Extreme Weather Events Impact Risk Tolerance and Time Preferences*

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February 5, 2025

Abstract

Patience and risk tolerance are important determinants of far-reaching life choices impacting welfare. We investigate the effect of extreme weather events on individuals' risk and time preferences in Indonesia. Matching high-resolution precipitation and longitudinal survey data, we illustrate that each additional year of low rainfall in a respondent's location increases the probability that they are risk averse and impatient. Exploiting within-person changes in exposure to rainfall between survey waves, we identify novel symmetry in these results - individuals who experience worsening conditions over time are more likely to be risk averse, while those experiencing improved conditions are more risk tolerant and patient.

JEL Classification Codes: D81, D91, I3, O13, Q54

Keywords: Climate variability, risk aversion, impatience

*We are grateful for comments from Amy Damon, Andrew Foster, Nicholas Ingwersen, and Dhanushka Thamarapni, and conference participants at the Liberal Arts Colleges Development Economics Conference and Population Association of America annual meetings and for research assistance from Cassie Minicucci. The project was reviewed and approved by the Colby College Institutional Review Board. Jaramillo - University of California, Berkeley; LaFave - Colby College; Novak - Reed College. Corresponding author: drlafave@colby.edu

1 Introduction

Many economic choices involve uncertainty and delayed gratification. An individual's willingness to take on risk and their level of patience are therefore fundamental factors in decision making across many contexts, including occupational choice, educational attainment, insurance adoption, technology use, saving and borrowing, migration, and risky behaviors (Kan, 2003; Bellemare and Shearer, 2010; Non and Tempelaar, 2016; Barsky et al., 1997; Bryan et al., 2014; Brick and Visser, 2015; Sutter et al., 2013).

Despite the importance of risk tolerance and patience in determining economic outcomes, how they vary across individuals and evolve over time is not well understood and remains an area of active inquiry. While many economic models assume risk tolerance and patience are innate and stable characteristics (Meier and Sprenger, 2015; Frederick et al., 2002; Harrison et al., 2005), a growing body of work illustrates that significant life events and changes in local environments can alter preferences (for reviews of this literature, see Schildberg-Hörisch (2018) and Mata et al. (2018)). Negative life events can cause people to feel elevated levels of stress or an increased cognitive load, both of which have been shown to increase risk aversion (Schildberg-Hörisch, 2018). This increased stress may also shift individuals away from goal-directed behavior or otherwise alter their willingness to delay gratification (Haushofer and Fehr, 2014). However, establishing causality is challenging as an individual's exposure to shocks is often confounded with their underlying characteristics, making it difficult to disentangle a shock's impact from preexisting attitudes.

This paper investigates how changes in the frequency of extreme weather events over a 14-year period (2001-2014) impact an individual's risk tolerance and patience. We overcome empirical challenges present in much of the related literature by matching high-resolution precipitation data with two waves of longitudinal household survey data from Indonesia to estimate how plausibly exogenous changes in the environment affect an individual's risk tolerance and patience over time. We find that each additional year of extremely low rainfall (measured as annual precipitation below the 15th percentile of the historical local distribution)[1] increases the probabilities that an individual is risk averse and impatient by 2.2 and 2.3 percentage points, respectively. These are substantial changes; moving from zero to the median number of low rainfall years corresponds to approximately seven percent increases in each outcome, a difference similar to the change across a quintile of the household per-capita expenditure distribution.

A novel contribution of our study is to show that preferences also adjust when conditions improve. By isolating the direction of within-person changes in rainfall realizations between survey waves, we find that individuals exposed to improved rainfall conditions become more risk tolerant and patient. For each additional year without a drought in the seven years preceding the second survey wave relative to the seven years preceding the first wave, individuals are 1.6 percentage points less likely to be risk averse and 2.3 percentage points less likely to be impatient, compared to those who experienced the same rainfall conditions in both periods.

We provide suggestive evidence that this symmetric response to changing rainfall patterns is, at least in part, a response to the economic conditions caused by extreme rainfall patterns. We demonstrate that households that experienced a drought in the previous 12 months have lower household per-capita expenditure. Further, we find larger effects on household expenditure and on risk and time preferences among respondents in rural areas, which are more economically dependent on agriculture (Kadir and Amalia, 2017), relative to urban areas. This mechanism is consistent with

[1]This definition of low rainfall follows Burke et al. (2015), McGavock and Novak (2023), and others and is justified in detail in Section 2.2.

Shah et al. (2012), who demonstrate that economic scarcity can lead to impatience and cognitive errors, and Liebenehm et al. (2024), who show that rainfall shocks increase risk aversion in rural Thailand and Vietnam, in part due to changes in agricultural prices.

While existing literature investigates the impact of adverse events on risk preferences, there is no consensus on the direction of the effects. Specifically, individuals became more risk tolerant when exposed to long-standing civil conflict in Burundi and Afghanistan (Voors et al., 2012; Callen et al., 2014), the 2004 Indian Ocean tsunami (Ingwersen et al., 2023), the 2011 Great East Japan Earthquake (Hanaoka et al., 2018), or the 2015 severe drought in Ethiopia (Holden and Tilahun, 2024). In contrast, people became more risk averse when exposed to earthquakes and floods in Indonesia (Cameron and Shah, 2015; Thamarapani and Rockmore, 2022), the major but short-lived Korean War (Kim and Lee, 2014), significant and relatively short-lived post-election violence in Kenya (Jakiela and Ozier, 2019), escalations in violent crime in Mexico (Brown et al., 2019), the global financial crisis (Necker and Ziegelmeyer, 2016), personal health shocks (Decker and Schmitz, 2024), rainfall variation in Ethiopia (Di Falco and Vieider, 2022), and micro-level negative economic and agricultural shocks in Thailand (Liebenehm et al., 2024). Our work is consistent with the second category of adverse events, which are largely less severe than those events that are shown to have increased risk tolerance.

Importantly, our study expands this literature by documenting how risk tolerance changes when conditions improve. Past work links increasing risk tolerance to improving macroeconomic conditions (Sakha, 2019; Sahm, 2012) or the decline of COVID-19 (Tsutsui and Tsutsui-Kimura, 2022), but few studies track individuals over sufficiently long periods to systematically examine effects of both positive and negative environmental shocks within the same population. Locations within our study setting experienced plausibly random changes in precipitation conditions during our study period.

This allows us to compare areas where conditions worsened, those that stayed consistent, and those where conditions improved to assess how individuals' risk and time preferences change when local conditions vary.

Research on how individual characteristics and shocks relate to time preferences is notably more limited. Existing work finds that more education and higher cognitive ability are associated with higher levels of patience (Lührmann et al., 2018; Falk et al., 2018; Jung et al., 2021; Dohmen et al., 2010; Falk et al., 2018). However, few studies examine the impacts of exogenous events on time preferences. Escobar Carias et al. (2024) find that high temperatures increase impatience among individuals in Indonesia, and Thamarapani and Rockmore (2022) find that the 2006 earthquake in Indonesia decreased impatience in women and increased impatience in men. Callen (2015) demonstrates that patience increased among Sri Lankans following the 2004 Indian Ocean earthquake and tsunami. Our work contributes to this limited literature by showing that impatience increases following exposure to rainfall shocks and decreases when conditions improve.

We also contribute methodologically by demonstrating an approach that is applicable to settings where researchers study within-unit variation in exposure to shocks. While many past studies implicitly assume that positive and negative shocks have symmetric effects, this may not necessarily be the case. Using panel data with low attrition, we are able to isolate how preferences change under both positive and negative deviations from past experiences and relax any imposed symmetry. This approach can be applied in other contexts where within-unit variation in exposure is used to estimate behavioral responses, such as changes in income, health, or economic policy.

Finally, the rich household survey data allows us to assess heterogeneous impacts by gender, rural-urban locality, and socioeconomic status, all of which are related to risk and time preferences (see, for example, Hanaoka et al. (2018); Booth et al. (2014); Riley and Chow (1992); Guiso and

Paiella (2008); Sahm (2012)). In doing so, we contribute to the inconclusive literature on the directional effects of adverse events on risk preferences and comment on plausible mechanisms driving our results.

Our findings suggest that low rainfall not only decreases household resources in a given year but also reduces the willingness to take risks and delay gratification, likely resulting in lasting impacts to household resources. Conversely, improvements in rainfall realizations can reverse these effects, underscoring the malleability of preferences in the face of shocks. This should encourage researchers studying behaviors influenced by risk and time attitudes (e.g., technology adoption, savings, and credit) to recognize that the results of their studies are likely impacted by local conditions at the time of data collection (Rosenzweig and Udry, 2019). Given that impatient and risk-averse decision making is meaningfully related to poverty (Haushofer and Fehr, 2014), our results underscore the need for social scientists to better understand the impacts of weather shocks on risk and time preferences. This is particularly true as climate change stands to make weather shocks both more extreme and frequent (Seneviratne et al., 2012).

2 Data

Examining how individual preferences respond to changes in environmental conditions requires detailed geographically referenced data on both individuals and weather patterns. We benefit from the longitudinal structure and extensive tracking of the Indonesia Family Life Survey (IFLS) to link individuals with local precipitation levels.

2.1 Indonesia Family Life Survey

The IFLS is a broad, continuing, population-based survey containing information on individuals, households, and their communities. The 1993 baseline, representative of 83 percent of the Indonesian population, enumerated 7,224 households spread across 13 of Indonesia's then 26 provinces. Since then, there have been four additional waves of the full survey—IFLS2 in 1997, IFLS3 in 2000, IFLS4 in 2007, and IFLS5 in 2014.

In each subsequent wave, IFLS tracks and interviews all members of the original households, their descendants, and any new members of the descendants' households, even if those individuals relocate. This tracking is done with incredibly high recontact rates; 90 percent of all surviving respondents were re-interviewed in IFLS3, IFLS4, and IFLS5 (Strauss et al., 2009; Thomas et al., 2012; Strauss et al., 2016). We focus on panel respondents from the third through fifth survey waves because a module measuring risk and time preferences for all individuals over the age of 15 is included in the fourth and fifth survey rounds, and we use lagged control variables from the third round.

Risk tolerance is measured by hypothetical questions offering a certain payout versus an equal-chance probability-based alternative. As the respondent moves through the module, they are presented with choices with varying levels of risk.[2] Figure 1a depicts the flow of questions. An initial screening-type question is included that asks the individual to choose between a certain amount of 800 thousand rupiah or an equal chance of 800 thousand and 1.6 million rupiah.[3] Those who choose

[2]The survey is specifically designed with the cultural context in mind, describing the options as "ways to earn money" and avoiding language around "lottery" or "gamble", which are forbidden in Islam.

[3]Mean monthly per-capita expenditure is approximately 1 million rupiah.

the first pay-off are prompted to reconsider their choice. If they do not switch, they exit the set of questions and are considered extremely risk averse (Ingwersen et al., 2023), or "gamble averse" following Hamoudi (2007).

[Figure 1 here]

Respondents who choose the uncertain pay-off continue on and face a series of questions designed to sort individuals based on their tolerance for risk. While it is possible to derive coefficients of relative risk aversion based on the values of the payouts, such measures require strong assumptions about the form of utility functions and are thought to be noisy measures of actual risk attitudes. Following Brown et al. (2019), who use a similar module from the Mexican Family Life Survey that formed the basis for the IFLS questions (Strauss et al., 2009), we use an indicator for the extreme of the distribution and define "most risk averse" as those individuals who never choose a pay-off combination with the potential to fall below the initial certain level of 800 thousand rupiah (index values 4 and 5 in Figure 1a).

This definition of risk aversion includes individuals classified as "gamble averse" by the initial screening question, constituting approximately 36 percent of person-wave observations. Although this percentage may seem high for a dominated option, it does not appear to be driven by misunderstanding, as these respondents were explicitly told they would profit from the alternative choice, yet over 80 percent did not switch.[4] Moreover, "gamble averse" individuals are not simply those with lower education levels, as they comprise a third of respondents with at least 12 years of education,

[4]The enumerator's statement is: "Are you sure? In option 2 you will get at least Rp 800 thousand per month and you may get Rp 1.6 million per month. In option 1 you will always get Rp 800 thousand per month." Strauss et al. (2009).

nor are they disproportionately Muslim, despite religious objections to gambling in Islam. These patterns align with studies using similar risk modules, including work on the Indian Ocean tsunami (Ingwersen et al., 2023), risk and migration in Indonesia and Ghana (Goldbach and Schlüter, 2018), and the Mexican Family Life Survey (Brown et al., 2019). Further, Escobar Carias et al. (2024) show that "gamble averse" individuals in IFLS exhibit systematic risk-avoidance behaviors in employment, entrepreneurship, and smoking. Together, this evidence demonstrates that the screening question captures meaningful variation in risk attitudes. For further support, we illustrate the robustness of our findings to excluding the "gamble averse" individuals or using the alternative risk aversion index rankings that separate this group into its own category (see Table 5).

The time preference module follows a similar structure where respondents are led through a series of choices as illustrated in Figure 1b. Here the choices are between a pay-off today versus a larger pay-off one year in the future, a widely-used type of money earlier or later question shown to meaningfully elicit attitudes over intertemporal decisions (Cohen et al., 2020; Alem et al., 2024). The module includes a screening question offering both 1 million rupiah in one year versus the same amount today. Those who choose the delayed pay-off are prompted to reconsider their choice and exit the module if they still prefer the one-year delay. These individuals have "extreme patience," or negative discounting rates.

Individuals who prefer the pay-off today are then asked questions in which the higher future pay-off amount varies in order to rank individuals according to their willingness to delay payment. For similar reasons as with risk attitudes, our outcome of interest is an indicator for those at the extreme of the distribution who always take the pay-off today. We define this group as "most impatient." We show in Table 5 that omitting those who select negative discounting rates or using the ordinal rankings lead to consistent findings.

The risk and impatience measures contribute to a growing body of work using preference modules in large-scale household surveys (Dohmen et al., 2011; Jung et al., 2021; Rubalcava et al., 2009; Hamoudi, 2007). The longitudinal design of the IFLS also assuages concerns that the hypothetical questions may not accurately represent attitudes toward real-stakes choices. As we compare the same individuals across time and find that a higher number of low rainfall years increases the probability of being risk averse and impatient, different responses between hypothetical and real pay-offs will cause bias only if low rainfall makes a given individual more likely to answer hypothetical payout questions in a risk averse or impatient way that is not reflective of their true attitudes or behavior. There is no evidence of such within-person differential reporting taking place rather than the survey capturing true attitude changes.

[Table 1 here]

Descriptive regressions in Table 1 illustrate the validity of the risk and time modules for measuring meaningful variation in preferences and behavior. These are consistent with Escobar Carias et al. (2024) who show results from a similar exercise with the same survey data. Panels A and B compare mean differences across those who are and are not most risk averse and impatient, respectively. Those who are most risk averse or impatient are less likely to have taken out loans and invest less in their own farm or non-farm businesses. Columns 3 and 4 illustrate that risk aversion and impatience are also associated with differences in preventative healthcare usage and self-employment. Risk averse individuals are no more likely to have used preventative healthcare in the last month, while those who are impatient are less likely to have used preventative services. The opposite association is present for self-employment, with risk averse individuals being less likely to be self-employed while the converse holds for those who are impatient.

2.2 Precipitation data

We combine the longitudinal preference data with high-resolution climate data from the University of Delaware Terrestrial Air Temperature and Precipitation project (Matsuura and Willmott, 2018). The UDel dataset reports monthly total rainfall collected primarily from ground stations and spatially interpolated to 0.5 degree x 0.5-degree gridcells, approximately 50km-squared over the study area. As preferences may reflect accumulated exposure, we aim to understand the conditions in the local environment leading up to the first observation of risk and time preferences in IFLS4 and then changes in the environment that occurred between the fourth and fifth survey rounds.

To match precipitation to individuals, we assign all households within an IFLS community the mean rainfall of gridcells within a 50km radius of the GPS coordinates of the community center, a range consistent with the precipitation grid size.[5] Our primary rainfall measure is a count of the number of years with abnormally low rainfall over the seven years preceding the survey to reflect the timing between the 2007 and 2014 IFLS waves. The UDel series provides sufficiently long-term data to calculate historical rainfall distributions at each location. Drawing on prior work linking rainfall to crop yields, income, and adverse events (e.g. Burke et al., 2015; Corno et al., 2020), we define a low-rainfall year as a year in which total precipitation is below the 15th percentile of the

[5]Results using a 25km radius are consistent in magnitude and statistical significance with those shown here.

historical distribution in the location.[6] The percentile values are determined by estimating a gamma distribution based on annual precipitation between 1970 and 2000 in the same location. This time frame serves as a pre, or training, period to define low rainfall from 2001 to 2007 and then from 2008 to 2014.

Figures 2a and 2b show the spatial pattern of this low-rainfall measure. Each cell is shaded to represent the number of years over the preceding seven-year period with rainfall below the historical 15th percentile for the location. Areas with no IFLS respondents are colored gray. As shown by the darker shading in Figure 2a, the 2001-7 period was considerably drier than the seven years between IFLS4 and IFLS5 for much of the area. This pattern aligns with climate science research on the interactions between El Niño and the Indian Ocean dipole, which contributed to particularly dry conditions leading up to IFLS4 and fewer droughts preceding IFLS5 (Pan et al., 2018). The median number of low-rainfall years experienced by respondents was 3 in the earlier 7-year period compared to 1 in the latter.

[Figure 2 here]

The longitudinal design of IFLS allows us to look at the relative changes a respondent experiences across these two time periods to determine if their environmental conditions improved over time, stayed the same, or worsened. Figure 2c illustrates the location-specific difference in the count of

[6]We match rainfall data to households based on their month of interview and current location so that the annual total represents the total for the 12 months leading up to the observation. Individuals who migrate between survey rounds are assigned rainfall in the fifth wave based on their IFLS5 location. Appendix tables A3 and A4 show that migration is not endogenous to the low-rainfall measure and that results are consistent if we instead use an intent-to-treat design that assigns migrants rainfall from their IFLS4 locations.

low-rainfall years between 2008-14 relative to 2001-7. Cells that are shaded green represent locations where there were fewer years of low rainfall from 2008 to 2014 than from 2001 to 2007. Red cells are areas with more years of low rainfall between the survey waves than leading up to the fourth round.

While conditions improved across much of Indonesia between the two time periods, there is considerable variation in the magnitude of the changes as well as the direction. The median change is two fewer low-rainfall years, with approximately 85 percent of individuals experiencing improved conditions, 10 percent a stable count of low rainfall, and five percent worsening conditions.[7]

Figure 2c represents the central identifying variation for the empirical analysis that follows. It is important to note that an individual's exposure to years of low rainfall is independent of their prior preferences or demographics (see Appendix Table A2).

While our procedure to calculate a meaningful marker of cumulative low rainfall stems from prior work in the literature (Burke et al., 2015; Corno et al., 2020; McGavock and Novak, 2023), there is no clear consensus on a best-practice (Dell et al., 2014). We choose this marker for several reasons. First, compared to looking at absolute amounts of rainfall, the reference values we use are specific to the community. This approach avoids confounding historically drier areas with a higher number of low-rainfall years, as the 15th percentile threshold varies with the rainfall distribution of the area. Second, the measure has clear impacts on household resources across the expenditure distribution. Table 2 reports results from regressions estimating the impact of low rainfall on monthly household per-capita expenditure (PCE). The IFLS expenditure module, which is well-validated and used throughout surveys in Indonesia, collects information on purchased and own-produced food,

[7] Appendix Table A1 shows the respondent-level transition matrix corresponding to Figure 2.

non-food, and durable goods.[8] The models include household fixed effects, time effects to account for inflation and other common temporal factors, and demographic controls to measure the effect of changes in experiencing low rainfall for a given household over time.

[Table 2 here]

Column 1 includes the full sample of households in our analysis and suggests low rainfall in the preceding 12 months is related to a statistically significant 5.4 percent reduction in monthly PCE. Columns 2 and 3 establish that while rural areas see an amplified 8.3 percent reduction in monthly PCE, households in urban areas remain impacted with a 4.6 percent reduction. Columns 4 through 6 examine distributional impacts by stratifying the sample into terciles based on per capita household expenditure in the third wave. Households across the distribution are significantly impacted by a low-rainfall year, with effects ranging from a reduction of 8.9 percent for those least well-off to a 4 percent reduction for those in the top tercile.

We are confident that our rainfall measure captures meaningful environmental changes. That said, we examine the robustness of our findings to alternative rainfall thresholds in Table 5 and show that our results are not sensitive to the specific definition of low-rainfall shocks.

[8]The recall period for each consumption good, e.g. weekly for food, monthly for utilities, or 12 months for medical spending, balances recall errors from longer periods with the frequency of purchases. We convert all expenditures to monthly equivalents, as is standard in the literature, and regress the measure on an indicator for low rainfall in the 12 months leading up to the survey.

2.3 Descriptive statistics

Our analysis sample consists of 17,911 individuals who completed the preference modules in both IFLS4 and IFLS5 and that link to geo-referenced precipitation data and demographic characteristics from IFLS3 onward.[9] Table 3 reports descriptive statistics separated by survey wave of key variables for this sample.

[Table 3 here]

The "most risk averse" and "most impatient" categories represent the majority of respondents for each indicator, with risk tolerance increasing across the two waves.[10] The sample is 55 percent female, with a mean age of 36 in 2007. Slightly less than half of respondents reside in rural areas, with the decrease over time representing both out-migration and rural areas that reclassify as urban.

2.4 Longitudinal tracking, attrition, and migration

The IFLS has an established reputation for its low attrition rates despite the challenges of its longitudinal tracking design following migrants across the archipelago (Thomas et al., 2012). The survey's 90 percent re-contact rates in both the fourth and fifth survey waves are notably higher than other large, population-based surveys. In light of the longitudinal nature of our analysis, we

[9] The use of lagged controls avoids confounding the observed low-rainfall measure with potentially endogenous variables if rainfall impacts, for example, household size or educational attainment.

[10] While the two indicators overlap, with approximately 47 percent of observations across the waves both risk averse and impatient and 16 percent recorded as neither, the discordant pairings of risk averse but patient, 17 percent, and risk tolerant but impatient, 20 percent, make up considerable shares of the population.

are concerned with whether attrition out of the survey is linked to changes in low rainfall between survey waves, as that could affect the representative nature of the sample. Additionally, given the IFLS's emphasis on tracking migrants, we also investigate whether migration between the survey waves is related to changes in low-rainfall exposure. Appendix Table A3 presents evidence that there is no meaningful relationship between low rainfall and attrition or district-level migration.

3 Empirical Approach

Our two empirical goals are to identify the impact of low-rainfall years on individual preferences and to assess whether the effects of worsening versus improving rainfall conditions move in opposite directions.

With risk and patience measures recorded in both the 2007 and 2014 waves, we approach the first goal by examining how the outcomes relate to changes in exposure to low rainfall with individual fixed effects regression models that take the following form:

$$y_{icmt} = \alpha_1 nlowrain_{cmt} + \gamma X_{i,t-1} + \mu_i + \mu_{mt} + \epsilon_{icmt} \tag{1}$$

where y_{icmt} is a binary indicator for if individual i living in community c interviewed in month m of survey wave t is in the most risk averse group, in the first set of results, or most impatient group, in the second set of results. $nlowrain_{cmt}$ is the count of low-rainfall years over the previous seven years in community c based on interview date mt. $X_{i,t-1}$ is a vector of time-varying demographic control variables measured in the previous wave to avoid confounding with impacts of the low-rainfall measure, μ_i are individual fixed-effects, and μ_{mt} month-year fixed effects capturing any seasonal or temporal patterns.[11]

The coefficient of interest, α_1, relates how an increase in the number of low-rainfall years impacts the probability of being risk averse or impatient. Individual fixed effects control for all stable, time-invariant, individual-level characteristics and ensure that α_1 is measured from a within-person comparison—i.e. the impact of how the change in rainfall individual i experienced relates to a change in their preferences. This strategy controls for significant sources of potential unobserved heterogeneity that may otherwise bias the rainfall and preference link. We present estimates of α_1 with and without individual fixed effects to emphasize this point.

After examining the results of equation (1), we then move to assess the directional effects of improving versus worsening rainfall conditions by relaxing the symmetry imposed by this specification. To do so, we reconsider the model in its first-difference form, where Δ represents the change for individual i between IFLS5 and IFLS4. Taking within-person differences removes the individual fixed effect from (1) and leads to the following:

$$\Delta y_{icm} = \alpha_1 \Delta nlowrain_{cm} + \gamma \Delta X_{i,t-1} + \mu_m + \epsilon_{icm} \tag{2}$$

With two time periods of longitudinal data, the coefficients on $nlowrain$ from equation (1) will match the coefficient on $\Delta nlowrain$ from equation (2). Month-year of interview effects for both rounds of the survey, μ_m, remain in the model to account for seasonality and observed changes in the outcome y not linked to changes in low rainfall or the lagged demographic controls.

[11] The lagged demographic controls are marital status, years of education, total household size and the number of children in the household, rural location, and household per-capita expenditure (PCE) quintile. All models also include respondent age and age-squared at the time of interview.

In this specification, $\Delta nlowrain$ now makes clear that the within-person variation includes both positive and negative values—positive numbers represent experiencing additional low-rainfall years, and negative values represent fewer low-rainfall years. Those who had the same number of low-rainfall years across the two time periods have no change, or $\Delta nlowrain = 0$. To estimate possible directional effects of rainfall changes, we define separate variables for $\Delta nlowrain$ based on the sign of the change. We use zero change as the reference group and define more low rainfall years, $\Delta nlowrain^{additional}$, as the count of additional years of low rainfall and fewer low rainfall years, $\Delta nlowrain^{fewer}$, as the count of the decrease in years of low rainfall in the following regression:

$$\Delta y_{icm} = \beta_1 \Delta nlowrain_{cm}^{additional} + \beta_2 \Delta nlowrain_{cm}^{fewer} + \gamma \Delta X_{i,t-1} + \mu_m + \epsilon_{icm} \tag{3}$$

where the β_1 and β_2 coefficients identify how experiencing an additional or fewer year of low rainfall relates to a change in preferences relative to those who experienced the same count of low rainfall years leading up to both rounds of the survey. Visually, this strategy compares the changes in the outcome for those individuals in red and green shaded areas of Figure 2c to those in the yellow cells—β_1 represents the change in preferences for different levels of red compared to yellow, and β_2 for levels of green compared to yellow.

The absence of links between low rainfall and demographics illustrated in Appendix Table A2 helps solidify that the observed variation in low rainfall is orthogonal to individual-level characteristics. β_1 and β_2 can then be interpreted as causal effects of worsening and improving conditions, respectively, rather than reflecting underlying trends in preferences that may differ across demographic groups who could be differentially exposed to worsening or improving conditions.

4 Findings

Table 4 presents estimates from equation (1) of the impact of low rainfall on indicators for being in the most risk averse and impatient classifications. Columns 1 and 4 treat the longitudinal data as pooled cross-sections with comparisons drawn between different individuals based on the number of years of low rainfall each individual experienced. Columns 2 and 5 then add individual fixed effects to restrict identification to within-person comparisons. Columns 3 and 6 are the full specifications that include the vector of lagged control variables. All regressions include month-year of interview fixed effects, controls for age and age-squared, and cluster standard errors at the individual and community-wave levels following Abadie et al. (2022).

[Table 4 here]

Columns 1 and 4 suggest statistically significant, but somewhat modest effects, of low rainfall on preferences—an additional year of low rainfall relates to 1.38 and 0.94 percentage point increases in the likelihood of being risk averse and impatient. However, by omitting the individual fixed effects and thereby comparing across individuals, these regressions are likely biased. For example, if individuals who are risk tolerant or patient are more likely to live in areas with more volatile rainfall patterns, the coefficients in columns 1 and 4 would be biased downward, while if they are less likely to live in more volatile climates, the coefficients would be biased upward.

The results in columns 2 and 5 suggest the former may indeed may be the pattern, as the magnitude of the effects and precision of the estimates grow considerably with the inclusion of individual fixed effects. Including the full vector of lagged controls in columns 3 and 6 only slightly attenuates these estimates, with the results illustrating 2.2 and 2.3 percentage point increases in the probability of being risk averse or impatient for each additional year of low rainfall. Moving from zero to two low-rainfall years, the median number in our sample, would represent approximately a seven percent increase in the probability of each outcome relative to their means. These are substantial changes and similar in magnitude to the association with moving up one quintile of the household per-capita expenditure distribution.

Table 5 shows alternative specifications and sensitivity analysis based on the models in columns 3 and 6 of Table 4. We later document heterogeneity of the impacts in Table 6 after disaggregating the direction of the within-person change in low rainfall. Panel A of Table 5 examines alternative preference measures. Column 1 removes individuals who report as "gamble averse" in either survey wave from the risk aversion analysis. The precisely-estimated 3.64 percentage point effect, relative to the 2.18 estimate in column 3 of Table 4, suggests the inclusion of this group may attenuate the baseline estimate rather than create any concerning, upward bias.[12] Column 2 removes those with negative discounting rates in either wave, approximately five percent of the sample, from the impatience analysis. The impact of low rainfall attenuates slightly to 2.03 from 2.30, but the results are not statistically different from each other. Columns 3 and 4 then replace the risk averse and impatient indicators with the ordinal risk and impatience rankings and estimate fixed effect ordered logit models (Baetschmann et al., 2015). These indices range from one to five. The results, reported as odds-ratios, suggest clear links in the expected direction where additional low-rainfall years move

[12]Forty-two percent of individuals remain in this analysis as the individual fixed effects require that observations are removed if the individual answers as "gamble averse" in either wave. Alterative test of the role of these respondents removes those who have the highest non-gamble averse risk ranking and leaves those who are "gamble averse" as the most risk averse reference category. This exercise results in an estimated effect of 1.76 (p-value = 0.03). Taken with the results in Table 5, we conclude that the inclusion or omission of the "gamble averse" responses does not drive the connection between additional low rainfall years and increases in risk aversion.

an individual up the scale toward the indicators used in the baseline specification.

[Table 5 here]

Panel B of Table 5 then examines non-linearities in the results in Table 4. The number of low-rainfall years ranges from zero to six in the sample, and we include separate indicators for each of the non-zero values, with zero low-rainfall years serving as the omitted reference category. Lagged controls and fixed effects remain in the models so that the coefficients measure the impact of an individual experiencing a change in their number of low-rainfall years relative to the reference category. If the impact of low rainfall is cumulative and more severe for those who experience a greater number of shocks, we expect that the coefficients would increase moving from one up to six years. Columns 5 and 6 are largely consistent with this pattern, with positive effects appearing for two and more years and generally increasing in magnitude for the higher number of shocks.

Panel C then assesses the sensitivity of the baseline results to using the 15th percentile as the threshold for low rainfall. We disaggregate the count from Table 4 into the number of years in each of five bins for the 5th through 25th percentiles. This approach allows us to test if more severe droughts have the largest effects, and at which point in the rainfall distribution the effects fade away. Results in columns 7 and 8 show the largest impacts for years below the 15th percentile, with rainfall years in the 15th to 20th also meaningfully impacting risk aversion. Those above the 20th percentile have smaller and not statistically significant relationships with either preference marker.

While this analysis emphasizes cumulative low-rainfall exposure, we also consider the dynamic timing of the low rainfall episodes. It is possible that recent shocks may be more salient and have stronger psychological or behavioral effects if individuals tend to respond more acutely to immediate changes in their environment (Haushofer and Fehr, 2014). Alternatively, distant shocks may exert a more pronounced influence if they generate persistent impacts that are delayed or outlast the immediate aftermath of the event (Hanaoka et al., 2018; Voors et al., 2012). This persistence could weaken the relative importance of recent events, particularly if individuals adjust to prolonged adversity.

To examine the potential role of timing, Panel D reports results from a reweighted specification where more recent low-rainfall years are given greater weight in the sum. We apply both linear and exponential weighting, assigning higher importance to more recent shocks. The results provide suggestive evidence that recent droughts have a larger impact, albeit marginally. Using linear weights, the coefficients increase to 2.37 for risk aversion and 2.65 for impatience, compared to 2.18 and 2.30 in the unweighted baseline model. Similarly, an exponential weighting approach produces comparable increases with coefficients of 2.34 for risk aversion and 2.75 for impatience. These patterns suggest that the proximity of drought exposure may play a role in shaping preferences, though disentangling this effect from cumulative exposure remains challenging.

To assess the additional robustness concern of endogenous migration potentially biasing the results, Appendix Table A4 repeats the analysis in Table 4 but assigns rainfall realizations in IFLS5 based on the individual's IFLS4 location. This is an intent-to-treat regression design. The reported coefficients are essentially identical to, and not statistically different from, the baseline findings in Table 4, suggesting movement between the waves does not overstate any impacts we find.

The results in Tables 4 and 5 suggest that the changes an individual experiences in their local environment have a meaningful impact on their preferences. We now seek to understand if the direction of the change matters, as the commonly-used approach in equation 1 forces symmetry on the effects of, for example, two fewer and two additional low-rainfall years. Table 6 reports results from estimating equation (3) to assess how worsening versus improving conditions relate to changes in preferences. These regressions are based on the first-differenced version of the results in Table 4, so there is now one observation per individual and the dependent variable is the change in the outcome. The same lagged controls as in the fixed effects regressions are included in their differenced form, and standard errors are clustered at the community level.

[Table 6 here]

Columns 1 and 2 report the effects of worsening and improving rainfall conditions on risk aversion and impatience. Individuals who experienced the same number of years of low rainfall between waves serve as the reference group. The results have clear directional patterns; an additional year of low rainfall conditions relates to being 7.96 percentage points more likely to be risk averse and 3.71 percentage points more likely to be impatient (though not statistically significant), while each fewer year of low rainfall relates to being 1.62 and 2.16 percentage points less likely to be risk averse and impatient, respectively. This is a novel result, as the plausibly random variation in local rainfall from 2001-14 creates the unique circumstance of seeing both improvement and worsening in the population. For both outcomes, we fail to reject that the effects are of the same magnitude but have opposite signs (p-values of 0.14 for risk aversion and 0.71 for impatience).

While previous literature establishes that adverse events affect risk aversion and impatience (Voors et al., 2012; Callen et al., 2014; Cameron and Shah, 2015; Thamarapani and Rockmore, 2022; Kim and Lee, 2014; Jakiela and Ozier, 2019; Brown et al., 2019; Necker and Ziegelmeyer, 2016), we additionally show that improvements in the local environment reduce risk aversion and impatience. This evidence further suggests that risk and time preferences are not innate characteristics but are malleable and responsive to environmental and economic conditions.

4.1 Heterogeneity

We assess heterogeneity in the response to changes in rainfall conditions along gender, rural-urban locality, and socioeconomic status since these characteristics are related to differences in risk and time preferences (Hanaoka et al., 2018; Thamarapani and Rockmore, 2022; Booth et al., 2014; Brown et al., 2019; Riley and Chow, 1992; Yesuf and Bluffstone, 2009; Guiso and Paiella, 2008; Sahm, 2012). Additionally, rural-urban locality and socioeconomic status affect a household's economic vulnerability to rainfall shocks. Appendix Table A5 displays descriptive statistics disaggregated by these characteristics. Women are 7.3 percentage points more likely to be risk averse (p¡0.01) and 0.6 percentage points more likely to be impatient than men (p=0.28). Individuals residing in rural communities and those in households with low per-capita expenditure are more likely to be risk averse and impatient (p-values ¡ 0.01) than individuals in urban localities or those with higher household per-capita expenditure.

Columns 3 through 8 of Table 6 report the results of estimating interacted versions of equation (3) where the effects of additional and fewer low rainfall years are allowed to vary by gender, rural-urban locality, and socioeconomic status.[13]

Columns 3 and 6 of Table 6 illustrate how the impact of worsening and improving conditions vary between men and women. The negative and significant interaction effects for improving conditions, -0.95 for risk aversion and -1.23 for impatience, suggest that preference changes in response to fewer low rainfall years are larger in magnitude (more negative) for women compared to men. We do not see statistically significant differences in the impact of worsening conditions between men and women, though we note that these estimates are noisy due to the fact that these changes are

[13]Location and socioeconomic status are defined based on IFLS4 to avoid confounding the change in rainfall conditions with the demographic division of the sample.

estimated on a relatively small number of observations. This, combined with findings that men's risk preferences are more responsive than women's to natural disasters in both Japan and Indonesia (Hanaoka et al., 2018; Thamarapani and Rockmore, 2022), suggests women may be less affected by adverse conditions *and* rebound more than men when circumstances improve.

Columns 4 and 7 of Table 6 show how changes in rainfall conditions differentially impact those in urban and rural localities. The positive and significant 2.62 interaction effect for improving conditions in column 4 nearly fully offsets the -2.95 main effect (p-value on the sum = 0.74) and suggests that individuals in rural localities are more likely to remain risk averse after conditions improve than those in urban localities. Recall that individuals in rural localities are also more likely to be risk averse on average (Appendix Table A5). We do not see significant differences in the impact of worsening conditions on risk aversion, though again note that these differences are estimated on relatively small samples. Column 7 shows that those living in rural localities are significantly more likely than those in urban localities to become impatient when faced with worsening conditions, but we do not see differential impatience responses to improving rainfall conditions. Overall, these results suggest that individuals living in rural localities are more likely to have their time preferences affected by worsening conditions, but are no more likely to have these impacts reversed by improved conditions. Because individuals in rural Indonesia are more dependent on rainfall for their livelihoods (Kadir and Amalia, 2017), these results support the hypothesized mechanism that rainfall conditions impact household well-being which in turn influences risk and time preferences.

Columns 5 and 8 display the differential responses to changing rainfall conditions for those in the bottom quintile of the household per-capita expenditure (PCE) distribution relative to those in the top 80 percent. Individuals in the bottom 20 percent are significantly more likely to be risk averse after facing worsening rainfall conditions than are those in wealthier households. We see no differential change in risk aversion between those in low vs higher PCE households in response to improved conditions. This suggests that households in the lower part of the expenditure distribution (who are more likely to be risk averse on average) are more responsive by worsening conditions, and their risk aversion does not rebound more than those in wealthier households once faced with improved conditions. We find no differential time preference responses based on household expenditure quintile.

5 Discussion

We use high-frequency precipitation data and rich longitudinal household survey data to estimate the impact of changing environmental conditions on risk attitudes and patience. Taken together, the results show a significant and meaningful impact of changes in rainfall conditions on individual risk and time preferences.

The setting and data are uniquely situated to show that both improving and worsening conditions impact preferences. We exploit this to identify novel symmetry in these results, finding that those who experience worsening conditions over time become more risk averse, while those experiencing improving conditions become more risk tolerant and patient. We find suggestive evidence of these results being driven at least in part by the economic consequences of low rainfall. Our heterogeneity analysis suggests that households seemingly most vulnerable to rainfall shocks (rural households and those in the bottom PCE quintile) experience large changes in risk aversion and impatience in response to worsening conditions, but are no more likely to experience offsetting preference changes in response to improving conditions.

Our findings contribute to a growing understanding of preference formation and environmental shocks, illuminating added nuance in the effects of climate change. As climate change stands to put already vulnerable populations in even more precarious situations (Seneviratne et al., 2012), it is crucial to have a comprehensive understanding of the effects of climate variability on the economic lives of those at risk. Risk and time preferences are fundamental to consequential economic decisions throughout one's lifetime (Bellemare and Shearer, 2010; Non and Tempelaar, 2016; Bryan et al., 2014; Brick and Visser, 2015). Key climate adaptation and resilience strategies depend on such decisions, including technology adoption and migration. Our results suggest that increasing climate variability will impact not only the urgency of these decisions but also individuals' willingness to make them. That risk and time preferences are malleable in response to both worsening *and* improving environmental conditions should encourage policymakers and researchers to advantageously time interventions that depend on these preferences.

Data Availability Statement

The data used in this manuscript is available from the Indonesia Family Life Survey and the University of Delaware Terrestrial Precipitation project. The linked analysis data uses Restricted Access GPS coordinates of IFLS communities and is not shareable under the IFLS Agreement for Use. Interested researchers can apply for the IFLS restricted data through this link. Analysis program files are available from the corresponding author by request.

References

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2022). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics 138*(1), 1–35.

Alem, Y., J. Loeser, and A. Mahajan (2024). Intertemporal choice bracketing. *NBER Working Paper No. 32683*.

Baetschmann, G., K. E. Staub, and R. Winkelmann (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 685–703.

Barsky, R. B., F. T. Juster, M. S. Kimball, and M. D. Shapiro (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *Quarterly Journal of Economics 112*, 537–579.

Bellemare, C. and B. Shearer (2010, 9). Sorting, incentives and risk preferences: Evidence from a field experiment. *Economics Letters 108*, 345–348.

Booth, A., L. Cardona-Sosa, and P. Nolen (2014). Gender differences in risk aversion: Do single-sex environments affect their development? *Journal of Economic Behavior & Organization 99*, 126–154.

Brick, K. and M. Visser (2015). Risk preferences, technology adoption and insurance uptake: A framed experiment. *Journal of Economic Behavior and Organization 118*, 383–396.

Brown, R., V. Montalva, D. Thomas, and A. Velásquez (2019, 12). Impact of violent crime on risk aversion: Evidence from the Mexican drug war. *Review of Economics and Statistics 101*, 892–904.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014). Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh. *Econometrica 82*, 1671–1748.

Burke, M., E. Gong, and K. Jones (2015). Income shocks and HIV in Africa. *Economic Journal 125*, 1157–1189.

Callen, M. (2015, 10). Catastrophes and time preference: Evidence from the Indian Ocean Earthquake. *Journal of Economic Behavior and Organization 118*, 199–214.

Callen, M., M. Isaqzadeh, J. D. Long, and C. Sprenger (2014, 1). Violence and risk preference: Experimental evidence from Afghanistan. *American Economic Review 104*, 123–148.

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

Cohen, J., K. M. Ericson, D. Laibson, and J. M. White (2020). Measuring time preferences. *Journal of Economic Literature 58*(2), 299–347.

Corno, L., N. Hildebrandt, and A. Voena (2020). Age of marriage, weather shocks, and the direction of marriage payments. *Econometrica 88*(3), 879–915.

Decker, S. and H. Schmitz (2024). Health shocks and risk aversion. *Journal of Health Economics 50*, 156–170.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature 52*(3), 740–798.

Di Falco, S. and F. M. Vieider (2022). Environmental adaptation of risk preferences. *The Economic Journal 132*(648), 2737–2766.

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2010). Are risk aversion and impatience related to cognitive ability? *American Economic Review 100*(3), 1238–1260.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association 9*(3), 522–550.

Escobar Carias, M., D. W. Johnston, R. Knott, and R. Sweeney (2024). Temperature's toll on decision-making. *The Economic Journal 134*(663), 2746–2771.

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde (2018, 05). Global Evidence on Economic Preferences. *The Quarterly Journal of Economics 133*(4), 1645–1692.

Frederick, S., G. Loewenstein, and T. O'Donoghue (2002, June). Time Discounting and Time Preference: A Critical Review. *Journal of Economic Literature 40*(2), 351–401.

Goldbach, C. and A. Schlüter (2018). Risk aversion, time preferences, and out-migration. Experimental evidence from Ghana and Indonesia. *Journal of Economic Behavior & Organization 150*, 132–148.

Guiso, L. and M. Paiella (2008, 12). Risk Aversion, Wealth, and Background Risk. *Journal of the European Economic Association 6*(6), 1109–1150.

Hamoudi, A. (2007). *Living Arrangements and Economic Decision-Making in Households and Families.* Ph. D. thesis, UCLA.

Hanaoka, C., H. Shigeoka, and Y. Watanabe (2018, 4). Do risk preferences change? Evidence from the Great East Japan Earthquake. *American Economic Journal: Applied Economics 10*, 298–330.

Harrison, G. W., E. Johnson, M. M. McInnes, and E. E. Rutström (2005). Temporal stability of estimates of risk aversion. *Applied Financial Economics Letters 1*(1), 31–35.

Haushofer, J. and E. Fehr (2014). On the psychology of poverty. *Science 344*(6186), 862–867.

Holden, S. T. and M. Tilahun (2024). Can climate shocks make vulnerable subjects more willing to take risks? *Environmental and Resource Economics 87*(4), 967–1007.

Ingwersen, N., E. Frankenberg, and D. Thomas (2023). Evolution of risk aversion over five years after a major natural disaster. *Journal of Development Economics 163*.

Jakiela, P. and O. Ozier (2019, 7). The impact of violence on individual risk preferences: Evidence from a natural experiment. *Review of Economics and Statistics 101*, 547–559.

Jung, D., T. Bharati, and S. Chin (2021). Does Education Affect Time Preference? Evidence from Indonesia. *Economic Development and Cultural Change 69*(4), 1451–1499.

Kadir, K. and R. R. Amalia (2017). Economic growth and poverty reduction: The role of the agricultural sector in rural Indonesia. *Proceedings ICAS VII Seventh International Conference on Agricultural Statistics*.

Kan, K. (2003). Residential mobility and job changes under uncertainty. *Journal of Urban Economics 54*, 566–586.

Kim, Y. I. and J. Lee (2014). The long-run impact of a traumatic experience on risk aversion. *Journal of Economic Behavior and Organization 108*, 174–186.

Liebenehm, S., I. Schumacher, and E. Strobl (2024). Rainfall shocks and risk aversion: Evidence from Southeast Asia. *American Journal of Agricultural Economics 106*(1), 145–176.

Lührmann, M., M. Serra-Garcia, and J. Winter (2018). The impact of financial education on adolescents' intertemporal choices. *American Economic Journal: Economic Policy 10*, 309–332.

Mata, R., R. Frey, D. Richter, J. Schupp, and R. Hertwig (2018). Risk preference: A view from psychology. *Journal of Economic Perspectives 32*(2), 155–172.

Matsuura, K. and C. Willmott (2018). Terrestrial air temperature and precipitation: 1900-2017 gridded monthly time series. version 5.01. University of Delaware. `https://psl.noaa.gov/data/gridded/data.UDel_AirT_Precip.html`. (last accessed March 11, 2024).

McGavock, T. and L. Novak (2023). Now, Later, or Never? Evidence of the effect of weather shocks on female genital cutting in Sub-Saharan Africa. *Journal of Development Economics 165*, 103168.

Meier, S. and C. D. Sprenger (2015, 05). Temporal Stability of Time Preferences. *The Review of Economics and Statistics 97*(2), 273–286.

Necker, S. and M. Ziegelmeyer (2016). Household risk taking after the financial crisis. *Quarterly Review of Economics and Finance 59*, 141–160.

Non, A. and D. Tempelaar (2016). Time preferences, study effort, and academic performance. *Economics of Education Review 54*, 36–61.

Pan, X., M. Chin, C. M. Ichoku, and R. D. Field (2018). Connecting indonesian fires and drought with the type of el niño and phase of the indian ocean dipole during 1979–2016. *Journal of Geophysical Research: Atmospheres 123*(15), 7974–7988.

Riley, W. and K. V. Chow (1992). Asset Allocation and Individual Risk Aversion. *Financial Analysts Journal 48*(6), 32–37.

Rosenzweig, M. R. and C. Udry (2019, 03). External Validity in a Stochastic World: Evidence from Low-Income Countries. *The Review of Economic Studies 87*(1), 343–381.

Rubalcava, L., G. Teruel, and D. Thomas (2009). Investments, Time Preferences, and Public Transfers Paid to Women. *Economic Development and Cultural Change 57*(3), 507–538.

Sahm, C. R. (2012). How much does risk tolerance change? *The Quarterly Journal of Finance 2*(04), 1250020.

Sakha, S. (2019). Determinants of risk aversion over time: Experimental evidence from rural Thailand. *Journal of Behavioral and Experimental Economics 80*, 184–198.

Schildberg-Hörisch, H. (2018). Are risk preferences stable? *Journal of Economic Perspectives 32*(2), 135–154.

Seneviratne, S., N. Nicholls, D. Easterling, C. Goodess, S. Kanae, J. Kossin, Y. Luo, J. Marengo, K. McInnes, M. Rahimi, et al. (2012). Changes in climate extremes and their impacts on the natural physical environment. In I. P. on Climate Change (IPCC) (Ed.), *Managing the Risks of*

Extreme Events and Disasters to Advance Climate Change Adaptation, Chapter 3, pp. 115–203. Cambridge University Press.

Shah, A. K., S. Mullainathan, and E. Shafir (2012). Some Consequences of Having Too Little. *Science 338*(6107), 682–685.

Strauss, J., F. Witoelar, and B. Sikoki (2016). *The Fifth Wave of the Indonesia Family Life Survey: Overview and Field Report: Volume 1.* Santa Monica, CA: RAND Corporation.

Strauss, J., F. Witoelar, B. Sikoki, and A. Wattie (2009, April). *The Fourth Wave of the Indonesia Family Life Survey (IFLS4): Overview and Field Report.* RAND Corporation.

Sutter, M., M. G. Kocher, G. R. Daniela, and S. T. Trautmann (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review 103*, 510–531.

Thamarapani, D. and M. Rockmore (2022). The Stability and Evolution of Risk Attitudes and Time Preferences After a Natural Disaster. *International Journal of Disaster Risk Reduction 70*, 102791.

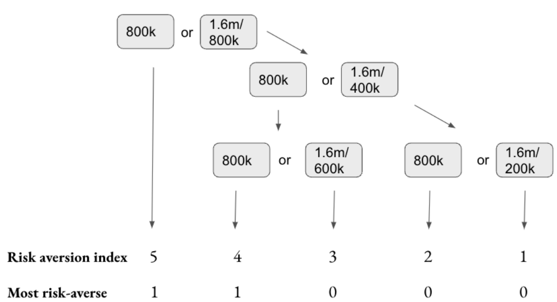
Thomas, D., F. Witoelar, E. Frankenberg, B. Sikoki, J. Strauss, C. Sumantri, and W. Suriastini (2012). Cutting the costs of attrition: Results from the Indonesia Family Life Survey. *Journal of Development Economics 98*(1), 108–123.

Tsutsui, Y. and I. Tsutsui-Kimura (2022). How does risk preference change under the stress of COVID-19? Evidence from Japan. *Journal of Risk and Uncertainty 64*(2), 191–212.

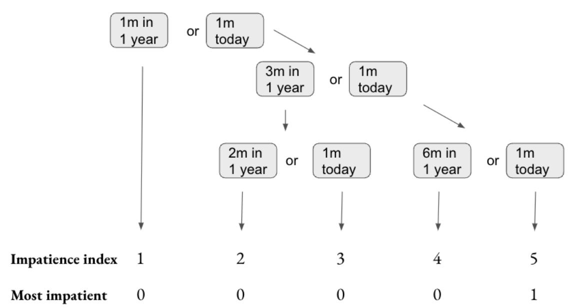
Voors, M. J., E. E. Nillesen, P. Verwimp, E. H. Bulte, R. Lensink, and D. P. V. Soest (2012). Violent conflict and behavior: A field experiment in Burundi. *American Economic Review 102*, 941–964.

Yesuf, M. and R. A. Bluffstone (2009). Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia. *American Journal of Agricultural Economics 91*(4), 1022–1037.

Figures



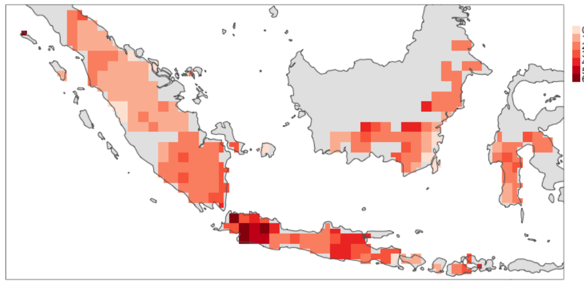
(a) Risk tolerance



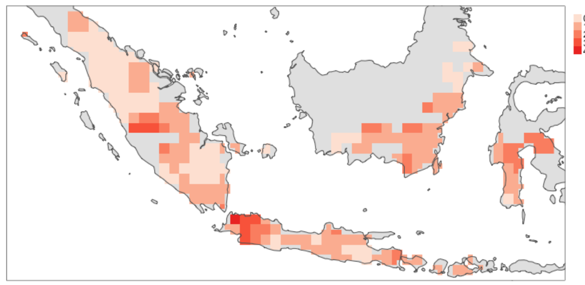
(b) Time preference

Figure 1: Preference question sequence

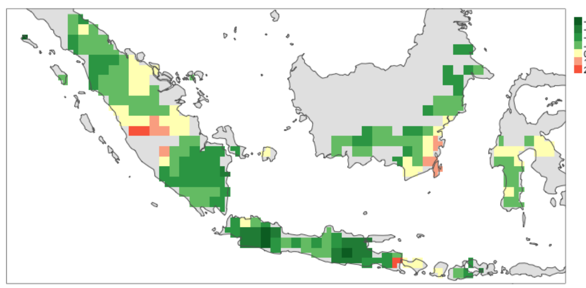
Figures 1a and 1b depict the flow of questions in the IFLS risk tolerance and time preference modules, respectively.



(a) Number of low rainfall years from 2001 to 2007 (leading up to IFLS4)



(b) Number of low rainfall years from 2008 to 2014 (between IFLS4 and 5)



(c) Change in number of low rainfall years

Figure 2: Low rainfall variation

Cells in figures 2a and 2b are shaded to represent the number of years over the preceding seven-year period with rainfall below the historical 15th percentile for the location. Darker colors represent more years of low rainfall. Areas with no IFLS respondents are colored gray. Figure 2c shows the difference in the count of low-rainfall years between 2008-14 relative to 2001-7. Green cells represent fewer years of low rainfall from 2008 to 2014 than from 2001 to 2007. Red cells are areas with more years of low rainfall between the survey waves than leading up to the fourth round.

Tables

Table 1: Associations between preference measures and behavior

	Take out a loan (=100)	Household business investment (IHS)	Any preventative healthcare visits (=100)	Self-Employed (=100)
	(1)	(2)	(3)	(4)
Panel A				
Most risk-averse (=1)	-1.58**	-0.43***	-0.09	-1.40**
	(0.71)	(0.05)	(0.42)	(0.56)
Mean	22.87	1.54	17.39	33.97
Panel B				
Most impatient (=1)	-3.01***	-0.25***	-1.10**	2.86***
	(0.74)	(0.06)	(0.43)	(0.57)
Mean	22.87	1.54	17.39	33.97
Observations	14,870	9,810	35,751	32,004

Robust standard errors clustered at the individual level in parentheses. Models are OLS regressions with observations pooled from IFLS waves 4 and 5 and including a survey wave indicator. Columns one and two include only household heads. Household business investments in columns 2 are measured as the inverse-hyperbolic sine. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Impact of low rainfall on household expenditure

Dependent Variable: log Household Per-Capita Expenditure						
					Tercile [...]	
	All	Rural	Urban	Bottom	Middle	Top
	(1)	(2)	(3)	(4)	(5)	(6)
Low rainfall in preceding 12mo.	-0.054***	-0.083***	-0.046**	-0.089***	-0.052**	-0.040*
	(0.016)	(0.029)	(0.022)	(0.031)	(0.023)	(0.023)
Observations	18,586	7,444	9,078	4,558	6,452	7,568

Sample is all household-wave observations included in the baseline preference analysis. Robust standard errors in parentheses clustered at the household and community-wave level. Low rainfall defined as a 12-month precipitation total below the 15th percentile for the location. Terciles in columns 4 through 6 are defined based on the household's position in the expenditure distribution in the third round of the IFLS. All models include household and survey wave fixed effects and household size and composition controls. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Sample Descriptive Statistics

	IFLS4 2007		IFLS5 2014	
	mean	s.d.	mean	s.d.
Most risk-averse (%)	70.9		56.4	
Most impatient (%)	69.3		65.1	
N. years of low rainfall	2.77	1.32	1.06	0.91
Female (%)	54.6		54.6	
Age	36.2	13.9	42.8	13.9
Married (%)	70.2		79.7	
Years of education	7.99	4.29	8.43	4.62
Household size	4.36	1.90	4.11	1.87
N. children (under age 15)	1.22	1.11	1.34	1.05
Rural (%)	49.4		41.3	
N. individuals	17911		17911	

This table displays descriptive statistics from IFLS waves 4 and 5. These are respondent-level means and standard deviations for demographic characteristics and our variables of interest: risk aversion, impatience, and number of years of low rainfall.

Table 4: Impact of low rainfall on risk aversion and impatience

	Most Risk Averse (=100)			Most Impatient (=100)		
	(1)	(2)	(3)	(4)	(5)	(6)
N. years of low rainfall	1.38**	2.19***	2.18**	0.94**	2.39***	2.30***
	(0.46)	(0.60)	(0.60)	(0.37)	(0.52)	(0.52)
Individual FE		yes	yes		yes	yes
Lagged controls			yes			yes
Mean dependent variable	63.6	63.6	63.6	67.2	67.2	67.2
N. observations	35,822	35,822	35,822	35,822	35,822	35,822

Robust s.e. clustered at the individual and community-wave level in parentheses. All models include month-year of interview effects, and controls for age and age squared. Lagged controls include household size, composition, per-capita expenditure quintile, education, marital status, and rural vs. urban location. *** $p<0.01$, ** $p<0.05$

Table 5: Sensitivity analyses

Panel A: Alternative preference measures

	Excluding [...]		Ordinal rankings - odds ratios	
	Gamble averse	Negative discounting	Risk	Impatience
	(1)	(2)	(3)	(4)
N. years of low rainfall	3.64***	2.03***	1.06***	1.10***
	(0.71)	(0.52)	[3.48]	[5.24]

Panel B: Non-linearities

	Most risk averse	Most impatient
	(5)	(6)
N. of low rainfall years:		
None - *reference category*		
1 year	1.80	-0.61
	(1.50)	(1.34)
2 years	6.40***	3.59*
	(2.17)	(1.89)
3 years	9.31***	3.55*
	(2.32)	(1.99)
4 years	8.78***	7.74***
	(2.82)	(2.39)
5 years	7.81**	11.97***
	(3.56)	(3.09)
6 years	18.17**	21.10***
	(7.11)	(5.53)

Panel C: Percentile threshold

	Most risk averse	Most impatient
	(7)	(8)
N. of low rainfall years		
≤ 5th percentile	2.90***	3.73***
	(0.84)	(0.71)
5th to 10th percentile	3.78***	2.08***
	(0.69)	(0.63)
10th to 15th percentile	2.31***	2.52***
	(0.73)	(0.70)
15th to 20th percentile	3.40***	1.23*
	(0.73)	(0.71)
20th to 25th percentile	0.55	0.85
	(0.80)	(0.69)

Panel D: Temporal Dynamics

	Most risk averse	Most impatient		Most risk averse	Most impatient
	(9)	(10)		(11)	(12)
N. years of low rainfall	2.37***	2.65***	N. years of low rainfall	2.34***	2.75***
linear weights	(0.86)	(0.75)	exponential weights	(0.99)	(0.86)

Robust s.e. clustered at the individual and community-wave level in parentheses. Ordinal risk and time outcomes in Panel A estimated with fixed effect, ordered logit models. Results are odds-ratios and Z-scores in brackets. Odds-ratios greater than one report the incremental increase in the likelihood of being in each risk averse or impatience category or a higher category compared to the odds of being in a less risk averse/impatient category for each additional year of low-rainfall. All models include date of interview effects, controls for age and age squared, and lagged controls for household size, composition, per-capita expenditure quintile, education, marital status, and rural vs. urban location. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Impacts of Worsening and Improving Conditions on Risk Aversion and Impatience

	Δ Most Risk Averse (=100)	Δ Most Impatient (=100)	Δ Most Risk Averse (=100)			Δ Most Impatient (=100)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reference level: Same n. low rainfall years								
N. additional years of low rainfall	7.96**	3.71	8.47**	6.69	6.36*	4.58	0.38	3.88
	(3.80)	(3.87)	(4.27)	(4.27)	(3.75)	(4.92)	(4.58)	(4.44)
N. additional years x I(female)			-0.90			-1.53		
			(3.96)			(4.67)		
N. additional years x I(rural community)				3.36			11.45*	
				(7.40)			(6.63)	
N. additional years x I(bottom 20% PCE)					10.34**			-1.23
					(4.62)			(6.21)
N. fewer years of low rainfall	-1.62*	-2.16***	-1.09	-2.95***	-1.71*	-1.48**	-2.27***	-2.20***
	(0.89)	(0.65)	(0.93)	(0.93)	(0.90)	(0.74)	(0.71)	(0.68)
N. fewer years x I(female)			-0.95*			-1.23**		
			(0.49)			(0.48)		
N. fewer years x I(rural community)				2.62***			0.18	
				(0.81)			(0.63)	
N. fewer years x I(bottom 20% PCE)					0.41			0.13
					(0.70)			(0.79)
N. Observations	17,911	17,911	17,911	17,911	17,911	17,911	17,911	17,911

Robust s.e. clustered at the community level in parentheses. All models include month-year of interview effects and controls for the changes in age and age squared and lagged changes in household size, composition, per-capita expenditure (PCE) quintile, education, marital status, and rural vs. urban location. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Online Appendix

Table A1: Individual level transition matrix

n. low rainfall years 2001-7	n. low rainfall years 2008-14: 0	1	2	3	4
0	165	493	3	1	
1	1409	1000	116	4	3
2	1063	2396	512	257	15
3	732	4165	232	36	18
4	966	1361	679	458	42
5	131	398	349	371	353
6	50	23	89	20	1

This table shows the respondent-level transition matrix that corresponds to Figure 2c. The cells in red show the number of respondents who experienced more years of low rainfall in the years leading up to IFLS5 compared to the years leading up to IFLS4. Cells in green show the number of respondents who experienced fewer years of low rainfall. White cells show the number of respondents who experienced the same number of years with low rainfall leading up to both survey waves.

Table A2: Predictability of years of low rainfall

	Dep. Var.: Number of years of low rainfall in [...]			
	IFLS4 (2001-7)	IFLS5 (2008-14)	IFLS5 (2008-14)	IFLS5 (2008-14)
	(1)	(2)	(3)	(4)
One wave (7-year) lag of [...]				
Age	0.006	0.002		0.001
	(0.004)	(0.003)		(0.003)
Age-squared	-0.0001**	-0.000		-0.000
	(0.00006)	(0.000)		(0.000)
Years of education	-0.005	0.002		0.002
	(0.008)	(0.005)		(0.005)
Married (=1)	0.031	-0.005		-0.006
	(0.036)	(0.024)		(0.024)
Household Expenditure	0.001	0.001		0.001
(Rp100,000/month)	(0.001)	(0.001)		(0.001)
Household Size	-0.016	-0.007		-0.008
	(0.014)	(0.009)		(0.009)
Most risk averse (=1)			-0.006	-0.002
			(0.018)	(0.018)
Most impatient (=1)			0.013	0.021
			(0.021)	(0.021)
Constant	2.934***	1.607***	1.584***	1.596***
	(0.511)	(0.207)	(0.179)	(0.208)
Observations	17,911	17,911	17,911	17,911

Dependent variables are the count of low rainfall years leading up to IFLS4 in column 1 and leading up to IFLS5 in columns 2-4. Demographics and preferences are measured in the survey wave previous to the rainfall measure. Columns 1 and 2 report results from regressions of an individual's low-rainfall count on their demographic characteristics measured in the previous wave of the survey. The statistically insignificant and null coefficients in both columns suggest no meaningful link between past demographics and low-rainfall exposure. Column 3 then considers if 2008-14 low rainfall is related to an individual's preference measures in 2007. (Note, this analysis is not possible with 2001-7 rainfall as the preference modules were not included in the 2000 (IFLS3) survey.) Again, we find statistically insignificant and small coefficients on both of the risk aversion and impatience indicators. Column 4 illustrates that preferences and demographics remain insignificant predictors of low rainfall when considered together. Robust standard errors in parentheses clustered at the community level. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Assessing Selective Attrition and Migration

	Not-observed in wave 5 (=1)		Migrated between districts (=1)	
	(1)	(2)	(3)	(4)
Change in low-rainfall years between	-0.001	-0.003	0.003	0.001
2008-14 & 2001-7 (IFLS5 - IFLS4)	(0.003)	(0.003)	(0.005)	(0.005)
Demographic controls		yes		yes
Constant	0.131***	0.449***	0.108***	0.382***
	(0.006)	(0.024)	(0.009)	(0.025)
Observations	21,385	21,385	17,911	17,911

Robust standard errors in parentheses clustered at the community level. Regressions relate binary indicators of attrition between waves 4 and 5 (in columns 1 and 2) and migration to a different district between waves 4 and 5 (columns 3 and 4) to the change in the low rainfall years between waves 4 and 5 at an individual's wave 4 location. Demographic controls measured as of the wave 4 interview are included in columns 2 and 4. The null and statistically insignificant coefficients on the change in rainfall in Columns 1 and 2 indicate that attrition is unrelated to rainfall among potential panel respondents in the fourth wave. Columns 3 and 4 test if migration to a different district between survey waves is related to the change in low rainfall. The small and statistically insignificant coefficients demonstrate that there is no meaningful relationship between district-level migration and the change in low rainfall. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Intent-to-treat analysis - assigning rainfall in IFLS5 based on IFLS4 location

	Most Risk Averse (=100)			Most Impatient (=100)		
	(1)	(2)	(3)	(4)	(5)	(6)
N. years of low rainfall based	1.31***	2.12***	2.10**	1.03***	2.43***	2.33***
on IFLS4 location	(0.46)	(0.61)	(0.61)	(0.37)	(0.52)	(0.52)
Individual FE		yes	yes		yes	yes
Lagged controls			yes			yes
Mean dependent variable	63.6	63.6	63.6	67.3	67.3	67.3
N. observations	36,020	35,838	35,838	36,196	36,196	36,196

Robust s.e. clustered at the individual and community-wave level in parentheses. All models include date of interview effects, and controls for age and age squared. Lagged controls include household size, composition, per-capita expenditure quintile, education, marital status, and rural vs. urban location. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A5: Stratified Sample Descriptive Statistics

	Male	Female	Urban	Rural	Middle and High PCE	Low PCE
	(1)	(2)	(3)	(4)	(5)	(6)
Most risk-averse (%)	59.7	66.9	62.7	64.6	63.0	66.3
	(0.4)	(0.3)	(0.4)	(0.4)	(0.3)	(0.6)
Most impatient (%)	66.9	67.5	65.0	69.4	66.5	70.6
	(0.4)	(0.3)	(0.4)	(0.4)	(0.3)	(0.6)
N. years of low rainfall	1.93	1.90	1.96	1.87	1.92	1.88
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Female (%)	0	100	54.6	54.5	54.4	55.5
			(0.4)	(0.4)	(0.3)	(0.6)
Age	39.7	39.3	39.0	40.0	39.4	39.7
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)
Married (%)	74.8	75.0	72.6	77.3	74.6	76.4
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.5)
Years of education	8.67	7.83	9.45	6.93	8.69	6.09
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
Household size	4.23	4.24	4.27	4.20	4.11	4.80
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Rural (%)	49.4	49.3	0	100	45.1	68.1
	(0.39)	(0.36)			(0.29)	(0.57)
N. observations	16278	19544	18140	17682	29202	6620

Table shows means and standard errors in parentheses for samples stratified as in the heterogeneity analysis of Table 6.