Environmental Factors Shape Risk Preferences *

Salvatore Di Falco[1] and Ferdinand M. Vieider[2]

[1] *Geneva School of Economics and Management, Switzerland, Salvatore.DiFalco@unige.ch*
[2] *Department of Economics, Ghent University, Belgium, ferdinand.vieider@ugent.be*

April 7, 2020

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 in the short run. We further show that historical rainfall characteristics and geographical features can explain over 40% of the variation in preferences across individuals in the long run. We exclude selection effects as a plausible explanation for these patterns. This provides strong evidence that preferences adapt to the environment.

Keywords: risk preferences; panel data; shocks

JEL-classification: C93; D03; D80; O12

*We gratefully acknowlege financial support by the Swiss National Science Foundation (SNF), and by the International Development Research Centre (IDRC). We thank the Environment and Climate Research Center (ECRC) at the Ethiopian Development Research Institute (EDRI) for logistical support. We are grateful to Mohammed Abdellaoui, Bart Cockx, Gerdie Everaert, Nick Netzer, Amma Panin, Arthur Robson, Laura Schechter, Aleksei Tetenov, Peter Wakker, and Jeffrey Wooldridge for helpful discussions. We thank Avichal Mahajan for invaluable research assistance. All errors remain our own.

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 prospects of entire countries (Galor and Michalopoulos, 2012; Doepke and Zilibotti, 2014). A consensus has started to emerge that preferences are malleable (Bowles, 1998; Voors, Nillesen, Verwimp, Bulte, Lensink and Van Soest, 2012; Cohn, Engelmann, Fehr and Maréchal, 2015; Schildberg-Hörisch, 2018). It thus appears desirable to understand what shapes risk preferences. Our ability to explain the variation in preferences over time and across individuals, however, remains limited. We contribute to this topic by systematically documenting the role of environmental factors in shaping risk preferences in both the short run and the long run. The results suggest that preferences systematically adapt to the local environment of the decision maker.

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, van Soest and Wengström, 2011; L'Haridon and Vieider, 2019). 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 et al., 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 present the results of a panel study conducted with subsistence farmers from across the Ethiopian highlands—the first of its kind. We obtained detailed, incentivized measures of the risk preferences of 900 respondents. We then linked the preference measures to a 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 for the same subjects over time. And last but not least, legal restrictions on migration in Ethiopia disqualify selection effects as a plausible explanation for the cross-sectional effects of the geographical features and historical rainfall patterns we document.

We analyze our data using a within estimator. As shown by Mundlak (1978), the within estimator produces estimates identical to those obtained by means of individual fixed effects in balanced panels. Other than fixed effects, however, our approach allows us to document the effect of fixed, time-invariant characteristics in one and the same regression as those of the time-varying effects, without having to compromise on the solidity of causal identification. This makes the setup uniquely suited for our purposes. We further show that the explicit modeling of the full stratified sampling setup we use is crucial in our econometric analysis. Not only does this serve to cluster the error terms at the level of the sample stratification (Cameron and Miller, 2015), it also has a substantive impact on the estimated residuals, and hence on their explanation based on fixed environmental characteristics across subjects.

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 show that the cross-sectional effects of the observed rainfall shocks go in the opposite direction of the time-changing effects in our panel data. This shows the added value of our findings over a literature that is to date prevalently cross-sectional.[1] In the long run, we find that environmental factors—beyond driving changes in preferences over time—also explain a large part of the variation in risk preferences across space. We find that historical rainfall and geographical

[1] 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 exogeneity according to the econometric definition of the term. This is indeed what drives the difference between the within and between estimators we document.

characteristics such as altitude and distance from the capital can explain over 40% of the cross-sectional variation in idiosyncratic preferences—an order of magnitude more than the variance typically explained by previous studies.[2]

It should be emphasized that the findings cannot be interpreted as simple movements along a utility function, but constitute genuine shifts in preferences. The differences we document across space hold for households at the same wealth level, thus excluding simple movements along a fixed utility function defined over lifetime wealth as postulated by expected utility theory. 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).

Notice also that selection effects are extremely implausible as an explanation for our results on long-term determinants. The latter closely track the results obtained from our within estimator over time, for which a causal explanation is beyond reasonable doubt. Selection effects are furthermore not consistent with the migration patterns observed in Ethiopia. The Ethiopian constitution prohibits any sale and exchange of land. The purported rationale is that state ownership of land is the best mechanism to protect the peasants against market forces and prevent migration of the farming population (MOIPAD, 2001). Permanent land transfers, via inheritance and donation, happen only to individuals who reside in the same location. As a result, rural-to-rural migration is virtually inexistent in Ethiopia. Rural-to-urban migration exists, but the observed migration and urbanization rates are inconsistent with the large differences in preferences we observe between rural districts. Long-ago migration coupled with the transmission of

[2] 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, Dawes, Johannesson, Lichtenstein and Wallace (2009) attribute 16% of the variance in risk preferences to genetic factors in a sample of Swedish twins.

preferences from generation to generation is implausible, given the high changeability of preferences over relatively short time periods that we document. Overall, our results thus paint a highly coherent picture of how the environment shapes individual preferences, providing strong evidence that preferences adapt to the environment.

In summary, this paper makes two contributions to the literature. First, we contribute to the consolidation of the literature on the effects of economic shocks on risk preferences (Voors et al., 2012; Cameron and Shah, 2015; Hanaoka, Shigeoka and Watanabe, 2018). Second, and more originally, we document general effects of the environment on preferences. Our paper thus goes significantly beyond the status quo by showing that preferences do systematically adapt to the environment of the decision maker. We start by a discussion of the literature on shocks and preferences in section 2. Section 3 describes the data we use. Section 4 presents our empirical approach, and section 5 describes the results. Section 6 provides a discussion, and section 7 concludes the paper.

2 Literature and contribution

2.1 The literature on shocks and preferences

In a pioneering study, Voors et al. (2012) found risk tolerance to increase for people directly affected by violence during the civil war in Burundi when compared to people who were not directly affected. They instrumented the potentially endogenous violence using distance from the capital and altitude, both of which were negatively correlated with violence. Once they controlled for village fixed effects, however, violence lost its significant effect on risk tollerance. Callen, Isaqzadeh, Long and Sprenger (2014) documented increased risk tolerance in subjects in the vicinity of violent episodes in Afghanistan, but only if they were primed for fear. They furthermore documented reactions that differed according to the choice list format used to elicit preferences, concluding that the recall of violent episodes increases people's 'preference for certainty'. Vieider (2018a), however, showed that their alleged 'preference for certainty' resulted in reality from systematic noise in their measurements. Kim and Lee (2014) showed that people living in areas in which intensive fighting took place during the Korean war were less risk averse over five decades later. They did not control for regional fixed effects. A different strand of this literature has focused on economic or environmental shocks, rather than violence. Page, Savage and Torgler (2014) found the likelihood of choosing a lottery ticket over a sure amount of money to be higher for people who had suffered higher self-declared losses in a recent flood. Cameron and Shah (2015) studied the impact of self-declared floods as well as objectively measured earthquakes on risk preferences in Indonesia, and found recent exposure to a disaster to result in increased levels of risk aversion.

A more recent literature has explicitly emphasized the use of state-of-the-art causal identification mechanisms. Cohn et al. (2015) conducted a controlled experiment with finance professionals, and found that participants being primed with a stock market boom subsequently made less risk averse choices than participants primed with a bust scenario. Jakiela and Ozier (2018) investigated the effects of episodes of violence following an election in Kenya on a survey containing a measure of risk taking to determine whether the arrival of the violence altered the detected patterns. They concluded that violence decreased risk taking in their sample, which was not directly exposed to the violence. Moya (2018) investigated the effect on risk aversion of violent trauma in Colombia at the extensive margin. He reported that more traumatized individuals tend to be more risk averse, and that this effect tends to vanish over time.

Most closely related to our setup are panel data investigations of risk preferences. Liebenehm (2018) used survey questions of risk taking deployed in Thailand and in Vietnam to study the effects of idiosyncratic versus covariate shocks. The use of potentially endogenous consumption levels as the main independent variable, however, and employment of a random effects model to analyze the data cautions against a causal interpretation of the results. Hanaoka et al. (2018) documented the effects on risk aversion of being exposed to a big earthquake in Japan using fixed effects. They did, however, find effects that were not coherent across demographic groups, and null in the aggregate data. Brown, Montalva, Thomas and Velásquez (2018) used two different sets of hypothetical lottery questions collected before and after the rise in violence due to the war on drugs in Mexico, and documented the effect of the letter on risk aversion. They concluded that a surge in violence over time increased risk aversion while controlling for individual fixed effects. To draw causal inferences, they assumed the violence to be exogenous.[3]

[3]While several other panel datasets including some measure of risk taking exist, they are often ill-suited for investigating causal determinants of 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 major exogenous shocks are rare. The presence of insurance and social safety nets means that the consequences also tend to be less dramatic in most cases. 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.

2.2 Within- versus between-effects of rainfall shocks

The papers discussed above have used a wide array of analytical approaches, and have reached disparate conclusions. Our first contribution is to add to the literature emphasizing precise causal identification strategies. We thus start by detailing the effects obtained from a longitudinal versus cross-sectional examination of our data. In particular, we deploy the standard within-between estimator suggested by Wooldridge (2015) as an alternative to the Hausman test—if the within and between estimators coincide, then the conclusions from a longitudinal and cross-sectional analysis of the data will yield the same results. If the two estimators differ, then the residuals are not independent from the predictors, imposing the use of a within or fixed effects estimator.

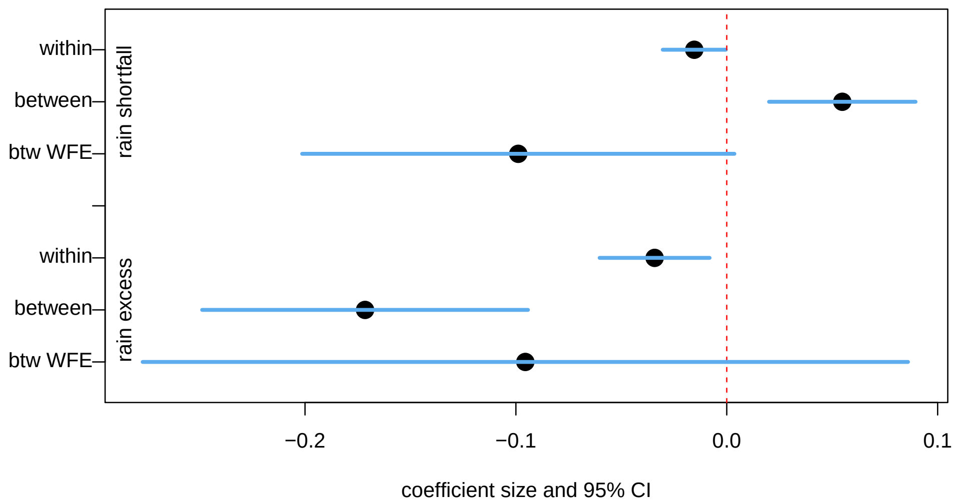


Figure 1: Within versus between effects of rainfall shocks

Graph of regression coefficients with 95% confidence interval. The shorthand 'btw WFE' stands for the between estimator with Woreda fixed effects.

Figure 1 shows the different estimators, separately for positive rainfall deviations from historical average values (floods) and negative rainfall deviations from historical averages (droughts). The within estimator clearly shows a negative effect of rainfall shocks on risk tolerance of both droughts and floods. In both cases, the between estimator significantly differs from the within estimator. For rain shortfalls, it indeed goes in the opposite direction, which may lead one to (wrongly) conclude that rainfall shortfalls increase risk tolerance based on the cross-sectional evidence. This shows the dangers of drawing inferences from cross-sections even in contexts where the shocks are exogenous, and random ex ante, as they are in our case. Once we add Woreda fixed effects the standard errors explode. This is unsurprising, since very little rainfall variation is observed within Woredas in any given year. While the between effects are no longer different from the within effects, they are also no longer different from zero. This would again yield very different—and ultimately misleading—inferences relatively to those obtained from the within estimator.

A major implication of these differences in the within and between estimators is that cross-sectional analysis of our data would necessarily result in biased conclusions. 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. One may also wonder about the underlying reason for these divergent effects. After all, our rainfall shocks are exogenous and random *ex ante*. Potential confusion may arise from different usages of the term 'exogenous'. Applied researchers often take that term to indicate that the predictor of interest is unaffected by any actions the study participants may undertake. This excludes reverse causality, and our measures unambiguously fulfil that criterion. In econometrics, however, 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 droughts then just indicates that these shocks by chance prevalently hit relatively risk tolerant districts during our study period (and vice versa for floods).

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 measures of shocks, the conclusions drawn would be mistaken 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. While this is a highly stylized example relying on there being only two regions with different preferences, the example readily generalizes to much larger numbers of distinct regions. Only once the number of regions goes to infinity while the shocks stay random can we be sure that this problem will no longer occur—a case approaching the gold standard of individual randomization.

2.3 Determinants of preferences

We now discuss the literature concerning what we see as our main contribution—the adaptation of preferences to the environment. In order to show adaptation, one needs not only to show significant effects on behaviour—the aspect on which most of the literature on shocks has focused. One also needs to show that whatever effects are found can explain a significant proportion of the variation in preferences. In a correlational study using a representative sample from the Netherlands, von Gaudecker et al. (2011) concluded that very little in the observed variance in preference parameters between individuals could be organized by observable characteristics. L'Haridon and Vieider (2019) replicated these findings using data from students obtained in identical experiments across 30 countries. They also qualified them, in the sense that at the aggregate level, about 50% of the variance between countries could be organized by a few macro-economic variables, most importantly, GDP per capita. Their account, however, was not causal.

Most closely related to our contribution are two studies documenting the effect of genetic factors. Cesarini et al. (2009) documented the genetic heritability of risk preferences using data on Swedish twins. They conclude that about 16% in the variation in preferences can be explained by genetics. Using data on Chinese twins, Zhong, Chew, Set, Zhang, Xue, Sham, Ebstein and Israel (2009) used a similar approach to conclude that genetic factors could explain 57% of the preference variance. The substantial difference in the effects estimated in these two studies may well result from the use of simplified three-equation models to quantify genetic effects (Cesarini et al., 2009 provide a discussion of the methodological issues). While this is a frequently-used assumption in twin studies, elsewhere this assumption has been shown to result in potentially large mis-estimations of the actual effect sizes (Bingley, Cappellari and Tatsiramos, 2019).

Our results on determinants of preferences contribute and add 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). Bouchouicha and Vieider (2019) tested the predictions of Galor and Michalopoulos (2012) and Doepke and Zilibotti (2014) using representative survey data for 78 countries, and found them to be largely supported.

The literature on shocks discussed above has thus far been purely empirical, which may contribute to explaining the disparate conclusions it has reached. A promising evolutonary model of adaptation has been proposed by Robson (2001), and further developed by Netzer (2009). The starting point of these models 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, Fiorillo and Schultz (2005) provided direct neurological evidence that dopamine receptors in the brain register reward magnitudes relative to expected magnitudes. The neurological account thus suggests modeling utility as a step function, with the steps corresponding to constant increases in utility. It can then be shown that the thresholds at which the jumps in utility take place should optimally be allocated in such a way as to maximize evolutionary fitness (Robson, 2001; Netzer, 2009). These insights produce testable predictions for how preferences should adapt to the surrounding environment in order to produce evolutionarily optimal outcomes. We will return to this point in the discussion.

3 Data and measurements

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 2 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.

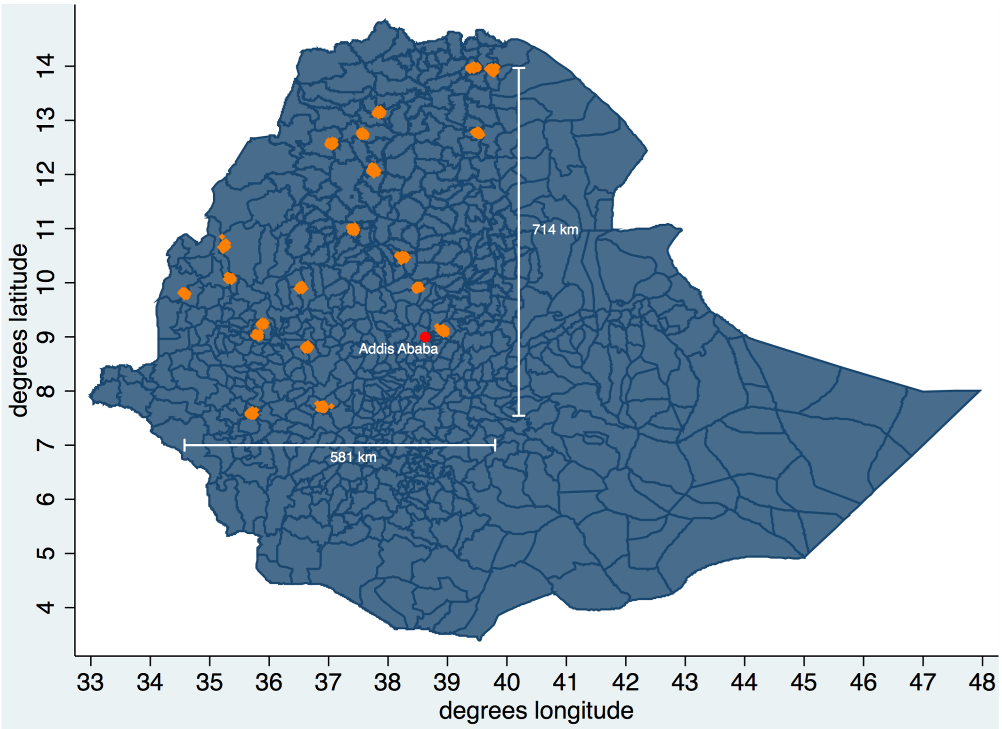


Figure 2: Geographical location of samples in Ethiopia

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. 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.

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

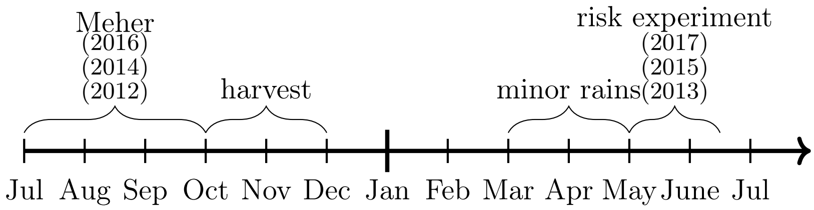


Figure 3: Time line of data collection

continue through September. Harvest takes place from October to November (figure 3). There further is a small rainy season in March to early May, used mostly for small vegetable crops. These small crops are mostly used for immediate consumption, and have a minor impact on the overall yearly food production. We thus use rainfall in the small rainy season as a placebo. 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 historical measures by area from 1981 to 2010. We define shocks as standardized negative and positive absolute deviations from these means:

$$d_{at} = \left| \frac{\ell_{at} - \mu_a}{sd_a} \right|, \tag{1}$$

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, μ_a is the local average historical rainfall from 1981 to 2010, and sd_a is the historical standard deviation in the same time span. This definition captures the informative value of the rainfall realization relative to historical realizations. The assumption underlying the use of this measure is that agricultural practices are adapted to local circumstances. In this sense, both shortfalls in rain or droughts, and excess rainfall or floods, may constitute a shock. We thus use separate measures of excesses and shortfalls in rain relative to the historical means.

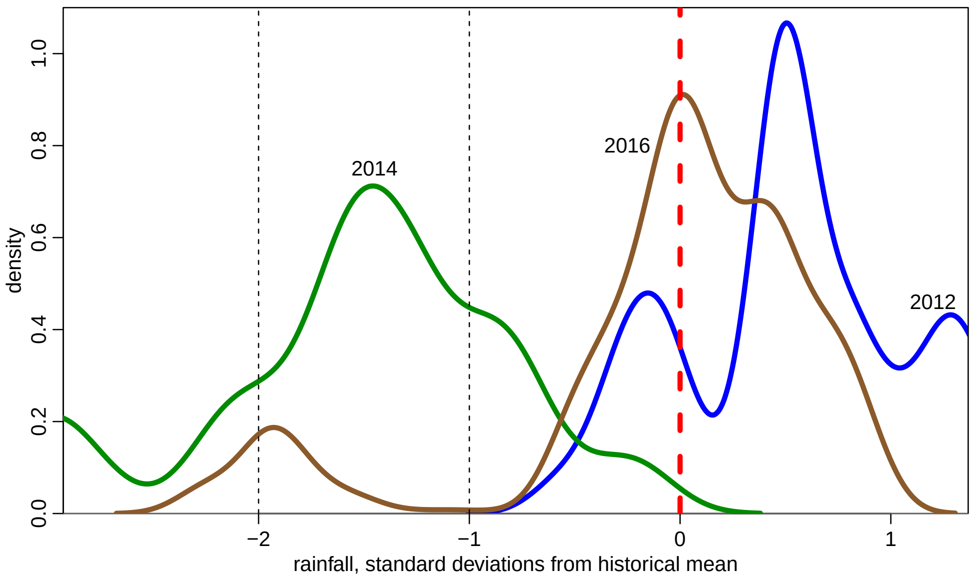


Figure 4: Rainfall deviations from historical average

The figure shows the rainfall deviations from the historical mean in each area in standard deviations, separately for each Meher season immediately preceding our experimental measurements. 2012 saw some light excess rainfall, while 2016 was largely normal, except for a few households how experienced a shortfall around 2 SDs. 2014 was characterized by extreme droughts that affected a large part of the sample, albeit to different degrees. The graph is cropped for better display, removing the most extreme 2.5% of the distribution to either side.

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 accounts 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 4 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 more than 1 SD in excess of the historical average. In 2014 we observe extensive droughts, with a majority of the sample experiencing shortfalls in rain between 1 and 2 SD 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.[4] 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 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.[5] 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, 2011; 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 $\{(30, 0); (60, 0); (120, 0);$

[4] 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).

[5] 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.

$(180, 0); (180, 60); (180, 120)\}$. 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.[6] 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 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 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, Beyene, Bluffstone, Dissanayake, Gebreegziabher, Martinsson and Mekonnen, 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, 2018b).

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

[6] 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.

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.

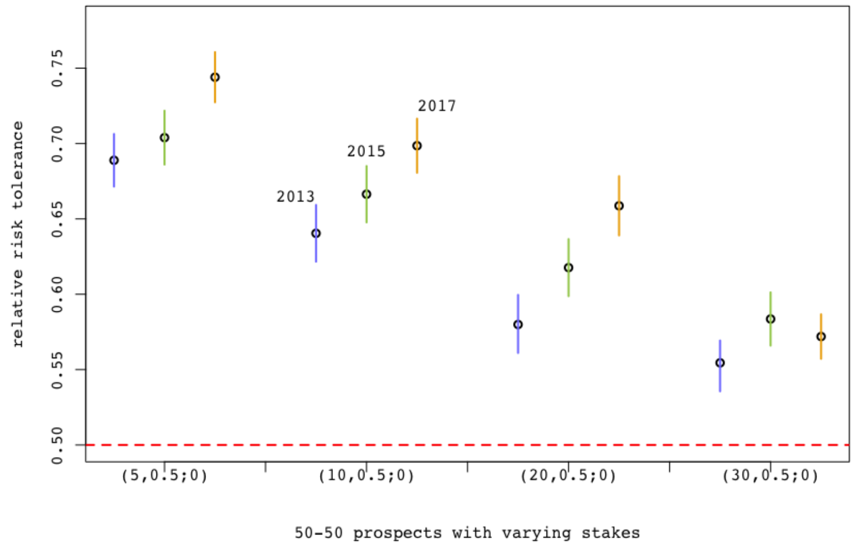
Descriptive insights on risk tolerance

Figure 5 shows risk tolerance for 50-50 prospects offering a prize of x or else 0. (Figure S4 depicts risk tolerance across probability levels, and indicates the typical pattern of relative risk tolerance declining in probability; see Fehr-Duda and Epper, 2012; L'Haridon and Vieider, 2019). The measure depicted in panel 5(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 5(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;[7] this holds both in an expected utility framework, and in generalizations thereof allowing for nonlinear probability weighting—see section S2 for details).

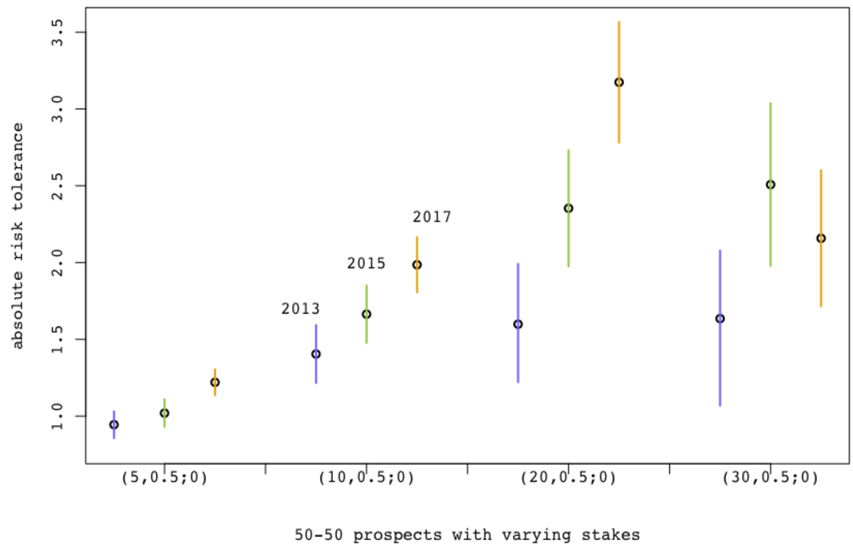
4 Econometric Analysis

We analyze our data by means of a within estimator in combination with an error structure that explicitly models our sampling framework. As famously shown by Mundlak (1978), the within estimator emulates the results of individual fixed effects. This implementation thus allows us to rigorously document the effects of time-changing characteristics. It further allows us to document the effects of time-invariant environmental features in one and the same regression. We augment the usual error structure by two

[7] *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.



(a) Relative risk tolerance



(b) Absolute risk tolerance

Figure 5: 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. We focus on tests of utility as stakes change for a given probability of 0.5, since such tests are valid not only for expected utility theory, but also generalizations such as prospect theory. Relative risk tolerance is defined as $\frac{ce-y}{x-y}$, where x is the higher and y the lower outcome of the prospect. This constitutes an index of risk tolerance *relative* to the outcome range (from a theoretical point of view, one can think of the measure as a decision weight under dual-expected utility; Yaari, 1987). The dashed horizontal line in panel (a) indicates risk neutrality. Absolute risk tolerance is defined as $ce - ev$ (i.e., a negative risk premium), 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).

additional error terms. An error term subordinate to the individual-year residual allows us to use several measurements per individual and year. An additional error at the level of the Woreda explicitly allows for spatial covariation in the individual-level residuals. This has the effect of clustering the errors at the level of stratification (Cameron and Miller, 2015, p. 318). It further has substantive implications for the inferences we draw on the effect of time-invariant environmental characteristics.

Our dependent variable consists of a measure of relative risk tolerance, $rt = \frac{ce-y}{x-y}$, where ce indicates the certainty equivalent, and x and y are the high and low outcome of the prospect, respectively. This is a measure of risk tolerance relative to the outcome range of the prospect, and can be thought of as a decision weight in Yaari's (1987) Dual Expected Utility model. This measure is convenient in terms of interpretation, and should not distract from the fact that our setup is model-free. We explicitly model heterogeneity between prospects, i, for a given subject, s, sampled from a district or Woreda, w, in a given year, t:

$$rt_{wsti} = \alpha_t + (S_{st} - \overline{S}_s)\beta_1 + \overline{S}_s\beta_2 + X_s\gamma + \omega_w + \nu_{ws} + \eta_{wst} + \epsilon_{wsti}. \tag{2}$$

The model consists of a regression part, $\alpha_t + (S_{st} - \overline{S}_s)\beta_1 + \overline{S}_s\beta_2 + X_{st}\gamma$, and of a composite error term, $\omega_w + \nu_{ws} + \eta_{wst} + \epsilon_{wsti}$. The matrix $\overline{S}_s = \frac{1}{T}\sum_{t=1}^{T}(S_{st})$ contains the intertemporal means of our time-changing rainfall shocks and controls, so that $(S_{st} - \overline{S}_s)$ contains per period deviations from the intertemporal means. Our primary interest is for the coefficient vector β_1, which contains the within-estimates, i.e. it captures how preferences change over time for the same individuals following shocks. The coefficients β_2 capture the between effects, i.e. the effects of the average shocks across the three years in the cross-section. The constant α is subscripted by t to indicate that we allow for time fixed effects. The matrix X_s contains fixed characteristics of the environment of a given subject s, with γ the vector of coefficients. One of the great advantages of the within estimator we use is indeed that we can document the effect of the environmental characteristics in X in the same regression used to document the effect of time-changing characteristics, without compromising on identification.

This brings us to the composite error term, $\omega_w + \nu_{ws} + \eta_{wst} + \epsilon_{wsti}$. The part $\nu_{ws} + \eta_{wst}$ represents a classic random-effects panel data model as typically used in conjunction with the within estimator, with $\eta_{wst} \sim \mathcal{N}(0, \sigma_t^2)$ and $\nu_{ws} \sim \mathcal{N}(0, \sigma_s^2)$, where σ_t and σ_s indicate the standard deviations at the time and subject level respectively (see e.g. Wooldridge, 2010, or Allison, 2009). We augment this basic error structure with two additional terms. The term $\epsilon_{wsti} \sim \mathcal{N}(0, \sigma_r^2)$ represents residuals at the level of the measurement, i, with σ_r^2 the residual variance. This allows us to use all measurements, rather than averaging over the different measurements obtained by individual in each year. The term $\omega_w \sim \mathcal{N}(0, \sigma_w^2)$ represents an additional hierarchy at the level of the Woreda, with σ_w^2 the Woreda-level variance. We insert this term to explicitly model our sampling framework. This clusters the standard errors at the level of the Woreda, thus providing conservative estimates of the standard errors (Cameron and Miller, 2015; Gelman, Carlin, Stern, Dunson, Vehtari and Rubin, 2014b). It furthermore has substantive implications for the analysis of time-invariant environmental characteristics, since it nests subject-level residuals ν_{ws} in Woreda-level residuals ω_w, instead of the overall mean α.

While the clustering is an important second-order effect of the additional error term, the effect on the individual-level intercepts is of first-order importance. Figure 6 plots the idiosyncratic preferences estimated based on equation 2 empty of covariates (i.e. the residuals $\alpha + \omega_w + \nu_{ws}$), against the residuals obtained from an otherwise equivalent model that drops the error term ω_w. The residuals estimated in the model without ω_w are pooled towards a global mean given by the intercept α, shown as a dashed vertical line in the graph. This means, inter alia, that estimates beyond 0.8 are entirely discounted as being unlikely (see Gelman and Pardoe, 2006, for technical details). This does not happen when the Woreda-level residuals are introduced, simply because respondents in the entire Woreda exhibit similarly high levels of risk tolerance. The individual-level residuals, ν_{ws}, are now pooled towards the Woreda-level residuals, ω_w, indicated by the dashed horizontal lines. This explicitly models the expectation that individuals within one and the same Woreda will be more similar to each other than individuals in different Woredas. It is important to note that this modeling choice follows from our stratification strategy, which thus also provides the justification for it.

The hierarchical model further allows us to document the co-variation in preferences across the various levels of analysis (Gelman and Hill, 2006; McElreath, 2016). A useful metric to achieve this is the intra-class correlation (ICC), defined as the proportion of variance captured at a given level relative to the overall level of variance. For instance, the ICC across time is defined as the level of variance across time relative to the sum of all four variance terms, $\rho(t) = \frac{\sigma_t^2}{\sigma_r^2 + \sigma_t^2 + \sigma_s^2 + \sigma_w^2}$. An intuitive interpretation of the ICC of a given level is that it captures the correlation between randomly drawn observations at that level (see Snijders and Bosker, 2012, for a textbook treatment), in this particular

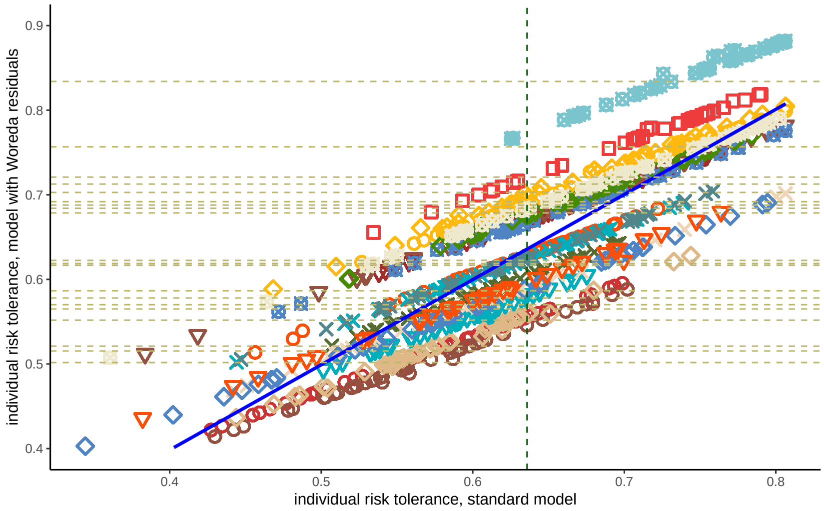


Figure 6: Plot of idiosyncratic risk tolerance in the model with and without Woreda-level residuals

example, the resemblance of two measurements obtained from the same individual in a given year. The ICC at the Woreda level obtained while abstracting from the variation across measurements and across time, $\rho(w|\sigma_r = 0, \sigma_t = 0) = \frac{\sigma_w^2}{\sigma_s^2+\sigma_w^2}$, then serves to quantify the geographic correlation of preferences within one and the same Woreda. The latter plays an important role in our data, given the geographical similarity of environmental circumstances and the ensuing spatial correlation in preference patterns.

5 Results

Co-variation in preferences across time and space

Some interesting insights can be obtained from a variance decomposition of our measures. The highest levels of variance registers at the residual level, with $\sigma_r^2 = 0.043$, and over time, with $\sigma_t^2 = 0.043$. Variance across subjects and Woredas is considerably lower at $\sigma_s^2 = 0.007$ and $\sigma_w^2 = 0.008$, respectively. We use these figures to quantify the extent of co-variation in preferences at various levels by analyzing the ICC. At the level of measurements in a single time period, we find an ICC of $\rho(t) = 0.42$, indicating that two random measurements taken for the same random individual in a random year show a correlation of 0.42 on average. This is consistent with the large variation in 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 in Western student data.[8] This suggests that the true correlation between any two tasks, after controlling for attenuation, is about 0.6.[9]

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, $\rho(s,w|\sigma_r^2 \equiv 0)$. We can interpret this as a correlation of the means per measurement period over time, which we quantify at $\rho(s,w|\sigma_r^2 \equiv 0) = 0.261$. This figure indeed corresponds closely to the raw correlations between the measures, shown in table S1 in the supplementary materials. Put differently, 74% of the total variation between aggregated measures takes place across time. This figure is in line with previous findings on the inter-temporal correlation of preferences (see Chuang and Schechter, 2015, for a review). Once we control for attenuation, this figure increases to 0.371—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 do look very different from each other, and should thus be expected to yield different results in regressions.

The final comparison we are interested in concerns the similarity of individuals within the same Woreda, i.e. the spatial co-variation of preferences at the level of sampling stratification. It is most meaningful to examine this measure while setting the inter-temporal variance to 0, $\sigma_t^2 \equiv 0$. 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 $\rho(w|\sigma_r \equiv 0, \sigma_t \equiv 0) = 0.568$. In other words, the idiosyncratic risk tolerance of two random individuals from a random Woreda shows a correlation of 0.568. To put this figure into perspective, we can compare it to the variance captured at the country level in cross-country comparisons of risk tolerance. Falk et al. (2018), Bouchouicha and Vieider (2019), and L'Haridon and Vieider (2019) present concordant evidence that the variation captured at the country level is

[8] 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.

[9] One can control for attenuation by dividing the correlation between two measures in different time periods by the square root of the product of the test-retest reliability in each of the two periods. Since we only have the test-retest reliability for 2017, we assume that reliability to be equal across periods. See e.g. Carroll, Ruppert, Crainiceanu and Stefanski (2006) for a textbook treatment.

about 10% of the total (none of these studies quantified variation across regions within countries). This suggests that the environment of a respondent plays a major role in the determination of her risk preferences. It also illustrates the importance of explicitly accounting for spacial co-variation in preferences at the Woreda level in the econometric analysis, since neglecting such co-variation would result in biased estimations.

5.1 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, we tink of the effects as passing 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 very noisy, and do not yield any sensible insights. This is not unique to our data, with several recent studies showing 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).

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. For an average prospect offering either €20 PPP or else nothing, a rainfall shock of 1.5 SDs reduces the CE by €3.59 PPP—an economically sizeable effect. For the largest shortfalls beyond 2 SDs, the curve starts bending slightly upward again. However, these effects are mostly driven by a handful of outliers experiencing a particularly severe drought, and should thus be interpreted with caution. Figure 8 shows the effect of rainfall lagged by one year. The effects are consistent with those of a drought immediately preceding the measurement, but weaker and less precisely identified.

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,

Table 1: Regression of risk-tolerance on rainfall shocks (within effects)

dep. var: risk-tolerance	(1)	(2)	(3)	(4)	(5)	(6)	(7)
rain shortfall	-0.011*	-0.087***	-0.108***	-0.128***	-0.209***	-0.207***	-0.218***
	(0.006)	(0.019)	(0.022)	(0.030)	(0.039)	(0.039)	(0.044)
rain excess	-0.032**	-0.215***	-0.218***	-0.221***	-0.291***	-0.287***	-0.402***
	(0.013)	(0.043)	(0.045)	(0.046)	(0.061)	(0.061)	(0.071)
rain shortfall sq.		0.028***	0.038***	0.036***	0.058***	0.057***	0.059***
		(0.007)	(0.008)	(0.009)	(0.012)	(0.012)	(0.012)
rain excess sq.		0.132***	0.139***	0.147***	0.200***	0.198***	0.265***
		(0.032)	(0.033)	(0.034)	(0.041)	(0.041)	(0.045)
rain shortfall lag 1			-0.005	-0.057***	-0.037*	-0.038*	-0.044**
			(0.014)	(0.020)	(0.021)	(0.021)	(0.021)
rain excess lag 1			0.028	-0.038	-0.023	-0.024	0.011
			(0.033)	(0.038)	(0.040)	(0.040)	(0.045)
rain shortfall lag 1 sq.			0.008**	0.015***	0.007	0.008	0.010**
			(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
rain excess lag 1 sq.			-0.005	0.023	0.014	0.015	0.013
			(0.016)	(0.018)	(0.019)	(0.019)	(0.022)
altitude * shortfall							-0.042***
							(0.011)
pos. skewness * shortfall							-0.015**
							(0.008)
animals * shortfall							0.042**
							(0.021)
animals * excess							0.075*
							(0.039)
year fixed effects	NO	NO	NO	YES	YES	YES	YES
rain dev. lag 2	NO	NO	NO	NO	YES	YES	YES
controls	NO	NO	NO	NO	NO	YES	YES
Nr. Households	906	906	906	906	906	906	906
R^2 over time	0.004	0.018	0.027	0.034	0.045	0.048	0.083

All coefficients shown in the table refer to within effects. Between effects are not shown to save space. Standard errors reported in parentheses. Stars signal significance at the 10% level (*), 5% level (**), and 1% level (***). The shorthand 'sq.' indicates the square of the deviations. Equation (1) only contains linear effects of positive and negative rainfall deviations. Equation (2) adds the squares of these measures. Subsequent regressions add the same rainfall variables lagged once (3), year fixed effects (4), and the lag 2 rainfall variables (5). Equation (6) includes the following time-varying controls: number of animals; access to irrigation (dummy); and non-farm income. Equation (7) contains interaction effects of rain shortfall and excess with standardized measures of altitude, positive skewness in the historical rainfall distribution, animals held, and the area of the land farmed (only significant effects reported because of space constraints). The inter-temporal R^2 is calculated as $1 - \sigma^2_{mo}/\sigma^2_{mj}$, where mo indicates the model empty of covariates, and mj refers to the model in the regression (see Snijders and Bosker, 2012, for a textbook treatment).

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 and at the intensive margin, with fewer subjects being affected by excess rainfall. 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

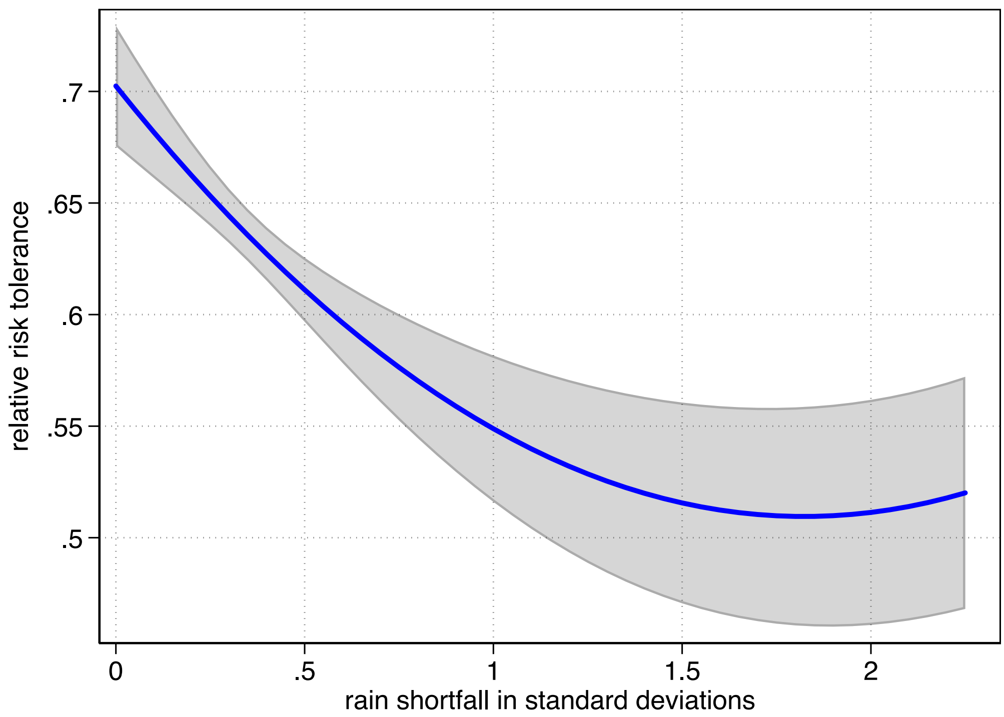


Figure 7: The effect of rainfall shortfalls
Graph of overall effect of rainfall shortfalls ('droughts') on relative risk tolerance. The solid blue line represents the mean effect of the polynomial. The grey area represents the the 95% prediction interval. Outliers based on the most extreme 5% of the sample are not shown.

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 (7). In particular, rain shortfalls have a stronger negative impact at high altitude, while excess rainfall has less of a negative impact at high altitude. 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 our intuition that what counts is the deviation in a given rainfall realization from to the historical distribution.

Before concluding this section, we examine the amount of inter-temporal variance explained by our model. Regression (6) in table 1 explains 4.8% of the inter-temporal variance. Adding the heterogenous treatment effects in regression (7) brings this figure to 8.3%. Much of the variation in preferences over time thus remains unexplained.

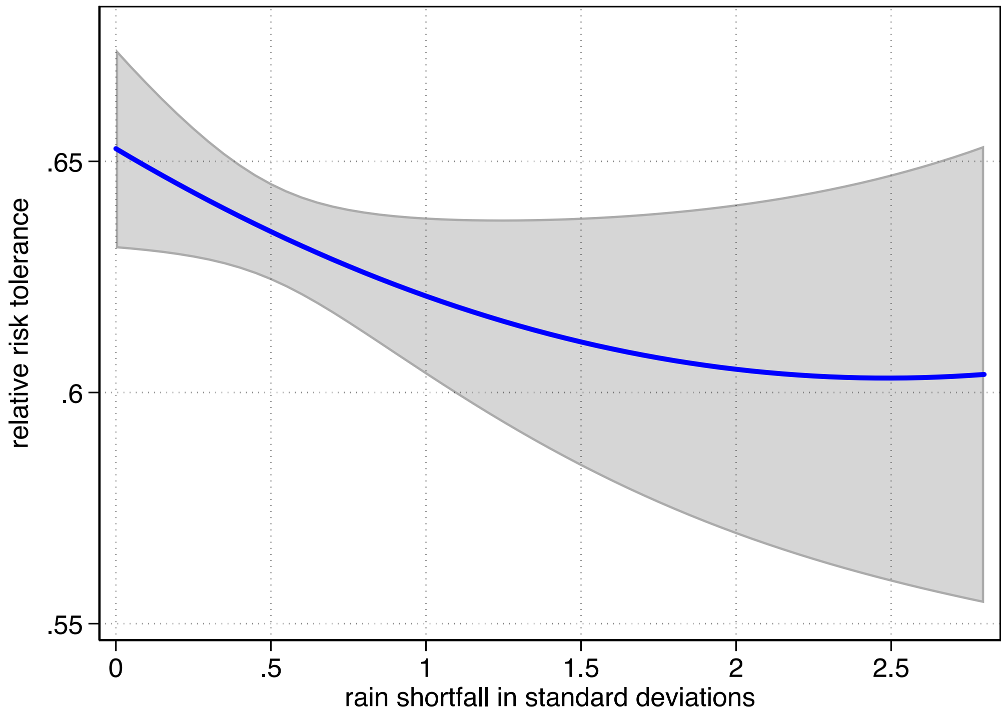


Figure 8: The effect of rainfall shortfalls, lag 1
Graph of overall effect of rainfall excesses ('floods') on relative risk tolerance. The solid blue line represents the mean effect of the polynomial. The grey area represents the 95% prediction interval. Outliers based on the most extreme 5% of the sample are not shown.

This suggests that aggregating over the unexplained inter-temporal fluctuation in risk tolerance will be at least as important as filtering out any effects of observable variables when it comes to stabilizing the estimates of idiosyncratic risk tolerance.

5.2 Environmental determinants of risk tolerance

We now examine correlates of idiosyncratic risk tolerance. We encode idiosyncratic risk tolerance as the means of the individual-level intercepts, defined as the sum of the individual-level and Woreda-level residuals, $\alpha_{2013}+\omega_w+\nu_{ws}$. This means that we capture individual-level preferences purified of the effects of shocks as captured in our model, and averaged over time. The basis for our analysis of idiosyncratic risk tolerance is formed by regression (6) in table 1. Using regression (7) instead does not affect our conclusions in any substantive way, but the effects become more difficult to interpret due to the presence of interaction terms including environmental characteristics in that regression.

We start from a graphical analysis of the raw correlations between idiosyncratic preferences and environmental characteristics. Figure 10 shows the correlation between the

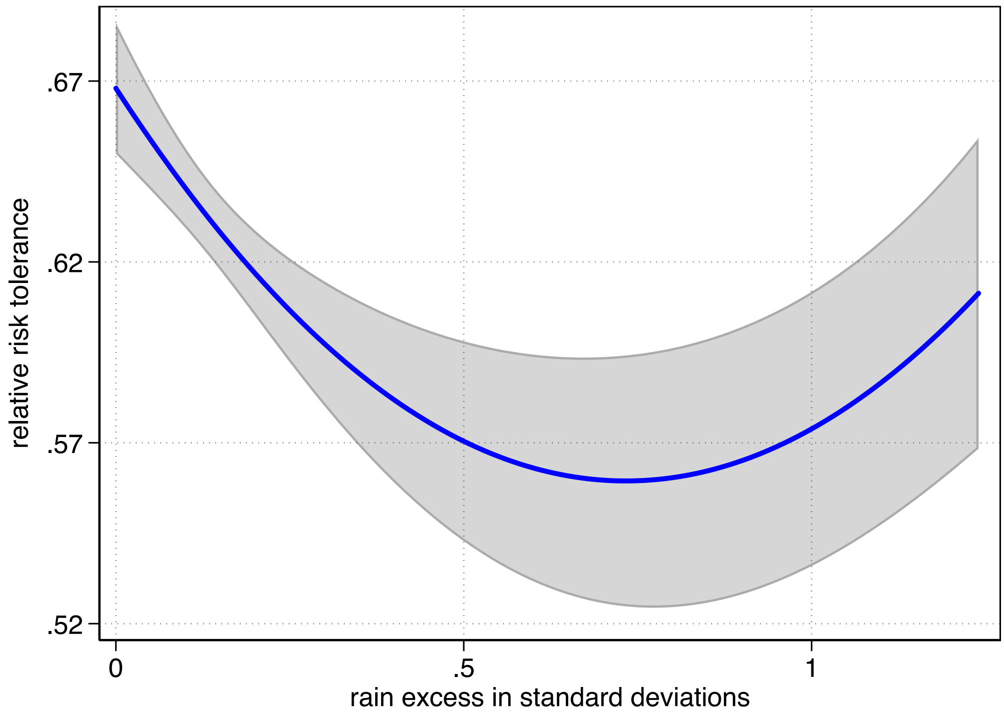


Figure 9: The effect of rainfall excesses
Graph of overall effect of rainfall excesses ('floods') on relative risk tolerance. The solid blue line represents the mean effect of the polynomial. The grey area represent the 95% prediction interval. Outliers based on the most extreme 5% of the sample are not shown.

standard deviation of historical rainfall in a given area and idiosyncratic risk tolerance. Risk tolerance decreases strongly in rainfall SD, at a decreasing rate. The curve is indeed slightly U-shaped, although the uptick for the largest levels of SD is not reliably estimated, given that we have few observations with such large values.

In addition to rainfall levels, geographical features may also impact preferences. 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 11 shows the correlation between idiosyncratic risk tolerance and altitude. Risk tolerance steeply declines with altitude, as expected.

Finally, figure 12 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. Notice that both distance to the capital and altitude appear to be strongly corre-

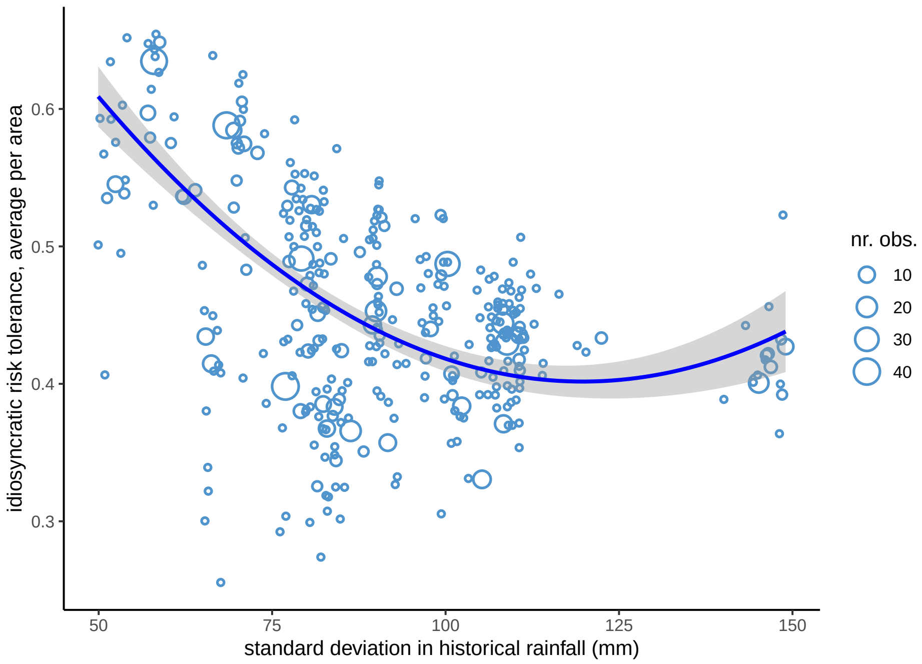


Figure 10: Correlations between historical rainfall SD and idiosyncratic risk tolerance

Graph of idiosyncratic risk tolerance against the standard deviation (SD) in historical rainfall. Since historical rainfall data differ by rainfall areas rather than individuals, we show idiosyncratic risk tolerance aggregated by area and weighed by the number of observations contained in each point.

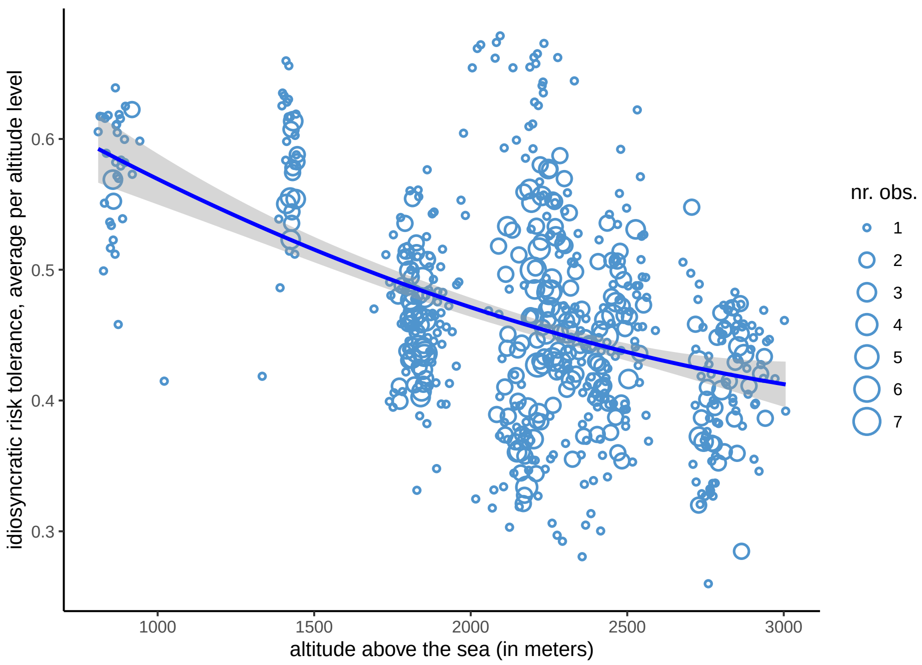


Figure 11: Correlations between altitude and idiosyncratic risk tolerance

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.

lated with risk tolerance, even though there was no occurrence of violence in the study regions in recent memory. This suggests that the positive relationship between exposure to violence and risk tolerance at the village level described by Voors et al. (2012) may be spurious, since altitude and distance to the capital could cause not only violence, but also risk aversion itself (i.e., higher altitude and greater distance from the capital would reduce risk tolerance, as well as reducing violence).

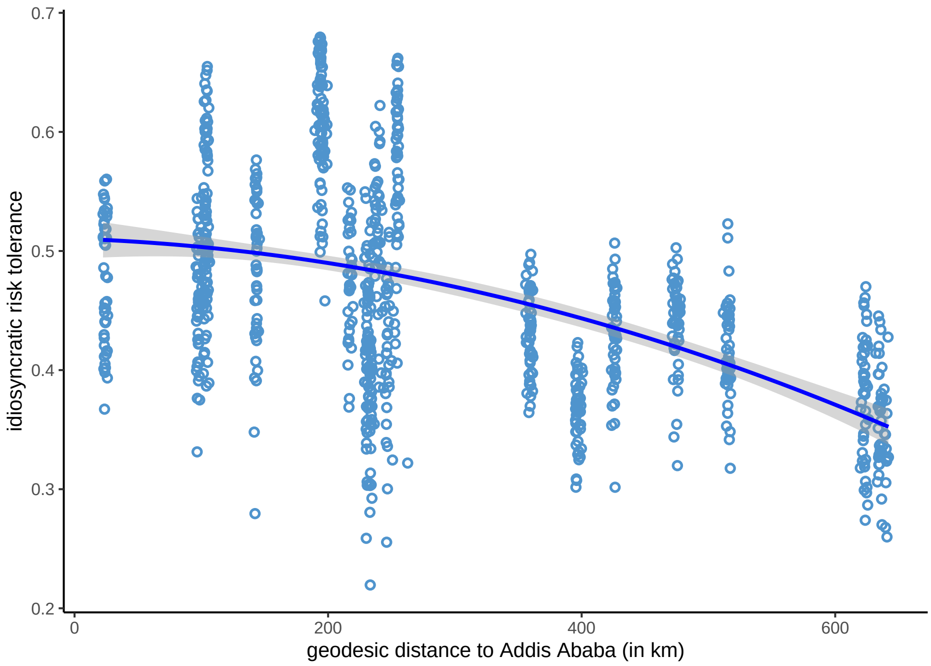


Figure 12: Correlations between distance to capital and idiosyncratic risk tolerance
Graph of idiosyncratic risk tolerance against geodesic distance from Addis Ababa.

We now enter all of these measures jointly into a regression framework. The regressions are shown in table 2. The regressions simply add environmental characteristics to regression (6) in table 1. The time-changing part shown in table 2 is not displayed again to save space, but remains unaffected. Regression (1) adds only the standard deviation in historical rainfall from 1981 to 2010. Regression (2) further adds the square of the standard deviation, regression (3) the altitude, regression (4) the square of the altitude, and regression (5) adds the geodesic distance to Addis Ababa. All effects have the signs we would expect based on the figures above, and all of them are statistically significant. Regression (6) further controls for the age and gender of the respondent, and for the land area farmed by the households. None of these variables is significant, and we omit them from the table.

Table 2: Risk-tolerance and environmental factors

	(1)	(2)	(3)	(4)	(5)	(6)
SD historical rain	-0.204**	-1.348***	-1.403***	-1.464***	-1.188***	-1.188***
	(0.080)	(0.423)	(0.362)	(0.342)	(0.367)	(0.368)
SD hist. rain sq.		0.593***	0.653***	0.684***	0.547***	0.546***
		(0.215)	(0.183)	(0.173)	(0.185)	(0.185)
altitude			-0.063**	-0.190*	-0.230*	-0.230*
			(0.026)	(0.115)	(0.121)	(0.123)
altitude sq.				0.032	0.051*	0.052*
				(0.029)	(0.031)	(0.031)
distance to Addis					-0.030***	-0.030***
					(0.011)	(0.011)
animals (intertemp. mean)	0.042*	0.039*	0.044*	0.048**	0.047**	0.047*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
controls	NO	NO	NO	NO	NO	YES
Nr. respondents	906	906	906	906	906	906
R^2 across respondents	0.238	0.359	0.415	0.428	0.429	0.429

The results reported are based on equation (6) in table 1, with the cross-sectional variables added to that specification. Standard errors reported in parentheses. Stars signal significance at the 10% level (*), 5% level (**), and 1% level (***). The shorthand 'sq.' indicates the square of a variable. Distances to Addis Ababa, the capital, is calculated using geodesic distance. Equations (1) to (5) control only for individual-level factors used as inter-temporal means of time-changing effects, including the inter-temporal mean of animals, the inter-temporal mean of irrigation, and the inter-temporal mean of non-farm income. Regression (6) introduces additional controls such as gender and age of the respondent, and area of land farmed. Only significant effects are reported to save space.

The environmental variables used in the regressions explain a large part of the variance in preferences across respondents. The historical SD in rainfall alone explains 24% of the variance in idiosyncratic risk tolerance, increasing to 36% when its square is added. Further adding altitude and the distance from the capital, we reach a figure of 43% of the overall variance across respondents that is explained by characteristics of the respondents' environment. This figure is one order of magnitude larger than typical values reported in the literature (see footnote 2). The reason for this superior performance is twofold. One, our subjects are highly dependent on the environment for their subsistence, and no institutionalized safety nets exist. We would thus expect environmental effects to be particularly strong. Two, filtering out the effects of shocks and aggregating across time stabilizes our individual-level preference measures. Indeed, given the large variation over time, it is unsurprising that regressions using cross-sectional data perform poorly—a cross-section measured in one year looks very different from the same cross-section measured in a different year.

The results also serve to highlight the importance of explicitly modeling the covariation in residuals at the Woreda level. Even though the environmental characteristics just highlighted vary across individuals, and not just Woredas, the great majority of the variation occurs between individuals located in different Woredas. This means that while we explain 43% of the total variation across individuals, given by $\omega_w + \nu_{ws}$, we explain fully 86% of the variation across Woredas, i.e. in ω_w alone. Ignoring the co-variation of preferences within one and the same Woreda would result in biased estimates in our context. This is not only true for the time-varying effects in table 1, where the hierarchical Woreda effect serves to adjust the standard errors. It holds even more for the cross-sectional results, where the individual-level residuals ν are nested within (i.e., have as their mean) the Woreda-level residuals ω in our setup, rather than converging towards the overall mean. Since hierarchical models tend to discount noisy outliers, this difference matters substantively for the inferences we draw.

6 Discussion

We have documented large differences in preferences across different environments. We are inclined to interpret these environmental effects causally. For one, the effects of the historical standard deviation are fully consistent with the changes over time we documented, for which a causal interpretation is beyond reasonable doubt. Selection effects do not provide a plausible explanation for these findings. Rural to rural migration is virtually inexistent 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 empirical evidence on economic migration in Ethiopia (De Brauw and Mueller, 2012). While rural to urban migration *does* exist, both the observed scale of migration and the urbanization rate in Ethiopia are too small to account for the large differences between Woredas we document. Finally, accounts based on selection preceding the current land distribution, several decades or even centuries ago, and subsequent transmission of preferences through the generations are difficult to reconcile with the strong impact of shocks over time.

We find that over 40% 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 over 50% 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 preferences and explained 16% of the variation—one of the highest proportions in the literature to our knowledge (though see also Zhong et al., 2009). 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 factors 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 chances of detecting environmental influences.

The effects we presented cannot be explained by mere movements along a fixed utility function. Assume for a moment that we only observe wealth effects (i.e. movements along a pre-existing utility function defined over lifetime wealth). 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. Controlling for wealth further does not impact our results. We thus conclude that moves along a pre-determined utility function cannot organize our results.

This raises the interesting question of what can account for the effects we observe. We consider the evolutionary models of Robson (2001) and Netzer (2009) to be the most promising possibility. If one allows for cognitive limits to the extent with which humans can detect changes in utility, then it is evolutionarily optimal for utility to adapt to the probability distribution of consumption opportunities present in the environment, so as to allocate scare cognitive resources where they are most useful. Preferences would then be expected to be updated following changes in perceptions of the likelihood of different consumption opportunities (Robson and Whitehead, 2017). This could then account for the shifts in preferences we observe over time. It could also account for the effects of fixed environmental characteristics. For instance, high variability in rainfall 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. Utility would then systematically adapt to the environment, with lower average consumption opportunities, as well as higher variability in consumption over time, resulting in increased risk aversion.

The account just presented may seem at odds with the high levels of risk tolerance we observe in Ethiopia in general—a finding that is consistent with the evidence from comparative studies showing high risk tolerance especially in Africa (Vieider et al., 2015; Falk et al., 2018; Vieider et al., 2018; Bouchouicha and Vieider, 2019). However, this is only an apparent contradiction. In rich countries, important decisions are relatively rare. Most decisions are taken over small to moderate amounts. To wit, people tend to overinsure moderate losses (Sydnor, 2010). The evolutionary model would thus predict 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. The model can thus reconcile the apparently contradictory findings of increased risk tolerance in poorer countries, and decreased risk tolerance in more vulnerable regions within those same countries.

7 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 within estimator emulating 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. Looking at historical rainfall metrics and fixed geographical characteristics, we uncovered effects that are highly consistent with the time-changing ones. In particular, we found idiosyncratic risk tolerance to decrease strongly in the standard deviation of historical rainfall, in altitude, and in distance to markets. We excluded selection effects as a plausible explanation for these effects. Overall, our results thus indicate that preferences adapt to the environment faced by the decision maker.

References

Abay, Kibrom A, Gashaw T Abate, Christopher B Barrett, and Tanguy Bernard (2018) *Correlated non-classical measurement errors, second best policy inference and the inverse size-productivity relationship in agriculture,* vol. 1710 (Intl Food Policy Res Inst)

Abdellaoui, Mohammed, Aurélien Baillon, Lætitia Placido, and Peter P. Wakker (2011) 'The Rich Domain of Uncertainty: Source Functions and Their Experimental Implementation.' *American Economic Review* 101, 695–723

Abdellaoui, Mohammed, Emmanuel Kemel, Amma Panin, and Ferdinand M. Vieider (2019) 'Measuring risk and time preferences in an integrated framework.' *Games and Economic Behavior* 115, 459–469

Allison, Paul D (2009) *Fixed effects regression models,* vol. 160 (SAGE publications)

Andersson, Ola, Jean-Robert Tyran, Erik Wengström, and Håkan J. Holm (2016) 'Risk Aversion Relates to Cognitive Ability: Preferences or Noise?' *Journal of the European Economic Association* 14(5), 1129–1154

Bingley, Paul, Lorenzo Cappellari, and Kostas Tatsiramos (2019) 'On the origins of socio-economic inequalities: Evidence from a "children of twins" design.' *Mimeo*

Bouchouicha, Ranoua, and Ferdinand M. Vieider (2017) 'Accommodating stake effects under prospect theory.' *Journal of Risk and Uncertainty* 55(1), 1–28

_ (2019) 'Growth, Entrepreneurship, and Risk-Tolerance: A Risk-Income Paradox.' *Journal of Economic Growth, forthcoming*

Bowles, Samuel (1998) 'Endogenous preferences: The cultural consequences of markets and other economic institutions.' *Journal of Economic Literature* 36(1), 75–111

Brooks, Peter, Simon Peters, and Horst Zank (2013) 'Risk behavior for gain, loss, and mixed prospects.' *Theory and Decision* 77(2), 153–182

Brown, Ryan, Verónica Montalva, Duncan Thomas, and Andrea Velásquez (2018) 'Impact of violent crime on risk aversion: Evidence from the mexican drug war.' *Review of Economics and Statistics*

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper (2010) 'Risk and Rationality: Uncovering Heterogeneity in Probability Distortion.' *Econometrica* 78(4), 1375–1412

Callen, Michael, Mohammad Isaqzadeh, James D. Long, and Charles Sprenger (2014) 'Violence and Risk Preference: Experimental Evidence from Afghanistan.' *American Economic Review* 104(1), 123–148

Cameron, A Colin, and Douglas L Miller (2015) 'A practitioner's guide to cluster-robust inference.' *Journal of Human Resources* 50(2), 317–372

Cameron, Lisa, and Manisha Shah (2015) 'Risk-taking behavior in the wake of natural disasters.' *Journal of Human Resources* 50(2), 484–515

Carroll, Raymond J, David Ruppert, Ciprian M Crainiceanu, and Leonard A Stefanski (2006) *Measurement error in nonlinear models: a modern perspective* (Chapman and Hall/CRC)

Cesarini, David, Christopher T. Dawes, Magnus Johannesson, Paul Lichtenstein, and Björn Wallace (2009) 'Genetic Variation in Preferences for Giving and Risk Taking.' *Quarterly Journal of Economics* 124(2), 809–842

Choi, Syngjoo, Shachar Kariv, Wieland Müller, and Dan Silverman (2014) 'Who Is (More) Rational?' *American Economic Review* 104(6), 1518–1550

Chuang, Yating, and Laura Schechter (2015) 'Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results.' *Journal of Development Economics* 117, 151–170

Cohn, Alain, Jan Engelmann, Ernst Fehr, and Michel André Maréchal (2015) 'Evidence for countercyclical risk aversion: an experiment with financial professionals.' *The American Economic Review* 105(2), 860–885

De Brauw, Alan, and Valerie Mueller (2012) 'Do limitations in land rights transferability influence mobility rates in Ethiopia?' *Journal of African Economies* 21(4), 548–579

Dercon, Stefan, and Catherine Porter (2014) 'Live Aid Revisited: Long-Term Impacts of the 1984 Ethiopian Famine on Children.' *Journal of the European Economic Association* 12(4), 927–948

Dercon, Stefan, and Luc Christiaensen (2011) 'Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia.' *Journal of Development Economics* 96(2), 159–173

Diamond, Jared (2005) *Collapse: How societies choose to fail or succeed* (Penguin)

Doepke, Matthias, and Fabrizio Zilibotti (2008) 'Quarterly journal of economics.' *The Quarterly Journal of Economics* 123(2), 747–793

— (2014) 'Culture, Entrepreneurship, and Growth.' In 'Handbook of Economic Growth,' vol. 2

— (2017) 'Parenting with style: Altruism and paternalism in intergenerational preference transmission.' *Econometrica* 85(5), 1331–1371

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner (2011) 'Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences.' *Journal of the European Economic Association* 9(3), 522–550

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde (2018) 'Global evidence on economic preferences.' *The Quarterly Journal of Economics, forthcoming* (4), 1645?1692

Fehr-Duda, Helga, Adrian Bruhin, Thomas F. Epper, and Renate Schubert (2010) 'Rationality on the Rise: Why Relative Risk Aversion Increases with Stake Size.' *Journal of Risk and Uncertainty* 40(2), 147–180

Fehr-Duda, Helga, and Thomas Epper (2012) 'Probability and Risk: Foundations and Economic Implications of Probability-Dependent Risk Preferences.' *Annual Review of Economics* 4(1), 567–593

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura Harrison, Andrew Hoell et al. (2015) 'The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes.' *Scientific data* 2, 15–66

Galor, Oded, and Stelios Michalopoulos (2012) 'Evolution and the Growth Process: Natural Selection of Entrepreneurial Traits.' *Journal of Economic Theory* 147(2), 759–780

Gelman, Andrew, and Iain Pardoe (2006) 'Bayesian measures of explained variance and pooling in multilevel (hierarchical) models.' *Technometrics* 48(2), 241–251

Gelman, Andrew, and Jennifer Hill (2006) *Data analysis using regression and multilevel/hierarchical models* (Cambridge university press)

Gelman, Andrew, Jessica Hwang, and Aki Vehtari (2014a) 'Understanding predictive information criteria for Bayesian models.' *Statistics and Computing* 24(6), 997–1016

Gelman, Andrew, John B Carlin, Hal S Stern, David B Dunson, Aki Vehtari, and Donald B Rubin (2014b) *Bayesian data analysis,* vol. 2 (CRC press Boca Raton, FL)

Hanaoka, Chie, Hitoshi Shigeoka, and Yasutora Watanabe (2018) 'Do risk preferences change? Evidence from panel data before and after the great east Japan earthquake.' *American Economic Journal: Applied Economics* 10(2), 298–330

Jakiela, Pamela, and Owen W. Ozier (2018) 'The Impact of Violence on Individual

Risk Preferences: Evidence from a Natural Experiment.' *Review of Economics and Statistics, forthcoming*

Kim, Young-Il, and Jungmin Lee (2014) 'The long-run impact of a traumatic experience on risk aversion.' *Journal of Economic Behavior & Organization* 108, 174–186

L'Haridon, Olivier, and Ferdinand M. Vieider (2019) 'All over the map: A worldwide comparison of risk preferences.' *Quantitative Economics* 10, 185–215

Liebenehm, Sabine (2018) 'Temporal stability of risk attitudes and the impact of adverse shocks—a panel data analysis from Thailand and Vietnam.' *World Development* 102, 262–274

Lobell, David B, George Azzari, Marshall Burke, Sydney Gourlay, Zhenong Jin, Talip Kilic, and Siobhan Murray (2018) *Eyes in the sky, boots on the ground: Assessing satellite-and ground-based approaches to crop yield measurement and analysis in Uganda* (The World Bank)

McElreath, Richard (2016) *Statistical Rethinking: A Bayesian Course with Examples in R and Stan* (Academic Press)

MOIPAD (2001) 'Federal democratic republic of ethiopia rural development policies, strategies and instruments (amharic).' Technical Report, Addis Ababa: Ministry of Information, Press and Audiovisual Department

Moya, Andrés (2018) 'Violence, psychological trauma, and risk attitudes: Evidence from victims of violence in colombia.' *Journal of Development Economics* 131, 15–27

Mundlak, Yair (1978) 'On the pooling of time series and cross section data.' *Econometrica* pp. 69–85

Netzer, Nick (2009) 'Evolution of time preferences and attitudes toward risk.' *American Economic Review* 99(3), 937–55

Noussair, Charles N., Stefan Trautmann, and Gijs van de Kuilen (2014) 'Higher Order Risk Attitudes, Demographics, and Financial Decisions.' *Review of Economic Studies* 21(1), 325–355

Page, Lionel, David A. Savage, and Benno Torgler (2014) 'Variation in risk seeking behaviour following large losses: A natural experiment.' *European Economic Review* 71, 121–131

Prelec, Drazen (1998) 'The Probability Weighting Function.' *Econometrica* 66, 497–527

Rahmato, Dessalegn (2008) 'Ethiopia: Agriculture policy review.' *Digest of Ethiopia's*

National Policies, Strategies, and Programs

Ridley, Matt (2003) *Nature via nurture: Genes, experience, and what makes us human* (New York: Harper)

Robson, Arthur J (2001) 'The biological basis of economic behavior.' *Journal of Economic Literature* 39(1), 11–33

Robson, Arthur J, and Lorne A. Whitehead (2017) 'Adaptive hedonic utility.' *Working Paper*

Schildberg-Hörisch, Hannah (2018) 'Are risk preferences stable?' *Journal of Economic Perspectives* 32(2), 135–54

Scholten, Marc, and Daniel Read (2014) 'Prospect theory and the "forgotten" fourfold pattern of risk preferences.' *Journal of Risk and Uncertainty* 48(1), 67–83

Simon, Herbert A (1956) 'Rational choice and the structure of the environment.' *Psychological review* 63(2), 129

Snijders, Tom A. B., and Roel J. Bosker (2012) *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling,* 2nd ed. (London: Sage Publications)

Sutter, Matthias, Martin G Kocher, Daniela Glätzle-Rützler, and Stefan T Trautmann (2013) 'Impatience and Uncertainty: Experimental Decisions Predict Adolescents' Field Behavior.' *American Economic Review* 103(1), 510–531

Sydnor, Justin (2010) '(Over)insuring Modest Risks.' *American Economic Journal: Applied Economics* 2(4), 177–199

Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen (2010) 'Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam.' *American Economic Review* 100(1), 557–571

Tobler, Philippe N, Christopher D Fiorillo, and Wolfram Schultz (2005) 'Adaptive coding of reward value by dopamine neurons.' *Science* 307(5715), 1642–1645

Vieider, Ferdinand M. (2018a) 'Certainty Preference, Random Choice, and Loss Aversion: A Comment on "Violence and Risk Preference: Experimental Evidence from Afghanistan".' *American Economic Review* 108(8), 2366–2382

Vieider, Ferdinand M (2018b) 'Violence and risk preference: Experimental evidence from afghanistan: Comment.' *American Economic Review* 108(8), 2366–82

Vieider, Ferdinand M., Abebe Beyene, Randall A. Bluffstone, Sahan Dissanayake, Zenebe Gebreegziabher, Peter Martinsson, and Alemu Mekonnen (2018) 'Measuring risk preferences in rural Ethiopia.' *Economic Development and Cultural Change* 66(3), 417–446

Vieider, Ferdinand M., Mathieu Lefebvre, Ranoua Bouchouicha, Thorsten Chmura, Rustamdjan Hakimov, Michal Krawczyk, and Peter Martinsson (2015) 'Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries.' *Journal of the European Economic Association* 13(3), 421–452

von Gaudecker, Hans-Martin, Arthur van Soest, and Erik Wengström (2011) 'Heterogeneity in Risky Choice Behaviour in a Broad Population.' *American Economic Review* 101(2), 664–694

Voors, Maarten J., Eleonora E.M. Nillesen, Philip Verwimp, Erwin H. Bulte, Robert Lensink, and Daan P. Van Soest (2012) 'Violent Conflict and Behavior: A Field Experiment in Burundi.' *American Economic Review* 102(2), 941–964

Wakker, Peter P. (2010) *Prospect Theory for Risk and Ambiguity* (Cambridge: Cambridge University Press)

Wooldridge, Jeffrey M (2010) *Econometric analysis of cross section and panel data* (MIT press)

_ (2015) *Introductory econometrics: A modern approach* (Nelson Education)

Yaari, Menahem E. (1987) 'The Dual Theory of Choice under Risk.' *Econometrica* 55(1), 95–115

Zhong, Songfa, Soo Hong Chew, Eric Set, Junsen Zhang, Hong Xue, Pak C. Sham, Richard P. Ebstein, and Salomon Israel (2009) 'The Heritability of Attitude Toward Economic Risk.' *Twin Research and Human Genetics* 12(1), 103–107

SUPPLEMENTARY MATERIALS (For online publication)

Environmental Forces Shape Risk Preferences

Salvatore di Falco and Ferdinand M. Vieider

Correspondence to: fvieider@gmail.com

S1 Additional descriptives rainfall data

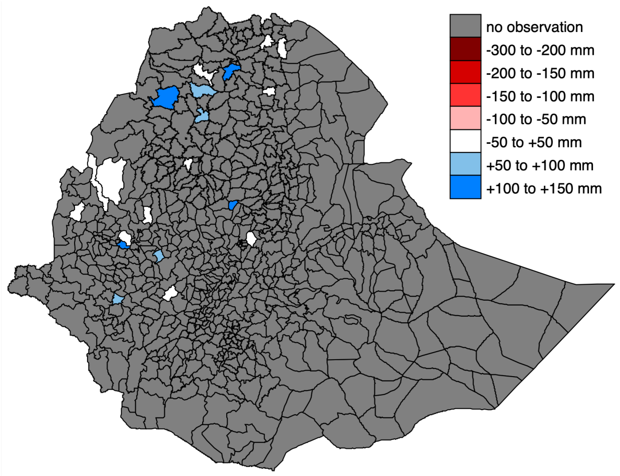
Figure S1 shows the geographical distribution of shocks during the three Meher seasons immediately preceding our risk measurements.

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.

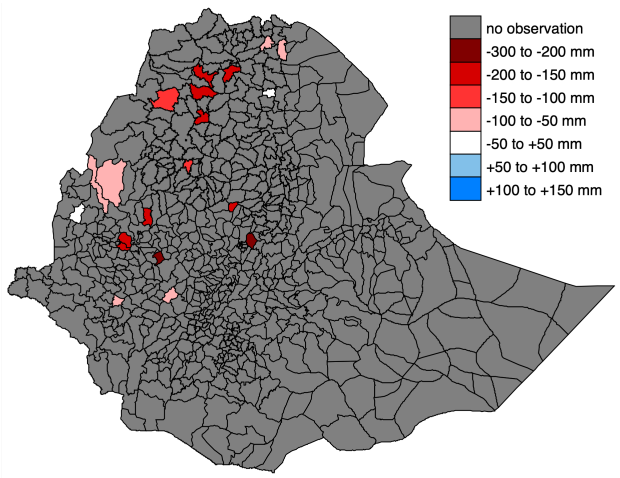
Figure S3 shows the equivalent figure for the measures lagged by 2 years, i.e. for 2010, 2012, and 2014. We have already discussed 2012 and 2014 in the main text, with 2010 thus providing the only new information. The rains in 2010 almost entirely fall into the region of $\pm$ 100 mm of the historical 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.

S2 Utility fit to risk data

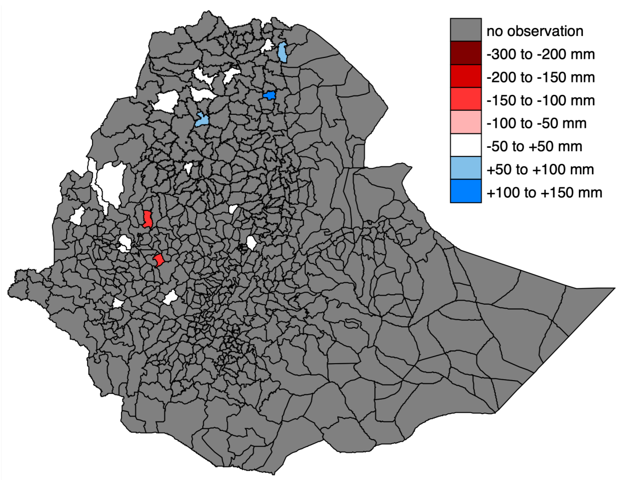
Figure S4 shows how relative risk tolerance changes across the probability range. Two findings stand out. One, we again find very high levels of risk tolerance. Indeed, we find significant risk seeking for all probability levels but the highest two, and only for the highest probability level do we find 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



(a) 2012



(b) 2014



(c) 2016

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

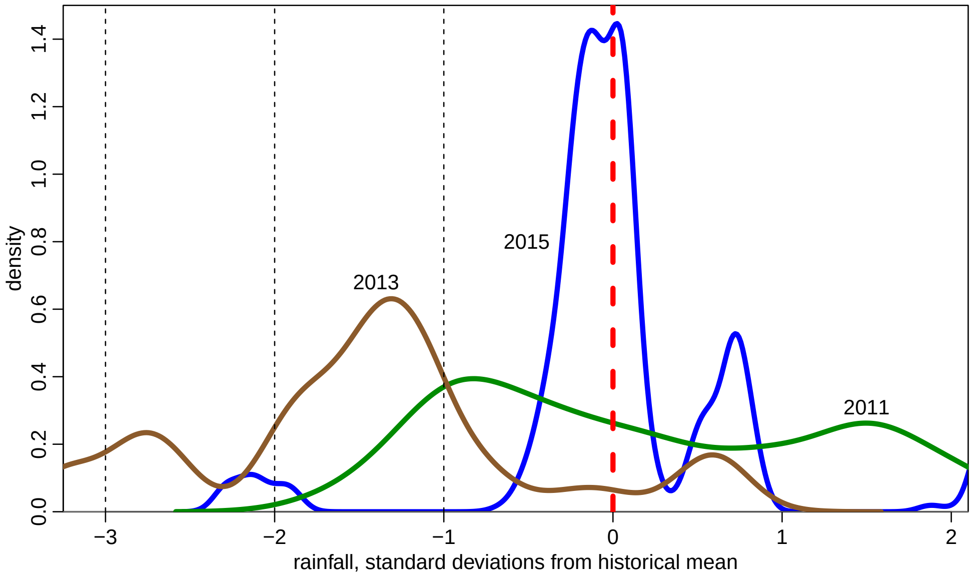


Figure S2: Average absolute rainfall deviations

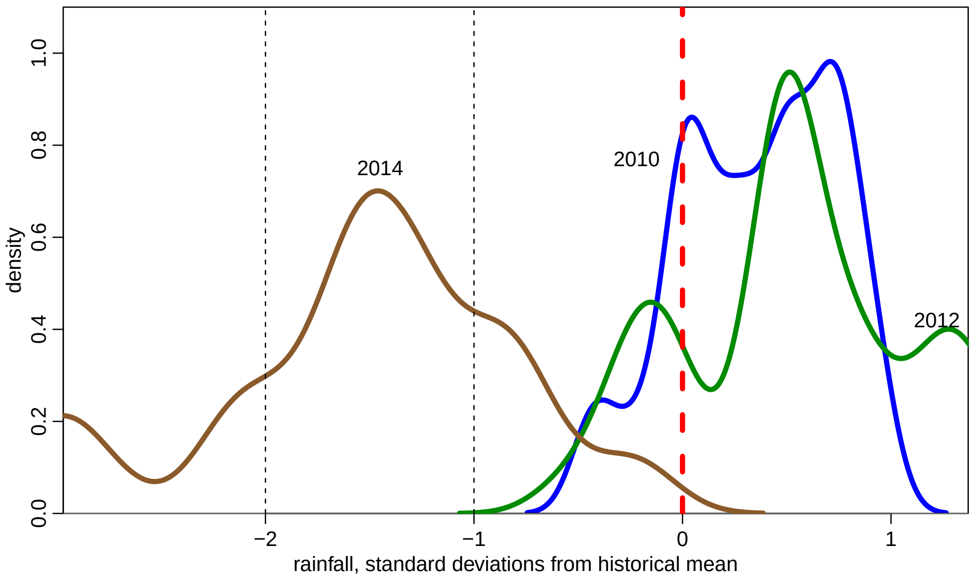


Figure S3: Average absolute rainfall deviations

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 absolute 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

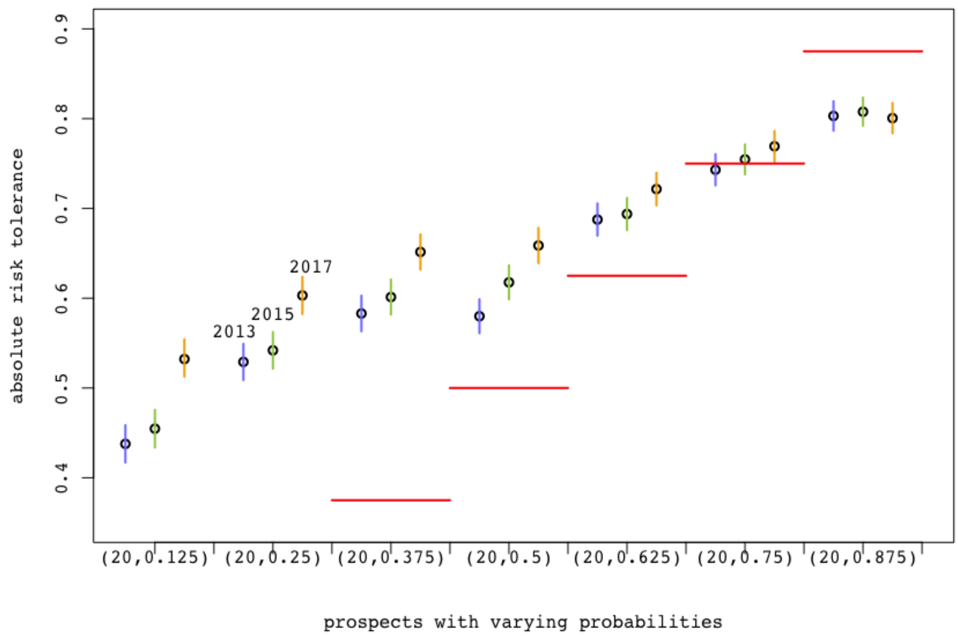


Figure S4: Relative risk tolerance across probabilities

and a prospect as follows:

$$u(ce) = w(p)u(x) + (1 - w(p))u(y), \tag{3}$$

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., 2011) 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:

$$u(x) = \frac{1 - exp(-\rho x)}{\rho} \tag{4}$$

$$u(x) = \frac{ln(1 + \rho x)}{\rho}, \tag{5}$$

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 ($p < 0.001$)	1	
2017	0.213 ($p < 0.001$)	0.265 ($p < 0.001$)	1

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:

$$\hat{\rho}(x, y) = \frac{\rho(x, y)}{\sqrt{\rho(x, x')\rho(y, y')}} \tag{6}$$

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)	(5)	(6)
Belg rain shortfall	0.004	0.166***	0.010	0.012	0.036	0.040
	(0.018)	(0.056)	(0.066)	(0.066)	(0.070)	(0.070)
Belg rain excess	0.009	0.092***	0.052*	0.036	0.017	0.018
	(0.006)	(0.023)	(0.028)	(0.031)	(0.035)	(0.035)
Belg rain shortfall sq.		-0.101**	0.017	0.023	0.094	0.089
		(0.045)	(0.053)	(0.053)	(0.064)	(0.064)
Belg rain excess sq.		-0.019***	-0.009	-0.007	0.001	0.001
		(0.006)	(0.007)	(0.007)	(0.009)	(0.009)
rain shortfall	-0.016**	-0.097***	-0.116***	-0.148***	-0.181***	-0.178***
	(0.007)	(0.022)	(0.025)	(0.032)	(0.046)	(0.046)
rain excess	-0.023	-0.169***	-0.204***	-0.209***	-0.353***	-0.347***
	(0.015)	(0.047)	(0.050)	(0.053)	(0.079)	(0.079)
rain shortfall sq.		0.029***	0.045***	0.049***	0.056***	0.055***
		(0.007)	(0.009)	(0.010)	(0.014)	(0.014)
rain excess sq.		0.113***	0.167***	0.171***	0.306***	0.302***
		(0.034)	(0.037)	(0.039)	(0.053)	(0.053)

Belg indicates the minor rainfalls used as a placebo. The other variables indicate the major rains, or Meher. Only unlagged variables reported for parsimony. The minor rains do not show any stable significant effects. The effects of the major rains, on the other hand, emerge unscathed. The regressions mirror those in table 1 in the main text, except for regression (7) with interaction effects, which is omitted from this table.

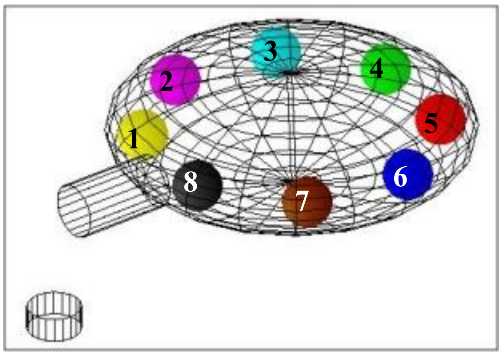
S5 Instructions for enumerators

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

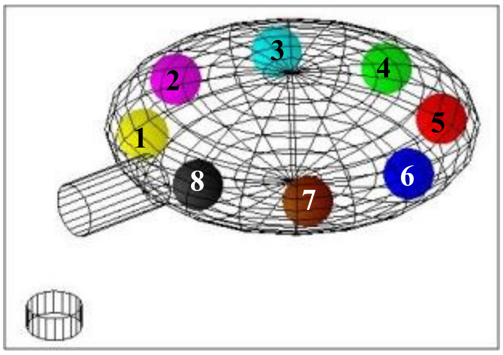
We are interested in the amount for which you will switch from preferring the lottery to preferring the sure amount. Most likely, you will prefer the lottery over a sure amount of 0, and at a certain point switch to the sure amount as the latter increases. Most likely, you would also prefer the sure 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.

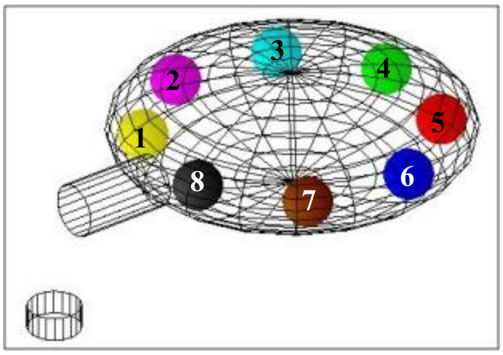
In case you have chosen the lottery for the randomly determined row, then that lottery will be played according to the probabilities indicated. You will then be paid the outcome corresponding to the ball you drew.

Decision 1

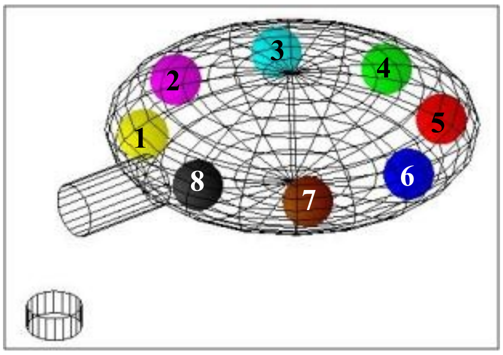


	Lottery	Sure	
	O	O	3 Birr for sure
	O	O	6 Birr for sure
	O	O	9 Birr for sure
	O	O	12 Birr for sure
	O	O	15 Birr for sure
	O	O	18 Birr for sure
	O	O	21 Birr for sure
	O	O	24 Birr for sure
Win **30 Birr** if one of the following balls is extracted:	O	O	27 Birr for sure
Win **0 Birr** if one of the following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

Decision 2

	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
Win **60 Birr** if one of the following balls is extracted:	O	O	42 Birr for sure
1 2 3 4	O	O	45 Birr for sure
	O	O	48 Birr for sure
Win **0 Birr** if one of the following balls is extracted:	O	O	51 Birr for sure
5 6 7 8	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:

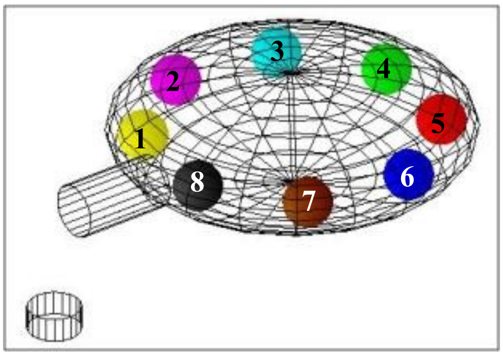
1 2 3 4

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



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

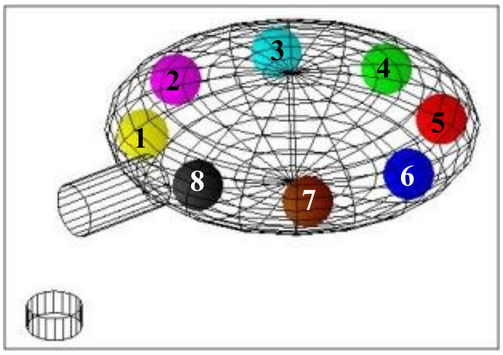
1 2 3 4

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

5 6 7 8

Lottery	Sure	
O	O	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
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:

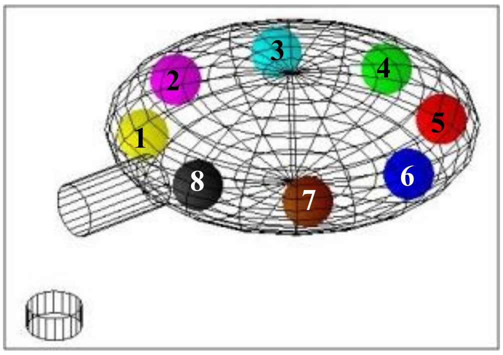
1 2 3 4

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:

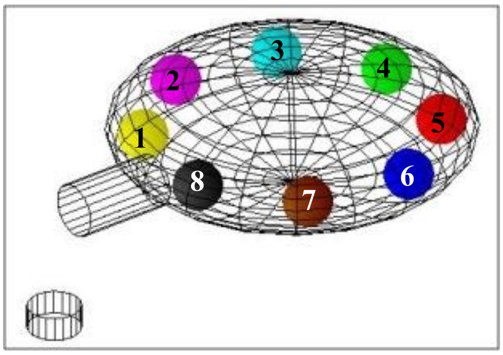
1 2 3 4

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:

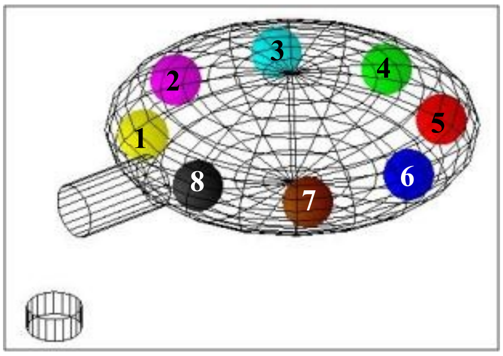
1

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

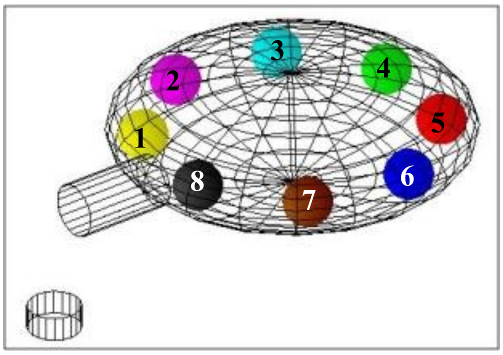
2 3 4 5 6 7 8

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

	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
Win **120 Birr** if one of the following balls is extracted:	O	O	72 Birr for sure
1	O	O	75 Birr for sure
	O	O	78 Birr for sure
Win **30 Birr** if one of the following balls is extracted:	O	O	81 Birr for sure
2 3 4 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

Decision 9



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

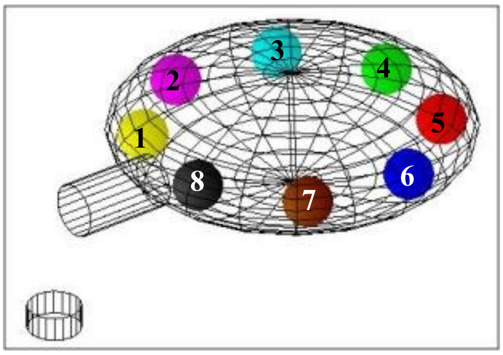
1 2

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:

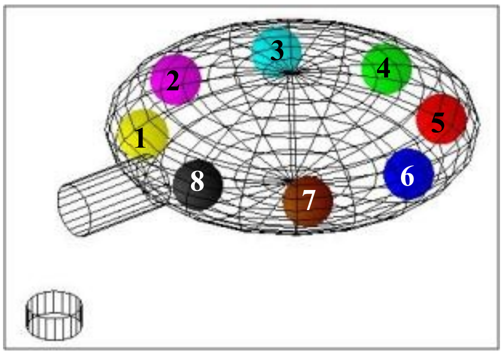
1 2 3

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:

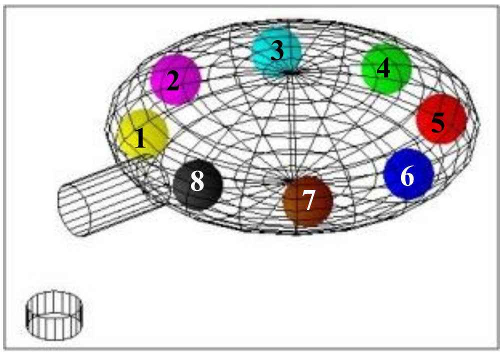
1 2 3 4 5

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:

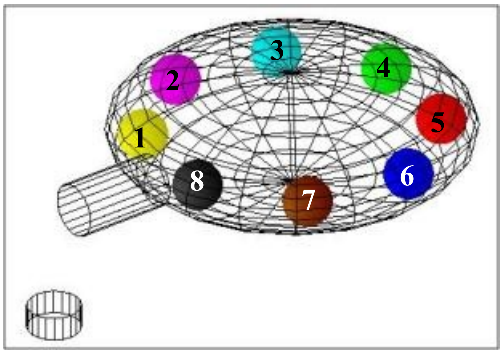
1 2 3 4 5 6

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:

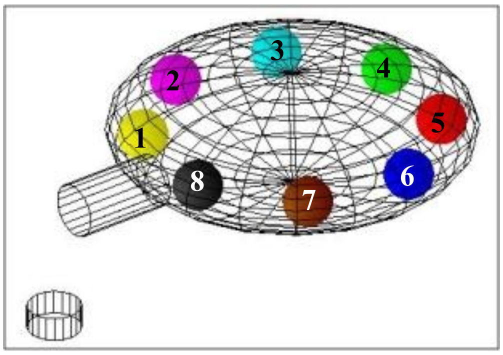
1 2 3 4 5 6 7

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:

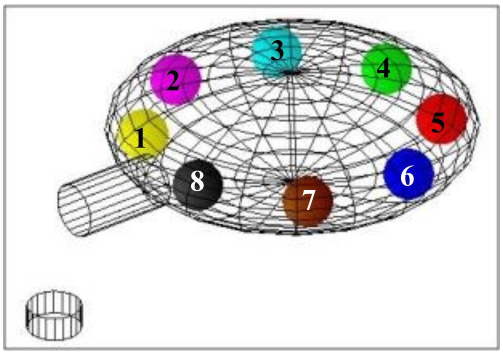
1 2 3 4 5 6 7

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:

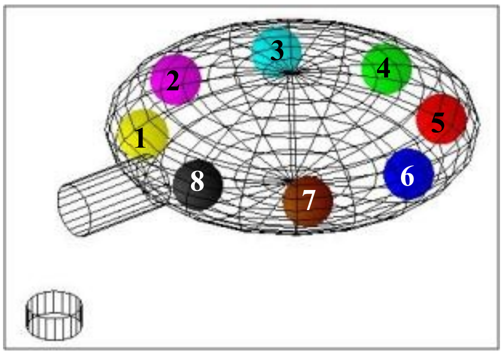
1 2 3 4

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:

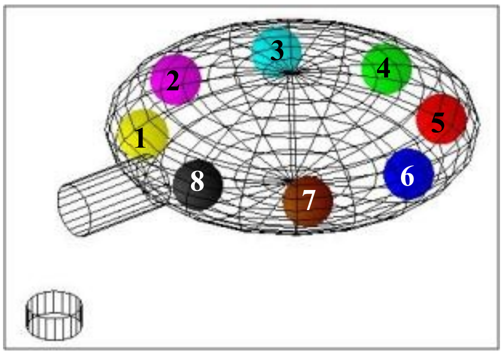
1

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

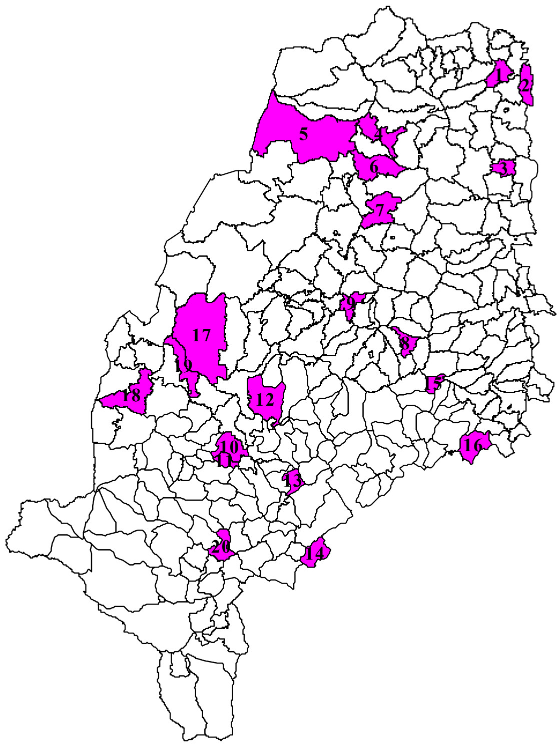


Figure 1. Map of woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names).

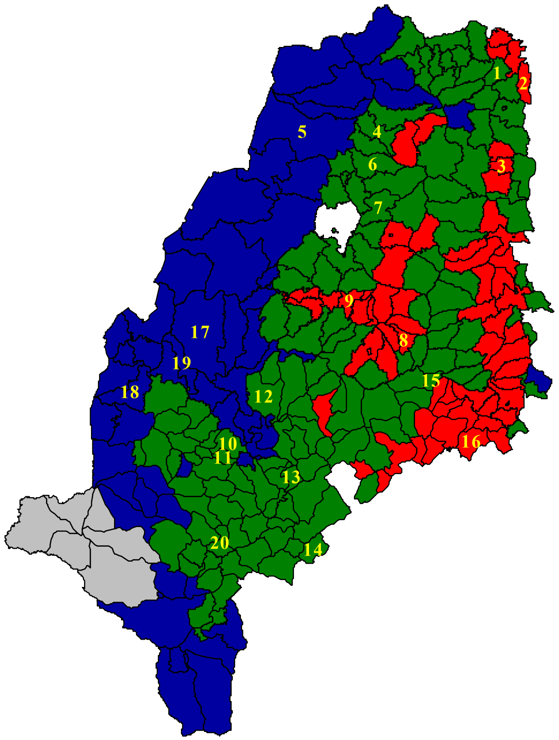


Figure 2. Thematic map of traditional agro-ecological zones and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

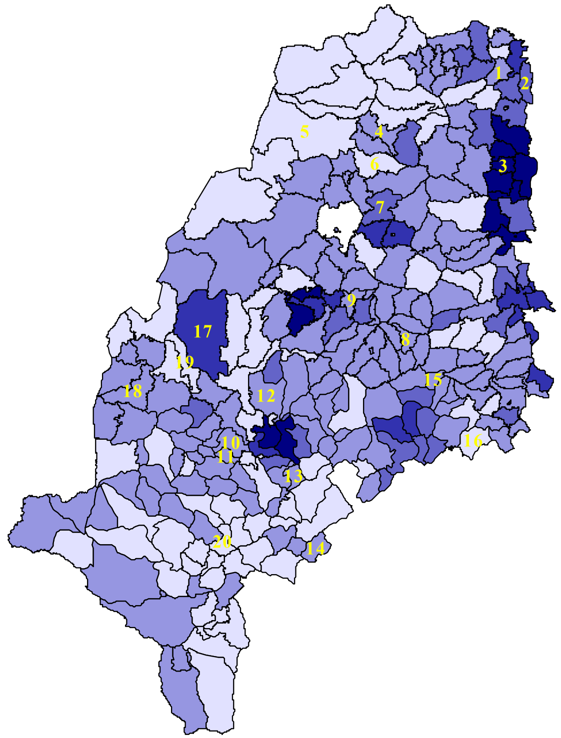


Figure 3. Thematic map of irrigation prevalence and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

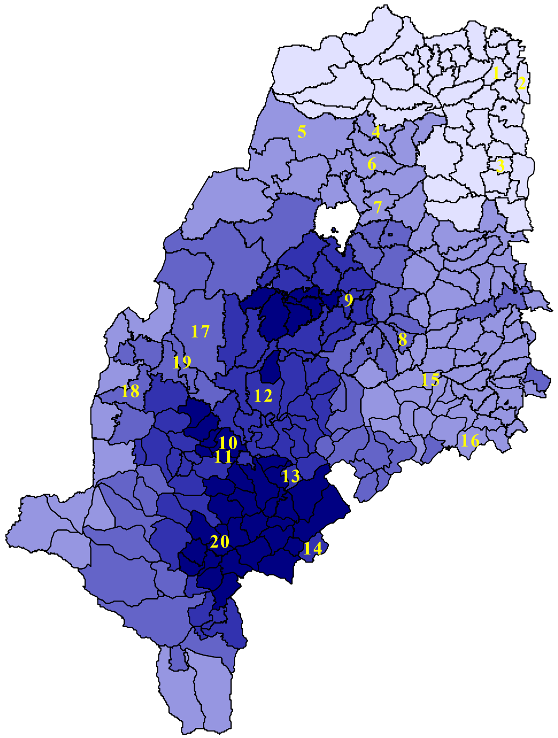


Figure 4. Thematic map of average total annual rainfall and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

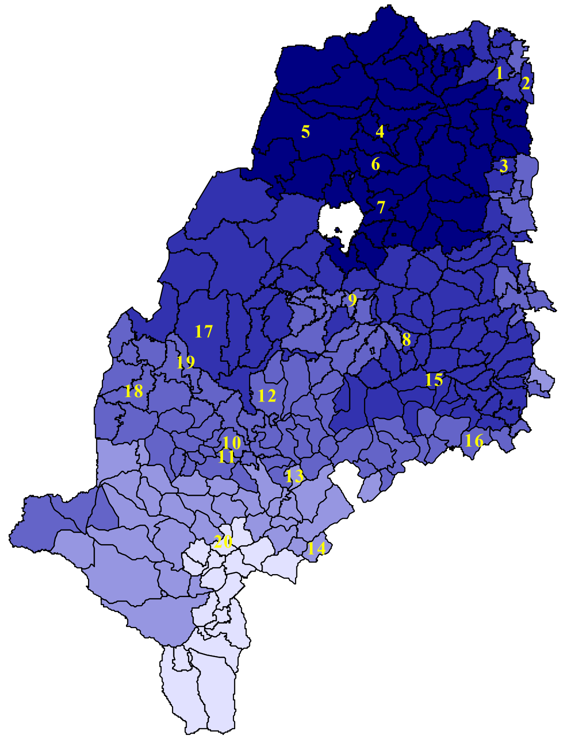


Figure 5. Thematic map of annual rainfall variation and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).

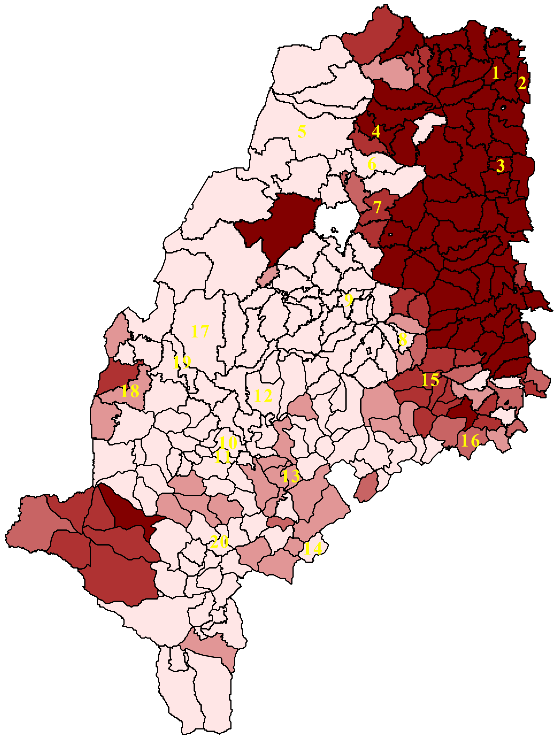


Figure 6. Thematic map of vulnerability and woredas selected for sample in Nile Basin of Ethiopia (see Table 1 for woreda names and above classification for details).