Ancient Origins of the Global Variation in Economic Preferences*

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May 1, 2017

Abstract

Variation in economic preferences is systematically related to both individual and aggregate economic outcomes, yet the origins of the worldwide preference variation have proved elusive. This paper uses globally representative data on risk aversion, time preference, altruism, positive reciprocity, negative reciprocity, and trust to uncover that contemporary preference heterogeneity has its long-run roots in the migration patterns of our very early ancestors: In dyadic regressions, differences in preferences between populations are significantly increasing in the length of time elapsed since the respective groups diverged from common ancestors, as proxied by genetic, linguistic, and predicted migratory distance measures. This result holds across a wide range of cross-country regressions as well as in within-country analyses that hold people's current locations constant. While temporal distance drives differences in all preferences, the patterns are strongest for risk aversion and prosocial traits.

JEL classification: D01, D03

Keywords: Risk preferences, time preferences, social preferences, temporal distance.

*An earlier version of this paper circulated as "The Ancient Origins of Cross-Country Heterogeneity in Risk Preferences". We thank Quamrul Ashraf, Oded Galor, and Ömer Özak for generous data sharing. Armin Falk acknowledges financial support from the European Research Council through ERC # 209214. Becker: Harvard University, ankebecker@fas.harvard.edu; Enke: Harvard University and NBER, enke@fas.harvard.edu; Falk: University of Bonn and Institute on Behavior and Inequality (briq), armin.falk@uni-bonn.de.

1 Introduction

Risk, time, and social preferences form the building blocks of a large class of models in both micro- and macroeconomics. Empirical work shows that experimental and survey measures of these preferences vary substantially within populations and – in line with economic models – predict a large set of individual-level economic decisions ranging from stock and labor market behavior over savings and schooling choices to volunteering, donating, and cooperation (e.g., Chabris et al., 2008; Meier and Sprenger, 2010; Dohmen et al., 2011; Sutter et al., 2013; Kosfeld and Rustagi, 2015; Cohn and Maréchal, 2015). Moreover, recent work has shown that preferences exhibit large variation not just between individuals, but also across countries. This cross-country variation is systematically related to many variables that economists are typically concerned about, including per capita income, entrepreneurial activities, donations and volunteering, and the frequency of armed conflicts (Falk et al., 2016). The insights that preferences exhibit large variation both across and within countries, and that this heterogeneity correlates with economic outcomes at both levels of aggregation, raise the question of the origins of large-scale preference variation.

Our starting point is the observation that a growing literature within behavioral economics has provided evidence that contemporary environmental conditions affect preferences within certain populations. For example, natural and field experiments have revealed the effects of exposure to violence, earthquakes, or specific circles of friends (e.g., Voors et al., 2012; Callen et al., 2014; Rao, 2015; Kosse et al., 2015; Hanaoka et al., 2015; Brown et al., 2017). In addition, while research in cultural economics and economic history has typically not focused on risk, time, and social preferences – perhaps due to a previous lack of meaningful cross-country data – the evidence in this literature still shows that changes in attitudes more generally can persist for a fairly long time (e.g., Fernández, 2007; Giuliano, 2007; Durante, 2009; Nunn and Wantchekon, 2011; Voigtländer and Voth, 2012; Alesina et al., 2013; Lowes et al., 2015; Heldring, 2016; Galor and Özak, 2016).

This paper takes these literatures a step further through a complementary approach in which we (i) focus on explaining the global variation in preferences, as opposed to heterogeneity within a given population, (ii) investigate the *very* deep origins of preference heterogeneity by considering explanatory events that predominantly date back much longer than a few hundred years, and (iii) consider six preferences and attitudes in a unified empirical approach. We do so by applying the above two stylized facts of environmental preference shocks and intergenerational persistence to the "Out of Africa hypothesis" of human development. Building on a simple dynamic model of preference formation, we document that the distribution of temporal distances between populations that was generated by mankind's ancient migration out of Africa has shaped today's heterogeneity in risk, time, and social preferences, both across and within countries, albeit to heterogeneous degrees across preferences.

According to the widely accepted "Out of Africa hypothesis", starting around 50,000-60,000 years ago, early mankind migrated out of East Africa and continued to explore and populate our planet through a series of successive migratory steps that are referred to as "great human expansion" (see Henn et al., 2012, for an overview). Each of these steps consisted of some sub-population breaking apart from the previous colony and moving on to found new settlements. This pattern implies that some contemporary population pairs have spent a longer time of human history apart from each other than others. As a result, the time elapsed since two groups shared common ancestors differs across today's population pairs. The key idea underlying our analysis is that these differential time frames of separation might have generated heterogeneity in preferences over risk, time, and social interactions. First, populations that have spent a long time apart from each other were exposed to different historical experiences and environments, which could affect preferences. Second, due to random genetic drift or local selection pressures, long periods of separation lead to different population-level genetic endowments, which might in turn shape attitudes. The paper develops a model of preference evolution in the presence of stochastic shocks to show that both the genetic and the experience-based channel imply the prediction that populations that have been separated for a longer time should exhibit larger (absolute) differences in preferences.

We investigate this hypothesis both across and within countries. For this purpose, the analysis combines data on economic preferences around the globe with proxies for long-run human migration patterns and the resulting temporal distances. Our data on preferences stem from the Global Preference Survey (GPS), which includes experimentally validated survey measures of risk, time, and social preferences of 80,000 people from a geographically and economically diverse set of 76 countries (Falk et al., 2016). These data allow the computation of nationally representative levels of risk aversion, patience, altruism, positive reciprocity, negative reciprocity, as well as trust.

The paper combines these data with three classes of proxies for the temporal patterns of ancient population fissions, i.e., proxies for the length of time since two populations shared common ancestors. (i) First, we employ the F_{ST} and Nei genetic distances between populations (Spolaore and Wacziarg, 2009, 2016). As population geneticists have long noted, whenever two populations split apart from each other in order to found separate settlements, their genetic distance increases over time due to random genetic drift. Thus, the genetic distance between two populations is a measure of *temporal distance* since separation. (ii) Second, we use two measures of *predicted* migratory distance between contemporary populations that proxy for the walking time between two locations and hence constitute a proxy for the predicted length of separation of two populations (Özak, 2010; Ashraf and Galor, 2013). (iii) Finally, we make use of the observation that linguistic trees closely follow the structure of separation of human populations and employ a measure of linguistic distance between two populations as explanatory variable. We collapse these measures into a summary statistic of temporal distance between populations. The origins of the vast majority of the variation in this temporal distance measure are thousands of years old.

The empirical analysis of the relationship between preferences and ancient migration patterns starts with documenting that the absolute difference in risk, time, and social preferences between two countries is significantly increasing in the respective populations' temporal distance. In quantitative terms, an increase of one standard deviation in temporal distance is associated with an increase in about 20% of a standard deviation of differences in preferences, which is a larger effect than the corresponding correlation between differences and per capita income and preference differences. An array of corresponding robustness checks establishes that our cross-country results are robust to employing all genetic, migratory, and linguistic distance variables separately. These results are strongest for risk aversion and the prosocial traits altruism, positive reciprocity, and trust; similar, but weaker, findings hold for patience and negative reciprocity. Second, we establish robustness with respect to (i) culture-dependent interpretations of the survey items, (ii) excluding entire continents from the analysis, and (iii) taking into account differences in individual-level observables across countries. Third, the paper provides evidence that multiple testing issues (that may arise because we analyze six different preferences and also employ multiple explanatory variables) do not drive the findings; if anything, accounting for multiple testing concerns by, e.g., collapsing all preference differences into one measure, or adjusting p-values using the false discovery rate (FDR) procedure (Anderson, 2012; Cantoni et al., forthcoming) only strengthen the results.

"Controlling" for contemporary environmental conditions is not necessarily meaningful in our context. After all, those very conditions could often represent the mechanisms underlying the effect of temporal distance on preference differences, in particular when geographic and climatic variables capture highly persistent variation across populations. Nonetheless, the analysis addresses potential concerns that only variation in contemporary environments generates the results through a set of conditional regressions. The results establish that the effect of temporal distance on differences in risk aversion and prosocial traits is robust to an extensive set of covariates, including controls for differences in the countries' demographic composition, their geographic position, simple geographic distance metrics, prevailing climatic and agricultural conditions, institutions, and economic development. In all of the corresponding regressions, the point estimate is very stable, which suggests that unobserved heterogeneity is unlikely to drive our results (Altonji et al., 2005). In contrast, the relationships between patience and negative reciprocity on the one hand and temporal distance on the other hand disappear once covariates are accounted for.

In a next step, the paper studies the subnational relationship between preferences and temporal distance. For this purpose, the analysis utilizes information on individuals' country of birth in the GPS. For each country of residence, we construct virtual populations by averaging preferences across respondents from a given country of birth (Fernández and Fogli, 2006; Giuliano, 2007), and then assign a within-country population pair the temporal distance of the respective countries of birth. In essence, the resulting regressions compare, say, the difference in preferences between Italians and Turks with that of Chinese and Norwegians, all of whom currently reside in Germany. These regressions include both country of birth and country of residence fixed effects, i.e., leverage variation in preferences and temporal distance, while holding the current location constant across populations.

The results of the within-country exercise are even stronger than those established in the cross-country case. Across all preferences, temporal distance is strongly predictive of preference variation. Again, these results survive a number of robustness checks including employing each temporal distance proxy separately, or accounting for differences in individual-level observables. Moreover, similar results hold when we repeat the exercise within subnational regions, as opposed to within countries. Arguably, this set of results not only adds credibility to our identification strategy, but also represents a methodological innovation on past work on temporal or genetic distance, which has exclusively considered cross-country variation.

Taken together, the results establish that – both across and within countries – the longer two populations have been separated in the course of human history, the more they differ in terms of their economic preferences. These patterns are smaller and less robust for patience and negative reciprocity, an insight that is potentially useful for theories on the evolution of preferences (Bisin and Verdier, 2001; Doepke and Zilibotti, 2013, 2014).[1]

Our work is part of a growing line of research that studies cultural variation in preferences through experiments or surveys across countries (e.g., Henrich et al., 2001; Herrmann et al., 2008; Apicella et al., 2014; Vieider et al., 2015; Bartling et al., 2015;

[1]The cross-country heterogeneity in patience and negative reciprocity is similar to, if not larger than, the heterogeneity in risk aversion and the prosocial traits, so that the weaker effects for the former preferences are not driven by a lack of variation.

Gächter and Schulz, 2016). By uncovering that population-level preference profiles are endogenous to temporal distance, we contribute to the emerging study of endogenous preferences (Bowles, 1998; Fehr and Hoff, 2011), in particular regarding their historical, biological, or cultural roots (Guiso et al., 2009; Durante, 2009; Voigtländer and Voth, 2012; Chen, 2013; Giuliano and Spilimbergo, 2014; Galor and Özak, 2016).

Our paper is also close to other work using concepts from population genetics.[2] Spolaore and Wacziarg (2009, 2016) find a strong relationship between genetic distance and income differences across countries. Ashraf and Galor (2013) and Ashraf et al. (2014) establish a hump-shaped relationship between national income and genetic diversity. Desmet et al. (2011) and Spolaore and Wacziarg (2015) show that genetic and linguistic distance correlate with differences in opinions and attitudes as expressed in the World Values Survey.

The remainder of this paper proceeds as follows. In Section 2, we develop our hypothesis on the relationship between the structure of migratory movements and preferences, while Section 3 presents the data. Section 4 discusses the cross-country evidence and Section 5 the within-country results, respectively. Section 6 concludes.

2 Preferences and the Great Human Expansion

According to the widely accepted "Out of Africa" theory of the origins and the dispersal of early humans, the single cradle of mankind lies in East or South Africa and can be dated back to roughly 100,000 years ago (see, e.g., Henn et al. (2012) for an overview). Starting from East Africa, a small sample of hunter-gatherers exited the African continent around 50,000-60,000 years ago and thereby started what is now also referred to as the "great human expansion". This expansion continued throughout Europe, Asia, Oceania, and the Americas, so that mankind eventually came to settle on all continents. A noteworthy feature of this very long-run process is that it occurred through a large number of discrete steps, each of which consisted of a sub-sample of the original population breaking apart and leaving the previous location to move on and found new settlements elsewhere. The main hypothesis underlying this paper is that the pattern of successive breakups and the resulting distribution of temporal distances across populations affected the distribution of economic preferences we observe around the globe

[2] While we partly work with genetic distance, our objective is different from twin studies on economic preferences (Cesarini et al., 2009, 2012). Whereas these papers aim at showing that genes explain part of the variation in preferences, we do not aim at separating genetic from experience-based mechanisms, partly because the long-run scope of our approach in combination with recent evidence for gene-culture coevolution render such a "nature vs. nurture" endeavor misguided (Manuck and McCaffery, 2014; Henrich, 2015). Twin studies alone also cannot explain our results because the intergenerational transmission rates they imply are much too small to play a role for our long-run analysis.

today.

In particular, the series of migratory steps implied a frequent breakup of formerly united populations. After splitting apart, these sub-populations often settled geographically distant from each other, i.e., lived in separation. There are at least two channels through which the length of separation of two groups might have had an impact on between-group differences in preferences.[3]

First, if two populations have spent a long time apart from each other, they were subject to different historical experiences. Recent work highlights that economic preferences are malleable by idiosyncratic experiences or, more generally, by the composition of people's environment (see, e.g., Callen et al. (2014) on risk preferences, Rao (2015) and Kosse et al. (2015) on prosocial attitudes, or Voors et al. (2012) on risk, time, and social preferences). Thus, the differential historical experiences which have accumulated over thousands of years of separation might have given rise to different preferences as of today.

Second, whenever two populations spend time apart from each other, they develop different population-level genetic pools due to random genetic drift or location-specific selection pressures. Given that attitudes like risk aversion, trust, and altruism are transmitted across generations and that part of this transmission is genetic in nature (Cesarini et al., 2009; Dohmen et al., 2012), the different genetic endowments induced by long periods of separation could also generate differences in preferences.

We now formally illustrate how both of these channels (historical experiences and genetic pools) yield the prediction that longer separation implies larger absolute differences in preferences. For this purpose, we conceptualize both idiosyncratic experiences and genetic changes through population-specific stochastic shocks. We then show that these shocks "add up" over time and hence generate a relationship between length of separation and preference differences. Importantly, neither the framework nor our empirical exercise distinguishes (or is even intended to distinguish) between genetic and experience-based mechanisms. Given recent evidence on gene-environment interactions (see Manuck and McCaffery, 2014, for an overview), the long-run focus of our analysis renders such a distinction fundamentally misguided.

An important assumption is how the population-specific shocks are distributed across populations and time. Evidently, making intuitively appealing assumptions such as "populations that have been separated for a shorter time and hence likely live close geographically are subject to more similar shocks", would trivially yield the prediction that temporal distance predicts preference differences. However, as we discuss in detail be-

[3]It is conceivable that differences in preferences are correlated with temporal distance proxies because of the structure of the population breakups *as such*, rather than the temporal distances that were caused by the population breakups. Section 6 provides a discussion of this issue.

low, we derive our prediction in its arguably starkest form by showing that preference differences should depend on temporal difference *even* if the shocks are independently distributed across time and space, i.e., shocks are random.

Formally, suppose that there is a set of N contemporary populations. In period $t = 0, 1, \ldots, T$, each population i has a scalar-representable preference endowment x_i^t. In period $t = 0$, all contemporary populations were part of one "parental" population and we normalize the preference endowment to $x^0 = 0$. Over time, populations successively broke apart from each other. For each time $t = 0, 1, \ldots$ let $\mathscr{P}_t$ be a partition of $\{1, \ldots, N\}$, that is, $\mathscr{P}_t$ is a collection of disjoint nonempty sets whose union is $\{1, \ldots, N\}$. The elements of $\mathscr{P}_t$ represent the different populations at time t. For each $t \geq 0$ and $i \in \{1, \ldots, N\}$ let $P_t(i)$ be the unique $A \in \mathscr{P}_t$ that contains i.

In each period, a given population's preference endowment is subject to a random shock, which could result from experiences or changes in the genetic pool, or both. That is, as long as two populations are not separated, they get hit by the same shock, but once they split up, they are subject to separate, and potentially different, shocks. For each $t \geq 1$ and each $A \in \mathscr{P}_t$ let ϵ_A^t be such a random shock. Even though this is technically redundant, we will assume that the shocks have mean zero to ease interpretation. Let

$$x_i^t = \sum_{\tau=1}^{t} \epsilon_{P_\tau(i)}^{\tau}.$$

That is, a population's preference endowment in period t is given by the sum of the accumulated shocks. The object of interest in the empirical analysis is the expression

$$E\left[\left|x_i^T - x_j^T\right|\right]$$

for $i, j \in \{1, \ldots, N\}$. We will show that under arguably very mild assumptions this absolute difference in preferences between populations i and j is increasing in the number of periods in which the populations were separated. Fix $T \geq 1$. For populations $i, j \in \{1, \ldots, N\}$ let $s_{ij} = |\{t \in \{1, \ldots, T\} : P_t(i) \neq P_t(j)\}|$. Thus, s_{ij} is the number of periods up to time T where i and j were separated.

To derive our main prediction, we will assume that the preference shocks are independently and identically distributed across time and populations. As noted above, this assumption *only* serves to derive the prediction in its starkest (and arguably nontrivial) form. As we discuss below, other assumptions would often trivially generate the prediction that longer separation induces larger preference differences.

Proposition 1. *Suppose the shocks ϵ_A^t, $A \in \mathscr{P}_t$, $t = 1, \ldots, T$, are i.i.d. nondegenerate* *integrable random variables. Let $i, j, k, l \in \{1, \dots, N\}$. Then*

$$s_{ij} > s_{kl} \qquad \Leftrightarrow \qquad E\left[\left|x_i^T - x_j^T\right|\right] > E\left[\left|x_k^T - x_l^T\right|\right].$$

The proof is in Appendix B.[4] The proposition says that if two populations are separated for a longer time period, their absolute difference in preferences will be larger, in expectation. Intuitively, this holds true because a longer time spent apart implies a larger number of idiosyncratic shocks, which – in expectation – generate larger *absolute* differences. To see the basic intuition, suppose that populations i and j are still one population in T, i.e., they got hit by the same sequence of shocks, so that their absolute difference in preferences is zero. Suppose further that populations i and k were separated for one period, implying that their absolute difference in preferences is given by $|x_i^T - x_k^T| = |\epsilon_i - \epsilon_k|$. In expectation, this expression is strictly greater than zero. The proposition shows that this intuition holds for arbitrary population breakups and time spans. Hence, we state the following testable hypothesis:

Hypothesis. *The absolute difference in preferences between two populations increases in their length of separation.*

Note that the assumptions in Proposition 1 are sufficient, but not necessary, to generate the prediction that longer separation implies larger expected absolute differences. In particular, the proposition assumes that the shocks be independently and identically distributed across time and space. Several remarks are in order.

Remark 1. *It is conceivable that the preference shocks are drawn from different distributions along the migratory path, say because the further populations migrate the larger the average preference shock. However, if preferences evolved* monotonically *along the migratory path, then temporal distance trivially ought to be predictive of preference differences, which is why we refrain from making such strong assumptions. In addition, there is no biological principle according to which the evolution of a scalar-representable trait must follow a monotonic path. While there are reasons to believe that traits like risk aversion, time preference, or altruism are subject to local selection pressures, these selection pressures might operate in different directions along the migratory path as groups of humans and their descendants pass through many different environments.*

Remark 2. *The assumption that preference shocks are independent of each other across space is likely to be unrealistic. However, again, making natural assumptions on the depen-*

[4]We are deeply indebted to Lorens Imhof for proposing the proof to us.

dence of the shocks across populations would trivially imply the prediction that populations with low temporal distance have more similar preference profiles.

3 Data

3.1 Risk, Time, and Social Preferences Across Countries

The data on risk, time, and social preferences are part of the Global Preference Survey (GPS), which constitutes a unique dataset on economic preferences from representative population samples around the globe. In a wide range of countries, the Gallup World Poll regularly surveys representative population samples about social and economic issues. In 76 countries, we included as part of the regular 2012 questionnaire a set of survey items which were explicitly designed to measure a respondent's preferences (see Falk et al., 2016, for a detailed description of the dataset).

Four noteworthy features characterize these data. First, the preference measures have been elicited in a comparable way using a standardized protocol across countries. Second, contrary to small- or medium-scale experimental work, we use preference measures of representative population samples in each country. This allows for inference on between-country differences in preferences, in contrast to existing cross-country comparisons of convenience (student) samples. The median sample size was 1,000 participants per country; in total, we collected preference measures for more than 80,000 participants worldwide. Respondents were selected through probability sampling and interviewed face-to-face or via telephone by professional interviewers. Third, the dataset also reflects geographical representativeness. The sample of 76 countries is not restricted to Western industrialized nations, but covers all continents and various development levels. Specifically, our sample includes 15 countries from the Americas, 24 from Europe, 22 from Asia and Pacific, as well as 14 nations in Africa, 11 of which are Sub-Saharan. The set of countries contained in the data covers about 90% of both the world population and global income. Fourth, the preference measures are based on experimentally validated survey items for eliciting preferences. In order to ensure behavioral relevance, the underlying survey items were designed, tested, and selected through an explicit ex-ante experimental validation procedure (Falk et al., 2015). In this validation step, out of a large set of preference-related survey questions, those items were selected which jointly performed best in explaining observed behavior in standard financially incentivized experimental tasks to elicit preference parameters. In order to make these items cross-culturally applicable, (i) all items were translated back and forth by professionals, (ii) monetary values used in the survey were adjusted along the median household income for each country, and (iii) pretests were conducted in 21 countries of various cultural heritage to ensure comparability. The preference measures are derived as follows (see Appendix A and Falk et al. (2016) for details):[5]

[5] The description of the survey items closely follows the one in Falk et al. (2016).

Risk Taking. The set of survey items includes two measures of the underlying risk preference – one qualitative subjective self-assessment and one quantitative measure. The subjective self-assessment directly asks for an individual's willingness to take risks: *"Generally speaking, are you a person who is willing to take risks, or are you not willing to do so? Please indicate your answer on a scale from 0 to 10, where a 0 means "not willing to take risks at all" and a 10 means "very willing to take risks". You can also use the values in between to indicate where you fall on the scale."*

The quantitative measure is derived from a series of five interdependent hypothetical binary lottery choices, a format commonly referred to as the "staircase procedure". In each of the five questions, participants had to decide between a 50-50 lottery to win €x or nothing (which was the same in each question) and varying safe payments y. The questions were interdependent in the sense that the choice of a lottery resulted in an increase of the safe amount being offered in the next question, and conversely. For instance, in Germany, the fixed upside of the lottery x was €300, and in the first question, the safe payment was €160. In case the respondent chose the lottery (the safe payment), the safe payment increased (decreased) to €240 (80) in the second question. In essence, by adjusting the safe payment according to previous choices, the questions "zoom in" around the respondent's certainty equivalent and make efficient use of limited and costly survey time. This procedure yields one of 32 ordered outcomes. The self-assessment and the outcome of the quantitative lottery staircase were then aggregated into a single index which describes an individual's degree of risk taking.

Patience. The measure of patience is also derived from the combination of responses to two survey measures, one with a quantitative and one with a qualitative format. The quantitative survey measure consists of a series of five hypothetical binary choices between immediate and delayed financial rewards. In each of the five questions, participants had to decide between receiving a payment today or larger payments in 12 months. Conceptually similar to the elicitation of risk preferences, the questions were interdependent in the sense that the delayed payment was increased or decreased depending on previous choices. The qualitative measure of patience is given by the respondent's self-assessment regarding their willingness to wait on an 11-point Likert scale, asking "how willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?".

Prosociality: Altruism, Positive Reciprocity, and Trust. The GPS includes six survey items which map into three prosocial traits: altruism, positive reciprocity, and trust. While these behavioral traits are conceptually distinct, they share in common that they are commonly associated with "positive" social interactions.

Altruism was measured through a combination of one qualitative and one quantitative item, both of which are related to donation. The qualitative question asked people how willing they would be to give to good causes without expecting anything in return on an 11-point scale. The quantitative scenario depicted a situation in which the respondent unexpectedly received € 1,000 and asked them to state how much of this amount they would donate.

People's propensity to act in a positively reciprocal way was also measured using one qualitative item and one question with a quantitative component. First, respondents were asked to provide a self-assessment about how willing they are to return a favor on an 11-point Likert scale. Second, participants were presented a choice scenario in which they were asked to imagine that they got lost in an unfamiliar area and that a stranger – when asked for directions – offered to take them to their destination. Participants were then asked which out of six presents (worth between € 5 and € 30 in € 5 intervals) they would give to the stranger as a "thank you".

Finally, to measure trust, people were asked whether they assume that other people only have the best intentions (Likert scale, 0-10).

Negative Reciprocity. Negative reciprocity was elicited through three self-assessments. First, people were asked how willing they are to take revenge if they are treated very unjustly, even if doing so comes at a cost (0-10). The second and third item probed respondents about their willingness to punish someone for unfair behavior, either towards *themselves* or towards a *third person*.

Discussion: Heterogeneity, Stability, and Behavioral Relevance. As discussed in Falk et al. (2016), the preference measures are constructed by linearly combining responses to the survey items using weights that are derived from the experimental validation procedure (Falk et al., 2015). All preference measures are then standardized to have mean zero and standard deviation of one. Falk et al. (2016) show that all preferences exhibit a large amount of variation across countries. For example, calculating t-tests of all possible pairwise country comparisons reveals that about 80% of all country differences are statistically significant at the 1% level, for each preference.

We investigate the origins of this heterogeneity through a bilateral regression approach in which absolute differences in preferences serve as dependent variable. Thus, we compute the absolute difference in a given trait and standardize these variables again. Furthermore, for each population pair, we calculate an overall summary statistic of preference differences by summing up these absolute differences across preference dimensions. This summary statistic can be understood as a measure of overall (multidimensional) preference dissimilarity, and hence as a proxy for cultural differences in contexts involving economic preference parameters.

Our objective of explaining preference differences through historical events implicitly assumes that preferences exhibt some degree of stability over time. While our data do not have a panel dimension, we can indirectly gauge population-level stability by comparing the preferences of young and old people. To this end, we compute the average preference among the young and old (split at age 40) and then correlate preferences of these two groups. If population-level preferences were very unstable, the correlation between young and old should be very low. However, in this exercise, the average correlation coefficient is $\rho = 0.91$, suggesting that preferences exhibit considerable population-level stability.

Finally, understanding the global variation in preferences is only meaningful to the extent that our measures capture behaviorally relevant heterogeneity. In this respect, the results in Falk et al. (2016) provide encouraging evidence because preferences are correlated with those behaviors one would expect: For example, patience correlates with educational attainment and savings, risk taking with self-employment, and the social preferences with various social behaviors including donating, volunterring, and helping friends and strangers. Moreover, these within-country correlations are similar across countries.

3.2 Proxies for Ancient Migration Patterns

We use three separate but conceptually linked classes of variables to proxy for the length of time since two populations split apart: (i) Genetic distance, (ii) predicted migratory distance, and (iii) linguistic distance.

Genetic Distance. First, whenever populations break apart, they stop interbreeding, thereby preventing a mixture of the respective genetic pools. However, since every genetic pool is subject to random drift ("noise") or local selection pressures, geographical separation implies that over time the genetic distance between sub-populations gradually becomes (on average) larger. Thus, the genealogical relatedness between two populations reflects the length of time elapsed since these populations shared common ancestors. In fact, akin to a molecular clock, population geneticists have made use of this observation by constructing mathematical models to compute the timing of separation between groups. This makes clear that, at its very core, genetic distance constitutes not only a measure of genealogical relatedness, but also of *temporal distance*.

Technically, genetic distance constitutes an index of expected heterozygosity, which can be thought of as the probability that two randomly matched individuals will be genetically different from each other in terms of a pre-defined spectrum of genes. Indices of heterozygosity are derived using data on allelic frequencies, where an allele is a particular variant taken by a gene. Intuitively, the relative frequency of alleles at a given locus can be compared across populations and the deviation in frequencies can then be averaged over loci. This is the approach pursued in the work of the population geneticists Cavalli-Sforza et al. (1994). The main dataset assembled by these researchers consists of data on 128 different alleles for 42 world populations. By aggregating differences in these allelic frequencies, the authors compute the F_{ST} genetic distance, which provides a comprehensive measure of genetic relatedness between any pair of 42 world populations. Using the same dataset, Cavalli-Sforza et al. (1994) also compute the so-called Nei distance for all population pairs, which has slightly different theoretical properties than F_{ST}. Since genetic distances are available only at the population rather than at the country level, Spolaore and Wacziarg (2009) matched the 42 populations in Cavalli-Sforza et al. (1994) to countries.[6] Thus, the genetic distance measures we use measure the expected genetic distance between two randomly drawn individuals, one from each country, according to the contemporary composition of the population. The key advantage of the genetic distance data relative to predicted measures of length of separation (see below) is that the measurement and imputation apply to *contemporary* populations. Thus, for example, the effects of smaller-scale migratory movements after the human exodus from Africa on the temporal distance between populations are by construction incorporated in these measures.

Recently, Spolaore and Wacziarg (2016) introduced a new dataset of cross-country F_{ST} genetic distances that is based on the work by Pemberton et al. (2013). While the data from Cavalli-Sforza et al. (1994) are based on classic genetic markers, this new dataset is based on microsatellite variation, covering 645 microsatellite loci and 267 populations, thus providing a more comprehensive and detailed coverage of world populations. Spolaore and Wacziarg (2016) again matched these population-level F_{ST} distances to countries using ethnic composition data from Fearon (2003). In sum, this more recent genetic distance measure has the same conceptual basis, but is based on different biological information and samples.

Predicted Migratory Distance. Rather than physically *measure* the genetic composition of populations to investigate their kinship, one can also derive *predicted* migration measures (Ashraf and Galor, 2013; Özak, 2010). Key idea behind using these variables

[6]To this end, the authors used ethnic composition data from Fearon (2003): the data by Cavalli-Sforza et al. (1994) contain information on the groups that were sampled to obtain genetic distance estimates, and these groups can be matched one-to-one to the ethnic groups that populate countries. Thus, the data from one group in Cavalli-Sforza et al. (1994) can be assigned to sub-populations in potentially multiple countries, so that, in principle, even the relatively small number of 42 populations is sufficient to compute genetic distances between more than 100 countries.

is that populations that have lived far apart from each other (in terms of migratory, not necessarily geographic, distance), have usually spent a large portion of human history apart from each other. Notably, these data are independent of those on observed genetic distance and thus allow for an important out-of-sample robustness check.

First, the derivation of the predicted migratory distance variable of Ashraf and Galor (2013) follows the methodology proposed in Ramachandran et al. (2005) by making use of today's knowledge of the migration patterns of our ancestors. Specifically, Ashraf and Galor (2013) obtain an estimate of bilateral migratory distance by computing the shortest path between two countries' capitals. Given that early humans are not believed to have crossed large bodies of water, these hypothetical population movements are restricted to landmass as much as possible by requiring migrations to occur along five obligatory waypoints, one for each continent. By construction, these migratory distance estimates only pertain to the *native* populations of a given pair of countries. Thus, in contrast to the genetic distance measures, these distance estimates need to be adjusted to the extent that the contemporary populations in a country pair differ from the native ones. While this objective is difficult to achieve for geographically scattered waves of temporally very distant events, adjustment for post-Columbian migration flows can be implemented using the "World Migration Matrix" of Putterman and Weil (2010), which describes the share of the year 2000 population in every country that has descended from people in different source countries as of the year 1500. To derive values of predicted migratory distance pertaining to the *contemporary* populations, we combine the dataset of Ashraf and Galor (2013) with this migration matrix. Thus, the contemporary predicted migratory distance between two countries equals the weighted migratory distance between the contemporary populations.[7] Ancestry-adjusted predicted migratory distance between two countries can be thought of as the expected migratory distance between the ancestors of two randomly drawn individuals, one from each country.

Second, as an additional independent measure of migratory distance, we use the so-called "human mobility index"-based (HMI) migratory distance developed by Özak (2010). This measure is more sophisticated than the raw migratory distance using the five intermediate waypoints in that it measures the walking time along the optimal route between any two locations, taking into account the effects of temperature, relative humidity, and ruggedness, as well as human biological capabilities. Given that the

[7]Formally, suppose there are N countries, each of which has one native population. Let $s_{1,i}$ be the share of the population in country 1 which is native to country i and denote by $d_{i,j}$ the migratory distance between the native populations of countries i and j. Then, the (weighted) predicted ancestry-adjusted migratory distance between countries 1 and 2 as of today is given by

$$\text{Predicted migratory distance}_{1,2} = \sum_{i=1}^{N}\sum_{j=1}^{N}(s_{1,i} \times s_{2,j} \times d_{i,j})$$

procedure assumes travel by foot (as is appropriate if interest lies in migratory movements thousands of years ago), the data do not include islands, but assume that the Old World and the New World are connected through the Bering Strait, over which humans are believed to have entered the Americas. The original data contain the travel time between two countries' capitals, which we again adjust for post-Columbian migration flows using the ancestry-adjustment methodology outlined above. Thus, this variable measures the expected travel time between the ancestors of two randomly drawn individuals, one from each country.

Linguistic Distance. Population geneticists and linguists have long noted the close correspondence between genetic distance and linguistic "trees", intuitively because population break-ups do not only produce diverging gene pools, but also differential languages. Hence, we employ the degree to which two countries' languages differ from each other as an additional proxy for the timing of separation. The construction of linguistic distances follows the methodology proposed by Fearon (2003). The Ethnologue project classifies all languages of the world into language families, sub-families, sub-sub-families etc., which gives rise to a language tree. In such a tree, the degree of relatedness between different languages can be quantified as the number of common nodes two languages share.[8] As in the case of predicted migratory distances, for each country pair, we calculate the weighted linguistic distance according to the population shares speaking a particular language in the respective countries today.

Construction of Composite Measure of Temporal Distance. In sum, we have access to six proxies for temporal distance.[9] Given that these measures follow different methods of construction and are likely to be plagued by measurement error, we exploit the complementarity of the different data sources by constructing a composite index of temporal distance. This index is computed as unweighted average of the standardized values (z-scores) of the two F_{ST} genetic distance measures (based on Cavalli-Sforza et al. (1994) and Pemberton et al. (2013), respectively), Nei genetic distance, predicted migratory distance, and linguistic distance. We do not include the HMI migratory distance

[8]If two languages belong to different language families, the number of common nodes is 0. In contrast, if two languages are identical, the number of common nodes is 15. Following Fearon (2003), who argues that the marginal increase in the degree of linguistic relatedness is decreasing in the number of common nodes, we transformed these data according to

$$\text{Linguistic distance } = 1 - \sqrt{\frac{\#\text{ Common nodes}}{15}}$$

to produce distance estimates between languages in the interval $[0, 1]$. We restricted the Ethnologue data to languages which make up at least 5% of the population in a given country.

[9]Appendix C reports raw correlations among these proxies.

variable in the composite measure because it results in a loss of almost 600 observations.

Our procedure of constructing the composite measure implies that genetic data receive a higher weight than linguistic and predicted migratory distance data. This appears appropriate in that there are strong ex ante reasons to believe that genetic distance is a higher-quality proxy for temporal distance than linguistic or predicted migratory data. For example, the migratory distance measures are by construction coarse in nature. In addition, migratory distance can only be adjusted for the post-1500 mass migratory movements that are captured in the "World Migration Matrix", but not for the smaller and more diverse migration waves that have taken place throughout modern history. Likewise, it is well-known that genetic distance appears to be a higher-quality measure of separation patterns than linguistic distance (Cavalli-Sforza, 1997). First, while languages generally maintain a certain structure over long periods of time, in some cases they change or evolve very quickly, for example when the colonial powers brought Indo-European languages into Africa, or when Arabic was brought to Egypt during the Muslim conquest. In addition, any quantitative measure of linguistic distance suffers from the fact that language trees are rather coarse in nature.

In sum, predicted migratory and linguistic distance are more likely to be plagued by measurement error, hence justifying a higher weight on genetic data. Nevertheless, to demonstrate robustness, Appendix D.2 reports analyses in which the composite measure is constructed as unweighted average of F_{ST} genetic distance, predicted migratory distance, and linguistic distance, so that all data types receive equal weight. In what follows, we present the main results using the composite temporal distance variable. We then report robustness checks in which we employ each temporal distance proxy (including HMI migratory distance) separately. Our sample covers 72 countries.[10]

4 Cross-Country Evidence

4.1 Baseline Results

Since temporal distance is a bilateral variable, our analysis necessitates the use of a *dyadic* regression framework, which takes each possible pair of countries as unit of observation. Accordingly, we match each of the 72 countries with every other country into a total of 2,556 country pairs and, for each trait, compute the absolute difference in (average) preferences between the two countries.[11] We then relate our temporal distance

[10]The GPS dataset includes 76 countries. However, one or more of the temporal distance proxies are missing for Bosnia and Herzegovina, Serbia, Suriname, and Tanzania.

[11]Since the analysis is not directional, each country pair is only used once, i.e., when country i is matched with country j, j cannot be matched with i.

measure to this absolute difference in preferences between the respective populations. Our regression equation is hence given by:

$$|\text{pref}_i - \text{pref}_j| = \alpha + \beta \times \text{temporal distance}_{i,j} + \gamma_i \times d_i + \gamma_j \times d_j + \epsilon_{i,j}$$

where pref_i and pref_j represent some average preference in countries i and j, respectively, d_i and d_j country fixed effects, and $\epsilon_{i,j}$ a country pair specific disturbance term.[12]

As is standard practice in dyadic analyses such as in gravity regressions of bilateral trade, every specification to be presented below will include country fixed effects d_i and d_j, i.e., a fixed effect for each of the two countries that appears in a country pair observation to take out any unobservables that are country-specific.[13] To illustrate, with country fixed effects, the regressions do not relate, say, the raw difference in preferences between Sweden and Mexico to the respective raw temporal distance. Rather, the regression relates the difference in preferences between Sweden and Mexico *relative* to Sweden's and Mexico's average differences in preferences in all country pairs to their temporal distance, again relative to all other temporal distances involving these two countries. For instance, if Mexico had very large differences in preferences to all countries, then the fixed effects would ensure that these uniform large differences are treated as a Mexico-specific effect, rather than attribute them to the bilateral relationships between Mexico and other countries. Thus, country-specific factors are netted out of the analysis and the regression equation estimates the bilateral effect of interest.[14]

Furthermore, regarding the noise term, because our empirical approach implies that each country will appear multiple times as part of the (in)dependent variable, we need to allow for clustering of the error terms at the country-level. We hence employ the two-way clustering strategy of Cameron et al. (2011), i.e., we cluster at the level of the first and of the second country of a given pair. This procedure allows for arbitrary

[12]In most bilateral regressions employed in this paper, clustering is done over the same groups as the fixed effects in the respective model. As discussed in Cameron et al. (2011), in such cases the estimated variance matrix is often non-positive semi-definite. At the same time, the subcomponent of the variance matrix that is associated with the regressor of interest (temporal distance) will often be positive semi-definite, so that inference is appropriate (Cameron et al., 2011). The authors recommend to partial the fixed effects out of all other variables rather than directly estimate them, because the resulting variance matrix will then often be positive semi-definite. In our estimations, the estimated variance matrices are indeed usually non-positive semi-definite, but these estimations yield virtually identical results as a procedure in which we first partial out the fixed effects (in which case the variance matrix is indeed positive semi-definite). This is consistent with the Monte Carlo studies reported by Cameron et al. (2011). For simplicity we hence stick with the standard procedure. All results using the two-step procedure of first partialing out fixed effects are available upon request.

[13]See also the working paper version of Spolaore and Wacziarg (2009).

[14]The empirical results suggest that such country fixed effects indeed go a long way in addressing omitted variable concerns. For instance, in the analyses to be presented below, for patience and negative reciprocity we sometimes observe statistically significant *negative* coefficients on temporal distance if country fixed effects are not included, which we find very hard to interpret. These results entirely disappear with country fixed effects.

correlations of the error terms within a group, i.e., within the group of country pairs which share the same first country or which share the same second country, respectively, see Appendix II of Spolaore and Wacziarg (2009).

Table 1 provides the results of OLS regressions of absolute differences in preferences on temporal distance as well as F_{ST} genetic distance as theoretically most appealing proxy for temporal distance. Throughout the paper, all regression coefficients (except for those of binary variables) are expressed in terms of standardized betas, i.e., both the dependent and the independent variables are normalized into z-scores and the dependent variable is then multiplied with 100, so that the coefficient can be interpreted as the percent change of a standard deviation in the dependent variable in response to a one standard deviation increase in the independent variable.

Columns (1) and (2) show that the summary statistic of preference differences (which consists of the sum of the absolute differences across preference dimensions) is strongly and significantly related to temporal distance. The associated t-statistic equals 5.7 and the point estimate suggests that a one standard deviation increase in temporal distance is associated with an increase of 23 percent of a standard deviation in differences in preferences.

Columns (3) and (4) provide evidence that temporal distance is a significant predictor of differences in average risk attitudes. In columns (5) through (10), we show that very similar results obtain for all of the prosocial traits, i.e., altruism, positive reciprocity, and trust. Given that these three traits are also positively correlated at the country-level, we keep the subsequent analysis concise by collapsing the three measures into a simple unweighted average that we refer to as "prosociality" and report robustness checks using each prosocial trait separately in the Appendix.[15]

Finally, columns (11)-(12) and (13)-(14) present analogous analyses using differences in patience and negative reciprocity as dependent variables. Across specifications, the point estimates are positive, but rather small in magnitude. These coefficients are statistically significant when we use the composite temporal distance measure, but not with F_{ST} genetic distance. As we discuss below, differences in patience and negative reciprocity are better predicted by the non-genetic temporal distance proxies, perhaps suggesting that the different proxy variables capture slightly different cultural or biological processes. In sum, differences in all preferences are increasing in the length of separation of the respective populations, albeit to different degrees.

[15]The country-level correlations between the three measures range between 0.27 and 0.71, see Falk et al. (2016). To derive the prosociality index, we computed a simple unweighted average of altruism, positive reciprocity, and trust at the individual level and collapsed this measure at the country-level.

Table 1: Preferences and temporal distance

	Dependent variable: Absolute difference in...													
	All preferences		Risk taking		Altruism		Pos. reciprocity		Trust		Patience		Neg. reciprocity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Temporal distance	0.22***		0.15**		0.025*		0.10**		0.19***		0.090*		0.036**	
	(0.04)		(0.07)		(0.01)		(0.04)		(0.05)		(0.05)		(0.01)	
Fst genetic distance		0.24***		0.17**		0.040**		0.13***		0.23***		0.039		0.018
(Cavalli-Sforza)		(0.04)		(0.08)		(0.02)		(0.05)		(0.06)		(0.03)		(0.02)
Observations	2556	2556	2556	2556	2556	2556	2556	2556	2556	2556	2556	2556	2556	2556
R^2	0.470	0.469	0.630	0.631	0.555	0.555	0.509	0.511	0.438	0.442	0.504	0.501	0.467	0.467

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Separate Temporal Distance Proxies

We extend our analysis by employing Nei genetic distance, F_{ST} genetic distance based on Pemberton et al. (2013), predicted migratory distance, predicted HMI migratory distance, and linguistic distance as explanatory variables. Columns (1) through (5) of Table 2 describe the relationship between differences in preferences and temporal distance. Columns (6) through (10) and columns (11) through (15) analyze the effect of temporal distance on differences in risk preferences and prosociality, respectively. Across specifications, the respective temporal distance proxies have a positive coefficient that is almost always statistically significant, hence showing that our results do not hinge on employing the composite temporal distance measure or Cavalli-Sforza et al.'s (1994) F_{ST} measure.[16]

Table 3 performs an analogous analysis for patience and negative reciprocity. The point estimates of the temporal distance proxies are always positive, but often not statistically significant. At the same time, the stronger results for linguistic distance perhaps suggest that different preferences might be subject to different biological or cultural processes and that these different processes are partly captured by the different temporal distance proxy variables.

4.3 Further Robustness Checks

Sub-Samples. A potential concern is that temporal distance might simply pick up regional effects. To address this, Appendix D.4 presents a set of regressions in which we exclude each continent one-by-one. This does not affect the results.

In many of the countries furthest from East Africa, the majority of the population is not indigenous. Our analysis addressed this aspect by employing observed genetic and linguistic distance as well as ancestry-adjusted migratory distance as inputs into the explanatory variable, which by construction pertain to contemporary populations. Still, to rule out that the mass migration post-1500 and its effect on temporal distances drives our results, Appendix D.4 presents the results of an additional robustness check in which we restrict the sample to countries in the Old World, i.e., we exclude Australia, the Americas, and the Caribbean. Reassuringly, the results are very similar to the baseline results.[17]

[16]Unreported regressions show that when we use non-ancestry adjusted migratory distance measures in the regressions (as opposed to the ancestry adjusted variables used throughout this paper), the results are weaker, again suggesting that the precise migration patterns of our ancestors need to be taken into account to understand the cross-country variation in preferences.

[17]To provide yet another piece of evidence that regional patterns do not drive our results, we construct an extensive set of 28 continental dummies each equal to one if the two countries are from two given continents. When we include this vector of fixed effects, we cannot condition on country fixed effects any longer because the resulting set of fixed effects would be too extensive to leave meaningful variation

Table 2: Robustness: Separate temporal distance proxies (1/2)

	Dependent variable: Absolute difference in...														
	All preferences					Risk taking					Prosociality				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Nei genetic distance	0.22^{***}					0.14^{**}					0.22^{***}				
	(0.04)					(0.07)					(0.05)				
Fst genetic distance (Pemberton)		0.22^{***}					0.18^{**}					0.15^{***}			
		(0.05)					(0.08)					(0.05)			
Migratory distance			0.20^{***}					0.12					0.13^{**}		
			(0.06)					(0.08)					(0.06)		
HMI migratory distance				0.22^{***}					0.25^{**}					0.12^{**}	
				(0.06)					(0.11)					(0.06)	
Linguistic distance					0.14^{***}					0.070^{*}					0.059^{**}
					(0.04)					(0.04)					(0.03)
Observations	2556	2556	2556	2016	2556	2556	2556	2556	2016	2556	2556	2556	2556	2016	2556
R^2	0.468	0.465	0.457	0.488	0.462	0.629	0.632	0.624	0.637	0.624	0.488	0.476	0.472	0.522	0.470

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness: Separate temporal distance proxies (2/2)

	Dependent variable: Absolute difference in...									
	Patience					Neg. reciprocity				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nei genetic distance	0.042					0.017				
	(0.04)					(0.02)				
Fst genetic distance (Pemberton)		0.080*					0.018			
		(0.05)					(0.01)			
Migratory distance			0.12*					0.038**		
			(0.06)					(0.02)		
HMI migratory distance				0.051					0.042	
				(0.04)					(0.03)	
Linguistic distance					0.097*					0.047***
					(0.05)					(0.02)
Observations	2556	2556	2556	2016	2556	2556	2556	2556	2016	2556
R^2	0.501	0.503	0.505	0.527	0.508	0.467	0.467	0.467	0.462	0.468

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Culture-Dependent Interpretations. In most cases, our preference measures are composed of a combination of qualitative and quantitative survey items. While these items have been tailored to be applicable in cross-cultural research and have been subject to an extensive pre-test in 21 countries of different cultural heritages (see Falk et al. (2016) for details), it is conceivable that the interpretation of the qualitative scales differs systematically across countries. If such a difference in interpretation was associated with temporal distance, our results might merely reflect contemporary differences in answering subjective self-assessments. The quantitative measures, on the other hand, are context-free hypothetical decisions over (purchasing power adjusted) monetary stakes in precisely defined choice contexts. Arguably, these measures do not suffer from the potential confound of being interpreted in different ways across countries. We hence replicate our main analysis using only quantitative preference measures. Appendix D.5 shows that the corresponding results are similar, if not stronger, than those reported above.

Our survey items were selected based on an experimental validation procedure with German experimental subjects. To ensure that our temporal distance measure does not spuriously pick up differences in interpretation related to linguistic differences from Germany, Appendix D.6 shows that controlling for the relative linguistic distance to Germany between countries in a pair does not affect the results.

Purging Preferences of Individual-Level Observables. To check for robustness against differential individual characteristics across countries, Appendix D.7 presents the results of a robustness check in which the dependent variable is not the raw (absolute difference in) preferences, but rather the (absolute difference in) residual preferences, after accounting for age, age squared, gender, educational attainment fixed effects, log household income p/c, and marital status fixed effects. The results are very similar to the baseline results.

Tail Observations. Appendix D.8 presents an extensive set of robustness checks in which we restrict the sample by excluding observations from the left or right tail of the distributions of temporal distance and preferences. These analyses show that the relationships between differences in risk taking and prosociality on the one hand and temporal distance on the other hand are not driven by outliers.

to identify our coefficient of interest off. Appendix D.3 presents the results, which are similar to those using country fixed effects.

4.4 Multiple Testing

Strictly speaking, our empirical analysis is subject to multiple testing concerns because we evaluate the null hypothesis "temporal distance does not affect preference differences" through estimations that feature six dependent and six independent variables, i.e., 36 different specifications. At the same time, such concerns are arguably greatly reduced by our procedure of collapsing all dependent and all independent variables into a summary statistic each. In doing so, we have only one regression specification to evaluate, and here overall preference differences are strongly related to temporal distance (see columns (1) and (2) of Table 1). We further address concerns about multiple testing in Appendix D.9 by presenting p-values which are adjusted using the false discovery rate (FDR) procedure (Anderson, 2012; Cantoni et al., forthcoming). Again, these results support the picture developed in the main text. For example, when we adjust the p-values in Table 1 (i.e., the baseline results using the composite temporal distance measure) across dependent variables, the adjusted p-values are even smaller than the unadjusted ones and temporal distance is uniformly and significantly linked to preference differences. At the same time, as Appendix D.9 shows, the results are again weaker for patience and negative reciprocity than for risk taking and the prosocial variables.

4.5 Conditional Regressions

The argument made in this paper is that the relationship between temporal distance on the one hand and preferences on the other hand reflects the impact of ancient migration patterns and the resulting distribution of temporal distances across populations, rather than *contemporary* differences in idiosyncratic country characteristics. We hence proceed by investigating the robustness of the relationship between temporal distance and preferences through conditional regressions. Throughout this section, it will be important to keep in mind that when we "control" for, say, geographic differences between countries, we are likely to "over-control". After all, differences in geographic and climatic conditions might be one of the channels through which temporal distance generates differences in preferences, in particular given that differences in climatic or geographic conditions are to a large extent very persistent. In what follows, our augmented regression specification will be:

$$|pref_i - pref_j| = \alpha + \beta \times \text{temporal distance}_{i,j} + \gamma_i \times d_i + \gamma_j \times d_j + \eta \times g_{i,j} + \epsilon_{i,j}$$

where g_{ij} is a vector of bilateral measures between countries i and j (such as their geodesic distance or the absolute difference in per capita income). Details on the definitions and sources of all control variables can be found in Appendix G.

We start our analysis by considering the summary statistic of preference differences. To check that our coefficient of interest does not spuriously pick up the effect of demographic differences or differential population characteristics, column (2) of Table 4 adds to the baseline specification the absolute differences in proportion of females, religious fractionalization, and the fraction of the population who are of European descent. This joint set of covariates reduces the point estimate of temporal distance by only about 10%, and the coefficient remains statistically significant.

A potential concern with our baseline specification is that it ignores differences in development and institutions across countries, in particular given that temporal distance has been shown to correlate with differences in national income (Spolaore and Wacziarg, 2009). Column (3) of Table 4 therefore introduces absolute differences in (log) GDP per capita, democracy, and a common legal origin dummy. The inclusion of this vector of controls reduces the temporal distance coefficient by 10%, but it remains well in the magnitude of the previous estimations and is statistically significant.

Human migration patterns (and hence temporal distance proxies) are correlated with geographic and climatic variables. To ensure that effects stemming from *contemporary* variations in geography or climate are not attributed to temporal distance, we now condition on an exhaustive set of corresponding control variables. Column (4) introduces four distance metrics as additional controls into this regression. Our first geographical control variable consists of the geodesic distance (measuring the shortest distance between any two points on earth) between the most populated cities of the countries in a given pair. Relatedly, we introduce a dummy equal to one if two countries are contiguous. Finally, we also condition on the "distance" between two countries along the two major geographical axes, i.e., the difference in the distance to the equator and the longitudinal (east-west) distance. Again, the introduction of these variables has virtually no effect on the coefficient of temporal distance.

Given that geographic distance as such does not seem to drive our results, we now control for more specific information about differences in the micro-geographic and climatic conditions between the countries in a pair. To this end, we make use of information on the agricultural productivity of land, different features of the terrain, and climatic factors. As column (4) shows, the inclusion of corresponding controls has no effect on the temporal distance point estimate. In sum, columns (4) and (5) suggest that the precise migration patterns of our ancestors, rather than simple shortest-distance calculations between contemporary populations, need to be taken into account to understand the cross-country variation in preferences.

Tables 5 and 6 repeat the conditional regressions for all preferences separately. Each

Table 4: Preferences and temporal distance: Robustness (1/3)

	Dependent variable: Absolute difference in all preferences				
	(1)	(2)	(3)	(4)	(5)
Temporal distance	0.22***	0.21***	0.19***	0.18***	0.18***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Δ Proportion female		0.052	0.071*	0.069*	0.064
		(0.03)	(0.04)	(0.04)	(0.04)
Δ Religious fractionalization		0.011	0.011	0.0089	0.0090
		(0.02)	(0.02)	(0.02)	(0.02)
Δ % Of European descent		0.010	-0.048*	-0.057**	-0.054*
		(0.02)	(0.03)	(0.03)	(0.03)
Δ Democracy index			0.014	0.017	0.013
			(0.04)	(0.04)	(0.04)
Δ Log [GDP p/c PPP]			0.16***	0.16***	0.16***
			(0.05)	(0.05)	(0.05)
Log [Geodesic distance]				0.064	0.061
				(0.04)	(0.05)
1 for contiguity				0.034	0.043
				(0.11)	(0.11)
Δ Distance to equator				0.0052	0.010
				(0.03)	(0.04)
Δ Longitude				-0.068*	-0.064*
				(0.04)	(0.04)
Δ Land suitability for agriculture					0.033
					(0.02)
Δ Mean elevation					-0.0037
					(0.04)
Δ SD Elevation					-0.0046
					(0.03)
Δ Ave precipitation					-0.0038
					(0.03)
Δ Ave temperature					-0.0054
					(0.04)
Δ Log [Area]					0.0049
					(0.03)
Colonial relationship dummies	No	No	Yes	Yes	Yes
Observations	2556	2556	2485	2485	2485
R^2	0.470	0.472	0.489	0.491	0.492

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

column follows the same logic as the corresponding column in Table 4. As Table 5 shows, the relationship between risk preferences and prosociality on the one hand and temporal distance on the other hand is robust to this large and comprehensive vector of covariates, even quantitatively.[18] This suggests that – in order for omitted variable bias to explain our results – unobservables would have to bias our results by much more than the very large and comprehensive set of covariates in our regressions (Altonji et al., 2005; Bellows and Miguel, 2009).

At the same time, as illustrated in Table 6, the effects on patience and negative reciprocity vanish once covariates are accounted for. Thus, consistent with the patterns reported above, it appears as if temporal distance has a stronger effect on risk preferences and prosocial traits than on patience and negative reciprocity.

5 Within-Country Evidence

5.1 Baseline Results

To provide evidence that temporal distance per se, rather than unobserved third factors, drives the relationship between preference differences and temporal distance, the empirical analysis employed a wide range of regression specifications and robustness checks including country fixed effects. Still, compared to between-country regressions, within-country analyses have the important advantage that they allow to hold constant many features of people's contemporary environments that are difficult to account for in cross-country analyses. In particular, our cross-country regressions compared people who currently reside in different environments.

This section makes further progress by considering variation in preferences and temporal distances within countries, across groups of people with different heritage. In other words, this section no longer considers variation across countries of residence, but variation across country of birth for a given country of residence. To this end, we use individual-level information about country of birth. In essence, these analyses will compare, say, the difference in preferences between French and Nigerians who currently live in the US with the difference between Italians and Japanese who also live in the US, or with the difference between Americans and Mexicans who live in the US. Thus, the unit of analysis is no longer a country pair, but rather a population-pair in a given country of residence.

Specifically, for 54 countries in our sample, we have information about the country of birth of our respondents. Among these 68,685 respondents are 2,430 immigrants.

[18]Appendix D.1 reports analyses for each of the three prosocial traits separately.

Table 5: Preferences and temporal distance: Robustness (2/3)

	Dependent variable: Absolute difference in...									
	Risk taking					Prosociality				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temporal distance	0.15**	0.14*	0.14**	0.15**	0.15**	0.16***	0.19***	0.19***	0.22***	0.22***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Population controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Economic and institutional controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Colonial relationship dummies	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Distance controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Geographic controls	No	No	No	No	Yes	No	No	No	No	Yes
Observations	2556	2556	2485	2485	2485	2556	2556	2485	2485	2485
R^2	0.630	0.631	0.631	0.635	0.637	0.480	0.481	0.490	0.493	0.493

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. See Table 4 for a complete list of the control variables. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Preferences and temporal distance: Robustness (3/3)

	Dependent variable: Absolute difference in...									
	Patience					Neg. reciprocity				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temporal distance	0.090*	0.013	-0.030	-0.059	-0.050	0.036**	0.048**	0.037*	-0.0049	-0.0084
	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Population controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Economic and institutional controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Colonial relationship dummies	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Distance controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Geographic controls	No	No	No	No	Yes	No	No	No	No	Yes
Observations	2556	2556	2485	2485	2485	2556	2556	2485	2485	2485
R^2	0.504	0.515	0.579	0.583	0.586	0.467	0.469	0.482	0.485	0.486

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. See Table 4 for a complete list of the control variables. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We compute the average level of a given preference at the country of residence times country of birth level, i.e., for each country of residence we compute the average preference for a given country of birth. This procedure gives rise to 558 "populations". We match each population with each other population, but only keep those population pairs that share a common country of residence to be able to conduct a within-country analysis. Then, as before, we assign temporal distances to population pairs based on their countries of origin. Using this procedure, we end up with 6,321 population pairs from 152 countries of origin who currently live in 54 countries. Note that these statistics imply that the sample of populations we use is larger than in the cross-country analysis because we now observe migrants from countries which are not covered in the GPS.

Working with migrants comes at the cost that the number of migrants from any given country of birth in a given country of residence is sometimes very small. To the extent that the preferences of a small number of people are not representative of the entire population, this introduces measurement error. We therefore estimate weighted least squares regressions in which each population-pair observation is weighted by the the sum of the log of the number of observations in both populations in a pair.[19] Our estimating equation is given by:

$$|\text{pref}_{i,z} - \text{pref}_{j,z}| = \alpha + \beta \times \text{temporal distance}_{i,j} + \gamma_i \times d_i + \gamma_j \times d_j + \gamma_z \times d_z + \epsilon_{i,j,z}$$

where $\text{pref}_{i,z}$ and $\text{pref}_{j,z}$ represent some average preference for people who currently reside in country z, yet were born in countries i and j, respectively. d_i and d_j are country of birth fixed effects. d_z are country of residence fixed effects, and $\epsilon_{i,j,z}$ a disturbance term. Thus, the regression equation is conceptually the same as in Section 4. As before, we employ a twoway-clustering strategy and cluster at the level of both countries of origin.[20]

Table 7 presents the baseline results. Across all preferences, temporal distance is strongly and significantly related to differences in preferences. The magnitude of the regression coefficients is slightly smaller, but overall similar to those in the cross-country analyses. Thus, temporal distance is predictive of preference differences even among people who share the same contemporary environments.

[19]Formally, the regression weights are given by $w = ln(1 + n_1) + ln(1 + n_2)$, where n_1 and n_2 denote the number of observations in a population pair. Very similar results hold with weights $w = \sqrt{w_1} + \sqrt{w_2}$ or linear weights $w = n_1 + n_2$, see Appendix E.1.

[20]Clustering at the country of residence or twoway-clustering at the level of both countries of origin times the country of residence yield very similar results.

Table 7: Preferences and temporal distance within country

	Dependent variable: Absolute difference in...						
	All pref.	Risk taking	Altruism	Pos. recip.	Trust	Patience	Neg. recip.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temporal distance	0.17***	0.067**	0.082***	0.069***	0.10***	0.13***	0.093***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
Country of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6321	6298	6321	6321	6264	6254	6198
R^2	0.306	0.234	0.256	0.230	0.271	0.221	0.264

Notes. WLS estimates, twoway-clustered standard errors (clustered at both countries of origin) in parentheses. The unit of observation is a population pair, which is defined as two groups who currently reside in the same country, but were born in different countries. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Temporal distance is computed from the respective population pairs' countries of origin. Each population-pair-observation is weighted by $w = ln(1+n_1)+ln(1+n_2)$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Robustness

Temporal Distance Proxies Separately. Akin to the between-country analysis, we present a set of regressions in which we employ each temporal distance proxy separately. As Tables 27 and 28 in Appendix E.2 show, preference differences are robustly related to temporal distance, regardless of which particular proxy we employ.

Accounting for Individual-Level Observables. As a second robustness check, again akin to the cross-country analyses, we make use of our individual-level covariates and "clean" preferences of observable characteristics. This exercise is particularly important in the present within-country context because our analyses are based on relatively small samples of people in a given population, rather than representative population samples. This implies the risk that the characteristics of migrants might differ substantially across countries of origin. To account for this, we again partial observable characteristics out of individual-level preferences and then aggregate the residuals. Table 8 presents the results. For each preference, we present two specifications, one in which we purge preferences of a sparse exogenous set of observables (age, age squared, and gender), and one in which preferences are cleaned of a comprehensive set of variables including age, age squared, gender, log household income p/c, education level fixed effects, and marital status fixed effects. Across specifications and preferences, temporal distance is strongly predictive of preference differences.

Table 8: Preferences and temporal distance within country: Residual preferences

	Dependent variable: Absolute difference in residual...									
	All preferences		Risk taking		Prosociality		Patience		Neg. reciprocity	
	Sparse	Full	Sparse	Full	Sparse	Full	Sparse	Full	Sparse	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temporal distance	0.18***	0.17***	0.071**	0.070**	0.10***	0.12***	0.13***	0.12***	0.099***	0.098***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Country of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6321	6321	6298	6087	6264	6054	6254	6043	6198	5987
R^2	0.308	0.298	0.248	0.265	0.251	0.236	0.221	0.225	0.254	0.246

Notes. WLS estimates, twoway-clustered standard errors (clustered at both countries of origin) in parentheses. The unit of observation is a population pair, which is defined as two groups who currently reside in the same country, but were born in different countries. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Temporal distance is computed from the respective population pairs' countries of origin. The dependent variable are residual (absolute differences in) preferences. In columns (1), (3), (5), (7), and (9), residual preferences are computed by regressing individual preferences on age, age squared, and gender and then aggregating the residuals by country of residence times country of birth. In the remaining colums, we follow the same procedure, but compute preference residuals from age, age squared, gender, log household income p/c, education level fixed effects, and marital status fixed effects. Each population-pair-observation is weighted by $w = ln(1+n_1) + ln(1+n_2)$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Within-Region Evidence. We can take the analysis yet another step further by comparing population pairs that have different countries of origin, but share a common *subnational region* of residence. To this end, we make use of regional identifiers in the GPS dataset, which are usually at the state or province level. For each subnational region, we then compute the average preference separately for each country of birth. Thus, the unit of observation is a population-pair in a given *region* of residence. This procedure gives rise to 2,245 "populations". As before, we match each population with each other population, but only keep those population pairs that share a common *region* of residence to be able to conduct a within-region analysis. Using this procedure, we end up with 5,042 population pairs from 126 countries of origin who currently live in 364 subnational regions across 52 countries. Table 29 In Appendix E.3 reports the results. Given that the number of observations within a population is even smaller than in the preceeding section, it is no surprise that the results are slightly weaker than before. Nevertheless, temporal difference is still systematically and significantly related to preference differences.

6 Conclusion

A growing body of empirical work highlights the importance of heterogeneity in risk, time, and social preferences for understanding a myriad of economic, social, and health behaviors. Indeed, not only are preferences correlated with individual-level behaviors, but also with country-level outcomes including comparative development, conflict, and institutional structures (Falk et al., 2016). Arguably, these correlations call for an understanding of the origins of the global variation in preferences. This paper has taken a first step towards understanding these deep roots. Our main contribution is to establish that a significant fraction of the global variation in economic preferences has its historical origins in the structure and timing of very distant ancestral migration patterns, which highlights that if we aim to understand the ultimate roots of preference heterogeneity, we might have to consider events very far back in time. These results also bear an interesting relationship to work on cultural evolution (e.g., Boyd and Richerson, 1988; Henrich, 2015). In particular, our findings provide indirect evidence that preferences are indeed subject to evolutionary processes, as is assumed in models of cultural or genetic evolution.

Assessing the mechanisms underlying the relationship between temporal distance and preference differences is inherently difficult. First, the temporal distance variables capture variation that has accumulated over hundreds or even thousands of years, many of which are characterized by poor data availability (and knowledge about living conditions in general). Second, a plethora of potential mechanism could cause the effect of temporal distance on contemporary differences in preferences, including environmental influences, historical shocks, or genetic drift, to name but a few. In this respect, it also appears unlikely that a single event is responsible for explaining the connection between temporal distance and preferences, hence further complicating an analysis of mechanisms. Finally, it is reasonable to assume that the underlying processes and relative importance of channels differ across preferences.

With these caveats in mind, we investigate one particular potential mechanism, i.e., monotonic selective migration. As explained above, the great human expansion consisted of a succession of discrete migratory steps, in each of which subpopulations split apart from their parental colonies to found new settlements elsewhere. The model presented in Section 2 posits that preference differences between populations arose through *post-breakup* shocks, driven by, e.g., different experience. However, it is also conceivable that the *breakups per se* caused the patterns we observe if the new founder populations systematically differed from their parental colonies. This would be the case if, for example, only the least risk averse types tended to split away. In such a scenario, preferences would evolve *monotonically* along the migratory path out of East Africa, hence mechanically producing the correlation between temporal distance and preference differences. If true, this would still leave the main insight of the paper – that the structure and timing of population breakups in the very distant past have left a footprint in the contemporary global distribution of preferences – intact. However, the interpretation of this relationship would change slightly. Because we only observe preferences today, we cannot evaluate whether systematic population breakups actually took place. Still, what is relevant for our purposes is to investigate whether the results of such systematic breakups are still visible in the data today and hence drive our results.

To investigate this issue, we regress the *level* of a given preference on (ancestry-adjusted) migratory distance from East Africa, i.e., Ethiopia. Table 30 in Appendix F provides an overview of the results and shows that our preference variables are generally not significantly correlated with migratory distance from East Africa. This pattern is indicative that – in line with our model – the relationship between temporal distance and preference differences is indeed driven by events *after* the various population breakups, rather than selective breakup patterns.[21]

[21] Slightly more subtly, it is also possible that the correlation between temporal distance and preference differences is driven by a monotonic evolution of the *dispersion* of the preference pool, akin to the serial founder effect in population genetics: if the dispersion of the preference pool decreased monotonically along the migratory path, then differences in preferences between later founder populations would mechanically be smaller than those between earlier ones because the respective parental preference pool has lower variation to begin with. However, as shown in Appendix F.2, the relationship between preference dispersion and migratory distance from Ethiopia is very weak.

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ONLINE APPENDIX

A Details on Global Preference Survey

Taken from Falk et al. (2016).

A.1 Overview

The cross-country dataset measuring risk aversion, patience, positive and negative reciprocity, altruism, and trust, was collected through the professional infrastructure of the Gallup World Poll 2012. The data collection process consisted of three steps. First, an experimental validation procedure was conducted to select the survey items. Second, there was a pre-test of the selected survey items in a variety of countries to ensure implementability in a culturally diverse sample. Third, the final data set was collected through the regular professional data collection efforts in the framework of the World Poll 2012.

A.2 Experimental Validation

To ensure the behavioral validity of the preference measures, all underlying survey items were selected through an experimental validation procedure (see Falk et al. (2015) for details). To this end, a sample of 409 German undergraduates completed standard state-of-the-art financially incentivized laboratory experiments designed to measure risk aversion, patience, positive and negative reciprocity, altruism, and trust. The same sample of subjects then completed a large battery of potential survey items. In a final step, for each preference, those survey items were selected which jointly performed best in explaining the behavior under real incentives observed in the choice experiments.

A.3 Pre-Test and Adjustment of Survey Items

Prior to including the preference module in the Gallup World Poll 2012, it was tested in the field as part of the World Poll 2012 pre-test, which was conducted at the end of 2011 in 22 countries. The main goal of the pre-test was to receive feedback on each item from various cultural backgrounds in order to assess potential difficulties in understanding and differences in the respondents' interpretation of items. Based on respondents' feedback and suggestions, minor modifications were made to several items before running the survey as part of the World Poll 2012.

The pre-test was run in 10 countries in central Asia (Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Russia, Tajikistan, Turkmenistan, Uzbekistan) 2 countries in South-East Asia (Bangladesh and Cambodia), 5 countries in Southern and Eastern Europe (Croatia, Hungary, Poland, Romania, Turkey), 4 countries in the Middle East and North Africa (Algeria, Jordan, Lebanon, and Saudi-Arabia), and 1 country in Eastern Africa (Kenya). In each country, the sample size was 10 to 15 people. Overall, more than 220 interviews were conducted. In most countries, the sample was mixed in terms of gender, age, educational background, and area of residence (urban / rural).

Participants in the pre-test were asked to state any difficulties in understanding the items and to rephrase the meaning of items in their own words. If they encountered difficulties in understanding or interpreting items, respondents were asked to make suggestions on how to modify the wording of the item in order to attain the desired meaning.

Overall, the understanding of both the qualitative items and the quantitative items was satisfactory. In particular, no interviewer received any complaints regarding difficulties in assessing the quantitative questions or understanding the meaning of the probability used in the hypothetical risky choice items. When asked about rephrasing the qualitative items in their own words, most participants seemed to have understood the items in exactly the way that was intended. Nevertheless, some (sub-groups of) participants suggested adjustments to the wording of some items. This resulted in minor changes to four items, relative to the "original" experimentally validated items:

1. The use of the term "lottery" in hypothetical risky choices was troubling to some Muslim participants. As a consequence, we dropped the term "lottery" and replaced it with "draw".

2. The term "charity" caused confusion in Eastern Europe and Central Asia, so it was replaced it with "good cause".

3. Some respondents asked for a clarification of the question asking about one's willingness to punish unfair behavior. This feedback lead to splitting the question into two separate items, one item asking for one's willingness to punish unfair behavior towards others, and another asking for one's willingness to punish unfair behavior towards oneself.

4. When asked about hypothetical choices between monetary amounts today versus larger amounts one year later, some participants, especially in countries with current or relatively recent phases of volatile and high inflation rates, stated that their answer would depend on the rate of inflation, or said that they would always

take the immediate payment due to uncertainty with respect to future inflation. Therefore, we decided to add the following phrase to each question involving hypothetical choices between immediate and future monetary amounts: “Please assume there is no inflation, i.e., future prices are the same as today’s prices.”

A.4 Selection of Countries

The goal when selecting countries was to ensure representative coverage of the global population. Thus, countries from each continent and each region within continents were chosen. Another goal was to maximize variation with respect to observables, such as GDP per capita, language, historical and political characteristics, or geographical location and climatic conditions. Accordingly, the selection process favored non-neighboring and culturally dissimilar countries. This procedure resulted in the following sample of 76 countries:
East Asia and Pacific: Australia, Cambodia, China, Indonesia, Japan, Philippines, South Korea, Thailand, Vietnam
Europe and Central Asia: Austria, Bosnia and Herzegovina, Croatia, Czech Republic, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Italy, Kazakhstan, Lithuania, Moldova, Netherlands, Poland, Portugal, Romania, Russia, Serbia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom
Latin America and Caribbean: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Guatemala, Haiti, Mexico, Nicaragua, Peru, Suriname, Venezuela
Middle East and North Africa: Algeria, Egypt, Iran, Iraq, Israel, Jordan, Morocco, Saudi Arabia, United Arab Emirates
North America: United States, Canada
South Asia: Afghanistan, Bangladesh, India, Pakistan, Sri Lanka
Sub-Saharan Africa: Botswana, Cameroon, Ghana, Kenya, Malawi, Nigeria, Rwanda, South Africa, Tanzania, Uganda, Zimbabwe

A.5 Sampling and Survey Implementation

A.5.1 Background

Since 2005, the international polling company Gallup has conducted an annual World Poll, in which it surveys representative population samples in almost every country around the world on, e.g., economic, social, political, and environmental issues. The collection of our preference data was embedded into the regular World Poll 2012 and hence made use of the pre-existing polling infrastructure of one of the largest professional polling institutes in the world.[22]

Selecting Primary Sampling Units

In countries in which face-to-face interviews are conducted, the first stage of sampling is the identification of primary sampling units (PSUs), consisting of clusters of households. PSUs are stratified by population size and / or geography and clustering is achieved through one or more stages of sampling. Where population information is available, sample selection is based on probabilities proportional to population size. If population information is not available, Gallup uses simple random sampling.

In countries in which telephone interviews are conducted, Gallup uses a random-digit-dialing method or a nationally representative list of phone numbers. In countries with high mobile phone penetration, Gallup uses a dual sampling frame.

Selecting Households and Respondents

Gallup uses random route procedures to select sampled households. Unless an outright refusal to participate occurs, interviewers make up to three attempts to survey the sampled household. To increase the probability of contact and completion, interviewers make attempts at different times of the day, and when possible, on different days. If the interviewer cannot obtain an interview at the initially sampled household, he or she uses a simple substitution method.

In face-to-face and telephone methodologies, random respondent selection is achieved by using either the latest birthday or Kish grid methods.[23] In a few Middle East and Asian countries, gender-matched interviewing is required, and probability sampling with quotas is implemented during the final stage of selection. Gallup implements quality control procedures to validate the selection of correct samples and that the correct person is randomly selected in each household.

[22] See http://www.gallup.com/strategicconsulting/156923/worldwide-research-methodology.aspx

[23] The latest birthday method means that the person living in the household whose birthday among all persons in the household was the most recent (and who is older than 15) is selected for interviewing. With the Kish grid method, the interviewer selects the participants within a household by using a table of random numbers. The interviewer will determine which random number to use by looking at, e.g., how many households he or she has contacted so far (e.g., household no. 8) and how many people live in the household (e.g., 3 people, aged 17, 34, and 36). For instance, if the corresponding number in the table is 7, he or she will interview the person aged 17.

Sampling Weights

Ex post, data weighting is used to ensure a nationally representative sample for each country and is intended to be used for calculations within a country. These sampling weights are provided by Gallup. First, base sampling weights are constructed to account for geographic oversamples, household size, and other selection probabilities. Second, post-stratification weights are constructed. Population statistics are used to weight the data by gender, age, and, where reliable data are available, education or socioeconomic status.

A.5.2 Translation of Items

The items of the preference module were translated into the major languages of each target country. The translation process involved three steps. As a first step, a translator suggested an English, Spanish or French version of a German item, depending on the region. A second translator, being proficient in both the target language and in English, French, or Spanish, then translated the item into the target language. Finally, a third translator would review the item in the target language and translate it back into the original language. If differences between the original item and the back-translated item occurred, the process was adjusted and repeated until all translators agreed on a final version.

A.5.3 Adjustment of Monetary Amounts in Quantitative Items

All items involving hypothetical monetary amounts were adjusted for each country in terms of their real value. Monetary amounts were calculated to represent the same share of a country's median income in local currency as the share of the amount in Euro of the German median income since the validation study had been conducted in Germany. Monetary amounts used in the validation study with the German sample were "round" numbers to facilitate easy calculations (e.g., the expected return of a lottery with equal chances of winning and losing) and to allow for easy comparisons (e.g., 100 Euro today versus 107.50 in 12 months). To proceed in a similar way in all countries, monetary amounts were always rounded to the next "round" number. For example, in the quantitative items involving choices between a lottery and varying safe options, the value of the lottery was adjusted to a round number. The varying safe options were then adjusted proportionally as in the original version. While this necessarily resulted in some (very minor) variations in the real stake size between countries, it minimized cross-country differences in the understanding the quantitative items due to difficulties in assessing the involved monetary amounts.

A.6 Wording of Survey Items

In the following, "willingness to act" indicates the following introduction: *We now ask for your willingness to act in a certain way in four different areas. Please again indicate your answer on a scale from 0 to 10, where 0 means you are "completely unwilling to do so" and a 10 means you are "very willing to do so". You can also use any numbers between 0 and 10 to indicate where you fall on the scale, like 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10.*

Similarly, "self-assessments" indicate that the respective statement was preceded by the following introduction: *How well do the following statements describe you as a person? Please indicate your answer on a scale from 0 to 10. A 0 means "does not describe me at all" and a 10 means "describes me perfectly". You can also use any numbers between 0 and 10 to indicate where you fall on the scale, like 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10.*

A.6.1 Patience

1. (Sequence of five interdependent quantitative questions:) *Suppose you were given the choice between receiving a payment today or a payment in 12 months. We will now present to you five situations. The payment today is the same in each of these situations. The payment in 12 months is different in every situation. For each of these situations we would like to know which you would choose. Please assume there is no inflation, i.e, future prices are the same as today's prices. Please consider the following: Would you rather receive 100 Euro today or x Euro in 12 months?*

   The precise sequence of questions was given by the "tree" logic in Figure 1.

2. (Willingness to act:) *How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?*

A.6.2 Risk Taking

1. *(Similar to self-assessment:) Please tell me, in general, how willing or unwilling you are to take risks. Please use a scale from 0 to 10, where 0 means "completely unwilling to take risks" and a 10 means you are "very willing to take risks". You can also use any numbers between 0 and 10 to indicate where you fall on the scale, like 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10.*

2. (Sequence of five interdependent quantitative questions:) *Please imagine the following situation. You can choose between a sure payment of a particular amount of money, or a draw, where you would have an equal chance of getting amount x or getting nothing. We will present to you five different situations. What would you prefer: a draw with a 50 percent chance of receiving amount x, and the same 50*

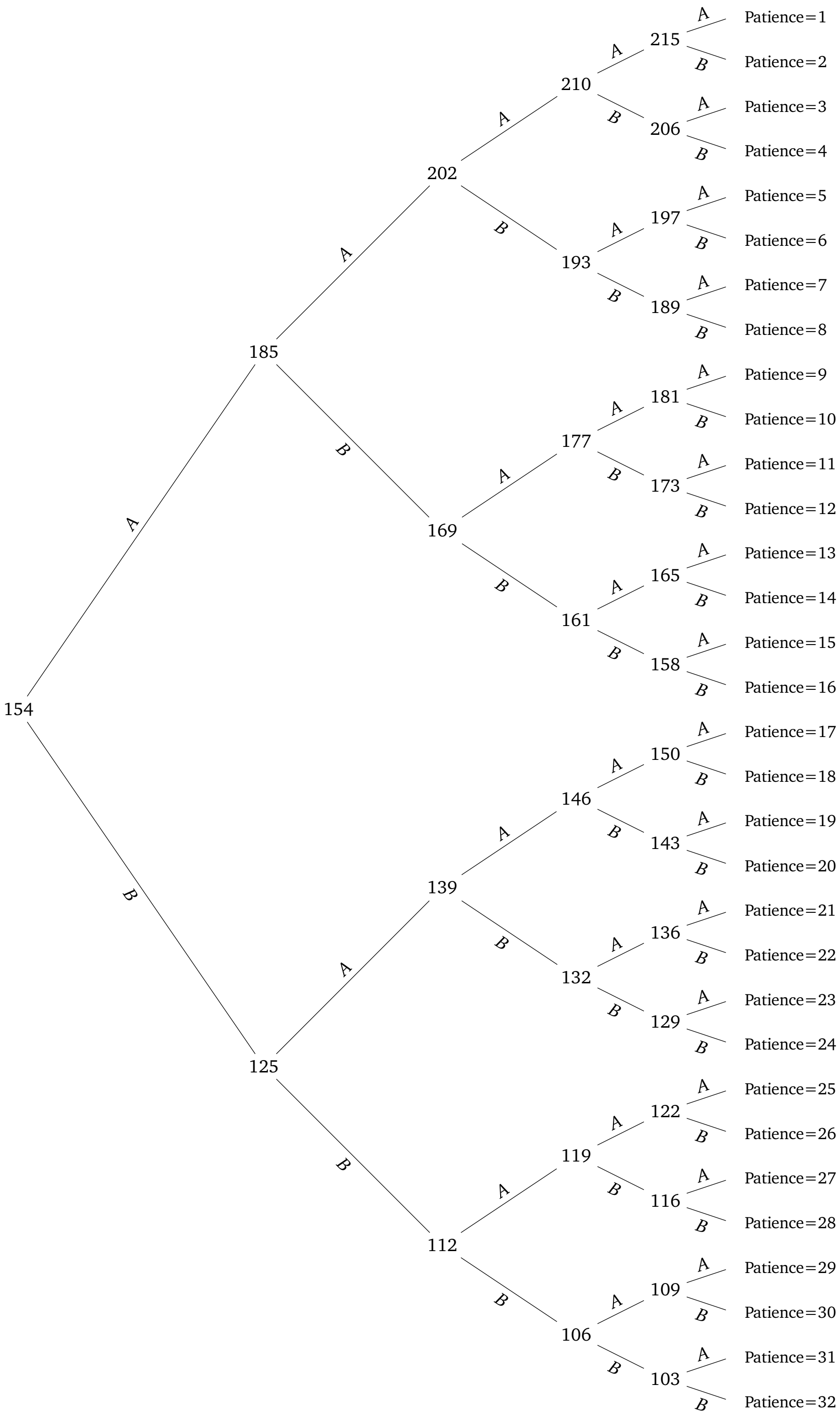

Figure 1: Tree for the staircase time task (numbers = payment in 12 months, A = choice of "100 euros today", B = choice of "x euros in 12 months". The staircase procedure worked as follows. First, each respondent was asked whether they would prefer to receive 100 euros today or 154 euros in 12 months from now (leftmost decision node). In case the respondent opted for the payment today ("A"), in the second question the payment in 12 months was adjusted upwards to 185 euros. If, on the other hand, the respondent chose the payment in 12 months, the corresponding payment was adjusted down to 125 euros. Working further through the tree follows the same logic.

percent chance of receiving nothing, or the amount of y as a sure payment? The precise sequence of questions was given by the "tree" logic in Figure 2.

A.6.3 Positive Reciprocity

1. (Self-assessment:) *When someone does me a favor I am willing to return it.*

2. *(Hypothetical situation:) Please think about what you would do in the following situation. You are in an area you are not familiar with, and you realize you lost your way. You ask a stranger for directions. The stranger offers to take you to your destination. Helping you costs the stranger about 20 Euro in total. However, the stranger says he or she does not want any money from you. You have six presents with you. The cheapest present costs 5 Euro, the most expensive one costs 30 Euro. Do you give one of the presents to the stranger as a "thank-you"-gift? If so, which present do you give to the stranger? No present / The present worth 5 / 10 / 15 / 20 / 25 / 30 Euro.*

A.6.4 Negative Reciprocity

1. (Self-assessment:) *If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to do so.*

2. (Willingness to act:) *How willing are you to punish someone who treats you unfairly, even if there may be costs for you?*

3. (Willingness to act:) *How willing are you to punish someone who treats others unfairly, even if there may be costs for you?*

A.6.5 Altruism

1. *(Hypothetical situation:) Imagine the following situation: Today you unexpectedly received 1,000 Euro. How much of this amount would you donate to a good cause? (Values between 0 and 1000 are allowed.)*

2. (Willingness to act:) *How willing are you to give to good causes without expecting anything in return?*

A.6.6 Trust

(Self-assessment:) *I assume that people have only the best intentions.*

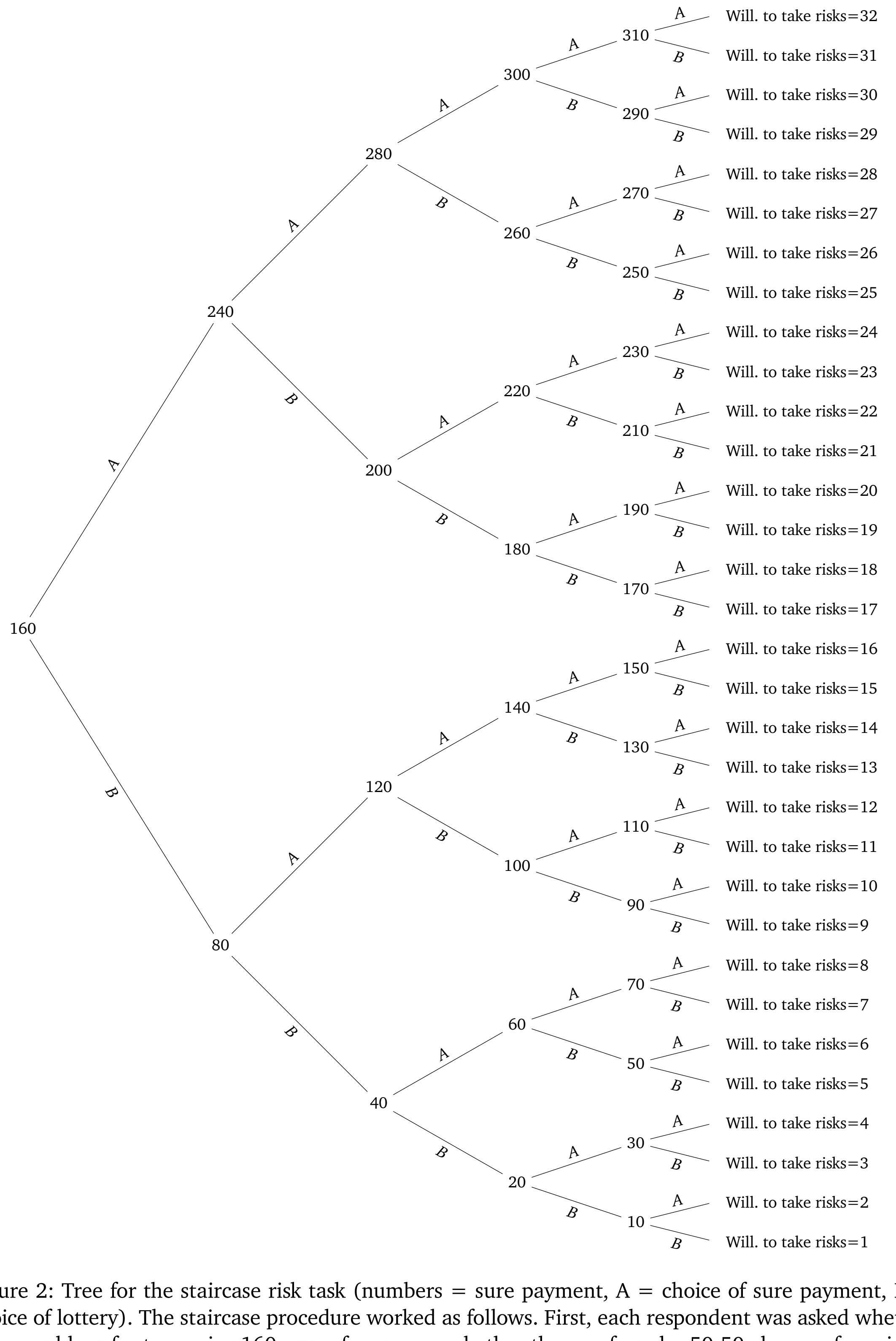

Figure 2: Tree for the staircase risk task (numbers = sure payment, A = choice of sure payment, B = choice of lottery). The staircase procedure worked as follows. First, each respondent was asked whether they would prefer to receive 160 euros for sure or whether they preferred a 50:50 chance of receiving 300 euros or nothing. In case the respondent opted for the safe choice ("B"), the safe amount of money being offered in the second question decreased to 80 euros. If, on the other hand, the respondent opted for the gamble ("A"), the safe amount was increased to 240 euros. Working further through the tree follows the same logic.

A.7 Computation of Preference Measures

A.7.1 Cleaning and Imputation of Missings

In order to efficiently use all available information in our data, missing survey items were imputed based on the following procedure:

- If one (or more) survey items for a given preference were missing, then the missing items were predicted using the responses to the available items. The procedure was as follows:
  - Suppose the preference was measured using two items, call them a and b. For those observations with missing information on a, the procedure was to predict its value based on the answer to b and its relationship to a, which was estimated by regressing b on a for the sub-sample of subjects who had nonmissing information on both, a and b (on the world sample).
  - For the unfolding-brackets time and risk items, the imputation procedure was similar, but made additional use of the informational content of the responses of participants who started but did not finish the sequence of the five questions. Again suppose that the preference is measured using two items and suppose that a (the staircase measure) is missing. If the respondent did not even start the staircase procedure, then imputation was done using the methodology described above. On the other hand, if the respondent answered between one and four of the staircase questions, a was predicted using a different procedure. Suppose the respondent answered four items such that his final staircase outcome would have to be either x or y. A probit was run of the "x vs. y" decision on b, and the corresponding coefficients were used to predict the decision for all missings (note that this constitutes a predicted probability). The expected staircase outcome was then obtained by applying the predicted probabilities to the respective staircase endpoints, i.e., in this case x and y. If the respondent answered three (or less) questions, the same procedure was applied, the only difference being that in this case the obtained predicted probabilities were applied to the expected values of the staircase outcome conditional on reaching the respective node. Put differently, the procedure outlined above was applied recursively by working backwards through the "tree" logic of the staircase procedure, resulting in an expected value for the outcome node.
  - If all survey items for a given preference were missing, then no imputation took place.

- Across the 12 survey items, between 0% and 8% of all responses had to be imputed.

A.7.2 Computation of Preference Indices at the Individual Level

For each of the traits (risk preferences, time preferences, positive reciprocity, negative reciprocity, altruism, and trust), an individual-level index was computed that aggregated responses across different survey items. Each of these indices was computed by (i) computing the z-scores of each survey item at the individual level and (ii) weighing these z-scores using the weights resulting from the experimental validation procedure of Falk et al. (2015). Formally, these weights are given by the coefficients of an OLS regression of observed behavior in the experimental validation study on responses to the respective survey items, such that the weights sum to one. In practice, for almost all preferences, the coefficients assign roughly equal weight to all corresponding survey items. The weights are given by:

- Patience:

$$\text{Patience } = 0.7115185 \times \text{ Staircase time } + 0.2884815 \times \text{ Will. to give up sth. today}$$

- Risk taking:

$$\text{Risk taking } = 0.4729985 \times \text{ Staircase risk } + 0.5270015 \times \text{ Will. to take risks}$$

- Positive reciprocity:

$$\text{Pos. reciprocity } = 0.4847038 \times \text{ Will. to return favor } + 0.5152962 \times \text{ Size of gift}$$

- Negative reciprocity:

$$\begin{aligned} \text{Neg. reciprocity } &= 0.5261938/2 \times \text{ Will. to punish if oneself treated unfairly} \\ &+ 0.5261938/2 \times \text{ Will. to punish if other treated unfairly} \\ &+ 0.3738062 \times \text{ Will. to take revenge} \end{aligned}$$

  As explained above, in the course of the pre-test, the negative reciprocity survey item asking people for their willingness to punish others was split up into two questions, one asking for the willingness to punish if oneself was treated unfairly and one asking for the willingness to punish if someone was treated unfairly. In order to apply the weighting procedure from the validation procedure to these items, the weight of the original item was divided by two and these modified weights were assigned to the new questions.

- Altruism:

$$\text{Altruism} = 0.5350048 \times \text{ Will. to give to good causes } + 0.4649952 \times \text{ Hypoth. donation}$$

- Trust: The survey included only one corresponding item.

A.7.3 Computation of Country Averages

In order to compute country-level averages, individual-level data were weighted with the sampling weights provided by Gallup, see above. These sampling weights ensure that our measures correctly represent the population at the country level.

B Proofs

Proof of Proposition 1. We have

$$x_i^T - x_j^T = \sum_{t=1}^{T} \epsilon^t_{P_t(i)} - \sum_{t=1}^{T} \epsilon^t_{P_t(j)} = \sum_{\substack{t=1,\dots,T,\\ P_t(i)\neq P_t(j)}} \left(\epsilon^t_{P_t(i)} - \epsilon^t_{P_t(j)}\right),$$

which is a sum of s_{ij} differences of shocks. Let $u_1, \dots, u_T, v_1, \dots, v_T$ be i.i.d. random variables having the same distribution as the ϵ^t_A. Then $x_i^T - x_j^T$ has the same distribution as $\sum_{n=1}^{s_{ij}}(u_n - v_n)$. A similar argument shows that $x_k^T - x_l^T$ has the same distribution as $\sum_{n=1}^{s_{kl}}(u_n - v_n)$. In particular,

$$E\left[\left|x_i^T - x_j^T\right|\right] = E\Big[\Big|\sum_{n=1}^{s_{ij}}(u_n - v_n)\Big|\Big]$$

and

$$E\left[\left|x_k^T - x_l^T\right|\right] = E\Big[\Big|\sum_{n=1}^{s_{kl}}(u_n - v_n)\Big|\Big].$$

The claimed equivalence will follow if we can show that

$$E\Big[\Big|\sum_{n=1}^{m}(u_n - v_n)\Big|\Big] < E\Big[\Big|\sum_{n=1}^{m+1}(u_n - v_n)\Big|\Big], \qquad m = 0, \dots, T-1. \tag{1}$$

We will apply Lemma 1 below. Fix $m \in \{0, \dots, T-1\}$ and let $y = \sum_{n=1}^{m}(u_n - v_n)$ and $z = u_{m+1} - v_{m+1}$. Then y and z are independent integrable random variables. Moreover, $E[z] = E[u_{m+1}] - E[v_{m+1}] = 0$ and since the shocks are nondegenerate,

$$\begin{aligned} P(z \neq 0) &\geq P(u_{m+1} > E[u_{m+1}], v_{m+1} < E[v_{m+1}]) \\ &= P(u_{m+1} > E[u_{m+1}])P(v_{m+1} < E[v_{m+1}]) > 0. \end{aligned}$$

Finally, for every $c > 0$, there exists $\xi \in \mathbb{R}$ such that $P(|\sum_{n=1}^{m} u_n - \xi| < \frac{c}{2}) > 0$. Hence,

$$\begin{aligned} P(|y| < c) &\geq P\Big(\Big|\sum_{n=1}^{m} u_n - \xi\Big| < \frac{c}{2}, \Big|\sum_{n=1}^{m} v_n - \xi\Big| < \frac{c}{2}\Big) \\ &= P\Big(\Big|\sum_{n=1}^{m} u_n - \xi\Big| < \frac{c}{2}\Big)^2 > 0, \end{aligned}$$

which shows that the support of the distribution of y contains the point 0. Inequality (1) now follows from Lemma 1. □

Lemma 1. *Let y and z be independent integrable random variables. Suppose that 0 is in the support of the distribution of y, $E[z] = 0$ and $P(z \neq 0) > 0$. Then $E[|y+z|] > E[|y|]$.*

Proof. Since y and z are independent, $E[z|y] = E[z] = 0$, and so

$$E[|y+z||y] \geq |E[y+z|y]| = |E[y|y]| = |y|. \tag{2}$$

Using the inequality $|y+z| \geq |z| - |y|$ and again the independence of y and z, we obtain

$$E[|y+z||y] \geq E[|z||y] - E[|y||y] = E[|z|] - |y|.$$

Hence, on the event $\{2|y| < E[|z|]\}$,

$$E[|y+z||y] > |y|.$$

The assumption that $P(z \neq 0) > 0$ implies that $E[|z|] > 0$, and since 0 is contained in the support of the distribution of y, $P(2|y| < E[|z|]) > 0$. That is, inequality (2) holds almost everywhere and the inequality is strict on a set of positive probability. Taking expectations we get $E[|y+z|] > E[|y|]$. □

C Raw Correlations Among Temporal Distance Proxies

Table 9: Raw correlations among temporal distance proxies

	Fst dist.	Nei dist.	Fst dist. (new)	Migratory dist.	HMI dist.	Linguistic dist.
Fst dist.	1					
Nei dist.	0.945***	1				
Fst dist. (new)	0.840***	0.832***	1			
Migratory dist.	0.519***	0.514***	0.775***	1		
HMI dist.	0.620***	0.633***	0.820***	0.923***	1	
Linguistic dist.	0.443***	0.393***	0.353***	0.0888***	0.193***	1

Pearson raw correlations. Fst dist. (new) refers to the Fst genetic distance measure based on Spolaore and Wacziarg (2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Additional Bilateral Regressions

D.1 Prosociality Variables Separately

Table 10: Prosociality and temporal distance: Robustness

	Dependent variable: Absolute difference in...														
	Altruism					Positive reciprocity					Trust				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Temporal distance	0.025^{*}	0.023	0.024	0.014	0.011	0.10^{**}	0.11^{**}	0.11^{**}	0.14^{**}	0.14^{**}	0.19^{***}	0.22^{***}	0.21^{***}	0.22^{***}	0.22^{***}
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)
Population controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Economic and institutional controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Colonial relationship dummies	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Distance controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Geographic controls	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
Observations	2556	2556	2485	2485	2485	2556	2556	2485	2485	2485	2556	2556	2485	2485	2485
R^2	0.555	0.555	0.556	0.557	0.558	0.509	0.509	0.511	0.513	0.514	0.438	0.441	0.456	0.457	0.459

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Alternative Computation of Temporal Distance Proxy

In the main text, temporal distance was proxied by (the z-score of) the unweighted average of Fst genetic distance, Nei genetic distance, predicted migratory distance, and linguistic distance. This section reports a robustness check in which temporal distance is computed as unweighted average of Fst genetic distance, predicted migratory distance, and linguistic distance. For each preference dimension, Table 12 reports two specifications, one without controls (except for country fixed effects), and one with the full vector of controls employed in the main text. The results closely mirror those reported above.

D.3 Continent Fixed Effects

Table 11: Preferences and temporal distance: Bilateral continent fixed effects

	Dependent variable: Absolute difference in...				
	All prefs.	Risk taking	Prosociality	Patience	Neg. reciprocity
	(1)	(2)	(3)	(4)	(5)
Temporal distance	0.17***	0.013	0.17**	0.19*	-0.028
	(0.05)	(0.04)	(0.07)	(0.10)	(0.03)
Continent FE	Yes	Yes	Yes	Yes	Yes
Observations	2556	2556	2556	2556	2556
R^2	0.496	0.652	0.501	0.541	0.479

Notes. OLS estimates, twoway-clustered standard errors in parentheses. The regressions do not include country fixed effects, but bilateral continent fixed effects. These 28 continental dummies are constructed from seven "continents", following the World Bank terminology: Sub-Saharan Africa, North Africa and Middle East, Europe and Central Asia, East Asia and Pacific, South Asia, Northern America, South America and Caribbean. These dummies are each equal to one if the two countries are from two given continents. For example, one of the dummies is equal to one if one country is from South Asia and one from Northern America, and one dummy is equal to one if both countries are from Europe and Central Asia. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Preferences and temporal distance: Alternative computation of temporal distance

	Dependent variable: Absolute difference in...									
	All prefs.		Risk taking		Prosociality		Patience		Neg. reciprocity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temporal distance	0.22^{***}	0.18^{***}	0.15^{**}	0.15^{**}	0.16^{***}	0.22^{***}	0.090^{*}	-0.050	0.036^{**}	-0.0084
	(0.04)	(0.05)	(0.07)	(0.07)	(0.04)	(0.05)	(0.05)	(0.04)	(0.01)	(0.02)
Population controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Economic and institutional controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Colonial relationship dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Distance controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Geographic controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2556	2485	2556	2485	2556	2485	2556	2485	2556	2485
R^2	0.470	0.492	0.630	0.637	0.480	0.493	0.504	0.586	0.467	0.486

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from F_{ST} genetic distance measures, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.4 Sub-Samples

Table 13: Robustness: Sub-samples

	Dependent variable: Abs. difference in all preferences Sample excludes...				
	Europe & Central Asia	Sub-Saharan Africa & Middle East	South and East Asia & Pacific	Americas	New World
	(1)	(2)	(3)	(4)	(5)
Temporal distance	0.22***	0.15**	0.25***	0.26***	0.26***
	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)
Observations	1081	1378	1653	1653	1596
R^2	0.497	0.464	0.483	0.445	0.448

Notes. OLS estimates, twoway-clustered standard errors in parentheses. In each column, the sample excludes a given world region. For example, in column (5), we exclude countries in the new world, , i.e., Australia, the Americas, and the Caribbean. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.5 Using Quantitative Preference Measures Only

We exclude quantitative preference measures and run our baseline analysis using quantitative measures only which are available for risk taking, patience, altruism, and positive reciprocity. Table 14 shows that the results remain unchanged.

D.6 Temporal Distance to Germany

Table 15 checks robustness against including relative linguistic distance to Germany.

D.7 Partialing Observables Out of Individual Preferences

This Appendix presents a robustness check in which we employ residual average preferences as dependent variable. To this end, we first regress all individual-level preferences on a set of observables, compute the residuals, and then aggregate the residuals up at the country level. We make use of a "sparse" and a "full" set of observables, where the sparse set only includes the exogenous characteristics age, age squared, and gender, and the full set age, age squared, gender, educational attainment fixed effects, log household income p/c, and marital status fixed effects. Table 16 presents the results.

Table 14: Quantitative preference measures and temporal distance

	Dependent variable: Absolute difference in...									
	All preferences		Risk taking		Altruism		Pos. reciprocity		Patience	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temporal distance	0.20***		0.17***		0.0059**		0.035*		0.45**	
	(0.04)		(0.07)		(0.00)		(0.02)		(0.20)	
Fst genetic distance (Cavalli-Sforza)		0.14***		0.13*		0.0028		0.030		0.30**
		(0.04)		(0.07)		(0.00)		(0.02)		(0.15)
Observations	2556	2556	2556	2556	2556	2556	2556	2556	2556	2556
R^2	0.514	0.504	0.532	0.525	0.692	0.691	0.503	0.502	0.501	0.496

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Robustness: Temporal distance to Germany

	Dependent variable: Absolute difference in...				
	All prefs.	Risk taking	Prosociality	Patience	Neg. reciprocity
	(1)	(2)	(3)	(4)	(5)
Temporal distance	0.21***	0.17**	0.16***	0.043	0.028
	(0.04)	(0.08)	(0.05)	(0.04)	(0.02)
Relative temporal distance to Germany	0.015	-0.038	0.0015	0.063	0.010
	(0.04)	(0.02)	(0.05)	(0.04)	(0.03)
Observations	2556	2556	2556	2556	2556
R^2	0.471	0.631	0.480	0.507	0.467

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Relative temporal distance to Germany is defined as the absolute difference between the temporal distances of each country in a pair to Germany. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.8 Excluding Tail Observations

Tables 17 through 21 present the results of regressions in which we restrict the sample of observations by excluding observations from the left or right tail of the distributions of temporal distance or the respective preference differences. Specifically, the regressions either utilize observations below the 90th percentile or above the 10th percentile of the distribution of a given variable.

Note that the location of any given country pair in the distribution of all bilateral variables may depend on whether country fixed effects are taken into account. For instance, if country A had very large temporal distances to all but one countries, and an average distance to country B, then restricting the sample by temporal distance would never exclude the $A-B$ observation. However, with country fixed effects, this may change, because (heuristically speaking) the fixed effects for country A take out the relatively large average temporal distance for country A, implying that the A—B pair has a very small temporal distance in terms of residuals. Thus, after accounting for country fixed effects, this observation might get excluded based on the above sample restriction criteria. Thus, we apply our robustness exercises to both types of distributions, i.e., to the distributions of raw variables and the distributions of residuals, see the tablenotes for further details.

Table 16: Preferences and temporal distance: residual preferences

	Dependent variable: Absolute difference in...									
	All preferences		Risk taking		Prosociality		Patience		Neg. reciprocity	
	Sparse	Full	Sparse	Full	Sparse	Full	Sparse	Full	Sparse	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temporal distance	0.15^{***}	0.10^{***}	0.025^{*}	0.035^{*}	0.050^{***}	0.030^{***}	0.031^{*}	0.011^{*}	0.013^{**}	0.0065^{**}
	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)
Observations	2556	2556	2556	2556	2556	2556	2556	2556	2556	2556
R^2	0.471	0.491	0.618	0.668	0.491	0.535	0.506	0.385	0.495	0.430

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Preferences and temporal distance: Excluding small and large values

	Dependent variable: Absolute difference in all preferences							
	Δ Prefs. > 10th pct		Δ Prefs. < 90th pct		Temporal dist. > 10th pct		Temporal dist. < 90th pct	
	Raw	Residual	Raw	Residual	Raw	Residual	Raw	Residual
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals	0.19***	0.13***	0.27***	0.26***	0.15**	0.15**	0.30***	0.30***
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.05)	(0.05)
Observations	2300	2300	2300	2300	2300	2300	2300	2300

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. In all columns, the sample is restricted to observations above or below a certain threshold, where the threshold is either computed with or without country fixed effects. For instance, in columns (1), the sample includes all observations whose absolute difference in risk taking is above the 90th percentile of the distribution of (raw) absolute differences in risk taking. In column (2), the sample includes all observations whose absolute difference in risk taking is above the 90th percentile of the distribution of residual absolute differences in risk taking after taking out country fixed effects. That is, we first regress absolute differences in risk taking on a vector of country fixed effects, compute the residual, and then restrict the sample based on the residuals. Likewise, in column (7), we restrict the sample to observations below the 90th percentile of the distribution of (raw) temporal distances, while column (8) applies the 90th percentile to the distribution of temporal distances after accounting for country fixed effects, i.e., after regressing temporal distance on country fixed effects and computing residuals. All regressions include country fixed effects: the "raw" regressions are standard fixed effects regressions; the "residual" regressions are estimated by (i) partialing country fixed effects out of differences in risk taking and temporal distance (on the full sample), (ii) restricting the sample, (iii) regressing residuals on each other. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: Risk preferences and temporal distance: Excluding small and large values

	Dependent variable: Absolute difference in risk taking							
	Δ Risk > 10th pct		Δ Risk < 90th pct		Temporal dist. > 10th pct		Temporal dist. < 90th pct	
	Raw	Residual	Raw	Residual	Raw	Residual	Raw	Residual
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals	0.18**	0.052	0.19**	0.20**	0.17**	0.17**	0.16*	0.16*
	(0.08)	(0.04)	(0.09)	(0.09)	(0.07)	(0.07)	(0.09)	(0.09)
Observations	2300	2300	2300	2300	2300	2300	2300	2300

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. In all columns, the sample is restricted to observations above or below a certain threshold, where the threshold is either computed with or without country fixed effects. For instance, in columns (1), the sample includes all observations whose absolute difference in risk taking is above the 90th percentile of the distribution of (raw) absolute differences in risk taking. In column (2), the sample includes all observations whose absolute difference in risk taking is above the 90th percentile of the distribution of residual absolute differences in risk taking after taking out country fixed effects. That is, we first regress absolute differences in risk taking on a vector of country fixed effects, compute the residual, and then restrict the sample based on the residuals. Likewise, in column (7), we restrict the sample to observations below the 90th percentile of the distribution of (raw) temporal distances, while column (8) applies the 90th percentile to the distribution of temporal distances after accounting for country fixed effects, i.e., after regressing temporal distance on country fixed effects and computing residuals. All regressions include country fixed effects: the "raw" regressions are standard fixed effects regressions; the "residual" regressions are estimated by (i) partialing country fixed effects out of differences in risk taking and temporal distance (on the full sample), (ii) restricting the sample, (iii) regressing residuals on each other. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Prosociality and temporal distance: Excluding small and large values

	Dependent variable: Absolute difference in prosociality							
	Δ Social > 10th pct		Δ Social < 90th pct		Temporal dist. > 10th pct		Temporal dist. < 90th pct	
	Raw	Residual	Raw	Residual	Raw	Residual	Raw	Residual
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals	0.18***	0.14***	0.19***	0.16***	0.17*	0.17*	0.19***	0.19***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.10)	(0.10)	(0.05)	(0.05)
Observations	2300	2300	2300	2300	2300	2300	2300	2300

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. In all columns, the sample is restricted to observations above or below a certain threshold, where the threshold is either computed with or without country fixed effects. For instance, in columns (1), the sample includes all observations whose absolute difference in prosociality is above the 90th percentile of the distribution of (raw) absolute differences in prosociality. In column (2), the sample includes all observations whose absolute difference in prosociality is above the 90th percentile of the distribution of residual absolute differences in prosociality after taking out country fixed effects. That is, we first regress absolute differences in prosociality on a vector of country fixed effects, compute the residual, and then restrict the sample based on the residuals. Likewise, in column (7), we restrict the sample to observations below the 90th percentile of the distribution of (raw) temporal distances, while column (8) applies the 90th percentile to the distribution of temporal distances after accounting for country fixed effects, i.e., after regressing temporal distance on country fixed effects and computing residuals. All regressions include country fixed effects: the “raw” regressions are standard fixed effects regressions; the “residual” regressions are estimated by (i) partialing country fixed effects out of differences in prosociality and temporal distance (on the full sample), (ii) restricting the sample, (iii) regressing residuals on each other. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20: Patience and temporal distance: Excluding small and large values

	Dependent variable: Absolute difference in patience							
	Δ Risk > 10th pct		Δ Risk < 90th pct		Temporal dist. > 10th pct		Temporal dist. < 90th pct	
	Raw	Residual	Raw	Residual	Raw	Residual	Raw	Residual
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals	0.11*	0.036*	0.080	0.078	0.0060	0.0060	0.13*	0.13*
	(0.06)	(0.02)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Observations	2300	2300	2300	2300	2300	2300	2300	2300

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. In all columns, the sample is restricted to observations above or below a certain threshold, where the threshold is either computed with or without country fixed effects. For instance, in columns (1), the sample includes all observations whose absolute difference in patience is above the 90th percentile of the distribution of (raw) absolute differences in patience. In column (2), the sample includes all observations whose absolute difference in patience is above the 90th percentile of the distribution of residual absolute differences in patience after taking out country fixed effects. That is, we first regress absolute differences in patience on a vector of country fixed effects, compute the residual, and then restrict the sample based on the residuals. Likewise, in column (7), we restrict the sample to observations below the 90th percentile of the distribution of (raw) temporal distances, while column (8) applies the 90th percentile to the distribution of temporal distances after accounting for country fixed effects, i.e., after regressing temporal distance on country fixed effects and computing residuals. All regressions include country fixed effects: the "raw" regressions are standard fixed effects regressions; the "residual" regressions are estimated by (i) partialing country fixed effects out of differences in patience and temporal distance (on the full sample), (ii) restricting the sample, (iii) regressing residuals on each other. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 21: Negative reciprocity and temporal distance: Excluding small and large values

	Dependent variable: Absolute difference in neg. reciprocity							
	Δ negrecip > 10th pct		Δ negrecip < 90th pct		Temporal dist. > 10th pct		Temporal dist. < 90th pct	
	Raw	Residual	Raw	Residual	Raw	Residual	Raw	Residual
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals	0.051**	0.038**	0.041**	0.042**	0.0049	0.0049	0.061**	0.061**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.03)	(0.03)
Observations	2300	2300	2300	2300	2300	2300	2300	2300

Notes. OLS estimates, twoway-clustered standard errors in parentheses. All regressions are conditional on country fixed effects. In all columns, the sample is restricted to observations above or below a certain threshold, where the threshold is either computed with or without country fixed effects. For instance, in columns (1), the sample includes all observations whose absolute difference in negative reciprocity is above the 90th percentile of the distribution of (raw) absolute differences in negative reciprocity. In column (2), the sample includes all observations whose absolute difference in negative reciprocity is above the 90th percentile of the distribution of residual absolute differences in negative reciprocity after taking out country fixed effects. That is, we first regress absolute differences in negative reciprocity on a vector of country fixed effects, compute the residual, and then restrict the sample based on the residuals. Likewise, in column (7), we restrict the sample to observations below the 90th percentile of the distribution of (raw) temporal distances, while column (8) applies the 90th percentile to the distribution of temporal distances after accounting for country fixed effects, i.e., after regressing temporal distance on country fixed effects and computing residuals. All regressions include country fixed effects: the "raw" regressions are standard fixed effects regressions; the "residual" regressions are estimated by (i) partialing country fixed effects out of differences in negative reciprocity and temporal distance (on the full sample), (ii) restricting the sample, (iii) regressing residuals on each other. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.9 Adjusting p-Values Using the FDR Procedure

This section reports p-values that are adjusted for multiple testing using the FDR procedure (see Anderson, 2012; Cantoni et al., forthcoming, for details). We start by adjusting the p-values in Table 1 which presents the baseline results. Here, to assess the null hypothesis "temporal distance does not affect preference differences", we group the regressions across dependent variables, for each temporal distance proxy. For example, we show p-values that are adjusted for the fact that in using our composite temporal distance summary statistic we employ six different dependent variables (columns (3), (5), (7), (9), (11), and (13)). Table 22 then presents adjusted p-values for the same regressions as in Table 1. Note that adjusted p-values can be smaller than adjusted ones, in particular if the set of regressions in a given category includes many rejections of the null. Indeed, the results show that the adjusted p-values are consistently smaller than the unadjusted ones, providing evidence that our results are not driven by multiple testing issues.

To delve deeper into this issue, Tables 23 and 24 present adjusted p-values for the regressions in Tables 2 and 3, respectively, i.e., regressions in which we employ all temporal distance proxies separately. To this end, we group regressions by dependent variable and then adjust p-values within that group across explanatory variables (in other words, in such an adjustment procedure, the null hypothesis is no longer "temporal distance has no effect on preference differences", but rather "temporal distance has no effect on risk preferences", for example). Thus, while the results presented above referred to multiple testing issues because we employ multiple dependent variables, the procedure reported here takes into account the multiplicity of explanatory variables. Again, the results support the picture derived in the main text: the relationship between the temporal distance proxies and risk taking or prosociality is robust, while the relationships between temporal distance and patience or negative reciprocity are often not statistically significant.

Table 22: Adjusted p-values for the regressions in Table 1

	Dependent variable: Absolute difference in...											
	Risk taking		Altruism		Pos. reciprocity		Trust		Patience		Neg. reciprocity	
Column in Table 1	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Unadjusted p-value	0.036	0.034	0.074	0.017	0.018	0.008	0.001	0.001	0.092	0.236	0.022	0.455
Adjusted p-value	0.045	0.036	0.047	0.025	0.038	0.021	0.002	0.001	0.049	0.105	0.038	0.179

Table 23: Adjusted p-values for the regressions in Table 2

	Dependent variable: Absolute difference in...														
	All preferences					Risk taking					Prosociality				
Column in Table 2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Unadjusted p-value	0.001	0.001	0.001	0.001	0.001	0.038	0.031	0.128	0.026	0.081	0.001	0.002	0.026	0.036	0.030
Adjusted p-value	0.001	0.001	0.001	0.001	0.001	0.068	0.068	0.068	0.068	0.068	0.001	0.006	0.023	0.023	0.023

Table 24: Adjusted p-values for the regressions in Table 3

	Dependent variable: Absolute difference in...									
	Patience					Neg. reciprocity				
Column in Table 3	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unadjusted p-value	0.238	0.097	0.056	0.256	0.056	0.449	0.214	0.028	0.108	0.010
Adjusted p-value	0.182	0.164	0.164	0.182	0.164	0.220	0.191	0.060	0.121	0.052

E Robustness Checks for Within-Country Analysis

E.1 WLS Weights

This Apendix provides a set of robustness checks for the within-country analysis against alternative regression weights for the WLS estimates. In Table 25, we replicate the baseline results from Table 7, except that we now use weights $w = \sqrt{n_1} + \sqrt{n_2}$. The results are almost identical to those using logarithmic weights.

In Table 26, we use weights $w = n_1 + n_2$. As discussed in the main text, these weights are not very sensible when we analyze the full sample of population pairs including those populations that currently reside in their country of birth. The reason is that these populations (e.g., Italians in Italy) are evidently sampled with much higher frequency than migrant populations, leading to a heavily right-skewed distribution of the number of observations. Thus, when we employ linear weights, all migrant populations are assigned very small weights, so that there is little variation left to identify effects of temporal distance. Nevertheless, Table 26 shows that the results using linear weights are slightly weaker, but overall similar to the baseline results.

Table 25: Preferences and temporal distance within country: Square root weights

	Dependent variable: Absolute difference in...						
	All pref.	Risk taking	Altruism	Pos. recip.	Trust	Patience	Neg. recip.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temporal distance	0.19***	0.057*	0.095***	0.077**	0.12**	0.15***	0.095***
	(0.05)	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
Country of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6321	6298	6321	6321	6264	6254	6198
R^2	0.307	0.252	0.261	0.251	0.283	0.242	0.286

Notes. WLS estimates, twoway-clustered standard errors (clustered at both countries of origin) in parentheses. The unit of observations is a population pair, which is defined as two groups who currently reside in the same country, but were born in different countries. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Temporal distance is computed from the respective population pairs' countries of origin. Each population-pair-observation is weighted by $w = \sqrt{n_1} + \sqrt{n_2}$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 26: Preferences and temporal distance within country: Linear weights

	Dependent variable: Absolute difference in...						
	All pref.	Risk taking	Altruism	Pos. recip.	Trust	Patience	Neg. recip.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temporal distance	0.23***	0.019	0.12***	0.11	0.15*	0.25***	0.086
	(0.09)	(0.06)	(0.04)	(0.07)	(0.09)	(0.07)	(0.05)
Country of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6321	6298	6321	6321	6264	6254	6198
R^2	0.336	0.334	0.313	0.335	0.359	0.328	0.381

Notes. WLS estimates, twoway-clustered standard errors (clustered at both countries of origin) in parentheses. The unit of observations is a population pair, which is defined as two groups who currently reside in the same country, but were born in different countries. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Temporal distance is computed from the respective population pairs' countries of origin. Each population-pair-observation is weighted by $w = n_1 + n_2$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E.2 Separate Temporal Distance Proxies

Table 27: Preferences and temporal distance within country: Separate proxies I

	Dependent variable: Absolute difference in...														
	All preferences					Risk taking					Prosociality				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Fst genetic distance (Cavalli-Sforza)	0.094^{***}					0.013					0.069^{**}				
	(0.03)					(0.03)					(0.03)				
Fst genetic distance (Pemberton)		0.14^{***}					0.057^{*}					0.092^{***}			
		(0.03)					(0.03)					(0.03)			
Migratory distance			0.20^{***}					0.078^{**}					0.11^{***}		
			(0.03)					(0.03)					(0.03)		
HMI migratory distance				0.26^{***}					0.11					0.11^{**}	
				(0.08)					(0.07)					(0.05)	
Linguistic distance					0.16^{***}					0.078^{***}					0.076^{***}
					(0.02)					(0.02)					(0.02)
Country of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6321	6321	6321	2556	6321	6298	6298	6298	2549	6298	6264	6264	6264	2537	6264
R^2	0.298	0.300	0.303	0.305	0.316	0.233	0.233	0.234	0.256	0.238	0.245	0.246	0.246	0.262	0.249

Notes. WLS estimates, twoway-clustered standard errors (clustered at both countries of origin) in parentheses. The unit of observation is a population pair, which is defined as two groups who currently reside in the same country, but were born in different countries. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Temporal distance is computed from the respective population pairs' countries of origin. Each population-pair-observation is weighted by $w = ln(1+n_1) + ln(1+n_2)$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 28: Preferences and temporal distance within country: Separate proxies II

	Dependent variable: Absolute difference in...									
	Patience					Neg. reciprocity				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Fst genetic distance (Cavalli-Sforza)	0.087^{***}					0.058^{*}				
	(0.03)					(0.03)				
Fst genetic distance (Pemberton)		0.10^{***}					0.070^{**}			
		(0.03)					(0.03)			
Migratory distance			0.12^{***}					0.12^{***}		
			(0.03)					(0.03)		
HMI migratory distance				0.20^{***}					0.12^{**}	
				(0.07)					(0.05)	
Linguistic distance					0.11^{***}					0.082^{***}
					(0.02)					(0.02)
Country of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6254	6254	6254	2518	6254	6198	6198	6198	2496	6198
R^2	0.217	0.218	0.218	0.226	0.226	0.261	0.262	0.264	0.237	0.267

Notes. WLS estimates, twoway-clustered standard errors (clustered at both countries of origin) in parentheses. The unit of observation is a population pair, which is defined as two groups who currently reside in the same country, but were born in different countries. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Temporal distance is computed from the respective population pairs' countries of origin. Each population-pair-observation is weighted by $w = ln(1+n_1) + ln(1+n_2)$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E.3 Within-Region Results

Table 29: Preferences and temporal distance within subnational regions

	Dependent variable: Absolute difference in...						
	All pref.	Risk taking	Altruism	Pos. recip.	Trust	Patience	Neg. recip.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temporal distance	0.12***	0.043	0.080***	0.044	0.078**	0.074**	0.065*
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Region of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country of origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5042	5023	5021	5042	4967	5004	4950
R^2	0.207	0.148	0.191	0.156	0.150	0.179	0.146

Notes. WLS estimates, twoway-clustered standard errors (clustered at both countries of origin) in parentheses. The unit of observation is a population pair, which is defined as two groups who currently reside in the same subnational region, but were born in different countries. The temporal distance variable is the composite measure constructed from the two F_{ST} genetic distance measures, Nei genetic distance, predicted migratory distance, and linguistic distance. Temporal distance is computed from the respective population pairs' countries of origin. Each population-pair-observation is weighted by $w = ln(1 + n_1) + ln(1 + n_2)$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F Monotonic Selective Migration?

F.1 Baseline Analysis

In order to test whether monotonic selective migration causes the association between temporal distance and contemporary differences in preference levels, we relate the level of each preference in a population to the distance of that population to Ethiopia on the migratory path. Thus, we estimate the following equation:

$$\text{pref}_i = \alpha + \beta \times \text{migratory dist. from Ethiopia}_i + \gamma \times x_i + \epsilon_i$$

where pref_i is the average trait in country i, x_i is a vector of covariates, and ϵ_i a disturbance term. Note that this regression does *not* constitute a special case of the bilateral migratory distance regressions discussed in Section 4, because here the dependent variable is the *level* of a given preference, rather than the absolute difference to East Africa, i.e., Ethiopia. Thus, the regressions estimated above do not imply any prediction on the sign or significance of β.[24]

[24]A special case of the general bilateral regression framework estimated in Section 4 would be

$$|\text{pref}_i - \text{pref}_{Ethiopia}| = \alpha + \beta \times \text{migratory dist. from Ethiopia}_i + \gamma \times |x_i - x_{Ethiopia}| + \epsilon_i$$

Since Ethiopia is not included in the Global Preferences Survey, we cannot estimate this equation.

As Table 30 shows, contemporary preference levels are generally not associated with migratory distance to East Africa.

Table 30: Average preferences and migratory distance to Ethiopia

	Dependent variable: Average ...							
	Risk taking		Prosociality		Patience		Neg. reciprocity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migratory Distance from Ethiopia	-0.016* (0.01)	0.010 (0.01)	0.0096 (0.01)	-0.0015 (0.02)	0.0011 (0.01)	0.026* (0.01)	-0.011 (0.01)	-0.012 (0.01)
Continent FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	74	74	74	74	74	74	74	74
R^2	0.038	0.298	0.009	0.265	0.000	0.303	0.023	0.164

Notes. OLS estimates, robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F.2 Dispersion of the Preference Pool

As mentioned in Section 6, the correlation between temporal distance and preference differences could be driven by a monotonic decrease of the *dispersion* of the preference pool along the migratory path, akin to a serial founder effect in population genetics. If the dispersion of the preference pool decreased monotonically along the migratory path, differences in preferences between later founder populations would mechanically be smaller than those between earlier founder population because the latter had larger variation in preferences to begin with.

To test whether the dispersion of the preference pool in a population is associated with its location on the migratory path, we relate the standard deviation of a population's preference trait to migratory distance from Ethiopia. We therefore estimate the following equation:

$$\text{sd\_pref}_i = \alpha + \beta \times \text{migratory dist. from Ethiopia}_i + \gamma \times x_i + \epsilon_i$$

where sd_pref_i is the standard deviation of the trait in country i, x_i is a vector of covariates, and ϵ_i a disturbance term. As Table 31 illustrates, the standard deviation in the different preference traits are generally unrelated to a population's migratory distance from Ethiopia.

Table 31: Preference dispersion and migratory distance from Ethiopia

	Dependent variable: Standard deviation in ...							
	Risk taking		Prosociality		Patience		Neg. reciprocity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migratory Distance from Ethiopia	-0.0051* (0.00)	0.0019 (0.00)	0.0042 (0.00)	0.0081 (0.01)	0.0082* (0.00)	0.0067 (0.01)	0.0033 (0.00)	0.0025 (0.01)
Risk taking		-0.0083 (0.04)						
Prosociality				-0.039 (0.04)				
Patience						0.32*** (0.04)		
Negative reciprocity								-0.19*** (0.04)
Continent FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	74	74	74	74	74	74	74	74
R^2	0.044	0.099	0.030	0.194	0.038	0.661	0.014	0.338

Notes. OLS estimates, robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Definitions and Data Sources of Main Variables

G.1 Explanatory Variables

Fst and Nei genetic distance. Genetic distance between contemporary populations, taken from Spolaore and Wacziarg (2009) and Spolaore and Wacziarg (2016), respectively.

Linguistic distance. Weighted linguistic distance between contemporary populations. Derived from the Ethnologue project data, taking into account all languages which are spoken by at least 5% of the population in a given country.

Predicted migratory distance. Predicted migratory distance between two countries' capitals, along a land-restricted way through five intermediate waypoints (one on each continent). Taken from Ashraf and Galor (2013).

HMI migratory distance. Walking time between two countries' capitals in years, taking into account topographic, climatic, and terrain conditions, as well as human biological abilities. Data from Özak (2010).

G.2 Covariates

Proportion female. Computed from the sociodemographic background data in the GPS.

Religious fractionalization. Index due to Alesina et al. (2003) capturing the probability that two randomly selected individuals from the same country will be from different religious / linguistic groups.

Percentage of European descent. Constructed from the "World Migration Matrix" of Putterman and Weil (2010).

Contemporary national GDP per capita. Average annual GDP per capita over the period 2001 – 2010, in 2005US$. Source: World Bank Development Indicators.

Democracy index. Index that quanties the extent of institutionalized democracy, as reported in the Polity IV dataset. Average from 2001 to 2010.

Colonial relationship dummies. Taken from the CEPII Geodist database at `http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6`.

Geodesic distance, contiguity, longitude, latitude, area Taken from CEPII GeoDist database. The longitudinal distance between two countries is computed as

$$\text{Longitudinal distance } = min\{|longitude_i - longitude_j|, 360 - |longitude_i| - |longitude_j|\}$$

Suitability for agriculture. Index of the suitability of land for agriculture based on ecological indicators of climate suitability for cultivation, such as growing degree days and the ratio of actual to potential evapotranspiration, as well as ecological indicators of soil suitability for cultivation, such as soil carbon density and soil pH, taken from Michalopoulosa (2012).

Mean and standard deviation of elevation. Mean elevation in km above sea, taken from Ashraf and Galor (2013). Data originally based on geospatial elevation data reported by the G-ECON project (Nordhaus, 2006).

Precipitation. Average monthly precipitation of a country in mm per month, 1961-1990, taken from Ashraf and Galor (2013). Data originally based on geospatial average monthly precipitation data for this period reported by the G-ECON project (Nordhaus, 2006).

Temperature. Average monthly temperature of a country in degree Celsius, 1961-1990, taken from Ashraf and Galor (2013). Data originally based on geospatial average monthly temperature data for this period reported by the G-ECON project (Nordhaus, 2006).