr for sure
1 2 3 4	O	O	75 Birr for sure
	O	O	78 Birr for sure
Win **0 Birr** if one of the following balls is extracted:	O	O	81 Birr for sure
5 6 7 8	O	O	84 Birr for sure
	O	O	87 Birr for sure
	O	O	90 Birr for sure
	O	O	93 Birr for sure
	O	O	96 Birr for sure
	O	O	99 Birr for sure
	O	O	102 Birr for sure
	O	O	105 Birr for sure
	O	O	108 Birr for sure
	O	O	111 Birr for sure
	O	O	114 Birr for sure
	O	O	117 Birr for sure
	O	O	120 Birr for sure
	O	O	123 Birr for sure
	O	O	126 Birr for sure
	O	O	129 Birr for sure
	O	O	132 Birr for sure
	O	O	135 Birr for sure
	O	O	138 Birr for sure
	O	O	141 Birr for sure
	O	O	144 Birr for sure
	O	O	147 Birr for sure
	O	O	150 Birr for sure

Decision 5



Win **180 Birr** if one of the following balls is extracted:

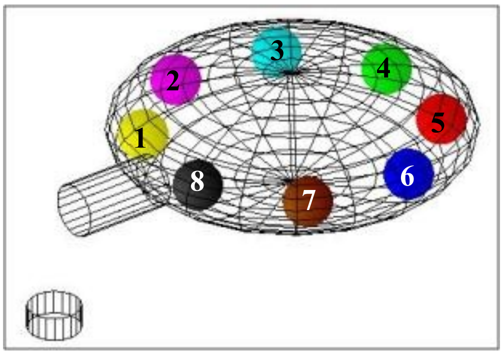
1 2 3 4

Win **60 Birr** if one of the following balls is extracted:

5 6 7 8

Lottery	Sure	
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure
O	O	120 Birr for sure
O	O	123 Birr for sure
O	O	126 Birr for sure
O	O	129 Birr for sure
O	O	132 Birr for sure
O	O	135 Birr for sure
O	O	138 Birr for sure
O	O	141 Birr for sure
O	O	144 Birr for sure
O	O	147 Birr for sure
O	O	150 Birr for sure
O	O	153 Birr for sure
O	O	156 Birr for sure
O	O	159 Birr for sure
O	O	162 Birr for sure
O	O	165 Birr for sure
O	O	168 Birr for sure
O	O	171 Birr for sure
O	O	174 Birr for sure
O	O	177 Birr for sure

Decision 6



Win **180 Birr** if one of the following balls is extracted:

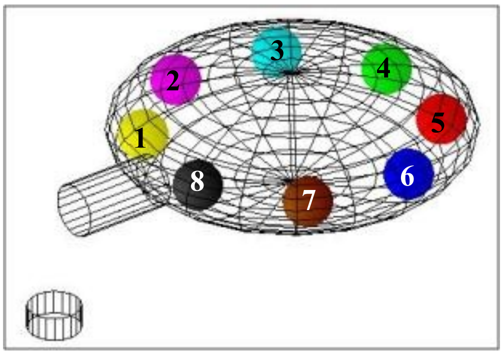
1 2 3 4

Win **120 Birr** if one of the following balls is extracted:

5 6 7 8

Lottery	Sure	
O	O	123 Birr for sure
O	O	126 Birr for sure
O	O	129 Birr for sure
O	O	132 Birr for sure
O	O	135 Birr for sure
O	O	138 Birr for sure
O	O	141 Birr for sure
O	O	144 Birr for sure
O	O	147 Birr for sure
O	O	150 Birr for sure
O	O	153 Birr for sure
O	O	156 Birr for sure
O	O	159 Birr for sure
O	O	162 Birr for sure
O	O	165 Birr for sure
O	O	168 Birr for sure
O	O	171 Birr for sure
O	O	174 Birr for sure
O	O	177 Birr for sure

Decision 7



Win **120 Birr** if one of the following balls is extracted:

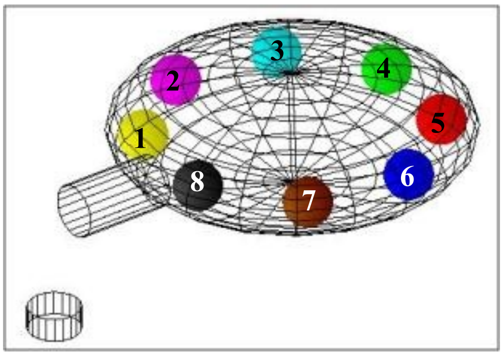
1

Win **0 Birr** if one of the following balls is extracted:

2 3 4 5 6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 8



Win **120 Birr** if one of the following balls is extracted:

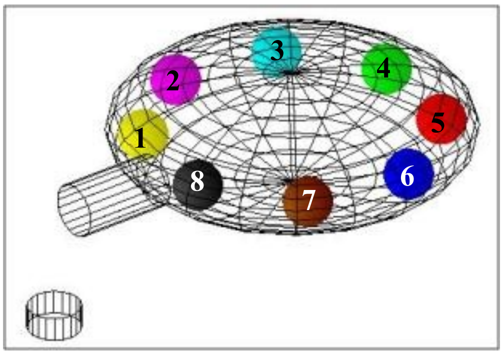
1

Win **30 Birr** if one of the following balls is extracted:

2 3 4 5 6 7 8

Lottery	Sure	
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 9



Win **120 Birr** if one of the following balls is extracted:

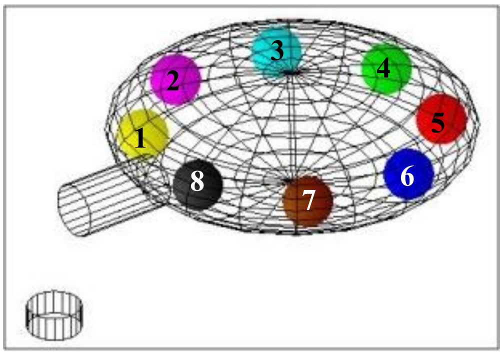
1 2

Win **0 Birr** if one of the following balls is extracted:

3 4 5 6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 10



Win **120 Birr** if one of the following balls is extracted:

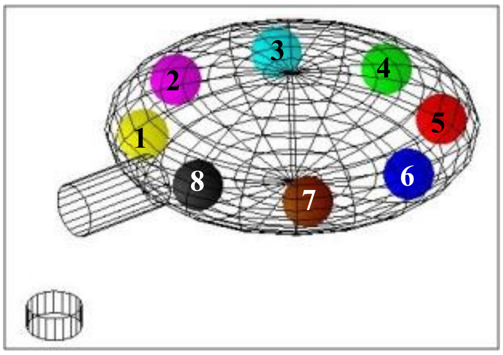
1 2 3

Win **0 Birr** if one of the following balls is extracted:

4 5 6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 11



Win **120 Birr** if one of the following balls is extracted:

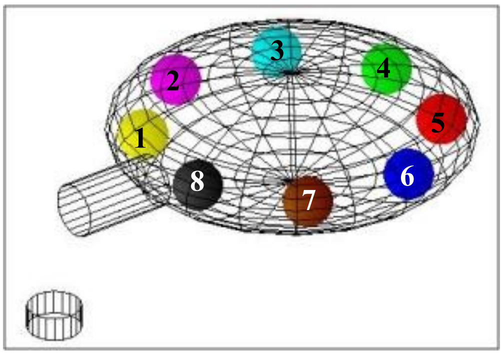
1 2 3 4 5

Win **0 Birr** if one of the following balls is extracted:

6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 12



Win **120 Birr** if one of the following balls is extracted:

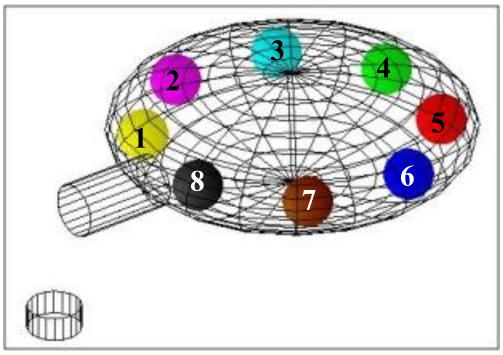
1 2 3 4 5 6

Win **0 Birr** if one of the following balls is extracted:

7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 13



Win **120 Birr** if one of the following balls is extracted:

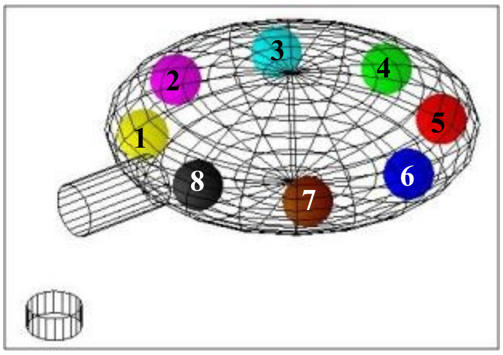
1 2 3 4 5 6 7

Win **0 Birr** if one of the following balls is extracted:

8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 14



Win **120 Birr** if one of the following balls is extracted:

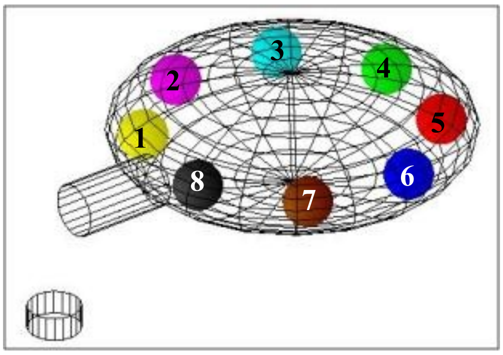
1 2 3 4 5 6 7

Win **30 Birr** if one of the following balls is extracted:

8

Lottery	Sure	
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 15



Win **120 Birr** if one of the following balls is extracted:

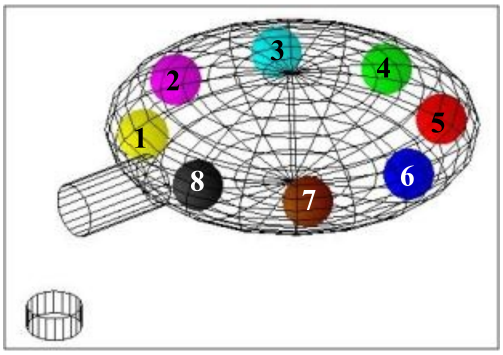
1 2 3 4

Win **0 Birr** if one of the following balls is extracted:

5 6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 16



Win **120 Birr** if one of the following balls is extracted:

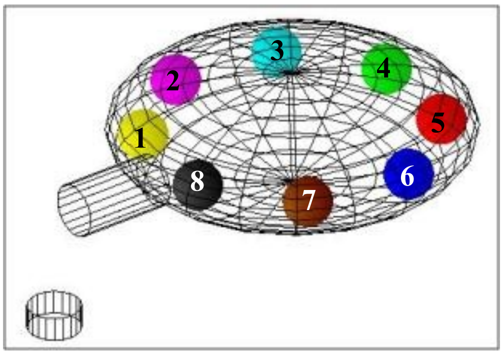
1

Win **0 Birr** if one of the following balls is extracted:

2 3 4 5 6 7 8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

Decision 17



Win **120 Birr** if one of the following balls is extracted:

1 2 3 4 5 6 7

Win **0 Birr** if one of the following balls is extracted:

8

Lottery	Sure	
O	O	3 Birr for sure
O	O	6 Birr for sure
O	O	9 Birr for sure
O	O	12 Birr for sure
O	O	15 Birr for sure
O	O	18 Birr for sure
O	O	21 Birr for sure
O	O	24 Birr for sure
O	O	27 Birr for sure
O	O	30 Birr for sure
O	O	33 Birr for sure
O	O	36 Birr for sure
O	O	39 Birr for sure
O	O	42 Birr for sure
O	O	45 Birr for sure
O	O	48 Birr for sure
O	O	51 Birr for sure
O	O	54 Birr for sure
O	O	57 Birr for sure
O	O	60 Birr for sure
O	O	63 Birr for sure
O	O	66 Birr for sure
O	O	69 Birr for sure
O	O	72 Birr for sure
O	O	75 Birr for sure
O	O	78 Birr for sure
O	O	81 Birr for sure
O	O	84 Birr for sure
O	O	87 Birr for sure
O	O	90 Birr for sure
O	O	93 Birr for sure
O	O	96 Birr for sure
O	O	99 Birr for sure
O	O	102 Birr for sure
O	O	105 Birr for sure
O	O	108 Birr for sure
O	O	111 Birr for sure
O	O	114 Birr for sure
O	O	117 Birr for sure

S6 Details sampling frame

Sampling Frame for BMZ Project "Food and Water Security Under Global Change: Developing Adaptive Capacity with a Focus on Rural Africa" in Ethiopia

Timothy Sulser
27 February 2006

The household sampling frame in Ethiopia was developed to ensure representation at the woreda level of rainfall patterns in terms of both annual total and variation; the four classes of traditionally defined agro-ecological zones (AEZs) found in the basin; vulnerability of food production systems through the proxy of frequency of food aid in the past ten years; and irrigation prevalence. All data used in this sample frame is from the forthcoming *Atlas of the Ethiopian Rural Economy* (Benson et al., in press).

Each woreda was classified according to the following criteria:

Agroecological Zone (traditional typology)
1 Kolla (blue)
2 Woina Dega (green)
3 Dega (red)
4 Bereha (grey)

Irrigation (percent of cultivated land under irrigation)
1 no data (lightest blue)
2 0 up to 2
3 2 up to 4
4 4 up to 8
5 8 and greater (darkest blue)

Average Annual Rainfall (total in mm)
1 0 up to 854 (lightest blue)
2 854 up to 1133
3 1133 up to 1413
4 1413 up to 1692
5 1692 and greater (darkest blue)

Rainfall Variability (coefficient of variation for annual rainfall)
1 0 up to 62.405 (lightest blue)
2 62.405 up to 80.691
3 80.691 up to 98.976
4 98.976 up to 117.262
5 117.262 and greater (darkest blue)

Vulnerability (number of years food aid received in past 10 years)

1 0 up to 2 (lightest red)

2 2 up to 4

3 4 up to 6

4 6 up to 8

5 8 and greater (darkest red)

Twenty woredas were selected such that across each of the above dimensions the proportion falling into each class for the sample matched as closely as possible the proportions for each class in the entire Nile basin. The selected woredas are indicated in Figure 1 and Table 1. From each of these woredas, 50 households will be randomly selected from municipal rosters to ensure adequate representativeness of the 1000 household sample. Figures 2 through 6 on the following pages present thematic maps for each of the sampling dimensions for the Nile basin.

Table 1. Key to woredas in sample.

1	Hawzen
	Atsbi
2	Wenberta
3	Endamehoni
4	Debark
5	Sanja
6	Wegera
7	Kemkem
8	Enemay
9	Quarit
10	Gimbi
11	Haru
12	Limu
13	Nunu Kumba
14	Kersa
15	Hidabu Abote
16	Bereh Aleltu
17	Wembera
18	Bambasi
19	Sirba Abay
20	GeshaDaka

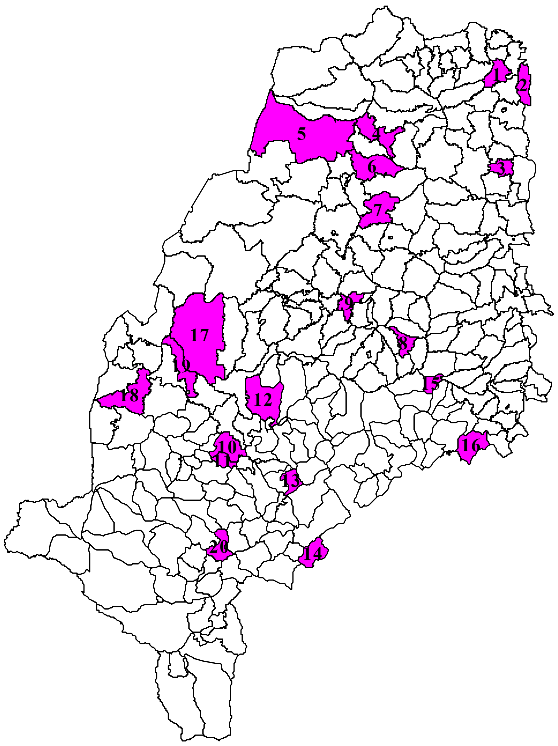


Figure 1. Map of woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names).

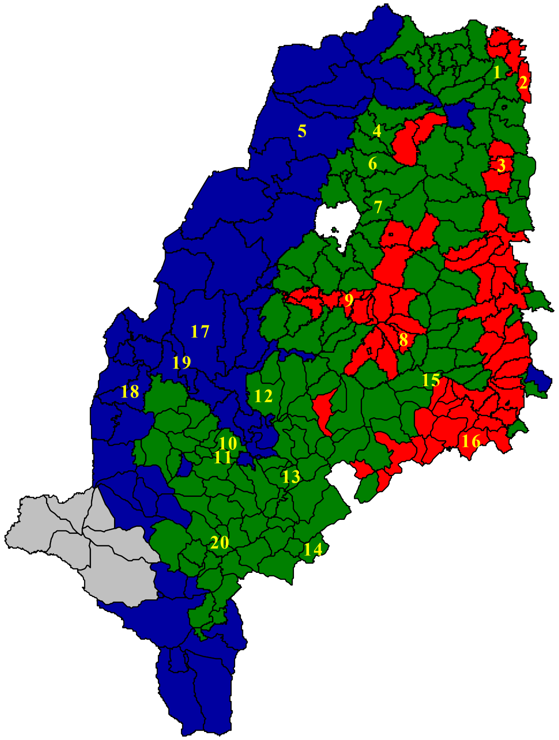


Figure 2. Thematic map of traditional agro-ecological zones and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

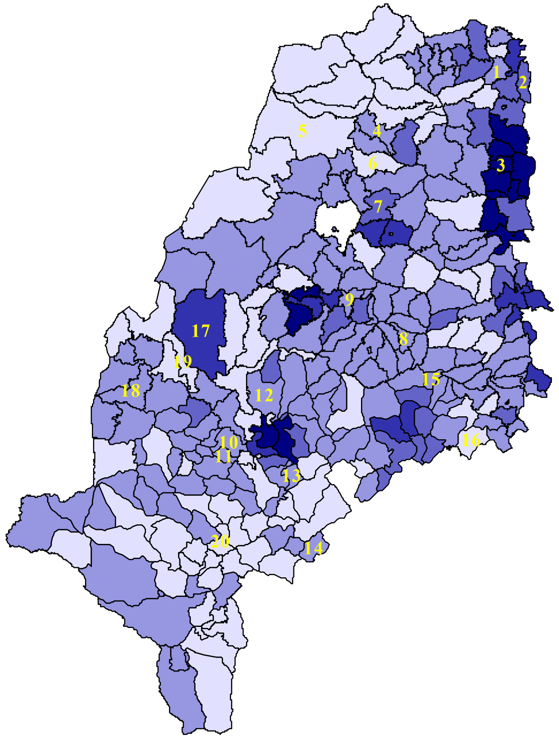


Figure 3. Thematic map of irrigation prevalence and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

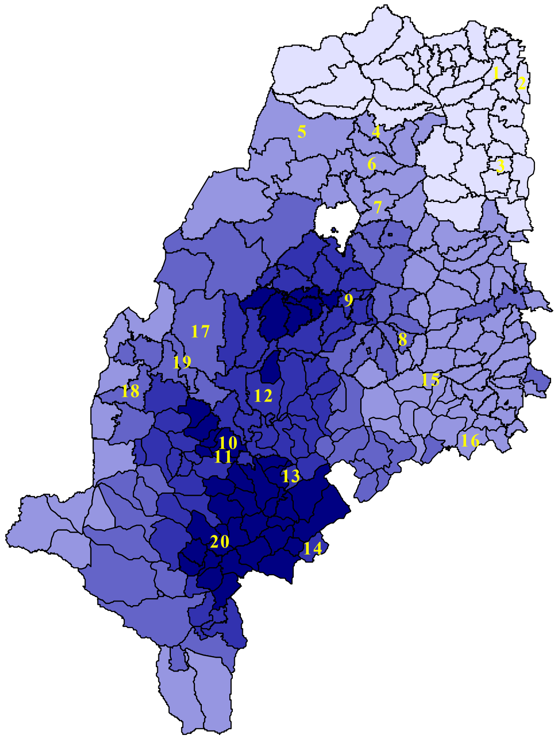


Figure 4. Thematic map of average total annual rainfall and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

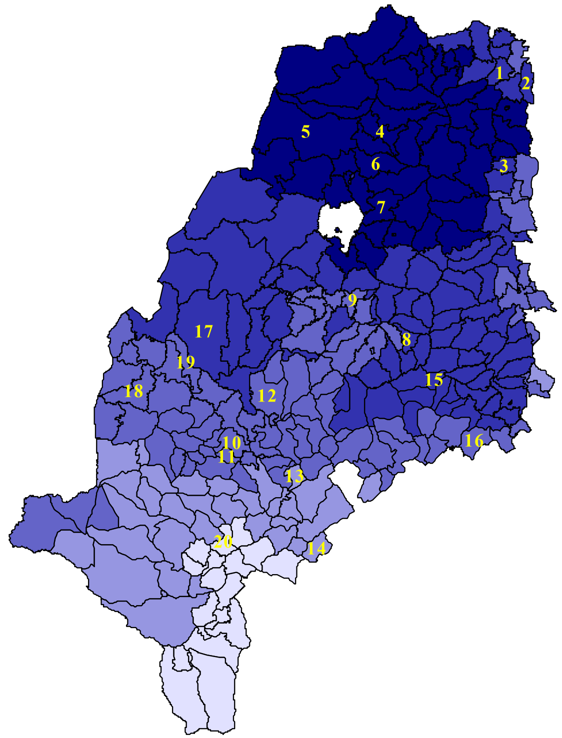


Figure 5. Thematic map of annual rainfall variation and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

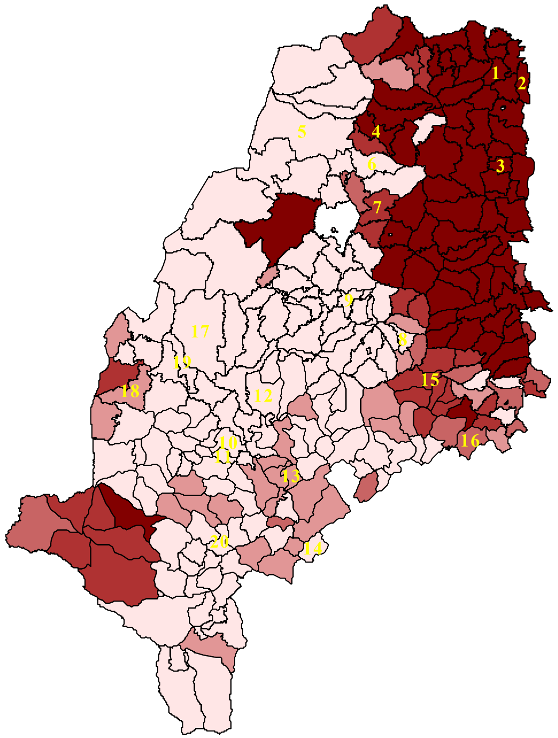


Figure 6. Thematic map of vulnerability and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).