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SPATIAL PATTERNS IN THE FORMATION OF ECONOMIC PREFERENCES

Spatial patterns in the formation of economic preferences*

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Abstract

We investigate whether and how strongly the local environment beyond the household can contribute to understanding the formation of children's economic preferences. We build on precise geolocation data for over 6000 children in rural Bangladesh, and use fixed effects, spatial autoregressive models and Kriging to capture the relation between the local environment and children's preferences. We show that models with spatial components explain a considerable part of so far unexplained variation in children's preferences. Moreover, the "spatial stability" of economic preferences exceeds the village level. Our results highlight the importance of the local environment in influencing the formation of children's preferences, which we quantify to be at least about as large as that of parental preferences.

1 Introduction

Economic preferences are a key concept in economic theory and empirical research supports their predictive power for major life outcomes and behaviors (Chabris et al., 2008; Burks et al., 2009; Meier and Sprenger, 2010; Meier and Sprenger, 2013; Sutter et al., 2013; Schneider and Sutter, 2020). Preferences emerge in childhood and adolescence and become more stable in adulthood (Heckman, 2007; Schildberg-Hörisch, 2018; Sutter et al., 2019). Yet, commonly examined determinants of preferences such as individual or household characteristics, including parental influences, leave a large share of observed preference heterogeneity unexplained (Dohmen et al., 2011; Chowdhury et al., 2022). In this paper, we therefore investigate whether and how strongly the local environment beyond the family can contribute to understanding the formation of children's and adolescents' preferences.

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Our empirical approach investigates the role of local environment in the most comprehensive possible manner, reflecting, among other aspects, the influence of neighborhood characteristics, culture and local institutions (e.g., Bigoni et al., 2016; Falk et al., 2018), current and past common shocks such as natural catastrophes or violent conflicts (see Chuang and Schechter, 2015 for an overview) and the influence of children's peers and the adult role models they are exposed to in everyday social interactions. In terms of the model of skill formation (Cunha and Heckman, 2007), local environment may be considered to reflect general public investments into children's skills.

We make use of extensive data collected in four districts of Bangladesh in 2019. We gathered experimental and survey measures of children's economic preferences, eliciting patience, risk attitudes and prosociality for nearly 6,000 children aged 6-16 from about 4,000 households. We complement this data with similar measures for parents' preferences, IQ, household characteristics, parenting style and with village-level surveys that asked for village characteristics and shocks such as floods. Importantly, we have the exact GPS location data of each household in our sample that were saved directly by the devices containing the GPS receivers, where we have taken extra measures to improve the precision of the collected location data.

Our comprehensive, empirical approach uses three different ways to capture the role of the local environment. We start with a fixed effects approach at different geographical levels: first by district and second on the most fine-grained level, the village-level. We then go beyond fixed effects by actually modeling the spatial dependencies – within and beyond the geographical levels. We do so using both Spatial Autoregressive (SAR) models and Kriging.

All three approaches demonstrate that children who live closer to each other are more similar in terms of their patience, risk attitudes and social preferences than those who live further apart, suggesting a major role of local environment for children's preference formation. Importantly, we show that all models with spatial components explain a considerable part of so far unexplained variation in children's preferences (i.e., even after controlling for previously known determinants of children's preferences such as children's gender, age and IQ as well as parental IQ, economic preferences, age, parenting style and the family's socio-economic status). In terms of predictive power, the role of local environment is comparable to the direct, intergenerational transmission of preferences from parents to children. Village-fixed effects are the best "model" in terms of in-sample R^2, but these are *expensive* models in that they require the estimation of many parameters (one per village) without increasing insights about the process behind the formation of children's preferences that leads to those village-specific intercepts. By contrast, a SAR model takes into account the importance of spatial interactions within and beyond villages. As a consequence, out-of-sample prediction improves, even though SAR models are more parsimonious alternatives compared to fixed-effects. Kriging offers a further alternative specification that can be interpreted as a random effects approach allowing for spatial dependencies. With our detailed, high-quality GPS input data, it leads to highest (out-of-sample) predictive precision, as it uses continuous distance data. Finally, we demonstrate that jointly experienced shocks at the local level – natural catastrophes that are common in the region we study – seem relevant for the observed spatial correlations in preferences, but even our comprehensive measures of such shocks capturing the largest share of our children's life span cannot remotely explain the considerable spatial patterns in preferences.[1]

We contribute to various strands of literature. First we add to the literature examining geographical differences in preferences. Falk et al. (2018) study cross-country differences and find variations of at least one standard deviation in each preference dimension. Using incentivized lab-in-the-field experiments (as we do, too), Bigoni et al. (2016) document a higher level of trust in two cities in the North of Italy compared to two cities in the South. From this observation, they conclude that preferences and beliefs may actually drive the typical North-South disparities in key economic outcomes. Similar to the latter approach, we zoom in on the local level and are able to add a much finer picture thanks to our unique large-scale dataset that combines measures of all three core dimensions of economic preferences with precise location data at the individual level. We can thus go far beyond only documenting regional differences, which we nonetheless do, using our village fixed effect models as a starting point. Our more sophisticated approaches, together with our rich data, allow for the identification of a "relevant range" of geographical similarities in preferences, which makes it possible to predict a surface of preference measures, giving an intuition about "how starkly" preferences change as one moves along the distance axis. The sharpest drop in co-variance for patience seems to happen at the village border, although there is substantial similarity within unions, too (an administrative unit made up of a few villages). Interestingly, for social preferences, the similarities seem to "reach" much further. While we show that shared shocks explain part of this variation, our results suggest that most of the variation is due to deeply rooted differences in local environment beyond shared shocks in the rather recent history.

Second, by focusing on the formation of economic preferences in childhood and adolescence we add to the literature on skill formation. Conceptually, the model of skill formation by Cunha and Heckman (2007), the seminal theoretical contribution to the development of children's skills in economics, serves as our theoretical framework. In this model, skills include cognitive skills like IQ and non-cognitive skills that encompass, among others, economic preferences. Skills are the product of genetic and environmental initial conditions at conception, parental characteristics (e.g., IQ, education, income) and parental or public investments in children. While previous research has largely focused on the role of in-utero experiences (see, e.g., Almond and Currie, 2011), parental characteristics as well as parents' time and monetary investments (see, e.g., Kosse and Pfeiffer, 2012; Bauer et al., 2014; Francesconi and Heckman, 2016; Kosse et al., 2020; Falk et al., 2021) and parenting style (see, e.g., Cobb-Clark et al., 2019; Doepke et al., 2019; Doepke and Zilibotti, 2019), our focus is on public investments beyond the family. Local environment reflects general public investments into children's skills in the most comprehensive possible manner: it jointly encompasses all aspects that children are exposed to beyond their family in their everyday life. This contrasts previous work on the influence of social environment beyond the family that typically focuses on specific childhood interventions or policy measures (see Kautz et al., 2014; Hendren and Sprung-Keyser, 2020, for overviews).

[1]Given that we can control for parental preferences, sorting cannot explain the observed, local similarities in children's preferences due to the very limited mobility of the population in our study area to begin with, and especially that of children.

Our third contribution is the combination of the previous two insights to the literature examining the determinants of time, risk and social preferences. In particular, we are able to quantify the substantial predictive power of local environment for children's preference formation compared to that of previously investigated drivers of preference formation. Previous work has documented the significant, albeit somewhat limited role of demographic and socio-economic characteristics in explaining economic preferences (Dohmen et al., 2011). For the case of risk preferences, for example, individual characteristics such as gender, age, height or IQ regularly explain (way) less than 10% of the overall variation (e.g., Dohmen et al., 2011). Taking into account the intergenerational transmission of preferences increases the share of variation explained. For example, Chowdhury et al. (2022) report an R^2 of about 15% for the case of patience when explaining risk, time and social preferences with parental preferences in addition to socio-economic and individual characteristics. Our findings regarding previously documented determinants are in line with these results: Using parental preferences as well as individual and household characteristics, we can explain up to 14% of variation in our time preference indices, where parental preferences account for about 6% of variation explained. We add explanatory power beyond what has been documented so far by quantifying the role of local environment in regression approaches. The increase in the R^2 due to spatial approaches modeling the local environment ranges from 6 percentage points when using Kriging to 5 percentage points using a SAR model for the case of patience, so that in total up to 18% of the variation can finally be explained in the sense of a correct out-of-sample prediction. In the case of prosociality and risk, the increase in the R^2 due to using the Kriging approach even outweighs the predictive power of all the commonly reported determinants together. In sum, our approach shows that the local environment is at least about as important as parental preferences in terms of explaining children's time, risk and social preferences. This highlights the important role that local influence factors beyond the family, such as institutions, role models, geographical conditions, for example, might have in the formation of children's preferences.

2 Data

2.1 Sampling and Data Collection

Data were collected in the districts Netrokona, Sunamganj, Chandpur and Gopalganj of Bangladesh with the help of a local, specialized survey firm (ECONS, Evaluation & Consulting Services Limited). These districts represent four of the eight administrative divisions of the country. In 2014, 11 subdistricts were initially chosen based on the availability of NGOs willing to collaborate (by implementing later payments to participants) and 150 villages were randomly drawn from these 11 subdistricts (see Chowdhury et al., 2022).

In order to establish a new sample of families, the 150 villages were re-visited in 2018 and for each village, a public primary school suitable for sampling school children was chosen. Typically, there was one school per village. However, a one-to-one village-school matching was not always possible due to some schools serving multiple villages. Thus, the process resulted in a selection of 135 elementary schools from which, for each of the 150 villages, five students were drawn from each of grade 2 to 5 via class lists, using a simple random sampling procedure.[2] Interviews with the sampled children, both parents (if available), and one sibling (if available) were conducted by ECONS at the families' homes. For our analysis, we use data from the second wave of data collection (collected in 2019). This contains the largest sample available to us, where we were able to elicit preferences for 6,329 children from 4,128 households.

A key aim of the data collection was to establish a large sample of families in which we measure both children's and parents' skills as comprehensively as possible. We therefore elicited economic preferences (time, risk, and social preferences), personality traits and cognitive skills via paper-and-pencil interviewing for up to four household members (one or two children aged 6 to 16 and their parents, where we omit children who did not understand the experimental measurement of all preferences, which applied to 20 children). A detailed description of the preference measures is provided below. To comprehensively measure IQ, we elicited measures of crystallized and fluid IQ, which together form overall IQ (Cattell, 1971), for children and their parents. We measure fluid IQ using the standard progressive matrices, digit span and symbol search tests of the well-established Wechsler Intelligence Scale for Children (WISC-IV) or the Wechsler Adult Intelligence Scale (WAIS-IV). For crystallized IQ, we used the word similarities test for children and the corresponding word meaning test for adults that are both subtests of the respective Wechsler Intelligence Scales (Wechsler, 2003).[3]

We complement this extraordinarily rich data on skills of whole families with several further data sources. First, before entering a household, interviewers recorded the GPS coordinates of each household with high precision levels.[4] We restricted the data to households for which we obtained GPS data, and moreover excluded households whose geographic information did not seem appropriate for the estimation of spatial models (i.e., we dropped children in villages with less than 10 observations and removed the top percentile of distances to the nearest neighbor), resulting in a final sample of 5,993 children in 3,921 households Figure A1 shows a map of Bangladesh with the selected districts and geolocations of our sample households.

Second, we added data from a paper-and-pencil questionnaire that mothers answered about their children. It elicited mothers' assessment of their children's strengths and difficulties (including their prosocial behaviors), personality traits (for children up to age 13) and information on their parenting style. For details on the parenting style measure and a complete list of items, see Table A4 in the appendix.

Third, we include data from a general household survey that was answered by either the household head or their spouse (whoever was the most knowledgeable person for the respective part) using computer-assisted personal interviews (CAPI). The household survey

[2] The randomly drawn children live in 168 villages, comprising the original 150 villages and a few additional ones from which children also attend our sample schools.

[3] The tests got adapted to the Bangladeshi context by local academics with expertise in the adaptation of WISC version IV.

[4] For example, one of the measures that we took to improve quality of automatically collected GPS location data was setting a timer that paused for several seconds between initiating the location search and saving the current location to allow for reception of further GPS signals from additional satellites that may improve precision.

covered information on socio-demographics, income, expenditures, employment, land ownership, credits and savings, and assets, crop production and household-level shocks such as severe health issues.

Finally, we use information from village-level surveys conducted in 2014, 2016 and 2018 to include information on shocks such as floods or murrains that affected the whole village. We use these measures of village-level shocks to show that our measure of the local environment encompasses much more than one or several of these shocks over the last couple of years (which is very often simply the total life-span of the children in our sample). Appendix Tables A5, A6 and A9 show descriptive statistics of all variables used in our analysis.

2.2 Measurement of Economic Preferences

Both for children and their parents, we measure three core dimensions of economic preferences: time, risk and social preferences. In order to comprehensively characterize individuals, we combine revealed preferences measured in incentivized experiments and validated survey scales. To finally obtain one measure per preference domain, we add the respective standardized experimental and survey measures for each domain, and standardize the result again, so that all our outcome variables have mean zero and standard deviation of 1. Doing so results in measures that are a synthesis of lab-in-the-field and survey assessments of skills which reflects the underlying skills' multi-dimensional nature (Falk et al., 2018; Kosse et al., 2020). Moreover, our approach reduces measurement error and potential demand effects (Hertwig and Ortmann, 2001).

2.2.1 Children: Experiments

Children participated in a sequence of experiments designed to measure time, risk and social preferences. The exact experimental protocols can be found in Appendix D.1. Experimentally elicited preference measures have important advantages. On top of being incentivized, they are constructed from revealed preferences in well-defined and controlled contexts. This gives them a readily-interpretable metric and allows for a straightforward comparison across individuals.

To elicit preferences, we relied on well-established measurement tools that, in the case of time and risk preferences, have been used in developing countries before. We still carefully pretested them in our context and, where necessary, adapted them to be suitable for children. We used standardized control questions to verify that participating children understood the instructions. When explaining the experiments, interviewers asked children in between to repeat the explanations. Each time, the interviewer noted down whether the child understood the game after the first, second or third explanation or whether they did not understand the game at this point. We consider children who answered each of the control questions correctly after at most three explanations given by the interviewer as having understood a game. Only 8 (15) [6] did not fully understand the rules of the games that we use to measure time (risk) [social] preferences after possibly repeated explanations. We exclude these children from the analysis.

The order of the experiments was randomly determined by rolling a die. Children were able to earn money or stars which were transformed into money after the experiments using age-specific exchange rates. One star's value equals approximately half of a child's weekly pocket money. Each child (and adult) received one star as a participation fee. All experiments took place in one-on-one settings in the families' homes. The interviewers ensured that members from the same household could not influence each other's decisions.

Time preferences. In order to measure children's time preferences, we followed a simple choice list approach, used by, e.g., Bauer et al. (2012) in a similar form for adults in rural India. Each child had to make six choices which consisted of trade-offs between smaller, sooner and larger, later rewards (see Appendix Table A1). The six choices were grouped into three choice sets, each consisting of two choices with the same time delay. The early payment took place either on the next day (choice sets 1 and 2) or in a month (choice set 3), the later payment in three weeks (choice set 1), three months (choice set 2) or four months (choice set 3), respectively. The choice sets were ordered randomly. Our experimental measurement of patience reflects the total number of patient choices. It is a simple count of the larger, but later reward choices among all six choices and hence ranges from 0 to 6.

Risk preferences. For the elicitation of children's risk preferences we applied a setup originally designed by Binswanger (1980) and widely used in developing countries, e.g., by Bauer et al. (2012) in India. Each child had to choose one out of six gambles that yielded either a high or a low payoff with equal probability (see Appendix Table A2). The low payoff was decreasing and the high payoff was increasing for each successive gamble. Choices of higher gamble numbers were associated with a higher willingness to take risks: in gambles 1 to 5, the expected value increased jointly with the variance, and in gamble 6 only the variance increased in comparison to gamble 5. We use the number of the chosen gamble as the experimental measure of risk preferences.

Social preferences. To assess children's social preferences, we followed an experimental protocol inspired by Fehr et al. (2008) and extended by Bauer et al. (2014). Children had to make four allocation choices dividing stars between themselves (x) and another child (y) of the same gender and roughly the same age, but unknown and unrelated. In each of the four choices (x,y), one option was the allocation (1,1), while the alternative allocation was designed to benefit one of the children more (see Appendix Table A3). As our experimental measure of prosociality, we take the share of stars the child has given to the other child across all four games: $y/(x+y)$. This share varies between 0.29 and 0.58, with higher values indicating more pronounced social preferences.

2.2.2 Children: Survey Measures

We complement the experimental measures of children's economic preferences with survey questions. To elicit their time and risk preferences, we ask children to assess themselves on 5-point Likert scales, using items from the well-established Global Preference Survey (Falk et al., 2018) that we slightly modified to make them more appropriate for children: "I am good at giving up something nice today (e.g., a reward) in order to get something even nicer in the future (e.g., a larger reward)" and "I often take risks". To assess children's social preferences, we rely on the Prosociality subscale of the widely used Strength and Difficulties Questionnaire (Goodman, 1997). Mothers answer the following five items on a five-point Likert scale: My child (i) is considerate of other people's feelings, (ii) shares readily with other children (treats, toys, pencils, etc.), (iii) is helpful if someone is hurt, upset or feeling ill, (iv) is kind to younger children, and (v) often volunteers to help others (parents, teachers, other children). The answers are equally-weighted and combined into one scale.

2.2.3 Preference Measures for Parents

While children's preferences are at the core of our analysis, we additionally measured parents' preferences to grasp children's everyday family environment as comprehensively as possible and to be able account for the intergenerational transmission of preferences. The elicitation of parents' preferences followed very similar or even identical protocols as for children. Details of the experimental protocols can be found in Appendix D.2. Moreover, parents answered the following survey questions from Falk et al. (2018) to elicit their time, risk and social preferences on 7-point Likert scales (1–completely unwilling, 7–very willing): "How willing are you to give up something today in order to benefit more in the future?", "How willing or unwilling are you to take risks?" and "How willing are you to give to good causes without expecting anything in return?".

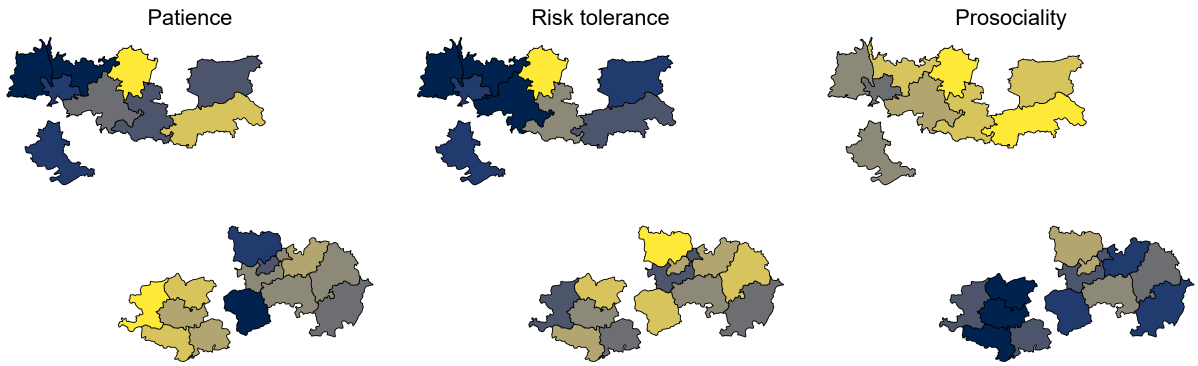
3 Visual Inspection

Below, we present an exemplary visual inspection of the average preferences by unions in the district Netrokona.[5] Unions are the fourth (and smallest) administrative division, following national, district and subdistrict and are made up of a few villages. We calculate the average preference in each union and plot these with different colors corresponding to different values. As can be seen in Figure 1, all three preference dimensions (time, risk and social preferences) show spatial correlations.

This raises the following questions: how important is the local environment on the village level and beyond in the formation of children's preferences? How does this compare to other, mainly family-based determinants of preferences that we are already aware of? How "stable" or "sticky" are economic preferences, that is, at what distance can we still say that one observation is a fairly good predictor of the given preference at another location (or at least correlated)? Do the answers to these questions vary across the different preference dimensions? The rest of this paper addresses these questions.

[5] Those for the other districts are presented in Figures A2 and A3 for Chandpur and Gopalganj, respectively. We do not show graphical evidence for Sunamganj since we only have few unions in that district.

Figure 1: Visual inspection of spatial correlations in children's preferences (union level, Netrokona)



Average preference by union for our sampled data in the district Netrokona, with low values in darker colors and high values in lighter colors. A map of the four districts with the exact location of our observations is in Figure A1.

4 Empirical Strategy

We take a flexible approach to measure the relevance of local environment. A child's preference y_i can be directly influenced by their parents' preferences, y_i^{mother} and y_i^{father}, by other household characteristics included as components of X_i and by the local environment, which is a function of the geolocation of a child's household:

$$y_i = \beta_0 + \beta_1 y_i^{\text{mother}} + \beta_2 y_i^{\text{father}} + \gamma X_i + \beta_3 f(\text{geolocation}) + \epsilon_i.$$

A common way to capture the unobserved local environment is to include fixed effects for the local administrative unit. In that case, β_3 is a vector of coefficients β_{3v}, one for each of the administrative units v, and f is simply a matrix consisting of ones and zeros that "assigns" the correct intercept β_{3v} to administrative unit v. When actually interested in these effects, e.g., for (out-of sample) prediction or for inference, a more informative approach is to consider a model that goes beyond just fixing unit-level intercepts by actually modeling these spatial differences between administrative units through considering the relation between observations that are close to each other. In the presence of spatial dependencies (see Section 3), such an approach is arguably also the more appropriate one, since observations cannot be assumed to be independent anymore. Spatial autoregressive (SAR) models or Kriging models both model spatial dependencies between the observations explicitly.

We assess the relevance of the local environment for explaining children's preferences by the increase in predictive quality that we achieve once we account for the local environment. In particular, we randomly split our sample in two subsamples. The first subsample, which we call *estimation sample*, consisting of 2/3 of the observations in our full sample, is used to fit our models for each preference measure. We then use the second subsample (the *test sample*) to predict the preference measures for the remaining 1/3 of observations, which have not been used for fitting the models. As we have measured the preferences of these children, too, we can compute the out-of-sample R^2, i.e., the share of variation in the preference measures in the second subsample that is explained by our model-based predictions.

4.1 Spatial Autoregressive Models

To understand the logic of spatial autoregressive (SAR) models, consider first the standard autoregressive AR(1) model:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 X + \epsilon_t,$$

which can also be written using the lag operator L,

$$Y = \alpha_0 + \alpha_1 L.Y + \alpha_2 X + \epsilon.$$

SAR models consider the effect of neighboring variables instead of the effect of lagged variables, by replacing the lag operator with a weighting matrix W, which usually depends on the distance between the observation of interest and its neighbors (note that we use matrix notation here, i.e., Y denotes a vector). Using the notation from above, we have

$$Y = \beta_0 + \beta_3 WY + \gamma X + \epsilon,$$

where $f(\text{geolocation}) = WY$.[6] The parameter β_3 is often interpreted as an endogenous interaction, where the economic preferences of a child are directly affected by the preferences of their neighbors. We interpret it not only as an endogenous interaction per se, but as a way to comprehensively capture all aspects of local environment. This means that a significant coefficient β_3 may, but does not necessarily imply that, e.g., the patience of a child is directly affected by the patience of their (child) neighbors. Instead, if observations are correlated across space this could reflect peer effects or that children are exposed to the same local environment, e.g., the same institutions, role models and shocks.

When fitting models with missing data, the usual solution is to omit the observations from the sample used for estimation, which can be justified when observations are independent. Yet, observations are not independent when spatially correlated. In particular with survey data, only partial neighborly relations are observed (only for the individuals surveyed). The observed units are more sparse than reality, and accounting for the structure of spatial correlations is more challenging. This "sparsity effect" typically leads to underestimating the spatial correlation parameter in SAR models (Lardeaux and Merly-Alpa, 2018). As a consequence, the results obtained from our SAR models present lower bounds of the relative contribution of the local environment to the formation of children's preferences.

[6]Additionally, one could allow for spatial correlation in the explanatory variables, but identification of each of these effects separately with the available information becomes unclear. For this reason, we focus only on the SAR term on Y.

Implementation. For the weighting matrix, several choices are common and results are to a certain degree sensitive to different definitions of the weighting matrix. The diagonal elements of the weighting matrix are set to zero, since an individual is not a neighbor of themselves. The weighting matrix is normalized for estimability, ensuring that the matrix is non-singular.

We consider two different weighting matrices. One of them aims at replicating the village fixed effects (W_{vil}) as closely as possible, by setting a weight of 1 if two children live in the same village and 0 otherwise. In our estimation sample, the number of children in each village has a mean of 24 and a median of 26 (see Appendix Table A7). The second weighting matrix is based on a *k-nearest neighbor* approach (W_{knn}). First, we calculate the minimum distance with which every child has at least one neighbor (700m) and then take the average number of neighbors within this distance, resulting in 27 neighbors, and assign a weight of 1 to these neighbors and 0 otherwise. This weighting matrix allows for important correlations among nearby units, independently of whether these units belong to the same administrative divisions or not (in our case villages). In some cases, W_{knn} only includes children from smaller geographical areas than W_{vil} (the largest village has 40 children in the estimation sample, see Table A7), but in most cases, it also includes children from larger geographical areas (27, which is the number of neighbors included in W_{knn}, is larger than the mean and median of children in villages, who would be included when relying on W_{vil}).

4.2 Kriging

Kriging is a spatial modelling approach developed by Danie Krige in the context of mining (Krige, 1951). The goal was to find natural resources at unsampled locations, using interpolations established with only a few boreholes (Krige et al., 1989; Oliver and Webster, 1990). The basic idea, as in SAR models, is that observations closer in space should be more similar to each other. For Kriging, this is technically incorporated by first estimating a correlation structure using observed data, which is then used to interpolate and predict new values. Thus, compared to SAR models, it uses a higher degree of structure (in the form of a fully specified correlation structure) to model the data. At the same time, Kriging is in general more flexible in modeling the strength of the relation between observations as a function of their distance. Nowadays, Kriging (in the specification used here) is often referred as equivalent to *Gaussian Process Regression* (GPR) as popularized for example in the machine learning literature (e.g., Rasmussen and Williams, 2005).[7]

For our Kriging approach, we model an observation $y(s_i)$ at location s_i as

$$y(s_i) = \sum_{k=0}^{p} f_k(s_i)\beta_k + e(s_i) = \beta_0 + \beta_1 y(s_i)^{\text{mother}} + \beta_2 y(s_i)^{\text{father}} + \gamma X(s_i) + e(s_i),$$

which is the sum of a linear, spatially non-constant 'trend' (to incorporate p-dimensional covariates) and an error $e(s_i)$. The error is the sum of the usual i.i.d. (mean-zero) error term

[7] Mathematically speaking, those versions of Kriging that can also be expressed with a Gaussian Process specification differ from GPR in "their approach and assumptions, in a similar way the Least Square method, [...] and the Likelihood method in regression do" (Marinescu, 2024).

and a spatial correlation structure (a Gaussian random field in our case) that depends only on the distances to other observations, but not on the exact location nor on the direction of the vector connecting two observations (i.e., it is assumed to be isotropic, which involves the assumption of stationarity). For the Gaussian random field (the spatial correlation structure that we use), a mean vector of 0 is assumed, i.e., $\mathbb{E}(e(s)) = 0$. The spatial correlation structure is then specified by means of a parametric correlation function (for which the parameters are estimated from the data in a first step). A correlation function $c(h)$ models the correlation as a function of distance h, and decreases monotonically. For $h \to \infty$, we have $c(h) \to 0$. Different choices for the correlation function are possible and common (Fahrmeir et al., 2013). The basic exponential correlation function, $c(h) = \exp(-(h/\varphi))$ for a distance $h > 0$ with range parameter $\varphi > 0$, balances simplicity and practicability, and implies that the correlation decays exponentially as a function of the distance.[8] The range parameter φ controls the "geographical stability" of the data in the sense that it controls the degree of decay in correlation between two points in space as modeled by $c(h)$. When assuming uncorrelated observations, that is $\mathrm{Cov}(\mathrm{e(s)}) = \sigma^2 \,\mathrm{diag}(1)$, ordinary least squares prediction results as a special case of the universal Kriging model.

Implementation. The first step of the two-step implementation procedure for Kriging consists in specifying the spatial correlation structure of $e(s)$. To this end, parameters of the parametric exponential correlation function are estimated from the data. We estimate the parameters using the Gstat package for R (Pebesma, 2004; Gräler et al., 2016). First, hyperparameters have to be selected: the cutoff and the bin width. Roughly speaking, the cutoff limits the distance until which a correlation between any two observations is to be assumed, while the bin width specifies the "step size". The cutoff needs to be high enough so that important variation in the correlation structure can be captured; however, it neither limits the range parameter or the distance until which a value is obtained from the so estimated correlation function $c(h)$. Practically, however, the range parameter can be expected to be lower than the cutoff. The bin width in turn serves to make the estimation more robust towards outliers, by specifying a distance within which several observations fall and are hence grouped for estimating the correlation structure. We chose these hyperparameters using cross-validation: We estimate the parameters of the exponential function for every combination of sensible values for the cutoff and the bin width, where we vary the cutoff from 2 to 100 kilometers and the bin width from 50 meters to 10 kilometers. We then choose the set of parameters for which the combination of the predictive quality of out-of-sample predictions for the preference measures and the fit of the exponential correlation function is maximized.[9] In the second implementation step of Kriging, we then finally fit the model to

[8] The basic exponential correlation function is a special case of two important classes of two-parameter correlation functions, the powered exponential class and the Matérn family. The latter is one of the most widely used and most flexible families (Fahrmeir et al., 2013), but it comes with the drawback of a more complex estimation procedure for the correlation structure. Our main results are very similar when relying on the two-parameter Matérn function, but computation time more than doubles.

[9] More specifically, the scoring function that we optimize is the out-of-sample R^2 for our preference measures multiplied by a factor 1 minus the generalized mean standard error resulting from fitting the correlation function. Hence, a large R^2 that results from a poor fit of the correlation function is as unlikely optimal as a perfectly fitted correlation function that, however, has no explanatory power for our data.

the data, assuming the spatial correlation structure implied by the estimated parameters.

For the Kriging approach, we take one randomly selected child per geolocation, resulting in 2606 observations (as multiple observations from the same geolocation lead to singularities and thus have to be excluded).

Since for our universal Kriging model, the mean prediction is unaltered compared to OLS (for assuming a Gaussian random field with mean vector 0, see above), the estimates from the OLS estimation are reprinted in the respective columns of the results tables. Standard errors for these estimates are not computed.

5 The Role of the Local Environment

In this section, we not only provide evidence of the existence of spatial correlations in the time, risk and social preferences of children, but also quantify to which extent the local environment contributes to explaining children's preferences. Overall, our results underline the importance of accounting for local environment when studying preference formation or aiming for a better understanding of preference heterogeneity.

Patience. We start by discussing the results for patience in Table 1, before we turn to risk and social preferences in Tables 2 and 3. All three tables are structured in the same way: the specifications underlying the first three columns investigate the predictive power of variables that are commonly studied drivers of children's preferences. We thereby set a benchmark to judge the additional predictive power of spatial components that we study from column 4 onwards.

In the first column, we use exogenous individual-level determinants of preferences (children's gender and age) as well as IQ to predict patience (see Sutter et al., 2019). Column 2 additionally includes comprehensive, possible family-level drivers of children's economic preferences that reflect family environment in a detailed manner, i.e., several proxies for the family's socio-economic status (see Falk et al., 2021), measures of parental age and IQ and parenting style (see, e.g., Cobb-Clark et al., 2019; Doepke et al., 2019; Doepke and Zilibotti, 2019). In column 3, we account for the intergenerational transmission of economic preferences (see, e.g., Dohmen et al., 2011; Chowdhury et al., 2022), by adding the respective preference measures of mothers and fathers.

Table 1 shows regression results for the patience index. Moving from column 1 to 2, the R^2 increases from 0.02 to 0.08. Intergenerational transmission is relevant as well, inducing an additional increase in the R^2 of about .07.

Table 1: Patience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.010	0.005	-0.007	-0.003	0.003	-0.003	-0.003	-0.000
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	
Ages 9-12	-0.279***	-0.236***	-0.216***	-0.210***	-0.185***	-0.205***	-0.201***	-0.286***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Ages 13-16	-0.283***	-0.226***	-0.199***	-0.202***	-0.187***	-0.195***	-0.194***	-0.286***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	
IQ score	0.005***	0.002*	0.001	-0.001	-0.001	-0.000	-0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Rich		0.147***	0.139***	0.066*	0.080**	0.100***	0.095***	0.122***
		(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	
Electricity in HH		0.429***	0.306***	0.178***	0.061	0.171***	0.144***	0.217***
		(0.05)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	
Age mother		-0.011***	-0.010***	-0.009**	-0.006	-0.008**	-0.008**	-0.006
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Age father		0.007**	0.007**	0.006**	0.002	0.005*	0.005*	0.005
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Literacy mother		0.100**	0.061	-0.024	0.010	0.023	0.022	0.019
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Literacy father		0.071**	0.042	-0.003	-0.009	0.018	0.012	0.064
		(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	
IQ score mother		0.000	0.000	-0.000	0.000	0.000	0.000	0.003
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
IQ score father		0.002	0.001	0.001	0.001	0.001	0.001	-0.002
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Patience mother			0.173***	0.090***	0.037**	0.103***	0.101***	0.171***
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Patience father			0.155***	0.091***	0.056***	0.104***	0.098***	0.159***
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Chandpur				0.709***				
				(0.05)				
Sunamganj				0.208***				
				(0.06)				
Gopalganj				0.540***				
				(0.04)				
Constant	-0.296***	-1.465***	-0.876***	-0.579**	0.178	-0.271	-0.225	-0.618**
	(0.11)	(0.23)	(0.23)	(0.23)	(0.35)	(0.22)	(0.22)	
W_{vil}.Patience						0.739***		
						(0.04)		
W_{knn}.Patience							0.515***	
							(0.03)	
Krig.: Pract. Range								13.92
Parenting style	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	No	No	No	No	Yes	No	No	No
Obs. (est. sample)	4050	4050	4050	4050	4050	4050	4050	2627
R2	0.02	0.08	0.15	0.20	0.28			
Pseudo R2						0.19	0.19	
Out-of-sample R2	0.01	0.05	0.13	0.11	0.08	0.16	0.16	0.17

Regressions include indicator variables for imputed observations of parents and parenting style. Models (1) to (7) are estimated with two thirds of the sample, while the remaining third is used to calculate the out-of-sample R^2. Model (8) is estimated with the same two thirds of the sample, but keeping only one randomly selected child per household, as explained in Section 4.2. Standard errors in parentheses, $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

From column 4 onward, we account for the local environment. Column 4 adds district fixed effects (FE), while column 5 includes village FE. Accounting for spatial differences, even in the coarsest form of district FEs, further improves R^2, in the case of patience to a similar degree as accounting for parental preferences. Model fit increases even more substantially in column 5 when adding village fixed effects.[10]

However, these FE specifications have three key disadvantages, even if one might be tempted to conclude that they perform relatively well in explaining the variation in children's preferences that stems from the local environment. First, FE models typically require the estimation of many parameters (up to one for each village in the village FE case), taking many degrees of freedom. Second, this approach heavily relies on (administrative) borders, that may be random, ambiguous, or simply unknown. Lastly, this approach does not *model* the local environment, and as such it can neither improve the prediction nor the understanding of children's preferences. In order to see this point, we consider out-of-sample predictions. We estimate all models in Tables 1 to 3 with two thirds of our whole sample (4050 observations), leaving one third as a test sample. The out-of-sample R^2 for the test sample is presented at the bottom of each table. It shows that, when district- or village-specific constants are unknown because the outcome of interest is not available to obtain them (as is typically the case in a standard prediction setting), the FE models do not perform better than without any consideration of spatial similarities in preferences.[11] In fact, they often even perform worse than the model in column 3, since the village- or district-level intercepts in the FE models capture part of the variation otherwise attributed to individual- and household-level drivers of children's preferences.

We therefore proceed by *modeling* the local environment through SAR models in columns 6 and 7 and using Kriging in column 8. Column 6 uses weighting matrix W_{vil}. This specification is as close as possible to village FE, but instead of estimating one constant per village, it estimates a coefficient for a global function of the villages' means. Column 7 uses weighting matrix W_{knn}, which considers neighbors based on geographical proximity instead of administrative divisions. In Table 1, we see from the pseudo-R^2 (defined here as the in-sample percentage of the variation that can be explained by the model) that the explanatory power of these two SAR models is comparable to including district fixed effects. The out-of-sample R^2, however, is by far the largest of the models considered so far.

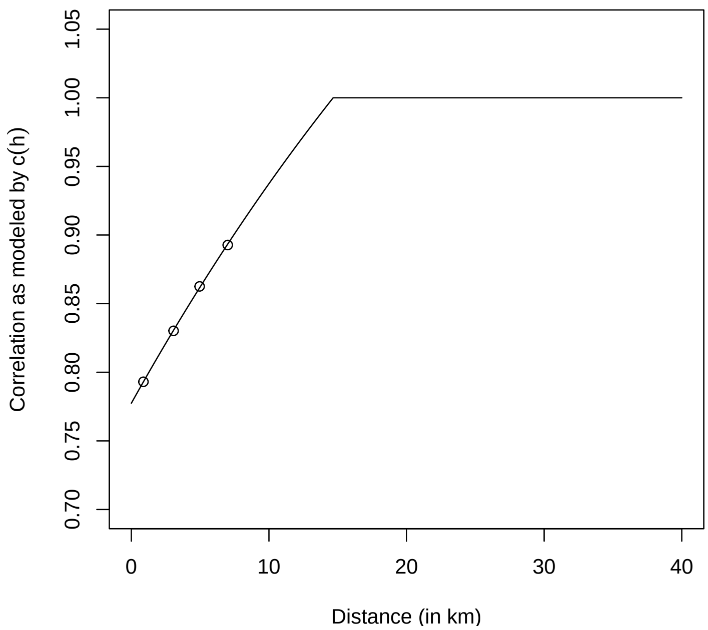
Results obtained via Kriging in column 8 are similar, reflecting the conceptual similarities in the approaches. While it is reassuring to see very similar results also for Kriging, there is more to learn from the Kriging approach here. Recall from section 4.2 that the correlation structure used for Kriging is estimated from the data. Figure 2 depicts a so-called correlogram for the patience index. A correlogram is a measure of the similarity of two children in terms of their preferences (i.e., a measure of their correlation) depending on the distance between

[10] In Section B, we analyze the role of measurement error for these conclusions with spatially correlated simulated data.From these analyzes, we conclude that accounting for measurement error leaves our conclusions unaffected.

[11] In our special case, the district- and village-specific constants are of course available (they are estimated with two thirds of the observations, i.e., the estimation sample) and could hence be used for the predictions of the test sample, but we omit them to reflect a normal prediction setting, i.e., a setting of extrapolation or out-of-sample prediction at new locations, where such estimations are not available.

the children's houses. Children who live further apart will vary more in their preferences than children who live close to each other in presence of spatial correlations. The value of the correlogram for a distance h is $1 - c(h)$. Its values are thus negatively related to the correlation as modeled by $c(h)$, that is, as the distance increases, we see a decrease in correlation, but an increase in the correlogram.

Figure 2: Spatial Correlations in Children's Preferences as a Function of Distance: Patience Index



Notes: This figure shows the evolution of the correlation structure ($1 - c(h)$ by convention) of our patience index as a function of distance between two observations as modeled by the corresponding (estimated) correlation function $c(h)$. Low values imply a high correlation, and a value close to 1 implies a negligible correlation.

From Figure 2, we conclude that the correlation is estimated to disappear completely after about 14 km, reaching 95% of its maximum after about 10 km. This means that the correlation changes only marginally for larger distances, and so the values at a distance of 13 km are not much different from those that we see for distances of about 20 km. Including these observations for our predictionsconsequently does not yield any notable improvement of predictive quality compared to including those at distances below 10 km. The patience of one child has thus little predictive quality for that of other children who might live at the end of the subdistrict (see Table A8)(at least compared to the predictive quality within villages).

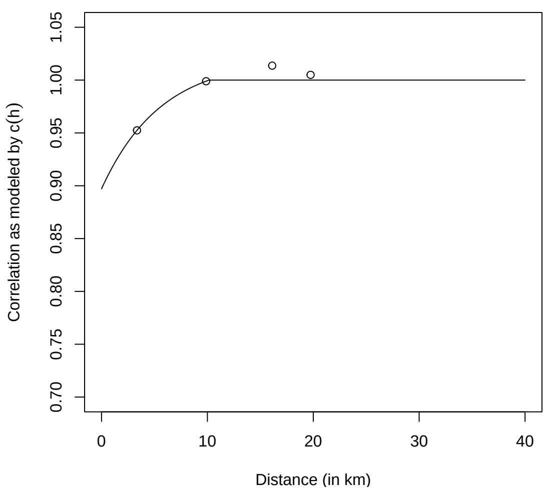
Risk and social preferences. Tables 2 and 3, which show the analyses for risk and social preferences, respectively, have the same qualitative results as we have just seen for time preferences, albeit at a somewhat reduced level of explained variation in some specifications. Yet, the conclusion stays the same: Accounting for the local environment improves predictive quality of our models for these preferences to about the same degree as the inclusion of parental preferences does – and in these two cases even exceeds that degree considerably.

There is one more noteworthy difference for prosociality to the case of patience (and to the case of risk, as well). Recall from Figure 1 that the color transitions between neighboring unions are much smoother for prosociality (right-most panel) than they are for patience (left-most panel) and risk (middle panel). In fact, the correlogram of prosociality approaches its maximum, i.e., the point of lowest estimated correlation, at a much larger distance. This suggests a considerably higher "geographical stability" of social preferences, meaning that we can expect any given observation to have predictive relevance for another one at much larger distances. From Figure 3b, we infer that the correlogram depicting the correlation structures of social preferences have not reached their maximum even at distances of about 15-20 km (they reach it after about 27 km). Hence, this preference dimension is much more stable across space and, in our setting, has a predictive power far beyond the village level. In fact, in our data, 18 km corresponds to about the mean and median distance of any two children within a subdistrict, with 27 km being the largest distance observed (see Table A8). Subdistricts are the second-highest administrative level, below the district level and above the union level, which is the underlying administrative unit of Figure 1 that groups several villages. Hence, we have evidence that in most cases, the predictive quality even exceeds the subdistrict level.

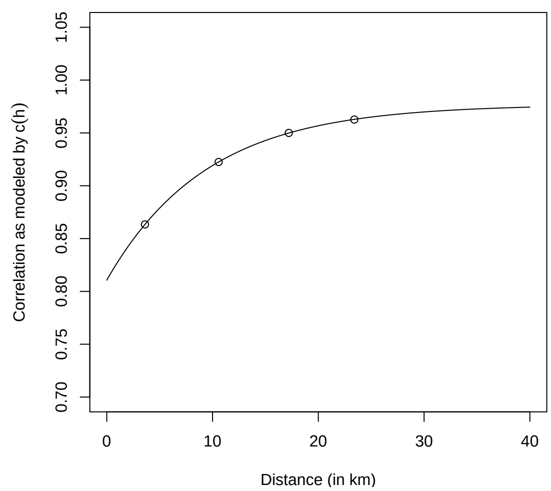
This also explains why the inclusion of observations beyond the village level in the SAR model with weighting matrix W_{knn} compared to only considering observations in the same village, as is done with the weighting matrix W_{vil}, makes quite a difference here: In the case of social preference, almost any additional observation within a subdistrict adds valuable information, and hence their inclusion increases the predictive power for social preferences, but not for patience, nor for risk (compare the out-of-sample R^2 in the last rows of columns 3, 6 and 7 in Tables 1, Tables 2 and 3).

For the data-informed weighting-approach inherent in Kriging, however, we see an even larger effect, as it uses continuous weights corresponding to the correlogram shown in Figure 3b. Then, the local environment even far beyond the village-level becomes important for social preferences. Consequently, the predictions become even better than those for patience, even though the standard set of explanatory variables has much less explanatory power in the case of social preferences (compare the out-of-sample R^2 in columns 3 in Tables 1 and 3). Hence, for prosociality, the local environment – and in particular that beyond the village level – seems to matter most for explaining children's preferences.

Figure 3: Spatial Correlations in Children's Preferences as Functions of Distance



(a) Risk Preference Index



(b) Social Preference Index

Notes: This figure shows the decay in correlation of our risk and social preference indices as functions of distance between two observations as modeled by the corresponding (estimated) correlation functions $c(h)$.

Table 2: Risk tolerance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.106***	-0.103***	-0.103***	-0.102***	-0.106***	-0.106***	-0.106***	-0.156***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	
Ages 9-12	0.115***	0.107**	0.108**	0.104**	0.100**	0.105**	0.108***	0.043
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Ages 13-16	0.176***	0.162***	0.162***	0.156***	0.168***	0.162***	0.164***	0.098
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	
IQ score	-0.004***	-0.002*	-0.002*	-0.001	-0.001	-0.002	-0.002	-0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Rich		-0.001	-0.002	0.051	0.081**	0.032	0.034	-0.024
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Electricity in HH		0.018	0.018	0.134**	0.060	0.014	0.037	-0.066
		(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.05)	
Age mother		0.001	0.001	0.000	0.003	0.002	0.002	-0.002
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Age father		-0.003	-0.003	-0.002	-0.004	-0.004	-0.004	0.000
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Literacy mother		-0.102**	-0.103**	-0.049	-0.011	-0.069*	-0.061	-0.144***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Literacy father		-0.038	-0.039	-0.009	0.010	-0.021	-0.023	0.003
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
IQ score mother		0.000	0.000	-0.000	-0.001	0.000	0.000	0.000
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
IQ score father		-0.000	-0.000	-0.000	-0.001	-0.000	-0.001	0.000
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Risk tolerance mother			0.011	0.035**	0.021	0.015	0.014	-0.002
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Risk tolerance father			-0.001	0.015	0.008	0.004	0.003	-0.010
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Chandpur				-0.503***				
				(0.05)				
Sunamganj				-0.353***				
				(0.06)				
Gopalganj				-0.272***				
				(0.04)				
Constant	0.304***	0.395*	0.395*	0.172	-0.178	0.269	0.275	0.379
	(0.11)	(0.24)	(0.24)	(0.24)	(0.38)	(0.23)	(0.23)	
W_{vil}.Risk tol.						0.671***		
						(0.05)		
W_{knn}.Risk tol.							0.503***	
							(0.03)	
Krig.: Pract. Range								8km
Parenting style	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	No	No	No	No	Yes	No	No	No
Obs. (est. sample)	4050	4050	4050	4050	4050	4050	4050	2627
R2	0.01	0.02	0.02	0.05	0.14			
Pseudo R2						0.02	0.02	
Out-of-sample R2	0.00	0.02	0.02	0.01	0.01	0.02	0.02	0.10

Regressions include indicator variables for imputed observations of parents and parenting style. Models (1) to (7) are estimated with two thirds of the sample, while the remaining third is used to calculate the out-of-sample R^2. Model (8) is estimated with the same two thirds of the sample, but keeping only one randomly selected child per household, as explained in Section 4.2. Standard errors in parentheses, $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 3: Prosociality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.101***	0.088***	0.084***	0.088***	0.074**	0.078***	0.080***	0.098**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	
Ages 9-12	0.251***	0.219***	0.214***	0.213***	0.202***	0.212***	0.204***	0.224***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Ages 13-16	0.463***	0.428***	0.424***	0.426***	0.404***	0.414***	0.408***	0.451***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	
IQ score	0.005***	0.004***	0.004***	0.003**	0.001	0.002*	0.002*	0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Rich		0.075**	0.071*	0.086**	0.055	0.053	0.054	0.090**
		(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	
Electricity in HH		-0.220***	-0.209***	-0.192***	-0.005	-0.118**	-0.116**	-0.280***
		(0.05)	(0.05)	(0.06)	(0.07)	(0.05)	(0.05)	
Age mother		0.007*	0.007*	0.006	0.004	0.007*	0.006*	-0.002
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Age father		-0.001	-0.002	-0.001	0.001	-0.001	-0.001	0.002
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Literacy mother		-0.057	-0.071*	-0.040	0.002	-0.038	-0.036	-0.047
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Literacy father		-0.039	-0.040	-0.025	0.007	-0.020	-0.010	-0.059
		(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	
IQ score mother		0.001	0.001	-0.000	-0.000	0.000	0.000	-0.002
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
IQ score father		0.004**	0.003**	0.002	0.002	0.003**	0.003*	0.004**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Prosociality mother			0.068***	0.061***	0.032**	0.049***	0.050***	0.061***
			(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	
Prosociality father			0.077***	0.075***	0.047***	0.061***	0.059***	0.074***
			(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	
Chandpur				-0.170***				
				(0.04)				
Sunamganj				0.117**				
				(0.06)				
Gopalganj				0.053				
				(0.04)				
Constant	-0.839***	-1.697***	-1.560***	-1.362***	-1.646***	-1.251***	-1.246***	-1.378***
	(0.11)	(0.23)	(0.23)	(0.24)	(0.36)	(0.22)	(0.22)	
W_{vil}.Prosociality						0.763***		
						(0.04)		
W_{knn}.Prosociality							0.547***	
							(0.03)	
Krig.: Pract. Range								26.84km
Parenting style	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	No	No	No	No	Yes	No	No	No
Obs. (est. sample)	4050	4050	4050	4050	4050	4050	4050	2627
R2	0.03	0.07	0.09	0.09	0.23			
Pseudo R2						0.10	0.11	
Out-of-sample R2	0.02	0.06	0.08	0.08	0.05	0.04	0.09	0.18

Regressions include indicator variables for imputed observations of parents and parenting style. Models (1) to (7) are estimated with two thirds of the sample, while the remaining third is used to calculate the out-of-sample R^2. Model (8) is estimated with the same two thirds of the sample, but keeping only one randomly selected child per household, as explained in Section 4.2. Standard errors in parentheses, $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Robustness. Our results are robust to changes in the *knn* parameter (using knn with 24 neighbors – as the mean of children in villages – or using knn with 41 neighbors – the number of neighbors within 700 meters for the whole sample), to the sample used for Kriging (with only one child per household) and to different random selections of the two-third estimation sample (3 different seeds).

Moreover, a rather small subsample of the sample used in this paper was exposed to one of two previous studies, either the *Arsenic RCT* or the *Lions Quest's Skills for Growing (LQ) RCT*. In Appendix C, we describe these RCTs in detail, before we demonstrate that the results reported in this paper remain qualitatively unchanged when taking exposure to these RCTs into account.

The role of shocks. Our approach differs from previous work by reflecting the role of local environment defined in the most comprehensive manner, i.e., jointly capturing *all* its aspects that may influence children's preference formation. An important focus of previous work has been on studying the impact of specific, exogenous shocks on economic preferences (of adults), with a particular emphasis on natural catastrophes such as floods, droughts and cyclones (e.g., Eckel et al., 2009; Page et al., 2014; Callen, 2015; Cameron, Lisa and Shah, Manisha, 2015; Chuang and Schechter, 2015; Said et al., 2015; Cassar et al., 2017; Hanaoka et al., 2018; Johar et al., 2022; Kuroishi and Sawada, 2024).

As Bangladesh is particularly prone to natural disasters such as floods, the common exposure of people living close to each other to such shocks may contribute substantially to the important role of local environment. Since our rich data contain information on shocks at the village level, we continue by quantifying their importance for the overall observed spatial correlation in economic preferences.

For this analysis, we use the variables *Flood, Cyclone* and *Drought*, which contain the number of times a village experienced the respective shock (minimum 0, maximum 3, obtained by adding up reported shock incidences for the 2-year period before each of the village surveys in 2014, 2016 and 2018). That is: These variables capture the number of shocks experienced in the 6 years prior to measuring our children's economic preferences, which corresponds to the entire life span for the youngest children in our sample. Appendix Table A9 presents descriptive statistics on these shock variables. Their pairwise correlations with children's preference are displayed in Appendix Table A10: All these shocks are significantly correlated with patience and risk tolerance, and two out of three with prosociality.

To understand the contribution of these shocks to the documented spatial patterns, we include them as explanatory variables in the regressions modeling spatial patterns. Table 4 shows how the SAR coefficient changes when these variables are included. For all preferences, the SAR coefficient is reduced, suggesting that the shocks are indeed underlying some of the spatial correlations in the data. The SAR coefficients, however, remain significant and large. After accounting for all four kinds of shocks, they decrease by between 2% (for prosociality) to 10% (for risk and patience) only.

Further evidence along these lines can be obtained by considering the out-of-sample R^2 with and without controlling for shocks. These figures are summarized in Table 5. We start by investigating the changes induced by controlling for shocks when using OLS regressions (in

Table 4: Contribution of natural catastrophes in SAR models in terms of SAR coefficient

	Patience	Risk tolerance	Prosociality
Without shocks	0.52	0.50	0.54
With shocks	0.47	0.45	0.53

Coefficients of the spatial component of SAR regressions using W_{knn} as the weighting matrix. The number of observations is slightly lower (N=3,808) than in column 3 of Tables 1, 2 and 3 since this analysis only includes data from the villages that have been surveyed since 2014 (i.e., observations from villages that have first been surveyed in 2018 for example are excluded for missing shock data).

the specification corresponding to column 3 of Tables 1, 2 and 3, that is, including parental preferences as control variables). As the upper panel of Table 5 (labeled 'OLS') shows, the inclusion of our shock variables increases the out-of-sample R^2 for all preferences by one (risk and prosociality) to two (patience) percentage points (compare the first and the last row of the upper panel). However, already with our basic SAR approach, accounting for spatial correlations still increases explanatory power for all three preferences by the same degree, even when controlling for shocks (compare the last rows indicated by 'All' of the upper and the middle panels (labeled 'OLS' and 'SAR', respectively). Finally, from the bottom panel (labeled 'KR'), we see that our sophisticated Kriging approach further increases predictive quality in a similar way as it was the case in Tables 1, 2 and 3 (where the sample is slightly larger), irrespective of whether the shock variables are accounted for or not. Moreover, we see that the changes induced in predictive power by explicitly accounting for shocks becomes negligible in Kriging (with changes in the out-of-sample R^2 only in the third digit in the case of prosociality, and in the fourth digit in the case of patience and risk tolerance).

Table 5: Contribution of natural catastrophes in OLS, SAR and Kriging models in terms of out-of-sample R^2

	Shock	Patience	Risk tolerance	Prosociality
	None	0.11	0.02	0.08
O	Floods	0.12	0.02	0.08
L	Cyclones	0.13	0.03	0.08
S	Drought	0.12	0.02	0.08
	All	0.13	0.03	0.09
	None	0.14	0.02	0.09
S	Floods	0.14	0.03	0.10
A	Cyclones	0.15	0.03	0.10
R	Drought	0.14	0.02	0.09
	All	0.15	0.04	0.10
K	None	0.16	0.09	0.19
R	All	0.16	0.09	0.19

Out-of-sample R^2 of OLS regressions, SAR regressions using W_{knn} as the weighting matrix, and of Kriging. The number of observations is slightly lower (N=3,808 in the estimation sample) than in Tables 1, 2 and 3 since this analysis only includes data from the villages that have been surveyed since 2014 (i.e., observations from villages that have first been surveyed in 2018 for example are excluded for missing shock data).

To summarize, the identified shocks that have been studied prominently in previous work and that should be particular relevant to our context are significant predictors of children's time, risk and social preference – but not even all of them jointly are enough to remotely explain the magnitude of the observed spatial correlations. We conclude that the local environment consists of many different factors and that the importance of a child's exposure to a given environment cannot even approximately be described by a few influence factors. Rather, it is the "full package" of exposure to factors beyond the own family (as reflected in our spatial models) that shapes children's preferences. Many of the specific factors are left to be explored in future research to enable a deeper understanding of the particularly powerful factors beyond the family environment that drive children's preference formation.

Summary. Our analysis has first confirmed previous results on individual- and family-level drivers of the formation of children's economic preferences: child age and gender as well as parental characteristics and parenting style are important predictors of children's preferences. Moreover, there is evidence of intergenerational transmission of preferences. Importantly, we then go beyond previous work by demonstrating and quantifying the key role of local environment outside of the family in understanding children's preference formation: a model that allows for interactions among close-by observations contributes at least about as much to model (predictive) quality (assessed by the out-of-sample R^2) as the direct influence of parents. In a novel approach to studying children's preference formation, our results reflect local environment in the most comprehensive possible way, capturing its overall influence instead of focusing on single aspects such as specific shocks, peers at school, role models, institutions or geographical conditions. This has also revealed interesting insights about the geographical "stability" of economic preferences: While patience in one village need not be a great predictor for patience in the neighboring village, this is different for prosociality: There, we estimate a positive correlation between observations up to the district level.

6 Conclusions

We provide novel and robust evidence that the local environment plays a critical role in the formation of children's economic preferences – patience, risk attitudes and prosociality – alongside, and in some cases exceeding, the influence of parental preferences and family environment. Using a uniquely rich dataset from rural Bangladesh that combines incentivized experimental measures, validated survey data and highly precise geolocation information for almost 6,000 children and their families, we quantify the extent to which the local environment helps explaining children's preferences. We find strong spatial patterns in preference formation, suggesting a major role for the local environment beyond the family in shaping these preferences.

Our empirical strategy leverages multiple modeling approaches – fixed effects, SAR models and Kriging – to capture and quantify the influence of local environmental factors. Across all three preference domains, spatial models substantially improve the explanatory and predictive power of our regressions, even after controlling for a comprehensive set of individual-, parental-, and family-level covariates. We first confirm results found in the existing literature: individual and parental characteristics as well as family environment are relevant to preference formation. However, the local environment outweighs them – its influence is comparable to and, in particular for prosociality, exceeds that of intergenerational transmission of preferences.

The implications of our findings are threefold. First, they point to the need for a broader understanding of the environment in models of skill and preference formation. While the canonical framework by Cunha and Heckman (2007) emphasizes specific investments as well as genetic endowments, our evidence suggests that spatial and community-level factors – such as local institutions, peer interactions, cultural norms, and shared experiences – also play a critical role in shaping economic preferences. This perspective complements and extends recent work that highlights the influence of social and institutional context on human behaviour (e.g., Bigoni et al., 2016; Falk et al., 2018).

Second, our study contributes to the emerging literature on the geography of preferences. While existing research has documented regional and cross-country variation in preferences, few studies have been able to detect and quantify spatial correlations at such a fine-grained scale. By leveraging highly precise GPS data and employing spatial econometric methods, we move beyond administrative boundaries to estimate the spatial reach of environmental influence. For patience, we find that spatial dependence dissipates sharply at the village level, pointing to a highly localized formation process. In contrast, for prosociality and risk attitudes, spatial correlations persist beyond village borders, suggesting broader, possibly regional, environmental effects.

Third, our analysis offers methodological insights for future research. Although village fixed effects are effective in capturing in-sample variation, they are less suitable for prediction and do not uncover the spatial processes underlying preference formation. In contrast, SAR models and Kriging approaches provide more flexible tools for modeling spatial dependencies, allowing for a better understanding of underlying mechanisms and stronger predictive performance. These methods are particularly well suited to contexts where administrative boundaries are imprecise or do not align with the actual reach of social and environmental influences.

While natural catastrophes such as floods, droughts and cyclones that have been the focus of previous work are significantly associated with children's economic preferences and explain part of the observed spatial variation, they do not approximately account for the spatial dependencies that we observe. This suggests that the local environment consists of many different factors, and that a single factor, or even a few factors, is insufficient to assess the extent to which the local environment shapes children's preferences. The persistence of spatial effects, even after controlling for these shocks, highlights the need to consider the local environment as a broad construct that includes both physical and socio-cultural dimensions of children's lived experiences.

These findings carry meaningful implications for policy. If children's economic preferences are shaped not only by household characteristics and parental influence but also by their surrounding environment beyond the family, then interventions aiming to promote traits such as patience, risk tolerance and prosociality must look beyond the household. Community-level programs, investments in local institutions and school-based initiatives may all play a role in shaping long-term behavioral outcomes. Moreover, the spatial heterogeneity we document points to the importance of tailoring such interventions to local conditions and social contexts to enhance their effectiveness.

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Appendices

Appendix A Additional Tables and Figures

Table A1: Time preferences experiment for children

Choice Set 1	2 stars tomorrow	vs.	3 stars in 3 weeks
	2 stars tomorrow	vs.	4 stars in 3 weeks
Choice Set 2	2 stars tomorrow	vs.	3 stars in 3 months
	2 stars tomorrow	vs.	4 stars in 3 months
Choice Set 3	2 stars in 1 month	vs.	3 stars in 4 months
	2 stars in 1 month	vs.	4 stars in 4 months

Choices consisting of trade-offs between smaller, sooner and larger, later rewards.

Table A2: Risk preferences experiment for children (example for ages 10 to 11)

Age 10 to 11	Low amount (50% chance)	High amount (50% chance)
Gamble 1	25	25
Gamble 2	22	48
Gamble 3	20	60
Gamble 4	15	75
Gamble 5	5	95
Gamble 6	0	100

Gambles (amounts in Bangladeshi Taka) yielding either a high or low payoff with equal probability used to measure risk preferences. Chosing one of the first four gambles indicates a (decreasingly) risk-averse choice, Gamble 5 a risk-neutral and Gamble 6 a risk-seeking choice.

Table A3: Social preferences experiment for children

Costly prosocial game	1 star for me 1 star for the other child (1,1)	vs. vs.	2 stars for me 0 stars for the other child (2,0)
Costless prosocial game	1 star for me 1 star for the other child (1,1)	vs. vs.	1 star for me 0 stars for the other child (1,0)
Costless envy game	1 star for me 1 star for the other child (1,1)	vs. vs.	1 star for me 2 stars for the other child (1,2)
Costly envy game	1 star for me 1 star for the other child (1,1)	vs. vs.	2 stars for me 3 stars for the other child (2,3)

Four different dictator games.

Table A4: Parenting style

Item	
Mothers assess on the scale 1 “never”, 2 “seldom”, 3 “sometimes”, 4 “frequently” and 5 “very frequently”	
Emotional warmth	
1	I use words and gestures to show my child that I love him/her.
8	I comfort my child when he/she feels sad.
13	I praise my child.
Inconsistent parenting	
5	I threaten my child with punishment, but don’t actually follow through with it.
16	I reduce punishments or lift them ahead of time.
18	It is hard for me to be consistent in my childrearing.
Monitoring	
3	I talk to my child about things he/she has done, seen, or experienced when he/she was out.
6	When my child is outside the home, I know exactly where he/she is.
15	I try to actively influence my child’s circle of friends.
Negative communication	
2	I criticize my child.
9	I shout at my child when he/she did something wrong.
14	I scold my child when I am angry at him/her.
Psychological control	
10	I feel that my child is ungrateful because he/she disobeys.
11	I stop talking to my child for a while when he/she did something wrong.
17	I am disappointed and sad when my child misbehaves.
Strict control	
4	I punish my child when he/she was disobedient.
7	I tend to be strict with my child.
12	I make it clear to my child that he/she should not oppose orders and decisions.

These items have been taken from the Panel Analysis of Intimate Relationships and Family Dynamics project’s parenting questionnaire (Thönnissen et al., 2019) and are, for example, also used in the German Socio-Economic Panel Study. The numbers in the left column indicate the order in which the items are included in the questionnaire.

Table A5: Economic preferences, Descriptive statistics

	Full sample					Estimation sample	
	mean	sd	min	max	N	mean	N
Patience children	1.9	2.0	0.0	6.0	5993	1.9	4050
Patience children survey	3.4	1.5	1.0	5.0	5993	3.4	4050
Risk children	4.3	1.3	1.0	6.0	5993	4.3	4050
Risk children survey	2.5	1.3	1.0	5.0	5993	2.5	4050
Prosocial children	0.5	0.1	0.3	0.6	5993	0.5	4050
Prosocial children survey	7.5	2.0	0.0	10.0	5770	7.4	3900
Patience mother	5.2	5.6	0.0	18.0	5929	5.1	4006
Patience mother survey	4.6	2.3	1.0	7.0	5929	4.5	4006
Risk mother	4.2	1.4	1.0	6.0	5929	4.2	4006
Risk mother survey	5.2	1.6	1.0	7.0	5929	5.2	4006
Prosocial mother	0.5	0.1	0.3	0.6	5929	0.5	4006
Prosocial mother survey	5.4	1.6	1.0	7.0	5929	5.3	4006
Patience father	5.1	5.2	0.0	18.0	5646	5.1	3807
Patience father survey	4.6	2.1	1.0	7.0	5646	4.6	3807
Risk father	4.3	1.3	1.0	6.0	5646	4.3	3807
Risk father survey	5.4	1.4	1.0	7.0	5646	5.4	3807
Prosocial father	0.5	0.1	0.3	0.6	5646	0.5	3807
Prosocial father survey	5.5	1.4	1.0	7.0	5646	5.5	3807

Experimental and survey measures of children's and parents' economic preferences. The estimation sample is a random selection of two thirds of the full sample. It is used to estimate the coefficients later applied to the remaining observations for out-of-sample prediction as a measure of model performance.

Table A6: Demographics, Descriptive statistics

	mean	sd	min	max	count
Female children	0.5	0.5	0	1	5993
Age children	11.1	2.5	6	16	5993
IQ score children	100.2	14.9	39	179	5993
Rich	0.2	0.4	0	1	5993
Electricity in HH	0.9	0.3	0	1	5993
Age mother	36.5	6.2	19	83	5929
Age father	44.0	7.9	18	84	5646
Literacy mother	0.7	0.5	0	1	5929
Literacy father	0.6	0.5	0	1	5646
IQ score mother	98.4	13.4	46	186	5929
IQ score father	99.3	12.1	57	180	5646
Emotional warmth	3.4	0.7	1	5	5853
Inconsistent parenting	2.6	0.8	1	5	5853
Monitoring	3.0	0.6	1	5	5853
Negative communic.	2.6	0.7	1	5	5853
Psychological control	1.9	0.7	1	4	5853
Strict control	2.7	0.8	1	5	5853

Individual and household level controls included in the main regressors, including survey measures for parenting style.

Table A7: Number of observations within administrative divisions

	Full sample				Estimation sample			
	mean	median	min	max	mean	median	min	max
District	1498	1495	665	2338	1012	1010	449	1581
Subdistrict	545	609	108	718	368	411	72	483
Union	84	59	2	326	57	40	2	220
Village	36	38	10	60	24	26	7	40

Statistics on the number of observations in each administrative division and villages, in the full sample and in the two thirds of the sample used for estimation.

Table A8: Maximum distance between children by administrative divisions (in km)

	mean	median	min	max	N
District	42.2	39.3	26.9	63.2	4
Subdistrict	18.7	18.0	11.6	26.8	11
Union	3.2	1.9	0.5	12.6	71
Village	1.8	1.1	0.2	10.8	168

Table A9: Natural catastrophes, Descriptive statistics

	mean	sd	min	max
Flood	0.3	0.5	0.0	2.0
Cyclone	0.9	0.7	0.0	2.0
Drought	0.3	0.5	0.0	2.0

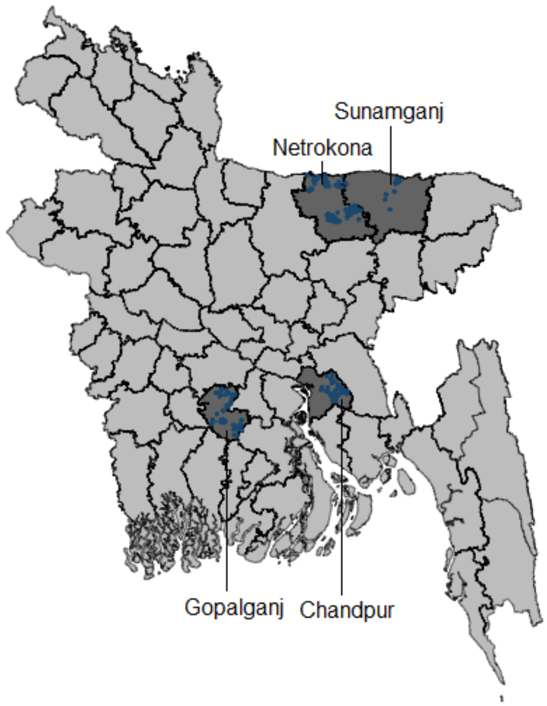
Number of natural catastrophes per village in the period 2014-2018 (N=147).

Table A10: Correlations between natural catastrophes and preferences

	Patience index	Risk index	Prosocial index
Flood	-0.11***	0.08***	0.10***
Cyclone	-0.25***	0.12***	0.04***
Drought	0.07***	0.03**	0.01

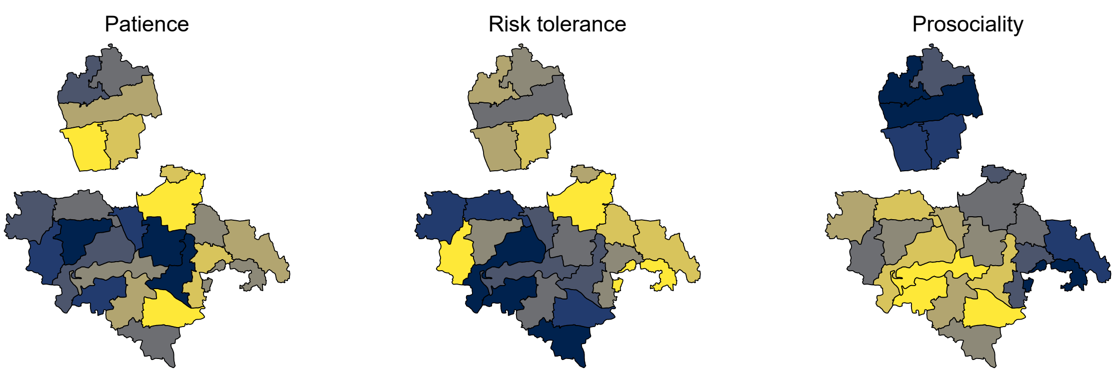
Pairwise correlations between natural catastrophes and children's preferences. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Figure A1: Geographical location of observations



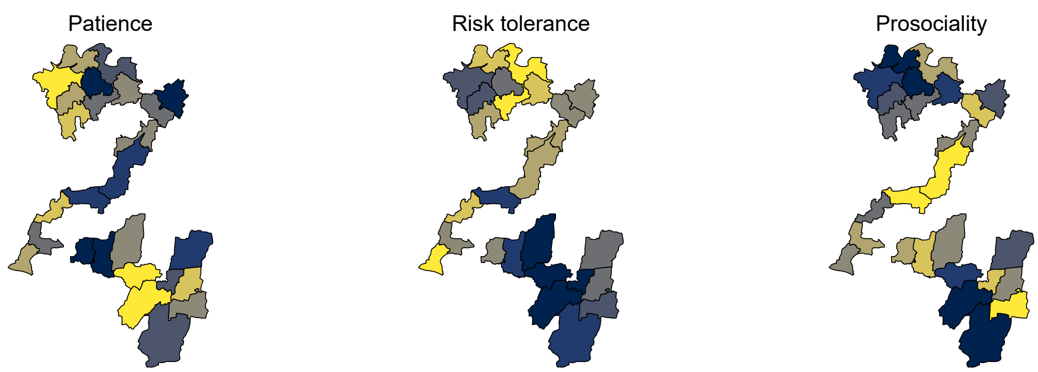
Map of Bangladesh with the four selected districts (dark grey) and the GPS coordinates of all children in the sample (in blue).

Figure A2: Visual inspection of spatial correlations in children's preferences (union level, Chandpur)



Average preference by union for our sampled data in the district Chandpur, with low values in darker colors and high values in lighter colors.

Figure A3: Visual inspection of spatial correlations in children's preferences (union level, Gopalganj)



Average preference by union for our sampled data in the district Gopalganj, with low values in darker colors and high values in lighter colors.

Appendix B Additional Analyses: Understanding the Role of Measurement Error – Simulations

In order to understand the role of measurement error in our measures of model fit, we simulate spatially correlated observations and observe what happens with the out-of-sample R^2 with and without measurement error in the dependent variables (children's preferences) and in parents' preferences.

We simulate 2500 observations at contiguous locations forming a 50x50 square. We generate villages by approximate "quadrants" formed by quintiles of latitude and longitude plus a random term. This results in 34 villages with a minimum of 39 and a maximum of 118 observations per village.

The Data Generating Process (DGP) is the following:

$$Y = \beta_0 + \rho W_{\text{vil}}\, Y + X\beta + \varepsilon \quad \text{with} \quad \varepsilon \sim \mathcal{N}(0,1)$$

$$X = (x, x_p), \quad \text{with} \quad x \sim \mathcal{N}(3,1) \quad \text{and} \quad x_p \sim \mathcal{N}(5,1)$$

Y represents children's preferences, x a composite of the individual- and household-level controls and x_p represents parents' preferences. The parameters are set to $\rho = 0.3$, $\beta_0 = 1$, $\beta = [0.4, 0.2]'$.

To include measurement error, once the dependent variable has been calculated according to the DGP, we add an error term $v \sim \mathcal{N}(0,1)$ that has the same variance as that of the standardized preference indices. A similar, independent error term is added to parents' preferences for the final part of the analysis.

The specifications in Table B1 that explore the role of measurement error in the dependent variable (children's preferences) are as follows:

- Columns 1/5: omits parental preferences and the spatial correlations
- Columns 2/6: additionally includes parental preferences
- Columns 3/7: additionally includes fixed effects for villages
- Columns 4/8: includes the SAR term (of the DGP) instead of village fixed effects

As in the main analysis, two thirds of the observations are used to estimate the models (training data) and the remaining third is used for out-of-sample predictions (out-of-sample R^2).

Table B1 shows that even if children's preferences are affected by measurement error the coefficients for x, x_p and the SAR term are unbiased in all specifications. We also see that only due to the variance of ε (which could be expected in any variable), R^2 is already low and out-of-sample R^2 is lower than the (in-sample) pseudo R^2. Since there are no fixed effect coefficients to be used out of sample, the performance of the village FE models in

Table B1: Simulations, regression results with and without measurement error in children's preferences

	No measurement error				Measurement error			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
x	0.41*	0.40*	0.41*	0.41*	0.45*	0.45*	0.46*	0.45*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
x_parent		0.21*	0.20*	0.20*		0.18*	0.17*	0.17*
		(0.03)	(0.02)	(0.02)		(0.04)	(0.04)	(0.04)
Constant	2.88*	1.85*	1.67*	1.07*	2.73*	1.85*	1.62*	1.08*
	(0.08)	(0.15)	(0.23)	(0.16)	(0.12)	(0.21)	(0.33)	(0.23)
W_{vil}.y				0.27*				0.26*
				(0.02)				(0.03)
Village FE	No	No	Yes	No	No	No	Yes	No
Observations	1681	1681	1681	1681	1681	1681	1681	1681
Pseudo R2	0.12	0.15	0.24	0.22	0.08	0.10	0.16	0.13
Out-of-sample R2	0.11	0.15	0.14	0.21	0.06	0.08	0.08	0.12

Regressions with spatially correlated simulated observations, without and with measurement error in the dependent variable. $^*p < 0.01$

columns 3/7 is not better than that of columns 2/6. According to the out-of-sample R^2, the true DGP in columns 4/8 clearly outperforms all other models.

The most important result of this simulation is that the SAR model (in column 8) does not show an "unfair" increase in performance compared to column 6 in the presence of measurement error when we compare this increase to the increase in performance of column 4 over column 2. From this we conclude that the (likely) presence of measurement error in our preference measures does not modify our main conclusions.

Table B2: Simulations, regression results with measurement error in the control variable (" parents' preferences")

	Measurement error in parents' preferences			
	(1)	(2)	(3)	(4)
x	0.41*	0.41*	0.41*	0.41*
	(0.03)	(0.03)	(0.02)	(0.03)
x_parent_error		0.11*	0.10*	0.10*
		(0.02)	(0.02)	(0.02)
Constant	2.88*	2.34*	2.16*	1.56*
	(0.08)	(0.12)	(0.21)	(0.14)
W_{vil}.y				0.27*
				(0.02)
Village FE	No	No	Yes	No
Observations	1681	1681	1681	1681
Pseudo R2	0.12	0.14	0.23	0.20
Out-of-sample R2	0.11	0.13	0.13	0.19

Regressions with spatially correlated simulated observations, with measurement error in the control variable (no measurement error in the dependent variable). $^*p < 0.01$

Table B2 shows the same specifications when there is measurement error in the control variable (which we interpret as parents' preferences) but no error in y (children's preferences). It is evident that the coefficient of parents' preferences is downward biased (comparing it to the first half of Table B1) but this does not affect the estimation of the SAR term. Also in this case, there is no evidence of an "unfair" increase in performance of the SAR models compared to standard OLS models due to the presence of measurement error.

Appendix C Robustness to Previous Studies

As mentioned in the main text, some of the households considered in our paper were exposed to one of two previous studies. We begin by briefly describing the two previous studies, the Arsenic RCT and the Lions Quest's Skills for Growing (LQ) RCT, before we demonstrate that the results reported in this paper remain qualitatively unchanged when taking into account that a subsample of our sample was exposed to these RCTs.

Arsenic RCT: Millions of rural households in Bangladesh regularly drink tubewell water as their main source of drinking water. Until the discovery of arsenic in the tubewell water in the mid-1990s, it was considered a safe and affordable option and was widely promoted by the Department of Public Health and Engineering (DPHE), with support from UNICEF, the World Bank, and similar organizations. Following the discovery of arsenic, the DPHE conducted a nationwide arsenic testing of all tubewells between 1999 and 2002. With support from NGOs, they labeled each tubewell as either green (indicating safe water) or red (indicating unsafe levels of arsenic) and launched a nationwide public information campaign.

Between 2014 and 2016, an RCT was conducted in the villages of our sample to assess the effectiveness of a public information campaign similar to the earlier DPHE campaign and the promotion of arsenic filters to encourage households to switch to arsenic-free drinking water, thereby possibly reducing their exposure to arsenic. All tubewells in the study villages were tested for arsenic and labeled either green or red again following the same protocol as the DPHE's nationwide campaign (which, according to regulations, should happen regularly anyhow but is not always enforced). In 23% of villages, households received information about the health risks of consuming arsenic-contaminated water (information treatment). In 22% of villages, this information was accompanied by an offer to purchase an arsenic water filter with cash on delivery (filter cash treatment). Households in another 22% of the villages received the same information, along with the option to buy the filter through a credit scheme (filter credit treatment). Further details about this RCT can be found in the study's pre-registration: https://www.socialscienceregistry.org/trials/11985/history/193353.

As can be seen in Table C1, 9.8% of the parents in our sample were exposed to the Arsenic RCT (the parents of 224+173+188=585 out of 585+3,933+1,475=5993 children). From a conceptual point of view, there is no reason to expect that information on the consequences of drinking arsenic-contaminated water and a possible reduction of the contamination (if any) should influence parents' or even children's economic preferences. Still, we demonstrate below that our main findings remain robust when controlling for exposure to the Arsenic RCT.

Lions Quest RCT: In 2019, we run an RCT implementing a well-established social and emotional learning (SEL) program, the LQ Skills for Growing program. The LQ program was implemented in grades 2 to 5 of the elementary schools of randomly assigned villages in our sample, while the other villages served as control group. 75.4% (3,933+224+173+188=4,518 out of the 5,993) children in our sample are untreated, while 24.6% (1,475) were exposed to the LQ program at school, see Table C1. Detailed information on program content is available here: https://www.lions-quest.org/our-programs/explore-our-sel-curriculum/elementary-school-social-and-emotional-learning/. Overall, the program aims at enhancing children's emotional

Table C1: Sample distribution in previous RCTs

	None	Lions Quest
None	3,933	1,475
Info only	224	0
Info plus filter (cash)	173	0
Info plus filter (credit)	188	0

Number of children who were exposed to one of the two RCTs previously conducted with this sample. 65.6% (3933 out of 5993) children in our sample were not directly or indirectly affected by any treatment. The parents of 585 children in our sample were part of one of the treatment groups of the arsenic RCT such that we cannot completely rule out indirect effects on their children. 1475 children were exposed to the Lions Quest RCT. No family was exposed to both RCTs.

intelligence, fostering prosocial interactions, and better decision-making. Based on the program's detailed documentation, we hypothesized that program participation increases children's self-control, patience and prosociality. We actually find that participation in LQ significantly enhances self-control and prosociality in elementary school children, with the treatment effects on self-control being significant for children in grade 2 and 3 only (i.e., at ages 7-9), see Breitkopf et al. (2025).

Robustness of our results: To assess the robustness of our findings with respect to the two referenced studies, we re-estimate key specifications of Tables 1 to 3 (columns 5 with village FE and column 7 with the SAR model using the weighting matrix W_{knn}), including controls for the arsenic RCT or the LQ RCT in Tables C2 and C3, respectively. Our results remain consistent with the original estimates. Moreover, the share of variation in children's preferences that is explained by these models remains, by and large, unaffected by controlling for exposure to any of these RCTs.

Table C2: Robustness to controlling for participation in arsenic RCT

	Patience		Risk tolerance		Prosociality	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.007	-0.002	-0.104***	-0.107***	0.085***	0.081***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Ages 9-12	-0.213***	-0.197***	0.114***	0.114***	0.214***	0.205***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Ages 13-16	-0.191***	-0.181***	0.183***	0.183***	0.422***	0.409***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
IQ score	0.001	-0.000	-0.002*	-0.002	0.004***	0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rich	0.139***	0.096***	-0.002	0.035	0.072*	0.055
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Electricity in HH	0.306***	0.143***	0.017	0.036	-0.208***	-0.115**
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Age mother	-0.010***	-0.008**	0.001	0.003	0.007*	0.006*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age father	0.007**	0.005*	-0.003	-0.004	-0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Literacy mother	0.061	0.022	-0.101**	-0.059	-0.072*	-0.037
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Literacy father	0.042	0.012	-0.038	-0.022	-0.041	-0.011
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
IQ score mother	0.000	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IQ score father	0.001	0.001	-0.000	-0.001	0.004**	0.003*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pref. idx mother	0.173***	0.100***	0.011	0.015	0.068***	0.050***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Pref. idx father	0.155***	0.098***	-0.002	0.002	0.077***	0.058***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Info only	-0.044	-0.100	-0.146*	-0.117	0.018	0.004
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Info plus filter (cash)	-0.076	-0.081	-0.034	-0.036	-0.069	-0.102
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Info plus filter (credit)	-0.026	-0.057	-0.182**	-0.174*	0.062	0.064
	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Constant	-0.890***	-0.244	0.368	0.246	-1.562***	-1.256***
	(0.23)	(0.22)	(0.24)	(0.23)	(0.23)	(0.22)
W_{knn}.Pref. index		0.516***		0.502***		0.547***
		(0.03)		(0.03)		(0.03)
Parenting style	Yes	Yes	Yes	Yes	Yes	Yes
Obs. (est. sample)	4050	4050	4050	4050	4050	4050
R2	0.15		0.02		0.09	
Pseudo R2		0.19		0.02		0.11

Regressions include indicator variables for imputed observations of parents and parenting style. Standard errors in parentheses, $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table C3: Robustness to controlling for participation in LQ RCT

	Patience		Risk tolerance		Prosociality	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.007	-0.002	-0.105***	-0.107***	0.083***	0.079***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Ages 9-12	-0.215***	-0.200***	0.104**	0.104**	0.211***	0.200***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Ages 13-16	-0.197***	-0.190***	0.147***	0.148***	0.412***	0.393***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
IQ score	0.001	-0.000	-0.002*	-0.002	0.004***	0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rich	0.138***	0.095***	-0.001	0.036	0.072**	0.056
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Electricity in HH	0.306***	0.145***	0.015	0.035	-0.211***	-0.119**
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Age mother	-0.010***	-0.008**	0.001	0.002	0.007*	0.006*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age father	0.007**	0.005*	-0.003	-0.004	-0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Literacy mother	0.060	0.021	-0.102**	-0.060	-0.070*	-0.035
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Literacy father	0.042	0.013	-0.039	-0.023	-0.040	-0.010
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
IQ score mother	0.000	0.000	-0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IQ score father	0.001	0.001	-0.000	-0.001	0.003**	0.003*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pref. idx mother	0.173***	0.101***	0.011	0.014	0.068***	0.050***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Pref. idx father	0.155***	0.098***	-0.001	0.003	0.077***	0.059***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Lions Quest	0.005	0.013	-0.043	-0.043	-0.031	-0.042
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Constant	-0.881***	-0.235	0.433*	0.309	-1.532***	-1.209***
	(0.23)	(0.22)	(0.24)	(0.23)	(0.23)	(0.22)
W_{knn}.Pref. index		0.515***		0.503***		0.547***
		(0.03)		(0.03)		(0.03)
Parenting style	Yes	Yes	Yes	Yes	Yes	Yes
Obs. (est. sample)	4050	4050	4050	4050	4050	4050
R2	0.15		0.02		0.09	
Pseudo R2		0.19		0.02		0.11

Regressions include indicator variables for imputed observations of parents and parenting style. Standard errors in parentheses, $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Appendix D Experimental Protocols

D.1 Experimental protocols for children

General setting

- **Age:** Children aged 6 to 16 will participate in a sequence of three experiments:
  1. Time preferences
  2. Risk preferences
  3. Social preferences
- **Order:** The order of the experiments will be randomly determined by the administrators, which is explained at the beginning of the experiments.
- **Incentive:** Each child will receive a token (a star) as a show-up fee, which s/he will be able to convert into money at the end of the experiments. In addition, children can earn money during the experiment as all experiments are incentivized. However, for each child, only one of the experiments will be paid out. Which experiment will be paid will be determined through a lottery that will be explained soon.
- **Exchange rate for incentives:** The exchange rate between stars and money will be age-specific and will be communicated at the beginning of the experiment. The conversion table is included here.
- **Venue:** The experiments will take place in children's home; a male administrator will deal with boys and a female administrator will deal with girls.
- **Instructions:** All enumerators/instructors must memorize the instructions and explain the game to the child. While they will not read the text word by word, they will stick closely to the wording of the experimental instructions. In addition, the explanation will involve control questions to check for understanding.
- **Timing:** Members who belong to the same household will sit simultaneously in separate parallel sessions. It is an important task of the interviewer to ensure that the decisions of a household member truly reflect his/her own decision only and that other household members do not try to influence the decisions, e.g. place them back to back or in separate rooms.
- **Control questions that check children's understanding:** Children's understanding of the rules of the various experiments will be documented.

General instructions

My name is ... Today I have prepared three games for you. In these games, you can earn money. Before we start, I will explain the rules of our games. How much money you will earn depends mainly on your decisions. At the end, only one of the games will be paid. Which game will be paid will be determined randomly after playing all three games. You will roll a die to determine which of the games gets paid. The rolled number will determine whether the first, second, or third game will be paid for. Each game is equally likely to be paid.

It is important that you understand the rules of all our games and play each of them carefully because each of them could be the one that is paid. Please listen carefully now. I will frequently stop during my explanation and allow you to ask questions. Therefore, please interrupt me anytime in case you have a question.

Are you okay so far? *Leave time for questions and answer them privately.*

1. Determine the sequence by rolling a die, and write down the sequence in which experiments are conducted:

1	=	risk, time, social
2	=	risk, social, time
3	=	time, risk, social
4	=	time, social, risk
5	=	social, time, risk
6	=	social, risk, time

Time preferences

Let us start with this game. Before we start, let me explain the rules of our game. In this game you can earn stars, which you can convert into money. Each star is equal to Taka ... (*use the age appropriate exchange rate*). The more stars you earn, the more money you get. That's why it is important that you understand the rules of our game. Please interrupt me anytime in case you have a question.

Are you okay so far? *Leave time for questions and answer them privately.*

1. Determine the order of explanation by rolling a die (blue, green, yellow):

1	=	blue, green, yellow
2	=	blue, yellow, green
3	=	green, blue, yellow
4	=	green, yellow, blue
5	=	yellow, blue, green
6	=	yellow, green, blue

Within each part (color) the order is fixed, i.e. always use blue sheet 1 before blue sheet 2, green sheet 1 before green sheet 2, yellow sheet 1 before yellow sheet 2.

The game works as follows. The game consists of six parts: two blue parts, two yellow parts, and two green parts (*when mentioning the parts, please point at the respective decision sheets*). In each part, you will need to make one decision. For example, in this green part you have to decide whether you prefer receiving 2 stars (*please point at the stars on the decision sheet*) tomorrow, in this case please tick THIS box (*point at the respective box*), or whether you prefer receiving 3 stars in 3 weeks, in that case please tick THAT box (point at the respective box). 3 weeks means 21 days and 21 nights. If you go for 2 stars tomorrow, you will get the money tomorrow. One of us will come to your home and deliver the money in an envelope with your name marked on it. If you wait, you will get money for 3 stars after 3 weeks. Again, one of us will come to your home and deliver the money in an envelope with your name on it.

In the second green part you have to decide whether you prefer receiving 2 stars (*please point at the stars on the decision sheet*) tomorrow, in this case please tick THIS box (*point at the respective box*), or whether you prefer receiving 4 stars in 3 weeks, in that case please tick THAT box (*point at the respective box*). If you go for 2 stars, you will get the money tomorrow. One of us will come to your home and deliver the money in an envelope with your name marked on it. If you wait, you will get money for 4 stars after 3 weeks. Again, one of us will come to your home and deliver the money in an envelope with your name marked on it.

Could you please repeat the rules of the game? *If the child is unable to repeat, please explain the game again; the child has to be able to repeat the correct meaning of the game autonomously.*

2. Child understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

The yellow parts are very similar to the green part. Here you see one of the decision sheets for the blue part. Again, 2 stars on the left-hand side, and 3 stars on the right-hand side. If you prefer receiving 2 stars tomorrow, you need to tick the left box. However, now if you prefer receiving 3 stars in 3 months, you need to tick the right box. 3 months means that about 90 days and nights will pass before you will get the money. On the second yellow sheet, again 2 stars on the left-hand side, and 4 stars on the right-hand side. If you prefer receiving 2 stars tomorrow, you need to tick the left box. However, now if you prefer receiving 4 stars in 3 months, you need to tick the right box. What do you think will happen if you tick THIS box? (*Please point at the box with the immediate (tomorrow) reward.*) What do you think will happen if you tick THAT box? (*Please point at the box with the delayed reward of 3 stars; the child has to answer the questions correctly, otherwise the experimenter has to repeat the explanation.*)

3. Child understood the game after:

1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

The blue parts are very similar to the green and yellow parts. Here you see the first decision sheet for the blue part. Again, 2 stars on the left-hand side, and 3 stars on the right-hand side. However, now the earlier payment takes place in 1 month, which means after 30 days and nights have passed. The later payment takes place in 4 months, which means after 120 days and nights have passed. If you decide to receive 2 stars, you need to wait 1 month, and if you decide to receive 3 stars, you need to wait 4 months. On the second blue sheet, again 2 stars on the left-hand side, and 4 stars on the right-hand side. If you prefer receiving 2 stars in 1 month, you need to tick the left box. However, if you prefer receiving 4 stars in 4 months, you need to tick the box on the right. What do you think will happen if you tick THIS box? (*Please point at the box with the reward in 1 month.*) What do you think will happen if you tick THAT box? (*Please point at the box with the delayed reward of 4 stars; the child has to answer the questions correctly, otherwise the experimenter has to repeat the explanation.*)

4. Child understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

If this game is paid, only one of the six decisions counts. That means you will receive the stars for one of the six parts only. The decisions are numbered from 1 to 6. After your decisions, you will roll a die (*please demonstrate*). Assume that it shows number 5. Now decision sheet 5 (the first blue sheet) is played for real. If you have checked the box on the left-hand side, you will receive the money for 2 stars in 1 month. If you have checked the box on the right-hand side, you will receive money for 3 stars in 4 months. The other five sheets do not count in this case. However, you need to make a decision for each of the six sheets because you do not know yet which part will be drawn at the end of the game. Could you please repeat the last part? Will you receive the stars for all six sheets? Do you need to make a decision for each of the six sheets? If the child answers incorrectly the experimenter has to repeat the explanation of this part.

5. Child understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

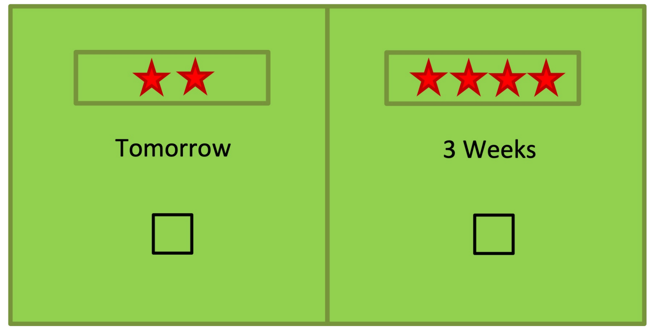
Please take your decision for each of the six sheets now (*place the decision sheets side by side on the table; the child should fill out the decision sheets from left to right*). Start with this part (*point at the first decision sheet (depending on the order of explanation)*) and continue with this part (*point at the second decision sheet*) and finally make your decision in this part (*point at the final decision sheet*). Take as much time as you need. In the meantime, I will turn around so that I do not disturb you. Just call me when you are done or have any questions.

6.	Decision taken on Green sheet 1:	1 = tomorrow, 2 = 3 weeks
7.	Decision taken on Green sheet 2:	1 = tomorrow, 2 = 3 weeks
8.	Decision taken on Yellow sheet 1:	1 = tomorrow, 2 = 3 months
9.	Decision taken on Yellow sheet 2:	1 = tomorrow, 2 = 3 months
10.	Decision taken on Blue sheet 1:	1 = 1 month, 2 = 4 months
11.	Decision taken on Blue sheet 2:	1 = 1 month, 2 = 4 months

Roll a die to determine which decision sheet would be paid if this game got selected for payoff in the end.

Decision sheet 1
(Green sheet 1)

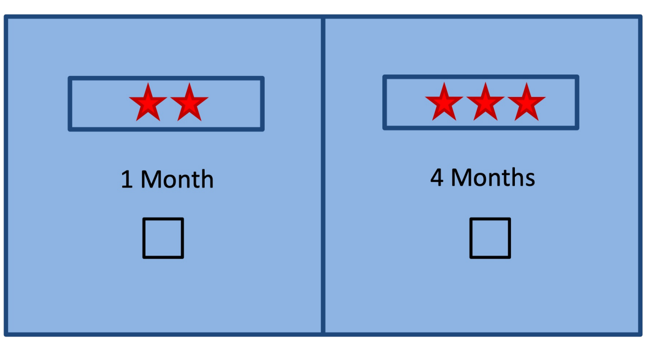
Decision sheet 2
(Green sheet 2)



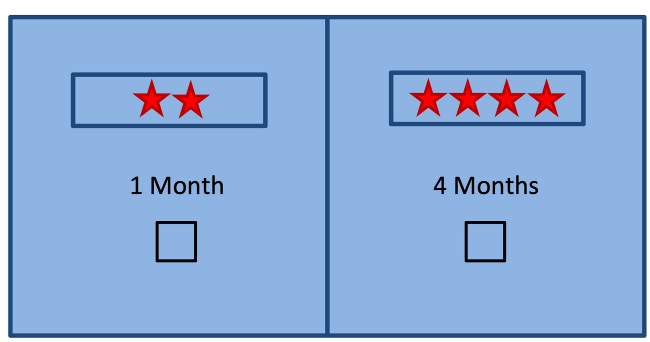
Decision sheet 3
(Yellow sheet 1)

Decision sheet 4
(Yellow sheet 2)

Decision sheet 5
(Blue sheet 1)



Decision sheet 6
(Blue sheet 2)



Risk preferences

Let us start with this game. Before we start, I will explain the rules of our game. Similar to other games, you can earn money in this game as well. How much money you will earn depends mainly on your decisions. That's why it is important that you understand the rules of our game. Please listen carefully now. I will frequently stop during my explanation and allow you to ask questions. Please interrupt me anytime in case you have a question.

Are you okay so far? *Leave time for questions and answer them privately.*

In this game, you need to select the gamble you would like to play from among six different gambles, which are listed below. You must select one and only one of these gambles.

If this game is selected for payment, you will have a 1-in-6 chance of receiving the money. The selection will be made by rolling a 6-sided die twice—first, you will roll the die to decide the gamble, and the second to decide the outcome of the particular gamble. For example, if you selected gamble number 4, then if the first roll of the die is 4, you would receive one of the payoffs of gamble number 4, which will be determined in the second roll. If the first roll of the die is not 4 and you have chosen gamble number 4, you would not receive any payments. Depending on the outcome of the first roll, the second roll would determine the outcome of the selected gamble. Each gamble has two possible outcomes—low and high. If 1, 2 or 3 is rolled, the outcome of the selected gamble is the low one, and if 4, 5 or 6 is rolled, the outcome of the gamble is the high one, and you would receive money accordingly.

Notice that the low outcome is decreasing and the high outcome is increasing for each successive gamble. For example, in the first gamble, both outcomes are identical. If you select it and then this number is rolled in the first roll, your payoff would be 25 (*please adjust for the appropriate age*) Taka. If on the other hand, you had selected gamble number 2, and if it is rolled on the first roll, your payoff could be 22 (*please adjust*) Taka or 48 (*please adjust*) Taka. In the second roll, if 1, 2 or 3 is rolled, you would receive 22 (*please adjust*) Taka, whereas if 4, 5 or 6 is rolled, you would receive 48 (*please adjust*) Taka.

Ask the child to repeat the game.

1. Child understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

Before you select the actual gamble involving money, we will have a practice session with candies. There are two gambles from which you need to select one:

	Outcome	Payoff	Chances	Your Selection
Gamble 1	LOW	1	50%	
	HIGH	1	50%	
Gamble 2	LOW	0	50%	
	HIGH	2	50%	

Both gambles have two outcomes. The first gamble pays 1 candy in both states, while the second gamble pays no (0) candy in the low state and 2 candies in high state. Which gamble would you like to play? Once you make your selection, you will first roll the die to decide the gamble, and then again roll the die to decide the outcome of the particular gamble. For example, if you selected gamble number 2, then if the first roll of the die is 2, you would receive one of the payoffs of gamble number 2, which will be determined in the second die roll. In the second die roll, if 1, 2 or 3 is rolled, the outcome of the selected gamble is the low one, which is 0 in gamble number 2. That means, you will not receive any candy. However, if 4, 5 or 6 is rolled, the outcome of the gamble is the high one, and you will receive 2 candies. Let us start this now.

Are you okay so far? *Leave time for questions and answer them privately.*

2. Gamble number picked involving candies:
Roll a die to determine whether gamble number 1 or gamble number 2 is payoff-relevant. If you have rolled a 1 or a 2, please roll the die a second time to determine whether the low or the high payoff is realized.

3. Select the table with the appropriate age:

$$\begin{aligned} 1 &= \text{age 6-7} \\ 2 &= \text{age 8-9} \\ 3 &= \text{age 10-11} \\ 4 &= \text{age 12-13} \\ 5 &= \text{age 14-15} \\ 6 &= \text{age 16} \end{aligned}$$

4. Gamble number picked:

Roll a die to determine whether gamble number 1 or gamble number 2 is payoff-relevant. If the outcome of the first die roll equals the gamble number picked (if 6. = 7.), please roll the die a second time to determine whether the low or the high payoff is realized.

Table 1: Age 6-7

Mark the gamble you like best with an X in the last column “Your Selection”
(mark only one of the six gambles):

	Outcome	Payoff	Chances	Your Selection
Gamble 1	LOW	13	50%	
	HIGH	13	50%	
Gamble 2	LOW	11	50%	
	HIGH	24	50%	
Gamble 3	LOW	10	50%	
	HIGH	30	50%	
Gamble 4	LOW	8	50%	
	HIGH	38	50%	
Gamble 5	LOW	3	50%	
	HIGH	48	50%	
Gamble 6	LOW	0	50%	
	HIGH	50	50%	

Table 2: Age 8-9

Mark the gamble you like best with an X in the last column “Your selection”
(mark only one of the six gambles):

	Outcome	Payoff	Chances	Your Selection
Gamble 1	LOW	19	50%	
	HIGH	19	50%	
Gamble 2	LOW	17	50%	
	HIGH	36	50%	
Gamble 3	LOW	15	50%	
	HIGH	45	50%	
Gamble 4	LOW	11	50%	
	HIGH	56	50%	
Gamble 5	LOW	4	50%	
	HIGH	71	50%	
Gamble 6	LOW	0	50%	
	HIGH	75	50%	

Social preferences

In this game you can earn stars, which you can convert into money. Each star is equal to Taka ... (*use the age appropriate exchange rate*). The more stars you will earn, the more money you will get. That's why it is important that you understand the rules of our game. Please listen carefully now. I will frequently stop during my explanation and allow you to ask questions. Therefore, please interrupt me anytime in case you have a question.

Are you okay so far? *Leave time for questions and answer them privately.*

In this game you have to decide how to divide stars between yourself and another child similar to you but from a different village. You will never know who exactly the other child is and the other child will not get to know you. However, I will ensure that the other child does indeed receive the money that corresponds to the stars that you will give to him/her. You will get four different decision sheets. You will need to decide how to divide stars between yourself and another child similar to you.

Are you okay so far? *Leave time for questions and answer them privately.*

There are two possible ways to allocate the stars: the option on the left-hand side and the option on the right-hand side. Please look at the decision sheet. With option "left" you get 1 star and the child from another village gets 1 star. 1 star equals ... Taka (*depending on the age group*). With option "right" you get 2 stars and the child from another village gets 0 stars.

Are you okay so far? *Leave time for questions and answer them privately.*

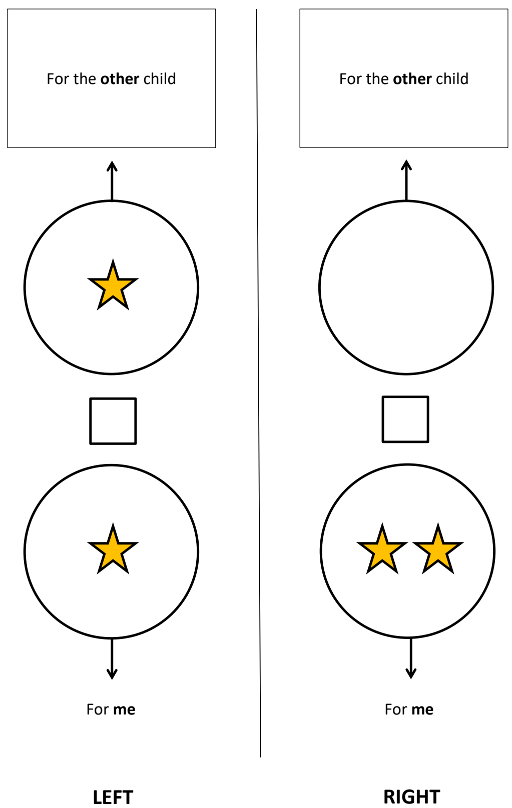
Depending on which option you want to choose, you should check the box at the left- or the right-hand side. You can choose either option "left" or option "right". If you would like to divide the stars according to option "right", which box would you have to check? Right, the box at the "right" side. How much would you earn and how much would the child from the other village with whom you are randomly matched earn in this case? Right, you would get ... Taka (*depending on the age group*) and the other child similar to you would get nothing.

1. Child understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

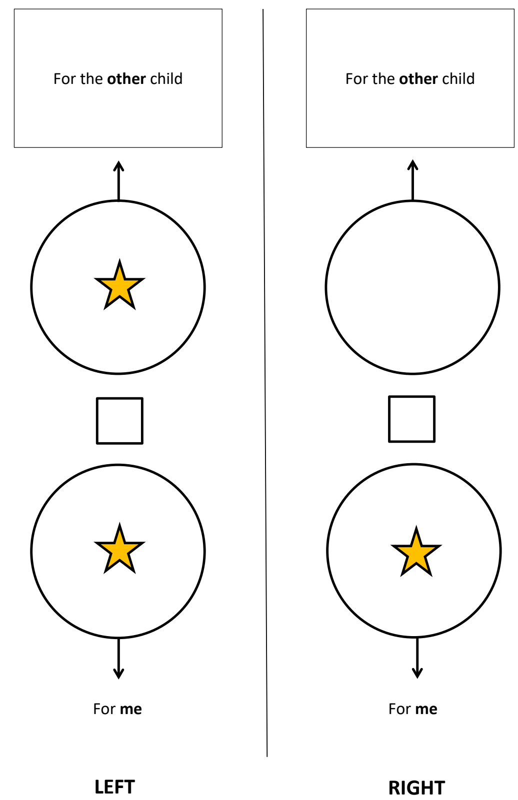
Are you okay so far? *Leave time for questions and answer them privately.*

As I mentioned earlier, you will get four decision sheets. The decision sheets differ from each other in the amount of stars that can be divided between you and the other child. Please choose one of the two options for each decision sheet. At the end of the game, you will roll a die (*show the process*). Here the number you roll corresponds to the sheet you will get paid for, meaning if you roll 1, you get paid for decision sheet 1 etc. If this game is selected for payment, you and the other child will be paid according to the selected decision sheet. If you roll a 5 or 6, no decision sheet will be paid.

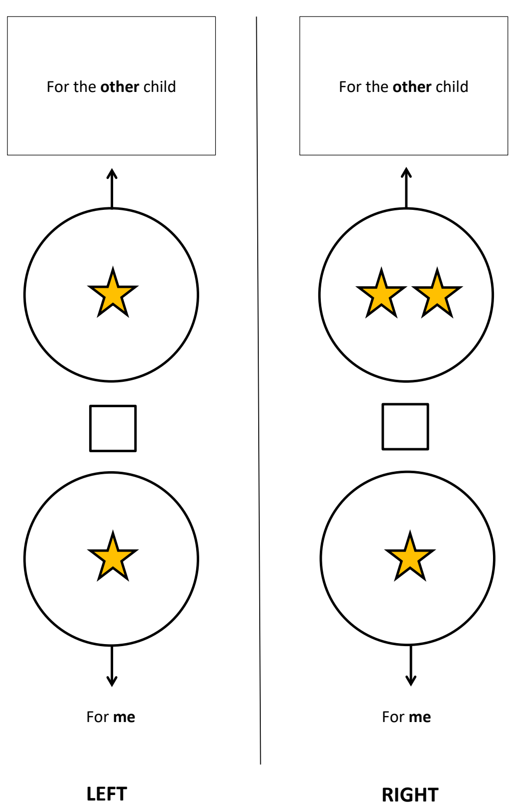
Decision sheet 1



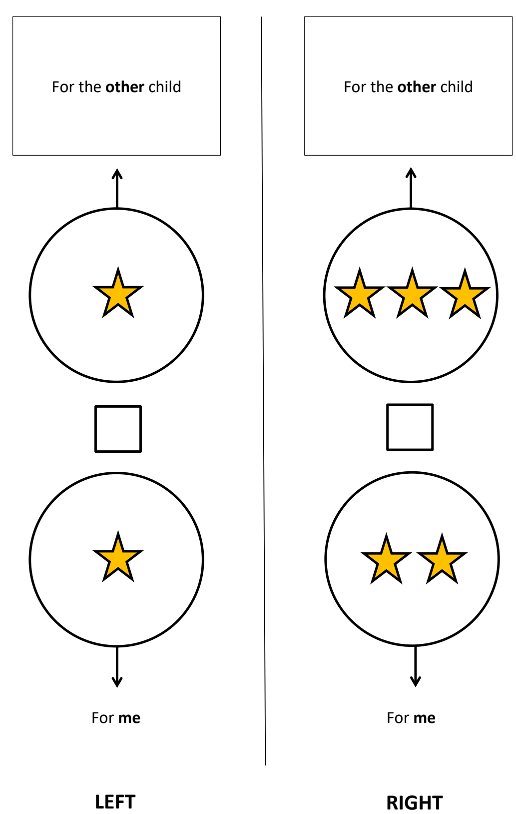
Decision sheet 2



Decision sheet 3



Decision sheet 4



2. Decision on first sheet: 1 = left, 2 = right
3. Decision on second sheet: 1 = left, 2 = right
4. Decision on third sheet: 1 = left, 2 = right
5. Decision on fourth sheet: 1 = left, 2 = rights

Roll a die to determine which decision sheet would be paid if this game got selected for payoff in the end.

D.2 Experimental protocols for adults

Time preferences

Let us start with this game. Before we start, let me explain the rules of our game. In this game you can earn money. That's why it is important that you understand the rules of our game. Please interrupt me anytime in case you have a question.

Are you okay so far? *Leave time for questions and answer them privately.*

1. Determine the order of explanation by rolling a die (blue, green, yellow) and write it down:

1	=	choice set 1, choice set 2, choice set 3
2	=	choice set 1, choice set 3, choice set 1
3	=	choice set 2, choice set 3, choice set 1
4	=	choice set 2, choice set 1, choice set 3
5	=	choice set 3, choice set 1, choice set 2
6	=	choice set 3, choice set 2, choice set 2

The game works as follows: The game consists of three choice sets. There are six choices in each choice set. You need to make a choice between two payment options: Option A or Option B. In each choice set, there are six such decisions that you need to make. Each decision is a paired choice between Option A and Option B. You will be asked to make a choice between these two payment options in each decision row. For example, (*assuming the first choice set is being randomly picked first*) in the first row, you need to make a choice between payment Option A and payment Option B where payment Option A pays you 100 Taka tomorrow and Option B pays you 105 Taka after 3 months from today. In the second choice, Option A pays you 100 Taka tomorrow, and Option B pays you 110 Taka in 3 months. In the third choice, Option A pays you 100 Taka tomorrow, and Option B pays you 120 Taka in 3 months. Notice that Option A remains unchanged while Option B is increasing.

If you go for 100 Taka tomorrow, you will need to tick Option A. If selected, one of us will come to your home and to deliver the money in an envelope with your name marked on it. If you wait, you will get 105 Taka after 3 months. Again, one of us will come to your home and to deliver the money in an envelope with your name marked on it.

Could you please repeat the rules of the game? *If the respondent is unable to repeat, please explain the game again; the respondent has to be able to repeat the correct meaning of the game autonomously.*

2. Respondent understood the game after:

1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

The second choice set is very similar to the first choice set. However, Option A now pays in 1 month, and Option B pays in 4 months. If you go for 100 Taka in 1 month, you will need to tick Option A. If selected, one of us will come to your home and deliver the money in an envelope with your name marked on it. If you wait 4 months, you will get 105 Taka after 4 months. Again, one of us will come to your home and deliver the money in an envelope with your name marked on it.

Could you please repeat the rules of the game? *If the respondent is unable to repeat, please explain the game again; the respondent has to be able to repeat the correct meaning of the game autonomously.*

3. Respondent understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

The third choice set is very similar to the second and first choice set. However, Option A now pays in 1 year, and Option B pays in 1 year and 3 months. If you go for 100 Taka in 1 year, you will need to tick Option A. If selected, one of us will come to your home and to deliver the money in an envelope with your name marked on it. If you wait 1 year and 3 months, you will get 105 Taka after 1 year and 3 months. Again, one of us will come to your home and to deliver the money in an envelope with your name marked on it.

If this game is paid, only one of the three choice sets counts. The selection will be made by rolling a 6-sided die twice—first to decide the set, and second to decide the choice. You will roll the die after your decisions (*please demonstrate*). In the first die roll, if 1, 2 or 3 is rolled, you will receive the money from the particular choice set, if 4, 5 or 6 is rolled, you will not receive any money. Depending on the outcome of the first die roll, the second die roll would determine the particular choice that you would be paid for. For example, if 3 is rolled in the second roll, you will receive the money from your decision concerning the third payoff alternative (*third row*) of the relevant choice set.

Could you please repeat the rules of the game? *If the respondent is unable to repeat, please explain the game again; the respondent has to be able to repeat the correct meaning of the game autonomously.*

4. Respondent understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

Please take your decision for each of the choice sets now (*place the decision sheets side by side on the table*). Start with this part (*point at the first decision sheet (depending on the order of explanation)*) and continue with this part (*point at the second decision sheet*) and finally make your decision in this part (*point at the final decision sheet*). Take as much time as you need. In the meantime, I will turn around so that I do not disturb you. Just call me when you are done or have any questions.

Roll a die to determine which decision sheet would be paid if this game got selected for payoff in the end.

Choice set 1

Payoff alternative	**Payment Option A** (pays amount below **tomorrow**)	**Payment Option B** (pays amount below **after 3 months**)	Annual interest rate in %	Preferred Payment Option (A or B)
1	100	105	20%	
2	100	110	40%	
3	100	120	80%	
4	100	125	100%	
5	100	150	200%	
6	100	200	400%	

Choice set 2

Payoff alternative	**Payment Option A** (pays amount below **after 1 month**)	**Payment Option B** (pays amount below **after 4 months**)	Annual interest rate in %	Preferred Payment Option (A or B)
1	100	105	20%	
2	100	110	40%	
3	100	120	80%	
4	100	125	100%	
5	100	150	200%	
6	100	200	400%	

Choice set 3

Payoff alternative	**Payment Option A** (pays amount below **after 1 year**)	**Payment Option B** (pays amount below **after 1 year 3 months**)	Annual interest rate in %	Preferred Payment Option (A or B)
1	100	105	20%	
2	100	110	40%	
3	100	120	80%	
4	100	125	100%	
5	100	150	200%	
6	100	200	400%	

Risk preferences

Let us start with this game. Before we start, I will explain the rules of our game. Similar to the other games, you can earn money in this game as well. How much money you will earn depends mainly on your decisions. That's why it is important that you understand the rules of our game. Please listen carefully now. I will frequently stop during my explanation and allow you to ask questions. Therefore, please interrupt me anytime in case you have a question.

Are you okay so far? *Leave time for questions and answer them privately.*

In this game, you need to select the gamble you would like to play from among six different gambles, which are listed below. You must select one and only one of these gambles.

If this game is selected for payment, you will have a 1-in-6 chance of receiving the money. The selection will be made by rolling a 6-sided die twice—first, you will roll the die to decide the gamble, and the second to decide the outcome of the particular gamble. For example, if you selected gamble number 4, then if the first roll of the die is 4, you would receive one of the payoffs of gamble 4, which will be determined in the second roll. If the first roll of the die is not 4 and you have chosen gamble number 4, you would not receive any payments. Depending on the outcome of the first roll, the second roll would determine the outcome of the selected gamble. Each gamble has two possible outcomes—low and high. If 1, 2 or 3 is rolled, the outcome of the selected gamble is the low one, and if 4, 5 or 6 is rolled, the outcome of the gamble is the high one, and you would receive money accordingly.

Notice that the low outcome is decreasing and the high outcome is increasing for each successive gamble. For example, in the first gamble, both outcomes are identical. If you select it and then this number is rolled in the first roll, your payoff would be 125 Taka. If on the other hand, you had selected gamble number 2, and if it is rolled on the first roll, your payoff could be 110 Taka or 240 Taka. In the second roll, if 1, 2 or 3 is rolled, you would receive 110 Taka, whereas if 4, 5 or 6 is rolled, you would receive 240 Taka.

Ask the respondent to repeat the game.

1. Respondent understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

Before you select the actual gamble involving money, we will have a practice session with candies. There are two gambles from which you need to select one:

	Outcome	Payoff	Chances	Your Selection
Gamble 1	LOW	1	50%	
	HIGH	1	50%	
Gamble 2	LOW	0	50%	
	HIGH	2	50%	

Both gambles have two outcomes. The first gamble pays 1 candy in both states, while the second gamble pays no (0) candy in the low state and 2 candies in high state. Which gamble would you like to play? Once you make your selection, you will first roll the die to decide the gamble, and then again roll the die to decide the outcome. For example, if you selected gamble number 2, then if the first roll of the die is 2, you would receive one of the payoffs of gamble number 2, which will be determined in the second die roll. In the second roll, if 1, 2 or 3 is rolled, the outcome of the selected gamble is the low one, which is 0 here. That means, you will not receive any candy. However, if 4, 5 or 6 is rolled, the outcome of the gamble is the high one, and you will receive 2 candies. Let us start this now.

Are you okay so far? *Leave time for questions and answer them privately.*

2. Gamble number picked involving candies:

Roll a die to determine whether gamble number 1 or gamble number 2 is payoff-relevant. If you have rolled a 1 or a 2, please roll the die a second time to determine whether the low or the high payoff is realized.

Mark the gamble you like best with an X in the last column "Your Selection"
(mark only one of the six gambles):

	Outcome	**Payoff**	**Chances**	**Your Selection**
Gamble 1	LOW	125	50%	
	HIGH	125	50%	
Gamble 2	LOW	110	50%	
	HIGH	240	50%	
Gamble 3	LOW	100	50%	
	HIGH	300	50%	
Gamble 4	LOW	75	50%	
	HIGH	375	50%	
Gamble 5	LOW	25	50%	
	HIGH	475	50%	
Gamble 6	LOW	0	50%	
	HIGH	500	50%	

3. Gamble number picked:

Roll a die to determine whether gamble number 1 or gamble number 2 is payoff-relevant. If the outcome of the first die roll equals the gamble number picked (if 6. = 7.), please roll the die a second time to determine whether the low or the high payoff is realized.

Social preferences

In this game you can earn stars, which you can convert into money. Each star is equal to Taka 100. The more stars you will earn, the more money you will get. That's why it is important that you understand the rules of our game. Please listen carefully now. I will frequently stop during my explanation and allow you to ask questions. Therefore, please interrupt me anytime in case you have a question.

Are you okay so far? *Leave time for questions and answer them privately.* In this game you have to decide how to divide stars between yourself and another person similar to you but from a different village. You will never know who exactly the other person is and the other person will not get to know you. However, I will ensure that the other person does indeed receive the money that corresponds to the stars that you will give to him/her. You will get four different decision sheets. You will need to decide how to divide stars between yourself and this person similar to you.

Are you okay so far? *Leave time for questions and answer them privately.*

There are two possible ways to allocate the stars: the option on the left-hand side and the option on the right-hand side. Please look at the decision sheet. With option "left" you get one star and the person from another village with whom you are randomly matched gets 1 star. One star equals 100 Taka. With option "right" you get 2 stars and the person from another village gets 0 stars.

Are you okay so far? *Leave time for questions and answer them privately.*

Depending on which option you want to choose, you should check the box at the left- or the right-hand side. You can choose either option "left" or option "right". If you would like to divide the stars according to option "right", which box would you have to check? Right, the box at the "right" side. How much would you earn and how much would the person from the other village with you are randomly matched earn in this case? Right, you would get 100 Taka and the other person similar to you would get nothing.

1. Respondent understood the game after:
1 = first explanation, 2 = second explanation, 3 = third explanation, 4 = did not understand

Are you okay so far? *Leave time for questions and answer them privately.*

As I mentioned earlier, you will get four decision sheets. The decision sheets differ from each other in the amounts of stars that can be divided between you and the other person. Please choose one of the two options for each decision sheet. At the end of the game, you will roll a die to determine the decision sheet out of four (*show the process*). Here the number you roll corresponds to the sheet you will get paid for, meaning if you roll 1, you get paid for decision sheet 1. If this game is selected for payment, you and the other person will be paid according to the selected decision sheet. If you roll a 5 or 6, no decision sheet will be paid.

[Decision sheets for adults are identical to those for children.]

2. Decision on first sheet: 1 = left, 2 = right
3. Decision on second sheet: 1 = left, 2 = right
4. Decision on third sheet: 1 = left, 2 = right
5. Decision on fourth sheet: 1 = left, 2 = rights

Roll a die to determine which decision sheet would be paid if this game got selected for payoff in the end.