The Global Variation in Risk and Time Preferences*

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Abstract

A growing body of empirical research has developed measures of economic preferences related to risk taking and intertemporal choice. This research has documented pronounced heterogeneity in preferences across and within societies, and also provided evidence that these differences are culturally transmitted. This chapter discusses existing data sets that allow for a comparable measurement across the globe, takes stock of commonalities and differences in approaches, and presents an extended synthetic cross-country data set that combines information from existing data sets. The analysis then establishes various empirical regularities, such as broadly similar patterns of heterogeneity across the globe, revealed by the different datasets, but also some systematic divergences by measurement approach, and substantial correlations of economic preferences with country-aggregate and individual-level outcomes and traits. We also briefly discuss international data sets measuring social preferences, and end with an outlook on avenues for future research.

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1 Introduction

Risk and time preferences are central components of economic decision making. Conceptually, preference parameters for risk taking and time discounting directly emerge from economists' standard utility framework. Empirically, they have been shown to be heterogeneous with respect to, e.g., gender (Croson and Gneezy 2009; Falk and Hermle 2018; Charness and Gneezy 2012), age (Dohmen et al. 2017), cognitive ability (Dohmen et al. 2010, 2018), and personality traits (Becker et al. 2012), and they are relevant for understanding choices related to, e.g., education, the labor market (Dohmen et al. 2011; Bonin et al. 2007; Golsteyn et al. 2014), investments and savings (Dohmen et al. 2011), or health behavior (Bergeot and Jusot 2023; Anderson and Mellor 2008).

A fairly recent and growing literature has measured people's preferences for time and risk on an international scale. The aim is to study worldwide variation in preferences and to assess the generalizability of results and patterns documented previously only in more limited, regionally focused samples. While these 'global' data sets differ in terms of the employed preference measures, population samples and survey methodology, research findings based on their data suggest that the variation in risk and time preferences across the globe is, at least partly, 'cultural' in nature. For example, differences in economic preferences between populations are larger for population pairs with greater ancestral distance, a measure for the time that has passed since two populations shared a common ancestor (Becker et al. 2020). Average levels of patience are higher in countries that had higher crop yields, rendering agricultural investments more attractive in pre-industrial times, consistent with cultural adaptation (Galor and Özak 2016). There is also evidence that preferences are transmitted 'socially', e.g., through parents (Dohmen et al. 2012; Kosse and Pfeiffer 2012; Falk et al. 2021b; Zumbuehl et al. 2021) or peers (Lahno and Serra-Garcia 2015; Kosse et al. 2020; Schwerter 2024), a key part of many definitions of culture.

This chapter intends to take stock of the research on the global variation in risk and time preferences, to highlight the differences and similarities across the different datasets, to summarize their key findings, and to identify empirical regularities that emerge robustly from the different studies. In doing so, we direct attention to studies that collect data on preferences for a sufficiently large number of countries around the world and that have representative population samples. In particular, we focus on the Global Preferences Survey (Falk et al. 2018, henceforth

GPS), the World Values Survey (Inglehart et al. 2020, henceforth WVS), and the preference data collected by Ruggeri et al. (2022, henceforth Ruggeri). In addition, we discuss data sets with global coverage that are based on convenience and student samples: the INTRA data (Rieger et al. 2015), the Maps data (Vieider et al. 2015; L'Haridon and Vieider 2019), and the GLOBE data (House et al. 2004), all of which are discussed in more detail below. To broaden the country-level coverage and reduce measurement error, we also create a new, synthetic dataset that can be used to study how country-level preference measures relate to country characteristics. We construct this dataset using a methodology that combines the existing datasets with global coverage to achieve comparable country-level measures of risk preference and patience for an extended range of countries. We denote this the Synthetic World Aggregate Preferences (SWAP) data.

The aforementioned datasets measure risk and time preferences in various ways, and also differ in some respects in terms of how data were collected. The Maps data contain measures from incentivized choice experiments. Although these are widely considered the gold standard in preference measurement, it is typically infeasible to collect them for large representative samples on a global scale. Most similar to these incentivized experiments, the GPS contains measures from hypothetical choice experiments. The GPS measures are constructed as the linear combination of measures—typically a combination of behavior in a hypothetical choice experiment and a qualitative self-assessment—that jointly best predict choices in incentivized preference elicitation tasks (Falk et al. 2023). The most commonly used type of measure across the other datasets are qualitative questions that ask the individual respondents to subjectively self-report their own willingness to take risks or to trade off future against present-day rewards. Regarding data collection methodology, some datasets were constructed mostly with telephone interviews, while others used in-person interviews or online survey platforms.

Given the differences in population samples, measures, survey methodology, countries covered, as well as the inherent challenges in comparing survey measures across different cultures, our objective is to shed light on the following questions: Do the different data sets reveal a similar global variation in preferences? Do countries that are classified as more risk averse or more patient in one dataset also exhibit higher average risk aversion and patience in another? Are the country-level correlates of preferences, such as GDP, consistent across data sets? Do the data sets reveal similar individual-level correlates across countries—for example, is the average gender gap in willingness to take risks present in all data sets? Comparing across datasets is valuable because it addresses a fundamental challenge in cross-country preference research: do differences in survey responses reflect genuine preference differences, or merely cultural variation in how respondents interpret or understand particular question wordings or formats? If the latter, we would expect country rankings and the relationships between preferences and outcomes to diverge across datasets. If, however, similar patterns emerge robustly despite variation in survey design, this suggests that cross-country differences in measured preferences capture, at least in part, actual underlying differences.

We document six empirical regularities that emerge robustly from the different data sets that share comparable (but far from identical) survey measures of risk and time preferences. First, these different data sets reveal similar patterns of heterogeneity in preferences across the globe, especially when considering direct measures of respondents' preferences and representative samples of the population. We conclude that differences in preference variation that do emerge across datasets can likely be attributed to differences in sample composition and measurement. Second, the stability of country-by-country rankings in economic preferences depends on the specific measures. We find higher stability for measures that ask individual respondents directly about their own preference, rather than asking about, e.g., their assessment of certain attributes in the general population of a country. Moreover, we find higher stability for measures based on representative population samples. Third, at the country level, economic preferences exhibit consistent correlations with aggregate characteristics such as income, education, and institutions. These are even stronger in the synthetic dataset that measures country-level risk preference and patience across an extended range of countries. Fourth, at the individual level, economic preferences show consistent patterns of differences between women and men. Women tend to be more risk averse and less patient. These gender differences emerge for the majority of countries in all datasets. Fifth, preferences show systematic heterogeneity across age groups. In particular, people's willingness to take risks declines with age, a pattern that emerges from various datasets for the majority of countries. Sixth, at the individual level, preferences show consistent correlations with socioeconomic status, as proxied by income. In many countries, individuals in higher income deciles are less risk averse and exhibit higher levels of patience.

In sum, our analyses reveal important consistencies regarding the nature of economic preferences across cultures. This is remarkable, given the variation in methodology and sampling procedures used in the different data sets. The observed consistencies within and between countries, and the relationships of economic preferences to important outcomes, underline the usefulness of running large-scale international assessments of preference measures, and suggest that differences in preferences are an important component of cultural variation.

The remainder of this chapter is structured as follows. Section 2 presents the conceptual background related to preference elicitation in large representative samples. Section 3 contains information about available data sets with global coverage that will be used for the empirical analysis. Section 4 presents evidence for the global distribution of preferences across the different data sets. Sections 5 and 6 discuss correlation patterns with country-level and individual-level variables. Section 7 provides a brief discussion of global variation in social and other preferences, and Section 8 concludes with an outlook regarding avenues for future work.

2 Measures of Risk and Time Preferences

2.1 Conceptual Background

Economic thinking about risk and time preferences has been shaped profoundly by utility theory, particularly expected utility theory (EUT) in the domain of risk preference (Von Neumann and Morgenstern 1944) and the discounted utility (DU) model in modeling time preference (Samuelson 1937; Frederick et al. 2002). Within the EUT framework, individuals are assumed to evaluate utility derived from lotteries over consumption by calculating their expected utility. This theoretical structure has strongly influenced economists' attempts to infer risk preferences from choices between lotteries. Likewise, the DU framework has led economists to use intertemporal trade-offs in consumption as a means of measuring time preference, typically by observing how individuals discount future outcomes relative to present ones.

As a result, elicitation protocols have been developed to measure risk preferences from lottery choices and time preferences from intertemporal trade-offs in controlled laboratory environments. The preferred methodology of economists has been to use real incentives for these measurements, with the aim of reducing noise due to factors like inattention. However, measuring risk and time preferences in controlled laboratory settings, and with real incentives, is time consuming and financially expensive to implement in large-scale studies, limiting the scope of analysis to small and often selective samples.

One potential solution to this challenge is to reduce the costs for elicitation by using non-incentivized versions of the traditional lottery and intertemporal-tradeoff protocols. There is evidence that hypothetical lottery measures, and hypothetical time preference measures, are correlated with, and sometimes extremely similar to, their incentivized counterparts (for an early survey and more recent work, see Camerer and Hogarth 1999; Falk et al. 2023; Brañas-Garza et al. 2023), consistent with measuring the same underlying trait albeit potentially with noise.

However, important measurement problems remain even when attempting to measure the preference parameters specified in the EUT or DU frameworks under controlled laboratory conditions with or without incentives, as the experimental environment may not be fully congruent with the theoretical framework. For instance, conceptually, EUT is defined over lifetime wealth, whereas laboratory lotteries typically involve small-stake monetary outcomes (Rabin 2000). Similarly, DU concerns consumption streams, yet experiments often use monetary rewards, which themselves can be re-allocated over time. Further complications arise because the utility function assumed in theory is not directly observable, making it difficult to infer deep preference parameters from observed choices.

In addition, economic theories such as the EUT and DU frameworks may be too narrow to capture the full range of factors shaping people's risk preferences and time preferences (see, e.g., Kahneman and Tversky 1979; Frederick et al. 2002).[1] If the theoretical framework itself captures only a limited aspect of how individuals evaluate risk or time, then lottery-choice and inter-temporal choice measures derived from it are likewise narrow. Consequently, such measures may miss important dimensions of how people perceive and respond to risk or time in everyday life, such as emotional, contextual, or motivational factors or broader notions of risk and delay that fall outside the expected utility or discounted utility model.[2] This raises a further measurement problem: if the underlying theory is incomplete or overly restrictive, measures based strictly on it may not capture the construct of interest, i.e., the broader disposition to take

[1]Empirical evidence shows that EUT often fails to predict actual behavior in real-world contexts (see, e.g., Charness et al. 2020) and that individuals' decisions frequently violate the axioms of expected utility (for surveys see, e.g., Starmer 2002; Barberis 2013). Likewise, intertemporal choices often violate the DU model (for a survey see, e.g., Cohen et al. 2020).

[2]Everyday decision-making is shaped largely by uncertainty rather than reflecting choices between lotteries with known outcome probabilities. As consequence, individuals may draw on how they typically decide under uncertainty even when confronted with lottery choices. When asked to assess their own willingness to take risks, they may therefore likewise refer to their inclination to make decisions under uncertainty, which may in fact describe their real-world behavior in risky situations more accurately.

or avoid risk or the willingness to delay gratification across contexts. Moreover, experimental elicitation protocols are fairly abstract and might lead to confusion, and the use of heuristics as consequence of a lack of familiarity.

In practice, economists therefore face a trade-off between maintaining theoretical closeness to EUT (or DU) and achieving empirical relevance. Measures closely aligned with EUT and DU are conceptually clear, which often makes them the preferred choice of behavioral and experimental economists, who are interested in measuring theoretically-rooted parameters. At the same time, these measures may be empirically narrow, especially in settings that require broader conceptualizations of risk and time preferences. This might be achieved by broader, more intuitive and naturalistic measures that can be obtained in survey settings and that are often used in studies in cultural economics, despite the cost of less direct interpretability within a specific theoretical framework.

One alternative for obtaining such broader measures is the use of qualitative questions that ask individuals to assess their own willingness to take risks or to forgo current consumption for future consumption. Although such measures lack a direct interpretation as parameters of EUT or DU models and may be affected by limited self-knowledge, reporting biases, or differences in scale use, they can capture broader, dispositional aspects of preference that manifest across multiple domains.[3] These measures also offer an alternative elicitation approach that may sidestep certain types of complexity specific to quantitative measures, such as complexities of evaluating probabilities and implied interest rates (e.g., Enke and Shubatt 2023), again with the caveat that retrieving an assessment of one's preference from introspection and scale use in reporting this answer has its own complexities. A further advantage is that they can be implemented at relatively low cost in large surveys. The following section briefly introduces standard incentivized elicitation protocols and then presents survey-based measures that are easier to implement and therefore especially suitable for large-scale studies.

Measuring risk and time preferences across diverse cultures also presents several challenges. First, survey wording may be interpreted differently across cultural contexts. The standard

[3]Evidence, in particular in psychology, has shown that risk preferences are highly context dependent, a feature missing in the standard EUT framework (see, e.g. Weber et al. 2002). Supporting this view, Dohmen et al. (2011) show that the best predictor of risky behavior in a given domain, e.g., holding stocks, is a qualitative question framed narrowly in that context, e.g., willingness to take risks in financial matters. They also find, however, that a broader question about willingness to take risks in general is the best all-around predictor across a range of risky domains, for example also predicting self-employment, smoking, and participating in risky leisure activities.

mitigation is back-translation: one individual translates questions into the local language, another translates back to the original, and if the meaning is preserved, this provides some reassurance of equivalence. This procedure is imperfect, however. Hypothetical quantitative measures may be less susceptible to cultural interpretation differences than qualitative measures, providing one reason to favor these for cross-country comparisons. On the other hand, they introduce other difficulties. Stake sizes must be adjusted for local income levels, typically using country-level average or median income, which is inherently imprecise. Cross-country variation in inflation can also be problematic, although questions can instruct respondents to assume a particular inflation rate. A second challenge in comparing measures of preferences across countries is that decision heuristics or responses to question complexity and framing may vary across countries due to factors such as education levels. Whether quantitative or qualitative measures better elicit true preference differences in the face of these factors remains unclear.

These challenges motivate the approach taken in this chapter: comparing results across multiple cross-country datasets that differ substantially in wording, structure, and the use of quantitative elements. To the extent that similar country rankings emerge across datasets—despite these methodological differences—the rankings are unlikely to be driven entirely by cultural variation in question interpretation, and may instead reflect genuine preference differences.

2.2 Risk Preferences

A commonly used tool to elicit risk preferences in behavioral economics literature is the multiple price list, in which respondents make choices between alternatives that involve different levels of risk.[4] This approach was introduced by Binswanger (1980, 1981) and has since been widely used in various variants (see, e.g., Holt and Laury 2002; Harrison et al. 2007; Dohmen et al. 2010).[5] Typically, these multiple price lists involve relatively small stakes. A prominent example is the is the laboratory design of Holt and Laury (2002), in which subjects face ten decisions between two lotteries with fixed outcomes but varying probabilities, with the probability of the first outcome increasing from 1/10 to 10/10. As most subjects switch from the safer to the riskier

[4]Other elicitation methods involving choices between risky prospects have been proposed in the economics and psychology literature (see, e.g., Gneezy and Potters 1997; Sharpe et al. 2000; Eckel and Grossman 2002; Andreoni and Sprenger 2012; Crosetto and Filippin 2013).

[5]Andersen et al. (2006) provide a discussion on the advantages and limitations of this approach.

option as probabilities change, individual risk aversion can be inferred from the switching point.[6]

An alternative lottery-choice measure with large but hypothetical stakes was introduced in the Health and Retirement Survey and analyzed by Barsky et al. (1997).[7] Respondents choose between a safe lifetime job and otherwise equivalent jobs offering different probabilities of income gains or losses. Instead of a multiple price list, this approach uses an adaptive staircase procedure (see Cornsweet 1962) in which each question is tailored to previous responses, successively narrowing the bounds around the respondent's indifference point. By focusing on the indifference region, this method achieves similar informational content with fewer questions.[8] Another advantage of the survey measure used by Barsky et al. (1997) is its domain-specific framing, which may enhance predictive power for employment-related risk choices; a disadvantage is that the narrow context may confound preferences with individual or environmental characteristics (e.g., age, labor market environment, etc.), requiring additional assumptions about unobserved heterogeneity. Its hypothetical nature also allows for high stakes that meaningfully vary lifetime wealth.

An alternative to incentivized or hypothetical lottery-choice experiments is the use of qualitative self-assessments of willingness to take risks. Dohmen et al. (2011) showed that answers to a qualitative self-report question are robustly correlated with choices in an incentivized price list lottery experiment. Respondents assess their general willingness to take risks on an 11-point Likert scale ranging from 0 ('not at all willing to take risks') to 10 ('very willing to take risks'). Although the correlation is imperfect, reflecting both noise and the possibility that self-assessments capture broader aspects of risk preferences relevant for behavior under risk or uncertainty, these findings validate that the qualitative measure has an overlap whith what is captured by incentivized lottery experiments.

A key advantage of qualitative self-assessments is that they require minimal survey time and do not involve incentivization, making them particularly well suited for inclusion in large-scale population surveys. This has led to their widespread use in surveys worldwide (see, e.g., Ding

[6]Simpler formats, such as choices between a lottery and a safe payment, have been used in subsequent work (Dohmen et al. 2010), and more refined designs have been implemented in large representative samples (see, e.g., Donkers et al. 2001; von Gaudecker et al. 2011). Surveys of methods are provided by Charness et al. (2013), and payoff-varying price lists have been proposed to account for probability weighting (Drichoutis and Lusk 2016).

[7]See also Kimball et al. (2008, 2009).

[8]Variants of this adaptive procedure have since been adopted in modern elicitation methods, including Falk et al. (2023) and Wang et al. (2024).

et al. 2010; Hardeweg et al. 2019) and their inclusion in major representative household panels, including the BHPS, HILDA, HRS, PSID, SOEP, and SHARE.

A recent development combines hypothetical lottery measures with qualitative self-assessments of willingness to take risks. Falk et al. (2023) compare the out-of-sample predictive power of linear combinations of roughly thirty different survey measures about willingness to take risks, and find that the strongest performance is achieved by combining a non-incentivized lottery experiment with the general risk question of Dohmen et al. (2011), with the qualitative measure adding explanatory power beyond the lottery task alone. A closely performing alternative combines a staircase lottery design with the general risk question. While predictive power is imperfect, consistent with noise and broader notions of risk preferences, this combined measure has been adopted for large-scale global fielding (Falk et al. 2018), where it predicts risky behaviors at the individual level and risk-related institutions at the country level.

Replications of the validation exercises in Falk et al. (2023) across countries yield similar mappings, but also suggests that quantitative elicitation formats, such as multiple price lists, are more reliable predictors and less sensitive to environmental heterogeneity than qualitative self-reports (see, e.g., Bauer et al. 2020; Kosfeld and Sharifi 2024; Kosfeld et al. 2025). The advantages of using multiple items for eliciting risk preferences are well-documented (see, e.g. Vieider et al. 2015; Menkhoff and Sakha 2017), partly reflecting measurement error in both quantitative and qualitative measures. Quantitative tasks require comprehension of probabilistic information and cognitive effort, which likely contributes to their correlation with cognitive ability (see, e.g., Dohmen et al. 2010; Andersson et al. 2016; Dohmen et al. 2018). Qualitative measures reduce some complexity but still rely on introspection and are subject to noise due to differences in scale use or risk perception, and are likewise related to cognitive ability (Dohmen et al. 2010).[9] As a result, measurement error is more pronounced in representative population samples than in student or otherwise selected samples (see, e.g., Dohmen et al. 2011).

2.3 Patience

The standard tools to elicit time preferences or, more generally, patience, are very similar. The goal is to isolate how much compensation an individual respondent would require to wait for

[9] For a formal treatment of survey responses and measurement error, see Falk et al. (2021a).

the realization of a later payoff instead of an earlier payoff. In studies eliciting patience using multiple price lists, participants typically face a series of choices that reveal their preferences for receiving rewards at different times (e.g., Coller and Williams 1999). Specifically, respondents choose between smaller, sooner rewards (e.g., $100 now) and larger, later rewards across multiple scenarios ($101, $102, ..., $150 12 months later). The switching point from sooner to later rewards provides a measure of their impatience, as reflected in their discount rate, because later rewards typically involve larger amounts (e.g., $108 in 12 months instead of $100 today, i.e., a discount rate of 8%). As for risk preferences, the elicitation of time preferences can involve incentivized choices or hypothetical versions of the same or similar choice scenarios, including staircase measures that use titration to identify an individual's discount rate under the assumption of the DU framework (for surveys, see, e.g., Frederick et al. 2002; Cohen et al. 2020).[10]

Again, an alternative approach to elicit measures of patience involves qualitative self-assessments. Here, respondents state their agreement with statements about individual patience. One example is the question about the respondent's willingness to give up something that is beneficial for them today in order to benefit more from that in the future, on a scale from 0 (unwilling) to 10 (very willing, see Falk et al. 2023). Responses to subjective self-assessments provide an ordinal measure of patience.

Various versions of non-incentivized quantitative measures, including price lists and staircases, as well as qualitative measures of patience have been validated as predictors of choices in incentivized multiple price list elicitations (see, e.g., Vischer et al. 2013; Falk et al. 2023). Falk et al. (2023) find that a combined measure including both quantitative and qualitative items has the best out-of-sample predictive power. The GPS data include such a combined measure, comprising a staircase measure and a qualitative self-assessment of patience (Falk et al. 2018). Fewer studies have implemented patience measures in large population-wide surveys than for risk preferences. Moreover, validation studies have found greater heterogeneity in the validity of subjective self-assessments for time preferences than for risk preferences (see, e.g., Bauer et al. 2020; Kosfeld and Sharifi 2024; Kosfeld et al. 2025).

[10]An additional complication for the elictation of time preferences arises in the presence of risk aversion, i.e., concave utility in the EUT framework (see Andersen et al. 2008, for details).

3 Data Sets with Global Coverage

This section introduces several data sets that contain preference measures elicited at a global scale or in a large sample of countries. We conduct a brief discussion of the data sets, focusing on those with roughly comparable measures of preferences and coverage. The discussion does not aim for an exhaustive list of global preference data, but rather focuses on the most extensive and easily accessible data sets.[11]

3.1 Representative Samples

3.1.1 Global Preferences Survey/Gallup

The Global Preferences Survey (GPS) measures risk, time, and social preferences (including altruism, positive reciprocity, negative reciprocity, and trust) for a sample of approximately 80,000 individual respondents drawn as representative samples from 76 countries around the world, covering 90 percent of both the world's population and global income (Falk et al. 2018).[12] The GPS was conducted as part of the Gallup World Poll in 2012. The survey items used in the GPS are based on an experimentally validated survey module (Falk et al. 2023). The survey items have been translated into local languages applying a back-translation procedure in addition to pre-testing for cultural appropriateness, and involve monetary stakes of comparable sizes across countries.

The measure of risk preferences combines a qualitative item assessing a respondent's subjective willingness to take risks and a quantitative item based on a series of hypothetical lottery choices. The qualitative item asks individuals to rate their willingness to take risks on a scale from 0 (unwilling) to 10 (very willing), following Dohmen et al. (2011). The quantitative item presents respondents with a sequence of five interdependent choices between a varying safe payment and a binary lottery offering either a positive payment or no payment, each with 50% probability. To ensure comparability across countries, payments were adjusted based on purchasing power parity and relative to median household income for each country. The responses are combined using weights derived from the validation of these survey items (see Falk et al. 2018, 2023, for details).

[11] Other work includes, e.g., Meissner et al. (2023) who use representative samples for eight European countries.
[12] See also https://gps.econ.uni-bonn.de/home.

Time preferences were elicited in a similar way, combining survey responses to a quantitative and a qualitative survey item. The quantitative item confronted respondents with five interdependent choices between an immediate payment and varying future payments with a 12-month delay, assuming no inflation. The qualitative survey question asked individuals to rate their willingness to forego something that is beneficial for them today in order to benefit more from that in the future, on a scale from 0 (unwilling) to 10 (very willing). As with risk preferences, the two measures were combined using weights established through the validation of the questions (see Falk et al. 2018, 2023, for details). More recently, Burro et al. (2022) elicited time preferences using a simpler (binary) question about preferences for an earlier or later income (PELI) in a sample of 65 countries and documented a high correlation with the GPS measures in the 44 countries for which both measures are available.

3.1.2 World Values Survey

The World Values Survey (WVS) is one of the most widely used cross-national surveys in the social sciences, containing a large number of survey items on human values, beliefs and attitudes (Inglehart et al. 2020).[13] Conducted globally almost every five years since 1981, the WVS provides representative comparative data, with seven waves available to date. Our analysis utilizes data from wave 6 (2010–2015), which was conducted around the same time as the other representative data sets. This wave includes responses from almost 90,000 individuals across 60 countries.[14]

While the WVS does not contain experimentally validated measures for economic preferences, it offers proxies frequently used in the literature.[15] Risk preferences are assessed through a qualitative self-evaluation question, asking respondents to what extent they think they are similar to a person for whom having an exciting life, taking risk and adventure are important. Responses are given on a six-point scale, ranging from "not at all like me" to "very much like me". Time preferences are not measured by asking respondents how they solve an intertemporal trade-off. Instead the WVS asks respondents whether they consider thrift, saving money and things to be particularly important qualities for children. This question is part of a list of 11 qualities, from

[13]See also www.worldvaluessurvey.org.

[14]Robustness checks with wave 5 (2004–2009) deliver similar results.

[15]The items in the WVS are constructed through rigorous protocols that ensure cross-national comparability, including independent back-translations, expert review, and comparisons against the master questionnaire.

which respondents can select up to five that they find most relevant. Since this measure does not elicit respondents' time preferences directly by confronting them with intertemporal trade-offs, we consider this measure to be fairly indirect, and potentially affected by other factors (such as education styles or altruism).

3.1.3 Ruggeri et al. (2022)

The data from Ruggeri et al. (2022) were collected using online tools via the Qualtrics survey platform and include responses from over 13,500 respondents from 61 countries. The sampling process involved multiple stages, starting from an initial convenience sample of 5–10 participants to ensure comprehension of survey questions. This was followed by the recruitment of approximately 30 participants in each country by local country teams to verify functionality. Finally, full-scale recruitment in the general population and data collection were conducted, but without ensuring representativeness.

The data collection aimed to investigate various "anomalies" in intertemporal choice behavior, including present bias and subadditivity. The empirical analysis below leverages the fact that the dataset includes measures of risk preferences and time preferences that are comparable to those included in the GPS and WVS data sets. Risk preferences were assessed using a survey question that asked respondents to choose their preferred option from a set of five alternatives: (i) a sure payment of $50, (ii) a binary lottery with 75% probability of obtaining $67 (25% probability of obtaining $0), (iii) a binary lottery with 67% probability of obtaining $75 (33% probability of obtaining $0), (iv) a binary lottery with 50% probability of obtaining $100 (50% probability of obtaining $0), (v) and a binary lottery with 25% probability of obtaining $200 (75% probability of obtaining $0).

Time preferences were elicited using several survey items. In the baseline scenario, respondents chose between an immediate payment (which corresponded to approximately 10% of the average national household income) or delayed payment of 110% of the immediate amount after 12 months. If they opted for the immediate payment, they were subsequently offered a delayed payment of 120% of the immediate amount. If they still preferred the immediate payment, they were presented with a final option of 150% of the immediate amount as the delayed payment. Conversely, participants who initially chose the delayed payment were given follow-up choices of 102% and 101%, respectively. Additional scenarios featured alternative stakes, including negative payments (losses) or varying time frames to extract subadditivity. A broader discounting score based on all scenarios, ranging from 0 (always preferring delayed gains or earlier losses) to 19 (always preferring immediate gains or delayed losses) was computed. For our analysis, we differentiate between two measures: the broader discounting score (referred to as the combined measure) and the initial survey item of the baseline scenario (single measure), which excludes loss aversion and other dimensions of intertemporal choice.

3.2 Convenience Samples and Student Samples

Not all data sets with preference measures at a global scale involve representative country samples or samples of the general population; some are elicited in more specific samples, such as university students. On the one hand, the fact that student samples are not representative of the broader population in each country might raise concerns about selection bias and external validity in a general population context. On the other hand, student samples offer the advantage of comparability with typical subject pools used in laboratory experiments for preference elicitation. In view of several existing studies that have used student samples or convenience samples to reveal global variation in economic preferences, we incorporate the largest respective data sets in our analysis.

3.2.1 INTRA Data (Rieger et al. 2015)

The International Test on Risk Attitudes (INTRA) is a data set that has been constructed by Rieger, Wang, and Hens in collaboration with researchers and labs at various universities around the world (see Rieger et al. 2015, for details). The preference data were collected from a sample of approximately 7,000 undergraduate students (primarily first- and second-year) across 53 countries. The average age was 21.5 years, and the gender distribution was roughly balanced.

The dataset includes survey measures for risk preferences, time preferences and other preferences (see Rieger et al. 2015; Wang et al. 2016; Rieger et al. 2021). Specifically, participants responded to 14 decision-making questions, including ten lottery-based questions to elicit risk preferences, three questions related to time preferences, and one question measuring ambiguity aversion. Additionally, the survey included questions on other attitudes and values, such as the Hofstede Values Survey Module (Hofstede and McCrae 2004), as well as questions on happiness and socio-demographic background. The monetary values used in the multiple price list tasks were denominated in local currency and adjusted based on the monthly average incomes and expenses of local students, while also accounting for purchasing power parity.

Risk preferences were elicited by measuring the participants' willingness to pay for various hypothetical lotteries involving gains with different probabilities (for details, see Rieger et al. 2015).[16] The analysis below relies on survey responses in which participants stated the maximum amount they would be willing to pay for different lotteries, e.g., a lottery offering a 40% chance of winning $0, and a 60% chance of winning the equivalent of $100.[17]

Time preferences were measured using a quantitative survey item eliciting respondents' preferences in decisions between an immediate payment and a delayed payment. Concretely, respondents were asked about whether or not they preferred varying payments $X delayed by one year to an immediate payment of $100.[18]

3.2.2 Maps Data (Vieider et al. 2015; L'Haridon and Vieider 2019)

Another dataset with global coverage includes measures of risk preferences from a sample of approximately 3,000 students in 30 different countries (see Vieider et al. 2015; L'Haridon and Vieider 2019). Preferences were measured by eliciting certainty equivalents for 44 binary prospects that varied in terms of payment amounts, probabilities, domains (gains or losses), and source of uncertainty (known or ambiguous probabilities). In addition, the dataset contains responses to a qualitative question assessing the general subjective willingness to take risks, identical to the validated measure used by Dohmen et al. (2011). As documented by Vieider et al. (2015), responses to this general risk question correlate with incentivized lottery choices both within and across countries. For our empirical analysis, we use the mean of the standardized responses to the general risk question and the certainty equivalent of the first lottery as our measure of risk preferences.

[16]Additional lotteries involving losses or mixed outcomes were used to elicit loss aversion.

[17]Alternative lotteries featured payoffs of $0 and $400 or $0 and $10,000, with probabilities of 10% and 90%. Our analysis includes respondents with complete answers to lotteries 1-6 in the study. The final measure is derived by winsorising responses at the 99th percentile, standardizing them and averaging across the six items.

[18]Alternative choices involved a binary decision between an immediate payment of $3,400 and a payment of $3,800 after one month. For the analysis, we use responses to items 1-3, including only respondents who provided answers to all three items. The final measure was derived by winsorizing responses at the 95th percentile, standardizing them, and averaging across the three items.

3.2.3 GLOBE Data (House et al. 2004)

The Global Leadership and Organizational Behavior Effectiveness Project (GLOBE) developed measures of societal culture, as reflected in shared motives, values, beliefs, and identities transmitted across generations. These measures span nine dimensions of societal culture, based on data collected from over 17,000 middle managers in 951 organizations in 62 countries (House et al. 2004).[19]

One of these dimensions, uncertainty avoidance, reflects the extent to which societies seek to mitigate uncertainty through social norms, rules, and procedures. The measure of uncertainty avoidance is based on responses to four questions assessing the extent to which a society relies on social norms, rules, and procedures to alleviate unpredictability of future events, and the tendency to seek orderliness, consistency, structure, formal procedures, and laws to cover situations in their daily lives. Each of these questions measures agreement on a Likert scale from 1 (strongly agree) to 7 (strongly disagree).

Time preferences are captured by a dimension on future orientation. This dimension consists of four questions about practices regarding planning for the future instead of taking life events as they occur. Responses are given on Likert scale from 1 to 7. Individual responses for both dimensions were aggregated at the country level by averaging.

Notably, these responses do not measure the uncertainty avoidance or future orientation of individual respondents but instead reflect country-level measures of risk attitudes and future orientation that are based on the assessment of managers and capture the broader cultural context in which they are embedded. As a result, the GLOBE data provide insights into aggregate (country-level) variation, but differ conceptually from the other data sets. Our interest in including the GLOBE is mainly for comparability with literature that has used this data set as a source of variation in culture related to risk and time preferences, and for comparison of the respective data patterns.

[19] See also the GLOBE Project website https://globeproject.com/study_2004_2007.

4 Economic Preferences: A Global View

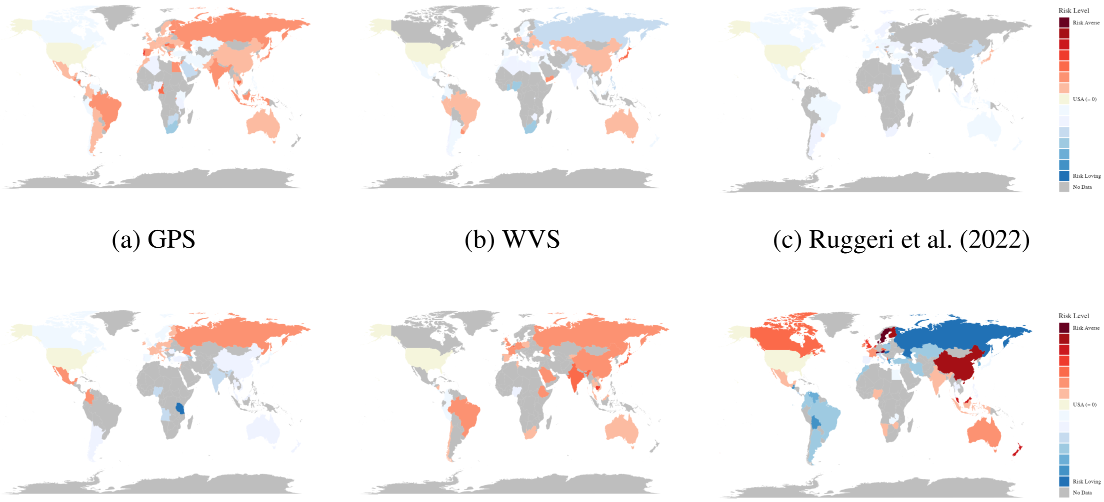
4.1 The Global Distribution of Preferences

We begin by documenting the global distribution of risk-taking and patience using maps, which show the geographic coverage and distribution of the respective measures across different datasets. To aid comparability despite variation in measurement approaches, we aggregate standardized individual-level measures to the country level. For the GLOBE data, which contains country-level observations only, the standardization is implemented at the country level and variation is therefore higher by construction than in country-level measures derived from data sets with individual-level observations. We then normalize these values relative to the corresponding average for the USA, which allows us to compare, across datasets, whether the measures for the willingness to take risk or patience for a particular country all deliver a similar value relative to the USA.

☐ Stylized Fact 1: Preferences exhibit considerable heterogeneity around the world.

4.1.1 The Global Distribution of Risk Preferences

Figure 1 presents the global distributions of risk preferences. Both the GPS and WVS reveal broadly similar global patterns. Relative to the USA, the average willingness to take risks in most countries, especially in Europe, Asia, and Oceania, is smaller (risk aversion is larger), but some countries, especially in Africa, exhibit a greater willingness to take risks (risk aversion is smaller). The color pattern, which is comparable in terms of scale (measured in standard deviations), is perhaps surprisingly similar, with Europe exhibiting populations that are about a fourth of a standard deviation less willing to take risks. Similar findings apply to Latin America, Asia, and Australia/Oceania. A notable difference is visible for India and Russia. The data collected by Ruggeri et al. (2022), on the contrary, which has a smaller worldwide coverage than the GPS or WVS, exhibit quite different patterns, with most countries more willing to take risks than the USA (except for Japan and Uruguay). The INTRA and Maps studies also cover a smaller number of countries, but use student samples. Similar to the GPS and WVS, the data sets indicate higher risk aversion in Europe compared to the USA. They also align in the ranking of some Latin American and Asian countries, though some inconsistencies exist. The INTRA data show a greater willingness to take risks in China—contrasting with the GPS, WVS, and Maps data, but aligning with the Ruggeri data. Meanwhile, the risk preference patterns in the GLOBE data partly resemble those in the representative samples, especially so for Western Europe, Asia and Oceania.[20]



(a) GPS (b) WVS (c) Ruggeri et al. (2022)

(d) INTRA (e) Maps Data (f) GLOBE

Figure 1: Average Willingness to Take Risk (Relative to USA)
Note: Country averages of standardized preference measures, ranging from dark red (very risk-averse) to dark blue (very risk-loving); values are normalized to the respective average for the USA (yellow).

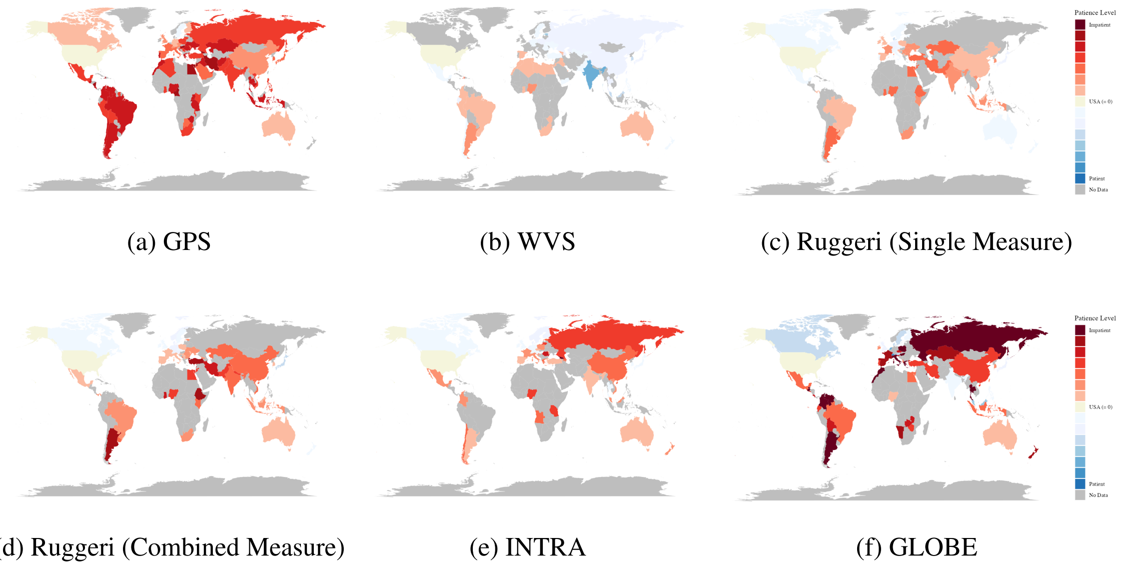
4.1.2 The Global Distribution of Patience

The analogous pattern for the global distribution of patience is depicted in Figure 2. According to the GPS, virtually all countries have populations that are, on average, less patient than the U.S. population. The pattern emerging from the other data sets is very similar. Specifically, the data from Ruggeri et al. (2022) closely align with the GPS data, showing that the populations of most countries are less patient than the U.S. population. This finding holds regardless whether using a comparable measure based on a trade-off between an immediate payment versus delayed payment or a combined measure incorporating different time delays in both the gain and loss domains. Also, the two data sets with global coverage of convenience samples—the INTRA data, which includes students and their mentors, and the GLOBE data, which surveys middle managers' assessments—exhibit patterns that closely resemble those found in the GPS data. The only

[20]As mentioned above, the comparison for the GLOBE data needs to be restricted to qualitative interpretations as the standard deviations are by construction higher than for the other data sets.

exception is the pattern observed in the WVS, which indicates that many countries—particularly in Europe and Asia—have more patient populations than the USA. One potential explanation for this discrepancy lies in the survey items used to elicit time preferences. The measure of patience in the WVS asks about qualities encouraged in children at home. In contrast, the measures used in GPS, Ruggeri et al. (2022), and the INTRA data set, which ask individuals about their own patience, are more closely aligned.

In sum, the findings document pronounced heterogeneity in economic preferences across the world. Moreover, the observed patterns are similar for comparable preference measures and samples. In this context, it is interesting to note that the results for the GPS and WVS align closely for risk preferences, a domain for which both data sets use at least one rather similar survey item. In contrast, results diverge for time preferences, where the elicitation methods differ significantly. A reversed pattern appears in the comparison between the GPS data and the data from Ruggeri et al. (2022): time preference measures are closely aligned, and so are the cross-country patterns, while risk preference measures and cross-country patterns differ. This suggests that the variations in empirical patterns are primarily driven by differences in the measurement methods, whereas differences in respondent samples have a more moderate impact.



(a) GPS (b) WVS (c) Ruggeri (Single Measure)

(d) Ruggeri (Combined Measure) (e) INTRA (f) GLOBE

Figure 2: Average Patience (Relative to USA)
Note: Country averages of standardized preference measures, ranging from dark red (very impatient) to dark blue (very patient); values are normalized to the respective average for the USA (yellow).

4.2 Cultural Heterogeneity

The significant heterogeneity in preferences across the world raises questions about systematic patterns. The variation could reflect stable differences arising from cultural heterogeneity, but an alternative possibility is that the rankings could be largely driven by noise. In this section we address the possibility of noise in two ways. We explore the robustness of preference rankings within any given dataset to noise arising from sampling variation. We then explore more rigorously whether different datasets yield similar rankings of countries, consistent with a systematic underlying cultural variation emerging from these multiple attempts at global measurement. From this analysis, we establish our second stylized fact:

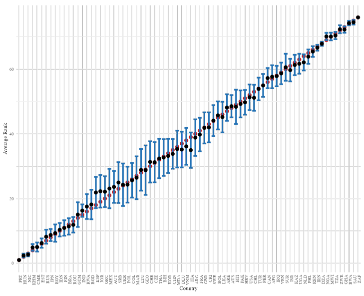
- ☐ Stylized Fact 2: Within data sets, rank correlations across countries are stable with respect to sampling. Between data sets, rank correlations across countries are positively correlated.

4.2.1 Cultural Heterogeneity: Risk

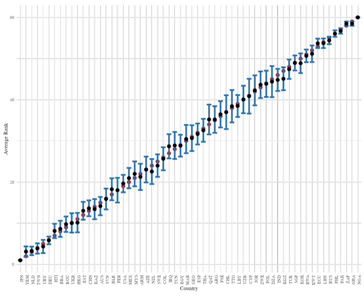
Although data sets such as the GPS and the WVS—and to a lesser extent the data from Ruggeri et al. (2022)—are designed to be representative of the general population, variation in sampling may influence a country's position in the global preference distribution. To investigate the stability of the global patterns of heterogeneity in risk preferences, we rank countries by their average willingness to take risks. We then replicate this ranking based on sub-samples of 30% of respondents for 100 iterations of sub-sampling. For each country, we calculate the rank correlation across iterations. The resulting correlations indicate a high consistency of rankings.[21] This is especially true for the data sets that rely on representative samples, the GPS and the WVS, which exhibit rank correlations between the 30%-sub-samples larger than 0.95 with very low dispersion (standard deviations of ranks are 3.61 and 2.34, respectively). The other data sets still exhibit average rank correlations around 0.7–0.8, but these are much less tightly clustered around the mean, so that re-sampling results in greater rank variability.[22] These results indicate that, at least for the WVS and GPS, sampling variation among respondents of a country contributes rather little to the measured global variation of risk preferences, making it plausible that country differences in risk preferences reflect cultural variation.

[21] The respective results are displayed in Figure A1.

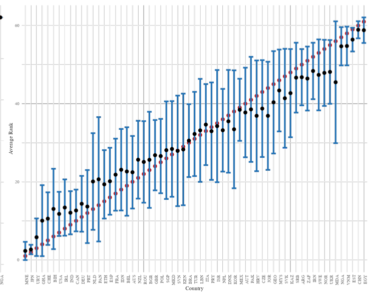
[22] The corresponding standard deviations are 9.62 for the data by Ruggeri et al. (2022), 6.21 for the INTRA data, and 4.11 for the Maps data.



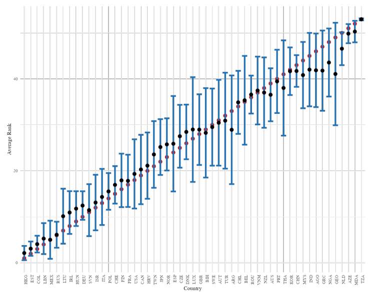
(a) GPS



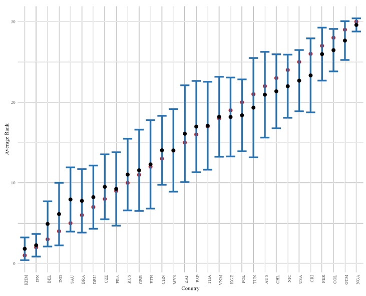
(b) WVS



(c) Ruggeri et al. (2022)



(d) INTRA



(e) Maps Data

Figure 3: Rank Consistency: Risk

Note: The figures plot average ranks and standard deviations for 100 iterations of taking a subsample of 30% of the observations of a country. The red dots represent the actual ranking based on the entire samples, and the countries are arranged in ascending order of these actual ranks. Blue whiskers represent standard deviations.

Figure 3 provides a complementary analysis by plotting the average ordinal ranking of countries based on the average willingness to take risks of their populations, along with the standard deviations of these ranks.[23] In the data sets with representative population samples, such as the GPS and WVS, country rankings show little sensitivity to re-sampling. Greater variability appears in the middle of the rank distribution compared to the extremes: If countries in the center of the distribution are closer in terms of the absolute average preference, the same degree of sampling variation (i.e., the same variation around the estimated mean) leads to higher variation in ranks. Data sets with less representative samples—Ruggeri et al. (2022), INTRA, and Maps—also exhibit some degree of rank stability, though with greater variation in the ordinal ranking of countries as indicated by the larger standard deviations.[24] This increased variability may stem from smaller sample sizes or more heterogeneous samples across countries.[25]

[23]Figure A2 in the Appendix presents the corresponding results for re-sampling with fixed absolute sample sizes (200 individuals).

[24]Due to the lack of information at the individual level, the GLOBE data is excluded from this analysis.

[25]For instance, student samples might be more selective in some countries than in others with respect to access to a tertiary education path and selection into particular programs, such as economics.

Since the data sets cover different sets of countries, the rank order plots are not directly comparable. To address this, we constructed plots using normalized ordinal ranks, ranging from 0 to 1. Instead of average risk-taking by country, these plots show average risk-taking by country rank. A similar result emerges, comparing across datasets: There is an (inverted) S-shaped pattern. Rankings at the extremes are stable and largely invariant, while the flat middle section indicates little heterogeneity, making rankings there susceptible to small sampling changes.[26] This is in line with the higher variability observed in the center of the distribution for the re-sampling exercise (Figure 3).[27]

We also examine how comparable country rankings are across different data sources. To do so, we compute cross-country correlations of the risk measures. We use the set of countries that overlap in each pairwise comparison. Table 1 shows that risk preference measures are positively correlated across most data sets, indicating broadly similar country rankings, although with substantial heterogeneity. The Ruggeri et al. (2022) ranking shows only a weak positive association with the GPS data, and the GLOBE project stands out as the only case with negative correlations relative to two other data sets. Clearly, these correlations are attenuated due the previously discussed imperfect within-dataset rank correlation that is due to sampling error.[28]

Note also that the raw correlations are not directly comparable as each pairwise estimate is based on a different number of overlapping countries. The GPS shows the largest overlap overall (with a total of 188 country-pairs across all other data sets). To assess which data set aligns most closely with the others, the bottom rows of Table 1 report a weighted overall correlation measure, where correlations are weighted by the number of overlapping countries and normalized relative to the GPS. The WVS exhibits the largest overall correlation of the risk preference measures with the other data sets, followed by the data by Ruggeri et al. (2022). However, GLOBE's negative correlation with two data sets casts doubt on the consistency of its measure of risk preferences, which is not surprising given that, in contrast to all other data sets, the GLOBE data is not based on respondents' measures of their own preferences, but captures managers' assessments of the country's population's tendency to avoid risks. Therefore, we also report the weighted score

[26]See also Appendix Figure A3.

[27]See also Appendix Figure A4.

[28]Correlations here and in the following are obtained without correcting for measurement error, i.e., coefficients might be underestimated. Appendix Table A1 shows the corresponding results for subsamples restricted to a similar age of respondents in the range 18–30.

when excluding the GLOBE's correlation coefficient. This paints a more consistent picture with all data sets exhibiting relatively high scores, with the GPS revealing the highest score.

Table 1: Correlation matrix between data sets: Risk

	GPS	WVS	Ruggeri	INTRA	Maps Data	GLOBE
GPS	-	0.31	0.05	0.30	0.33	-0.19
WVS	38	-	0.22	0.12	0.27	0.31
Ruggeri	43	32	-	0.22	0.38	0.10
INTRA	40	29	39	-	0.07	-0.13
Maps Data	25	19	18	19	-	0.25
GLOBE	42	33	35	37	18	-
Relative overall	1.00	1.45	1.08	0.81	0.99	0.23
Relative overall (excluding GLOBE)	1.00	0.81	0.72	0.76	0.63	

Note: Rank correlations are taken of all common countries between two data sets (risk). Top right are Spearman correlation coefficients, bottom left are number of overlapping countries between the data sets. The relative overall correlation is constructed as the weighted sum of correlation coefficients, with the number of overlapping countries between two data sets as weights, and normalized to the respective sum for the GPS for comparability.

4.2.2 Cultural Heterogeneity: Patience

The analysis of cultural heterogeneity for patience yields similar patterns. We find that re-sampling does not greatly affect the country ranking in patience, with rank correlations exceeding 0.95 for the two representative data sets, the GPS and the WVS, and little variation (standard deviations of 2.86 and 2.54, respectively).[29] The corresponding rank correlations for the data sets based on convenience samples and students are only moderately lower.[30]

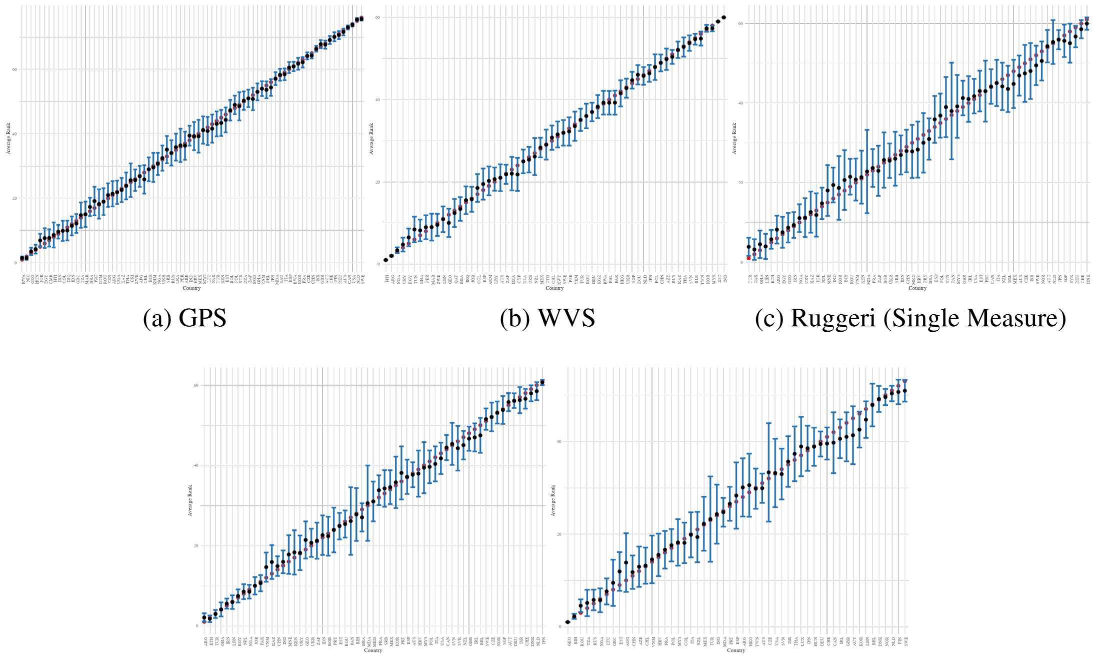
Figure 4 documents the rank consistency for each of the data sets.[31] The rank correlation obtained with each data set is largely insensitive to resampling. Again, the stability is slightly weaker for countries in the center of the respective rank distribution.[32]

[29]See Appendix Figure A5 for the resulting distributions of rank correlations based on 100 replications with sub-samples of 30% of respondents.

[30]The respective standard deviations are 5.26 and 3.69 for the baseline measure and the combined measure, respectively, in the data by Ruggeri et al. (2022), and 4.44 for the INTRA data.

[31]The corresponding figure for re-sampling based on an absolute number of draws is shown in the Appendix, see Figure A6.

[32]Likewise, Appendix Figure A7 shows the corresponding figure for the normalized ranks.



(a) GPS (b) WVS (c) Ruggeri (Single Measure)

(d) Ruggeri (Combined Measure) (e) INTRA

Figure 4: Rank Consistency: Time

Note: The figures plot average ranks and standard deviations for 100 iterations of taking a subsample of 30% of the observations of a country. The red dots represent the actual ranking based on the entire samples, and the countries are arranged in ascending order of these actual ranks. Blue whiskers represent standard deviations.

Table 2 shows the respective correlation results for patience obtained with different data sets. Again, the results show substantial heterogeneity. Interestingly, however, the results reveal an even more coherent picture than for risk preferences: All correlations of patience measures across data sets are positive, indicating the consistency of measures across data sets, but the correlations vary in size. The largest correlations are found between the measures contained in the GPS and in the data by Ruggeri et al. (2022) and in the INTRA data. Naturally, the two scores provided by Ruggeri et al. (2022) are highly correlated with each other and therefore only one of them is included in the respective weighted sums. Unsurprisingly, the highest relative overall correlation is obtained for the GPS data, closely followed by the other data sets except the WVS. Given that the WVS exhibits the lowest correlation coefficients across all data sets, this suggests that the measure might capture different dimensions of time preferences or other traits.[33]

Summing up, we find considerable stability with respect to sampling within data sets. The stability between data sets is primarily driven by the respective preference measures contained in

[33] Appendix Table A2 contains the corresponding results for the subsample of respondents aged 18–30.

the data sets.

Table 2: Correlation matrix between data sets: Patience

	GPS	WVS	Ruggeri (Single)	Ruggeri (Combined)	INTRA	GLOBE
GPS	-	0.39	0.66	0.69	0.66	0.62
WVS	38	-	0.41	0.44	0.03	0.23
Ruggeri (Single)	43	32	-	0.92	0.56	0.55
Ruggeri (Combined)	43	32	61	-	0.66	0.52
INTRA	40	29	39	39	-	0.60
GLOBE	42	33	35	35	37	-
Relative overall (S)	1.00	0.38	0.86		0.74	0.78
Relative overall (C)	1.00	0.39		0.90	0.77	0.76

Note: Rank correlations are taken of all common countries between two data sets (patience). Top right are Spearman correlation coefficients, bottom left are number of overlapping countries between the data sets. The relative overall correlation is constructed as the weighted sum of correlation coefficients, with the number of overlapping countries between two data sets as weights, and normalized to the respective sum for the GPS for comparability. The relative overall correlations are constructed by excluding one of the Ruggeri measures: (S) considers only the single measure, while in (C) only the value of the combined measure is used.

4.3 Extending the Scope: Global Variation in Risk and Time Preferences

One shortcoming of the analysis of economic preferences using different data sets with numerous countries is the limited overlap of countries across data sets. This, together with the heterogeneity in measures of risk and time preferences, implies that the information on global variation in preferences is limited by the comparability of measures across different samples of countries. For instance, the overlap of countries in the GPS with any other of the data sets comprises at most 43 countries, and the subset of countries for which all data sets of global coverage are available is down to 8 for measures of risk preferences and 15 for measures of time preferences. While the limited overlap in the sets of countries used in different datasets makes comparison more difficult, a silver lining is that combining the different datasets could expand the total number of countries for which there is at least one type of measure for each preference. Combining the information from different data sets is also a potential way to reduce measurement error because for many countries a synthesized data set contains multiple observations.

The main challenge to aggregating the different datasets is isolating common factors from the various measures of these preferences that involve different survey items, response scales, and country samples. Here, we follow an approach proposed by Rieger et al. (2021) for the case of time preferences. This approach combines the standardized preference measures from different data sets by using a principal component analysis (PCA) and extracting a common preference factor. The corresponding PCA weight for a particular measure that is missing in a country (since the respective measure has not been elicited in this country) is set to zero, and the PCA weights are renormalized to sum to one for each country. The synthetic measure of global preference variation is then obtained by predicting the weighted average of standardized measures for each country.

We apply this methodology separately to measures of risk preferences and of time preferences using all available data sets, except for restricting to one of the two versions of the Ruggeri data (single measure) for time preferences. The corresponding synthetic measures will be denoted as Synthetic World Aggregate Preferences for Risk (SWAP-Risk) or Time (SWAP-Time), respectively. We note that one might construct measures of global variation in preference that overcome the challenge of small overlap and different measures in different ways. Nevertheless, we illustrate this procedure as a useful tool of how to combine different data sets with individual responses to particular preference measures to obtain a data set with larger scope and broader global coverage. Moreover, it is straightforward to extend the procedure to incorporate other data sets or newly available studies with the same or different measures.

Table 3 presents summary statistics of the resulting synthetic global preference measures in terms of the number of countries for which the synthetic measures are constructed and the correlations of the synthetic measures with the various individual-level measures of risk and time preferences from the different data sets.

Figure 5 shows the emerging world maps for global variation in risk preferences and patience. The respective values for the individual countries are listed in Appendix Table A3.

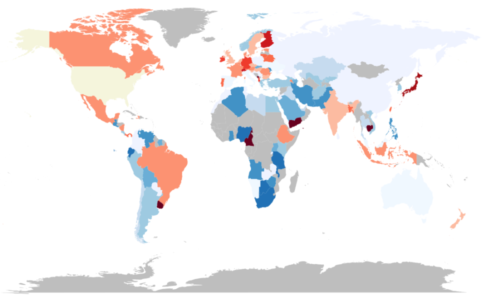
4.4 Potential Deep Determinants of Cultural Heterogeneity in Risk and Time Preferences

Evidence of cultural heterogeneity in risk and time preferences raises many fascinating questions about where such differences might come from. In this section we briefly survey a recently

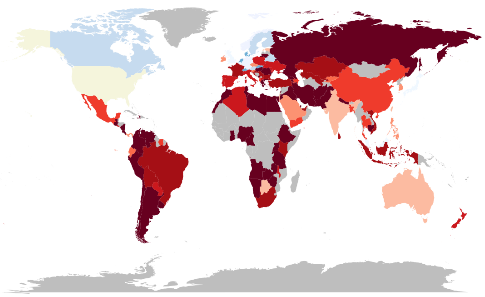
Table 3: Construction of Synthetic Global Preference Measures

	Risk (SWAP-Risk)		Time (SWAP-Time)	
	Number of Countries Overlap	Correlation Coeffi-cient	Number of Countries Overlap	Correlation Coeffi-cient
GPS	76	0.66	76	0.86
WVS	60	0.76	60	0.72
Ruggeri	61	0.67	61	0.87
INTRA	53	0.53	53	0.77
Maps Data	30	0.61		
GLOBE	57	0.60	57	0.80
Total	116		116	

Note: The table lists the contributions of the different data sources to the Synthetic World Aggregate Preferences (SWAP) measures, in terms of the number of countries and the correlation coefficient.



(a) Risk



(b) Time

Figure 5: Synthetic Global Preference Measures: Average Risk and Patience (Relative to USA)
Note: Standardized values per country, ranging from dark red (very risk-averse / very impatient) to dark blue (very risk-loving / very patient) in comparison to USA.

emerging literature that has sought to understand deep determinants of preference differences across countries, restricting our attention to studies that span multiple countries. We also extend previous work on how differences in risk and time preferences around the globe are related to ancient migration patterns, exploring robustness to a broader range of datasets and countries.

From a theoretical perspective, heterogeneity in preferences is likely to be the result of heterogeneous environmental conditions and evolutionary dynamics that lead to a selection of specific preference types, partly in combination with other traits such as cognitive intelligence (see, e.g., Robson 2001; Robson and Samuelson 2011). Primary candidates for such environmental conditions are mortality risk (Robson and Samuelson 2010) or the frequency of decisions and the severity of decision errors (Netzer 2009). In addition, social interactions, population composition, and societal interactions have been shown to determine the emergence of stable preference patterns (Alger et al. 2019; Alger and Weibull 2020).

One strand of empirical research examines the relationship of preferences, especially risk preferences, to geography, environment, and lifestyle of ancestors. Howden and Levin (2023) use GPS data and country-level panels to show that lifetime exposure to greater climatic variation reduces individuals' willingness to take risks. They interpret this as operating through an informational channel about higher background risk. Geography has also been implicated in shaping risk preferences through its influence on occupations and lifestyles. Cai et al. (2022) combine historical ethnographic data on sea-fishing with the GPS measure of risk preference to demonstrate that having sea-fishing ancestors is associated with greater willingness to take risks. They argue that this can reflect the ancient sorting of individuals into sea-fishing according to willingness to venture onto the risky environment of local seas, and subsequent transmission of their risk preferences to later generations. Chan and Luo (2025) show, using GPS data, that having ancestors who had a pastoral occupation (herding) is associated with increased willingness to take risks. They argue that this occupation exposed ancestors to idiosyncratic risks, and that the development of tactical responses to risk, like herd diversification, may have instilled a greater tolerance for risk that was transmitted to subsequent generations. Similarly, Nazarova (2024) finds in WVS data (and other data sources) that ancestral nomadic lifestyles — shaped by environmental factors like availability of animals suitable for long-distance travel — predict greater willingness to take risks. Geographic factors have also been linked to cross-country differences in patience. Galor and Özak (2016) demonstrate that pre-industrial suitability of local land for agricultural investment is associated with the development of patience, as measured by WVS data. The proposed channel is that returns to investment fostered a future-oriented mindset that was passed on in the form of patience.

Various within-country studies have also documented relationships of risk preferences and patience to environmental factors, especially extreme weather events and disasters, with adverse events generally decreasing willingness to take risks and decreasing patience (Cameron and Shah 2015; Cassar et al. 2017; Hanaoka et al. 2018; DiFalco and Vieider 2022; Jaramillo et al. 2025).

A second strand of research has investigated the relationship of preferences to cultural factors of religion and language. Although ancient, such factors are socially constructed, raising the possibility that they are not determinants, but rather could have co-evolved with certain preferences. Chen (2013) studies the relationship of linguistic structure to patience as proxied by savings behavior across a large set of countries, finding that languages that force a stark separation between present and future are associated with a lesser propensity to save, and Falk et al. (2018) show similar findings of reduced patience using the GPS patience measure and a broader set of countries.[34] Studies on religion and preferences have mainly used subject pools from individual countries, and have found that Catholics are relatively more willing to take risks than, e.g., Protestants (Noussair et al. 2013; Benjamin et al. 2016), while finding little evidence of a relationship between religion and patience (Benjamin et al. 2016).

A third approach has been taken by Becker et al. (2020), who seek to explain absolute differences across countries rather than preference levels. They show that ancient migration patterns out of Africa help explain the global distribution of risk and time preferences. Using GPS data, they find that populations separated longer by earlier migrations exhibit significantly greater differences in risk preferences. There is a positive, but smaller and not statistically significant impact of time of separation on differences in patience. The authors hypothesize that one mechanism through which ancestral temporal difference may magnify preference differences is through distinct historical experiences.

[34] Roberts et al. (2015) replicate the analysis in Chen (2013) accounting for relatedness among languages, and find robust although weaker relationships.

Table 4: Absolute Preference Difference and Ancestral Distance

	Dependent variable: Absolute difference in preference level						
	GPS	WVS	Ruggeri	INTRA	Maps Data	GLOBE	SWAP-Risk
Panel A: Risk							
Ancestral distance	0.24^{***}	0.10	0.00	0.13^{*}	0.05^{*}	0.06^{***}	0.13^{**}
	(0.09)	(0.07)	(0.05)	(0.07)	(0.03)	(0.01)	(0.05)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,701	1,653	1,653	1,326	435	1,596	6,105
R^2	0.63	0.48	0.52	0.66	0.58	0.46	0.60
	GPS	WVS	Ruggeri (S)	Ruggeri (C)	INTRA	GLOBE	SWAP-Time
Panel B: Patience							
Ancestral distance	0.06	0.27^{***}	0.24^{**}	0.23^{**}	0.09^{*}	0.04	0.12^{***}
	(0.04)	(0.07)	(0.10)	(0.10)	(0.05)	(0.04)	(0.04)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,701	1,653	1,653	1,653	1,326	1,596	6,105
R^2	0.53	0.59	0.32	0.45	0.72	0.46	0.45

Note: Ancestral distance is measured in terms of a composite index of ancestral genetic distance following Becker et al. (2020). The index is computed as unweighted average of the standardized values of two measures of genetic distance, see text. The index is standardized. Country fixed effects are included and standard errors are clustered for both countries separately.

We extend the analysis of Becker et al. (2020) across multiple datasets, using various preference measures and a larger set of countries. The variable of interest is a composite measure of ancestral genetic distance.[35] Table 4 replicates their findings, confirming that greater ancestral distance predicts larger absolute differences in average risk preferences between countries. In contrast to Becker et al. (2020), we find that the relationship is even stronger for patience. Notably, the synthetic datasets also show significant, quantitatively large associations with ancestral distance, suggesting preferences are deeply rooted in cultural differences and demonstrating the value of combining datasets for cross-validation.

5 Economic Preferences: Country-Level Correlates

In this section, we explore whether the preference measures obtained from different data sets as well as the synthetic global preference data set exhibit comparable correlations with country-level characteristics. This analysis provides several insights. First, it offers an additional way to validate whether the preference measures across different data sets capture comparable information. Second, it assesses whether the associations between different economic preferences and aggregate correlates found in the literature remain robust across different data sets, which are based on different measures and population samples. Strictly speaking, this analysis should be restricted to data sets with representative population samples. However, for completeness and comparability with previous studies that have used these preference measures as proxies for cultural variation across countries or populations, we also include data sets based on more selective samples, such as student samples.

We conduct the analysis for different dimensions of characteristics: income per capita and democracy as two measures that are frequently used in the literature to capture variation in socio-economic development and institutional quality, respectively. In addition, we present results for correlates that have been used in previous work on single data sets (see, e.g., Falk et al. 2018) so that the following analysis complements existing studies by providing a sense of the comparability of the results across preference measures from different data and of the systematic variation in preferences as a part of culture.

[35] In contrast to Becker et al. (2020), we only construct the index as the unweighted average of the standardized values of two measures of genetic distance (based on Spolaore and Wacziarg 2017), but not linguistic distance.

□ Stylized Fact 3: Preferences exhibit consistent cross-country correlations with socio-economic development.

5.1 Aggregate Correlates: Risk

Table 5 presents the results for the correlation between countries of various aggregate variables with measures of risk preferences from the different data sets. Each coefficient corresponds to a separate regression with the corresponding number of observations.

Estimates in the first column capture the relationship between risk preferences and GDP per capita as a measure of overall economic development. The results reveal a negative correlation of willingness to take risks and the level of development for all data sets. Moreover, the relation is not statistically significant for the GPS, Ruggeri and Maps data. At first sight, this finding appears surprising, as higher incomes are typically associated with a higher willingness to take risks at the level of individuals or households (see, e.g., Dohmen et al. 2011). However, this finding aligns with earlier results that have reported a similar unconditional association across countries (see, e.g., Falk et al. 2018). The literature also suggests a discrepancy in the association between risk preferences and income at the aggregate and household level: the relationship of risk tolerance with GDP is typically found to be negative, whereas the relationship with income within countries is positive (see Falk et al. 2018; Bouchouicha and Vieider 2019).

The results in the second column refer to the correlation of risk preferences with self-employment, measured in terms of the self-employment share in the working-age population. The decision to become self-employed is associated with more risky earnings than employed work, and thus constitutes a deliberately risky choice that has been shown to correlate with risk preferences in previous literature (see, e.g., Barsky et al. 1997; Dohmen et al. 2011). In fact, the results indicate that the cross-country correlation between the average willingness to take risks and self-employment across countries is positive. As with GDP per capita, the correlation is not statistically significant for the GPS, Ruggeri and Maps data.

The third set of results refers to the relation between country-level variation in risk preferences and country-level variation in expenditures for research and development (R&D), measured as share of GDP. The estimates reveal a negative correlation for preference measures from all data sets. While surprising at first sight, this correlation largely reflects the negative correlation with overall development as proxied by GDP per capita. The fourth column includes results for education.

The last set of results pertains to institutional quality, measured by an index of the quality of democratic institutions. Democracy has been used extensively as a proxy for inclusive institutions that are viewed as a determinant of economic development that is potentially even more fundamental than human capital (see, e.g., Acemoglu et al. 2014). Across all data sets except for the Maps data, a negative correlation with the democratic quality index is observed, but it is only significant for the Ruggeri and INTRA data.

Overall, the synthetic global measure of risk preferences (SWAP-Risk) captures these overall patterns and exhibits significant associations with all country-level covariates: negative with GDP per capita, R&D, the education level and democracy, and positive with the self-employment share. This illustrates its potential usefulness in providing a global measure of risk preferences with a broad coverage of countries. Moreover, this measure accounts for approximately 4–17 % of the cross-country variation in aggregate correlates, which is comparable to the variation accounted for by other measures of cultural heterogeneity used in previous work.[36]

5.2 Aggregate Correlates: Patience

Table 6 contains the corresponding results for patience. As before, the first column contains the results for GDP per capita as an overall measure of economic development. All data sets reveal a strong positive and (with the exception of the WVS) significant association between patience and GDP per capita. It should be noted, however, that a positive association might be the result of mechanisms that run both ways. On the one hand, patience induces greater incentives for investment, knowledge accumulation and other activities that are beneficial for economic development in the long-run (see, e.g., Sunde et al. 2022). On the other hand, a higher level of economic development and better living conditions might foster greater patience (see, e.g., Sunde et al. 2024). Again, the discrepancy in the pattern obtained with the WVS might be related to the measurement of patience, which might capture traditional education styles focusing on instilling conservative values to children, rather than individual patience.

[36]For instance, in analysis comparable to that in Table 5, the cross-country variation in GDP per capita explained by trust is 13-17% (using GPS or WVS measures of trust and the respective samples), 5% by individualism, 8.9% by religiosity, and 1.2% by a composite measure of civic values (all based on WVS measures).

The second column contains the results for the savings rate as a proxy for capital accumulation. The association is positive but weak for most data sets, with the GPS exhibiting the strongest association among all data sets. The third set of results refers to total factor productivity (TFP) whose association with patience is positive for measures from all data sets, with the exception of the WVS. The fourth column contains results for the correlation of time preferences with education, measured in terms of average years of schooling. Education can be seen as an alternative measure of overall economic development in light of the relevance of human capital for productivity and development (Diebolt and Hippe 2018; Sunde et al. 2022). The estimates reveal a positive and significant correlation between patience and education for all data sets. The last set of results for aggregate correlates refers to institutional quality, measured by an index of the quality of democratic institutions. The resulting pattern shows positive and significant associations, except for the WVS and the GLOBE data, for which the correlations are insignificant.

Taken together, these findings are largely consistent with earlier results of consistent patterns for data sets that have comparable measures of risk and time preferences, and diverging patterns for data sets with measures that are less closely linked to the underlying preference and thus less reliable. Specifically, it is notable how the patterns for time preferences obtained with the WVS deviate. This could reflect the fact that the measure of time preference in the WVS refers to respondents' assessment that "patient" behavior in specific domains is an important trait to be instilled in children, rather eliciting respondents' own patience. Similarly, the GLOBE data exhibit differing patterns while the responses reflect an assessment of middle managers about the cultural predispositions in the overall population, rather than the respondents' own traits.

Also here, the synthetic global measure of time preference (SWAP-Time) exhibits significant associations with all aggregate correlates, and thereby offers a useful complement to the individual data sets. Moreover, the explanatory power of this measure for variation in aggregate correlates is considerable, especially for GDP and education.[37]

Taken together, the aggregate results show that risk and time preferences constitute an important and behaviorally relevant part of a society's culture. Above and beyond other cultural

[37] In view of a recent literature on religious norms and modernization in sociology, additional results for an index of secular values show similar patterns. Specifically, the secularization index exhibits a mostly negative association with the willingness to take risks (except for a positive association in the data by Ruggeri et al. (2022)), and a positive association with patience.

markers, such as religion, values or social norms, economic preferences are systematically associated with central country-level outcomes and account for a similar or even larger fraction of the respective cross-country variation than other measures of cultural heterogeneity.

6 Economic Preferences: Individual-Level Correlates

6.1 General Patterns

In this section, we turn to the relationships of economic preferences to individual-level traits. Specifically, we focus on three dimensions of heterogeneity that have been found to correlate with individual preferences: gender, age, and socio-economic status (in terms of household income). Whereas gender and age are plausible drivers of preference heterogeneity at the individual level, the mechanisms behind the correlation between preferences and socio-economic status could potentially go both ways. In fact, existing evidence supports the notion of stable preferences and systematic heterogeneity along these dimensions (Sahm 2012; Schildberg-Hörisch 2018; Frey et al. 2017; Falk et al. 2021b). Moreover, while our analysis does not aim for causal statements, it builds on earlier research that has shown systematic heterogeneity in preferences along these dimensions (Dohmen et al. 2011; Falk et al. 2018; Frey et al. 2021).

Table 7 contains the results of regressions of measures of risk preferences in different data sets on a core set of individual characteristics—gender, age, and socio-economic status. The age profile is captured by a quadratic specification in light of previous evidence for non-linear age profiles (e.g., Dohmen et al. 2017). For each data set, we present the results for two specifications, without and with controls for socio-eocnomic status (income). All specifications account for country-specific differences in risk preferences in terms of country fixed effects.

A first insight from the results concerns the relative importance of within-country variation in risk preferences as compared to between-country variation. Estimates from specifications without controls other than country fixed effects reveal that systematic between-country variation only accounts for 10-15% of the total variation in risk preferences.[38] This finding, which is in line with earlier reports, suggests that a major part of variation in preferences is not accounted

[38]Specifically, the R^2 from the respective regressions of a specification with country fixed effects are 0.1 for the GPS, 0.11 for the WVS, 0.03 for the data by Ruggeri et al. (2022), 0.12 for the INTRA data, and 0.08 for the Maps data. The GLOBE data only contains observations at the country level.

for by systematic variation between populations of countries.

The estimation results for the individual characteristics show a consistent gender difference in risk preferences: Women are significantly less willing to take risks than men across all data sets. In terms of age profile, the estimates suggest a lower willingness to take risks at higher ages, although the age profiles are concave for some data sets, convex for others, and insignificant in the INTRA and Maps data. Finally, a higher income is associated with a greater willingness to take risks.

Table 8 contains the corresponding results for patience. Also in this preference domain, systematic variation between countries only accounts for a small fraction of the total variation.[39]

The estimation results for the individual characteristics reveal more heterogeneous patterns than for risk preferences. Specifically, women tend to be more impatient in the GPS data and in the data by Ruggeri et al. (2022), at least when the contrast in the baseline scenario is used to measure patience. The results for the combined measure reveal no significant gender difference, as do the results for the INTRA data. In contrast, the results obtained with the WVS data reveal a positive effect, suggesting greater patience among female respondents. The age patterns are similar across data sets and suggest a hump-shaped (concave) age profile, except for the WVS. Also, the effect for socio-economic status is different across data sets. These results provide further evidence for the sensitivity of the findings with respect to the specific preference measures contained in the surveys. The patience measure in the WVS consistently delivers different results from the patience measures in the other data sets.

[39] Specifically, between-country variation only accounts for 0.14 of the variation in the GPS data (in terms of an R^2), 0.11 in the WVS, 0.09 in the raw measure and 0.23 in the combined measure of the data by Ruggeri et al. (2022), and 0.21 in the INTRA data.

Table 5: Regression Coefficients for Aggregate Correlates: Risk

	Dependent variable:				
Risk measured in:	GDP per capita (in logs)	Self-employment share	R&D	Education (in years)	Institutions: Democracy
GPS	-0.581	12.175	-0.610	-0.570	-3.246
	(0.391)	(8.570)	(0.458)	(0.924)	(2.040)
Observations	75	76	51	72	74
R^2	0.029	0.027	0.035	0.005	0.034
WVS	-0.890**	19.656**	-1.058**	-2.154**	-1.912
	(0.387)	(9.303)	(0.482)	(1.050)	(2.735)
Observations	59	59	43	53	58
R^2	0.085	0.073	0.105	0.076	0.009
Ruggeri	-1.040	21.635	-0.944	-1.737	-14.030***
	(0.673)	(16.718)	(0.863)	(1.831)	(3.290)
Observations	61	61	49	54	60
R^2	0.039	0.028	0.025	0.017	0.239
INTRA	-1.118***	37.345***	-0.500	-2.395***	-5.128***
	(0.245)	(6.320)	(0.385)	(0.615)	(1.535)
Observations	53	52	43	47	51
R^2	0.289	0.411	0.040	0.252	0.186
Maps Data	-0.613	24.973	-1.984**	-1.003	1.822
	(0.679)	(16.904)	(0.733)	(1.826)	(4.120)
Observations	30	30	24	28	30
R^2	0.028	0.072	0.250	0.011	0.007
GLOBE	-0.403***	5.045*	-0.549***	-0.677**	-0.688
	(0.123)	(2.801)	(0.136)	(0.281)	(0.755)
Observations	57	56	44	55	56
R^2	0.164	0.057	0.279	0.099	0.015
SWAP-Risk	-0.305***	6.824***	-0.461***	-0.543**	-1.221**
	(0.097)	(2.151)	(0.115)	(0.244)	(0.560)
Observations	114	115	80	103	112
R^2	0.081	0.082	0.171	0.047	0.041

Note: Sources: Penn World Tables (GDP per capita), World Bank (self-employment, R&D), Barro-Lee Educational Attainment Data Set (average years of schooling), Polity V (democratic quality, polity2-index). All data is for the year 2010.

Table 6: Regression Coefficients for Aggregate Correlates: Time

	Dependent variable:				
Time measured in:	GDP per capita (in logs)	Savings Rate	TFP	Education (in years)	Institutions: Democracy
GPS	1.607***	0.053**	0.238***	3.599***	5.359***
	(0.271)	(0.021)	(0.058)	(0.633)	(1.608)
Observations	75	75	62	72	74
R^2		0.077	0.222	0.316	0.134
WVS	0.639	0.040	-0.144	2.405**	2.324
	(0.410)	(0.034)	(0.103)	(1.041)	(2.802)
Observations	59	59	48	53	58
R^2	0.041	0.023	0.041	0.095	0.012
Ruggeri (Single)	2.037***	0.041	0.230**	4.429***	6.431***
	(0.259)	(0.027)	(0.098)	(0.768)	(1.835)
Observations	61	61	51	54	60
R^2	0.512	0.038	0.102	0.390	0.175
Ruggeri (Combined)	1.414***	0.011	0.124*	3.292***	5.095***
	(0.169)	(0.019)	(0.068)	(0.487)	(1.182)
Observations	61	61	51	54	60
R^2	0.542	0.006	0.063	0.467	0.243
INTRA	0.840***	0.041**	0.320***	1.761***	3.004**
	(0.167)	(0.016)	(0.064)	(0.646)	(1.144)
Observations	53	53	48	47	51
R^2	0.332	0.122	0.353	0.142	0.123
GLOBE	0.321**	0.020**	0.046	0.754***	0.966
	(0.127)	(0.009)	(0.029)	(0.277)	(0.750)
Observations	57	57	54	55	56
R^2	0.104	0.089	0.045	0.123	0.030
SWAP-Time	0.606***	0.019***	0.086***	1.441***	1.803***
	(0.083)	(0.007)	(0.021)	(0.200)	(0.545)
Observations	114	114	89	103	112
R^2	0.322	0.068	0.156	0.341	0.091

Note: Sources: Penn World Tables (GDP per capita, savings, TFP), Barro-Lee Educational Attainment Data Set (average years of schooling), Polity V (democratic quality, polity2-index). All data is for the year 2010.

Table 7: Individual-Level Correlates: Risk

	GPS		WVS		Ruggeri		INTRA	Maps Data	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 if female	-0.205***	-0.199***	-0.216***	-0.212***	-0.161***	-0.160***	-0.249***	-0.138***	-0.140***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)	(0.040)	(0.039)	(0.041)
Age	-0.001	-0.002	-0.025***	-0.024***	-0.017***	-0.018***	0.003	-0.020	-0.022
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)	(0.032)	(0.026)	(0.026)
$(\text{Age})^2/100$	-0.012***	-0.011***	0.014***	0.014***	0.012**	0.013**	-0.001	0.047	0.047
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.005)	(0.055)	(0.042)	(0.041)
Income (in logs)		0.067***		0.312***		0.024			0.177***
		(0.008)		(0.043)		(0.015)			(0.054)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79,439	79,439	86,220	83,504	13,269	13,267	6,367	2,939	2,675
R^2	0.15	0.16	0.16	0.16	0.05	0.05	0.13	0.09	0.09

Note: Standard errors are clustered at the country level.

Table 8: Individual-Level Correlates: Patience

	GPS		WVS		Ruggeri (Single)		Ruggeri (Combined)		INTRA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 if female	-0.074***	-0.070***	0.039***	0.036***	-0.139***	-0.140***	0.013	0.012	0.013
	(0.013)	(0.013)	(0.012)	(0.011)	(0.028)	(0.028)	(0.019)	(0.019)	(0.023)
Age	0.007***	0.006***	0.004**	0.004**	0.019***	0.020***	0.002	0.003	0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.005)	(0.005)	(0.019)
$(Age)^2/100$	-0.015***	-0.014***	0.001	0.000	-0.022***	-0.022***	-0.006	-0.006	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.006)	(0.006)	(0.026)
Income (in logs)		0.046***		-0.095**		-0.015		-0.015	
		(0.009)		(0.037)		(0.013)		(0.013)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79,472	79,472	89,319	86,149	13,269	13,267	13,237	13,235	6,364
R^2	0.16	0.16	0.12	0.12	0.10	0.10	0.23	0.23	0.22

Note: Standard errors are clustered at the country level.

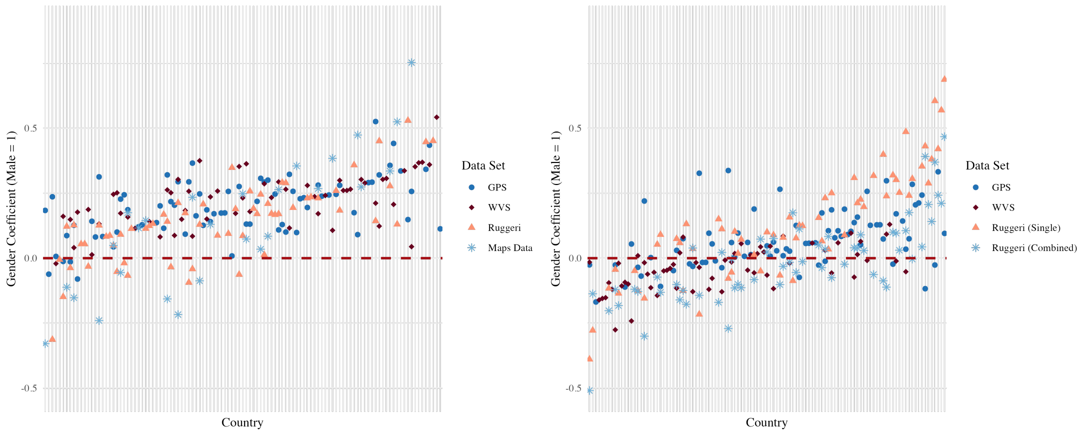
6.2 Gender Differences Across Countries

To investigate the universality of these findings, we consider whether and to what extent these patterns hold in the different countries contained in the respective data sets. As a first dimension, we consider the differences in preferences between women and men.

□ Stylized Fact 4: Preferences exhibit consistent patterns of differences between women and men.

The literature has documented consistent differences in the willingness to take risks between women and men, with women typically being found to be less willing to take risks than men. This perception is based on survey evidence for gender differences in risk (Charness and Gneezy 2012) and evidence in psychology (see, e.g., Byrnes et al. 1999, for a meta study that reports evidence for women being more risk averse). These gender differences are present in many countries, comprising both patriarchal and matriarchal societies (Gneezy et al. 2009; Falk et al. 2018) and seem to become visible around puberty (Khachatryan et al. 2015). More recent evidence suggests that above and beyond mean differences in preferences between women and men, men exhibit greater variability (Thoeni and Volk 2021). In addition, gender differences in risk (and other) preferences have been shown to decline with the level of economic development and gender equality (Falk and Hermle 2018). Recent work suggests that this association, sometimes referred to as gender equality paradox, is accounted for by systematic cultural variation across countries (Berggren and Bergh 2025).

Figure 6(a) plots the results for gender differences in terms of the coefficients for gender from regressions of individual responses to the question about the willingness to take risks on gender, age, and household income. The regressions allow for country-specific gender coefficients, but hold the age and income coefficients constant across countries and include country-specific intercepts. The results reveal almost exclusively positive coefficient estimates, indicating that in almost all countries and across all data sets, men are more willing to take risks than women, thus generalizing the results from Table 7. Specifically, the coefficient estimates are negative (i.e., women are more willing to take risks then men) in 4 out of 76 countries in the GPS data, only in one (out of 60) countries in the WVS, in 12 out of 61 countries in the data by Ruggeri et al. (2022), and eight out of 27 countries in the Maps data.



(a) Risk

(b) Time

Figure 6: Gender Differences

Note: This figure plots gender differences in preferences across countries for each data set. Positive values indicate that men are more risk-loving/patient than women.

Existing evidence is less conclusive when it comes to gender differences in time preferences. According to earlier meta-studies on the relation between time preference (delay of gratification) and gender, women are more patient (Silverman 2003), whereas more recent evidence appears to find the opposite (Falk et al. 2018; Falk and Hermle 2018).

The results depicted in Figure 6(b) are consistent with this (mixed) evidence. In a majority of countries and data sets, men appear to be more patient than women, although the opposite is found for a considerable set of countries and data sets, complementing the estimates shown in Table 8. Importantly, these patterns do not appear to be driven by specific data sets or questions.

Another pattern that has gained attention in the recent literature is the extent to which gender differences in preferences vary by the level of economic development. Evidence suggests that gender differences in preferences are greater in economically more developed and more gender equal countries (Falk and Hermle 2018; Cuevas et al. 2021). Replicating this analysis by relating the country-specific gender coefficients for risk and time preferences for the different data sets (as in Figure 6) to GDP per capita delivers a similar pattern: on average, gender differences are more pronounced in richer countries (see Appendix Figure A8). In fact, the estimated slope coefficients for the large and representative data sets (GPS and WVS) are quantitatively very similar, while the relation is less pronounced in the samples with convenience and student samples.

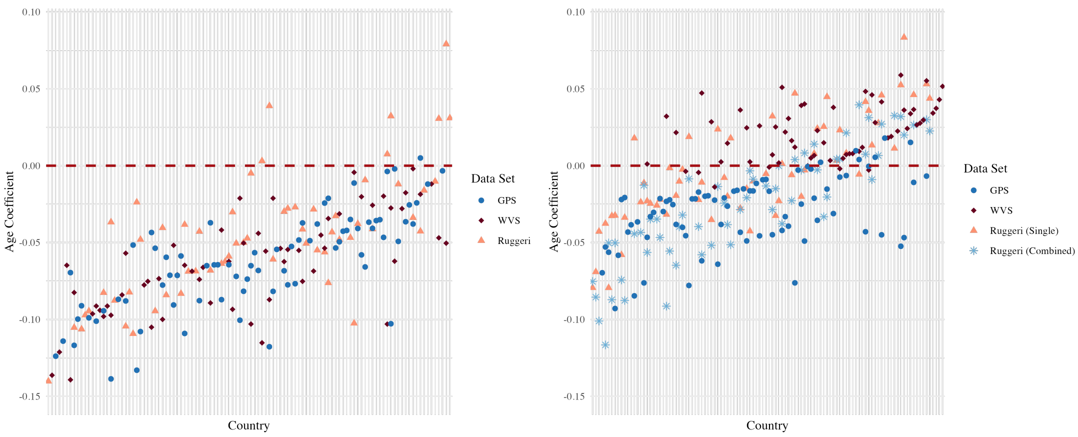
6.3 Differences by Age

The second dimension of individual heterogeneity in economic preferences we study is age. Here, we investigate the universality of heterogeneity in preferences across age groups.

☐ Stylized Fact 5: Preferences show systematic heterogeneity across age groups.

Conceptually, one might think of different reasons for expecting risk preferences and time preferences to be correlated with age. These include life-time experiences (Kettlewell 2019), cohort differences (Dohmen et al. 2017), as well as variation in the prospective length of life (Sunde et al. 2024). Existing evidence has found a declining propensity to take risks at higher ages (Dohmen et al. 2011; Mata et al. 2011; Josef et al. 2016; Mata et al. 2016; Dohmen et al. 2017; Fitzenberger et al. 2022).

In line with existing evidence, Table 7 shows a negative age gradient in the willingness to take risks. This gradient is close to linear and universal across all data sets. The regression results are robust to more flexible specifications of the age profile. Specifically, the results are similar in terms of the coefficients for age bins in regressions that also control for gender, household income, and country-specific intercepts.[40] The only exceptions are outliers for some age bins in data sets with non-representative samples (INTRA and Maps).



(a) Risk (b) Time

Figure 7: Age Coefficients

Note: This figure plots the age coefficients for the different of countries for the different preferences and datasets. To obtain the age group coefficients, gender, income and country fixed effects are included in the model.

[40]See Appendix Figure A9.

Figure 7 reports the corresponding results for country-specific age patterns (based on five-year age groups) in regressions of risk preferences and time preferences on gender, income, and country fixed effects. As for the gender differences, this analysis sheds light on the universality of age patterns across countries. Overall, the majority of age coefficients on risk preferences is negative (189 out of 197 coefficient estimates), indicating that the willingness to take risks declines with age in almost all countries and data sets. [41] While the estimates in Table 7 suggest a hump-shaped age pattern in patience on average, the picture for country-specific linear age patterns for patience is less uniform, with 157 out of 258 coefficients being negative and a greater discrepancy in the estimates across data sets.[42] Moreover, there is greater variability at higher ages across data sets.[43] Patience declines monotonically with age in the GPS, stays almost constant across age groups in the data by Ruggeri et al. (2022), and increases with age in the WVS. Again, this might be related to the measure for patience elicitiation in the WVS, which might reflect parenting style and altruistic values, rather than individual time preferences. The other data exhibit less coherent patterns and more variability across age groups.

Moreover, these overall age patterns exhibit moderate heterogeneity. For instance, the gender differences are fairly comparable across age groups.[44] At the same time, the differences across age groups exhibit some visible differences between women and men. In particular, the age profiles for women are less pronounced than those for men.[45]

6.4 Differences by Socioeconomic Status

The third dimension of preference heterogeneity is socio-economic status, as reflected by individual income.

- ☐ Stylized Fact 6: Preferences exhibit consistent correlations with socioeconomic status at the individual level.

To explore preference heterogeneity in this dimension, we present the coefficient estimates for income bins (in terms of country-specific income deciles) from regressions of individual

[41] The Ruggeri data data exhibit positive age coefficients for 7 countries and negative coefficients for 54 countries. The corresponding numbers are 1 vs. 75 in the GPS, and exclusively negative coefficients in the WVS data.

[42] In particular, while only 6 out of 76 countries exhibit a positive age coefficient in the GPS data, the corresponding number for the WVS data is 53 out of 60.

[43] See Appendix Figure A9.

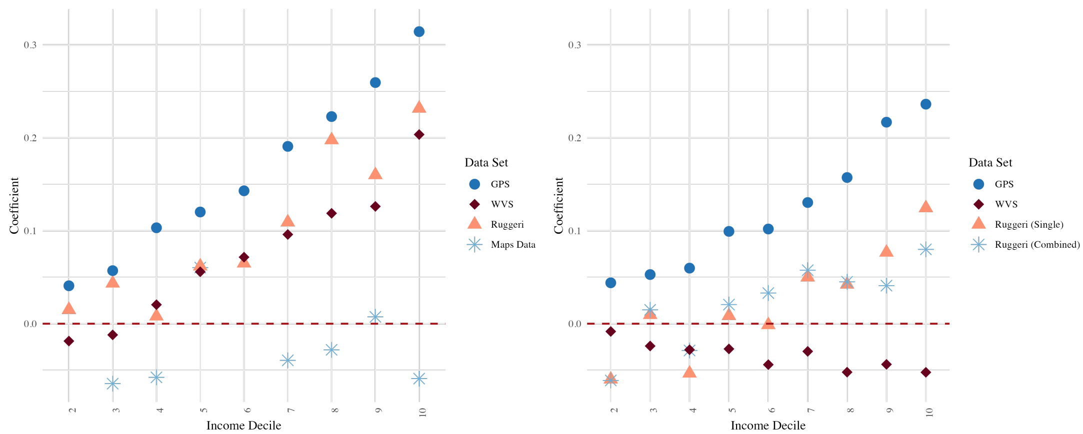
[44] See Appendix Figure A10.

[45] See Appendix Figures A11 and A12.

responses to the question about the willingness to take risks (or patience), with additional controls for gender, age bins, and country-specific intercepts.

Figure 8(a) presents the corresponding results for the willingness to take risks. Consistent with the estimates in Table 7, the results when allowing for country-specific associations reveal an almost uniformly positive income gradient: individuals in higher income groups are more willing to take risks. This pattern is consistent with, and generalizes, earlier findings in the literature (see, e.g. Dohmen et al. 2011; Falk et al. 2018; Bouchouicha and Vieider 2019).

A similar pattern is found for patience, as indicated by the results of a positive income gradient shown in Figure 8(b) for the GPS data and the data by Ruggeri et al. (2022). Again, the WVS data on patience reveal the opposite pattern, which is presumably due to the measure for patience, complementing the findings of Table 8.



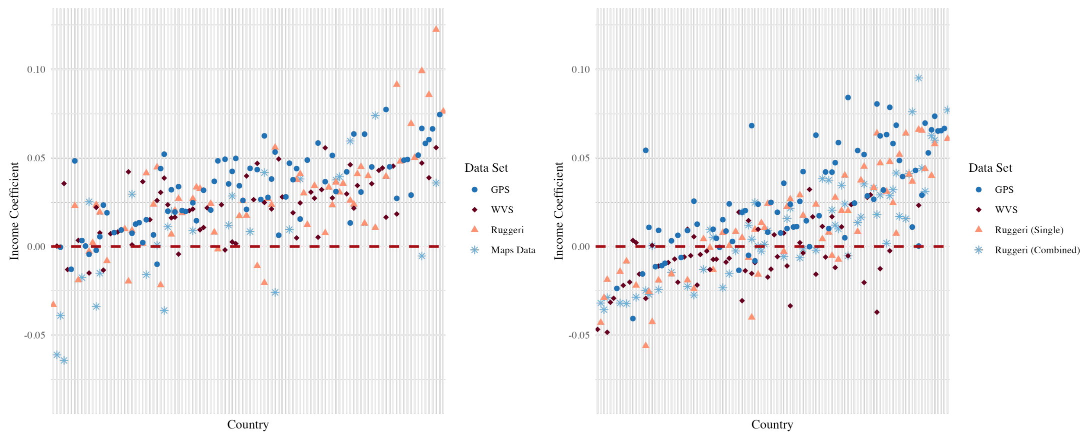
(a) Risk (b) Time

Figure 8: Differences by Socioeconomic Status: Income Deciles
Note: This figure plots the coefficients of income deciles for the different preferences and datasets. To obtain the income coefficients, gender, age group, and country fixed effects are included in the model. Coefficients are measured relative to income decile 1.

To explore the universality of these patterns across countries, Figure 9 plots the country-specific slope coefficients for income in regressions that account for gender and age, as in the previous estimates. The results reveal that individual income and willingness to take risks exhibit a positive association in a large majority of country observations (195 out of 225 coefficient estimates are positive). These patterns are even more pronounced for the data sets based on representative samples.[46]

[46]The income coefficients are positive in 71 of 76 countries in the GPS data, in 55 of 60 countries in the WVS, and in 52 of 61 countries in the Ruggeri data. In contrast, in the Maps data, which is mostly based on a sample of

A similar pattern emerges for the association between income and patience, although the pattern is slightly more mixed (163 out of 258 coefficient estimates are positive). A closer look reveals, however, that this discrepancy can be mostly explained by different findings in the WVS data with the patience measure that refers to patience as a desirable trait for children rather than individual patience.[47]



(a) Risk

(b) Time

Figure 9: Income Decile Coefficients

Note: This figure plots the income decile coefficients for the different of countries for the different preferences and datasets. To obtain the income decile coefficients, gender, age group, and country fixed effects are included in the model.

Also correlations of economic preferences with individual income exhibit only moderate heterogeneity. Specifically, the patterns are very similar regardless of whether considering the entire sample of countries, or when restricting attention to high-income and low-income countries, respectively.[48]

7 Extending the Scope: Global Variation in Other Preferences

The main focus of this article is on risk and time preferences. There are, however, also large, international data sets that cover other types of preferences, in particular social preferences. In the following, we discuss a few examples. We note that, unlike time and risk preferences, there is

students, only 17 of 28 coefficients are positive.

[47]The GPS data exhibits positive coefficients in 64 out of 76 countries, and the Ruggeri data exhibit positive coefficients in 40 (39) of 61 countries for the basic (combined) measure of time preference, whereas the WVS only delivers positive income coefficients in 20 out of 60 countries.

[48]For details, see Appendix Figures A13 and A14.

little overlap in the specific notion of the respective preference measures, rendering a comparison between data sets difficult.

The GPS contains three measures of social preferences, together with a measure of trust (see Falk et al. 2018). The preference measures assess three important facets of social preferences, altruism, positive reciprocity and negative reciprocity, respectively. Altruism is measured with the help of two items. The first is the self-reported willingness to donate to a charity, in terms of the amount individuals would donate in case they won the equivalent of 1,000 Euros in a lottery. The second measures the self-assessed willingness to share with others without expecting anything in return (measured on a Likert scale from 0 to 10). Positive reciprocity is based on responses to two items as well. A qualitative item asks whether a respondent is willing to return a favor on an 11-point Likert scale. A quantitative item elicits willingness to reciprocate a favor, where the reward varies according to six levels of values. Negative reciprocity is measured with the help of three survey items, the individual willingness to take revenge when treated unjustly, even at a cost, willingness to punish unfair behavior toward themselves or toward a third party (all measured on a Likert scale). As shown in Falk et al. (2018), altruism, positive reciprocity and trust are significantly positively correlated. All preference measures also show significant variation between countries and vary systematically with important economic and social outcomes, both at the individual and the country-level. At the individual level, for example, altruism correlates well with individual willingness to donate money, volunteer time or help a stranger, while positive reciprocity is positively associated with having friends one can count on or being in a relationship. At the country-level, negative reciprocity is, for example, correlated with conflict and a "culture of honor" as shown in detail in Cao et al. (2021).

The World Values Survey (WVS) also contains a measure related to notions of altruism. It refers to the agreement as to whether or not it is important to teach children that being selfish (or unselfish) is important. The WVS and the GPS measures have an overlap of 36 countries and display a weak positive rank order correlation of 0.09. In terms of rank stability within data sets, the pattern for altruism is similar to that for risk and time preferences. Specifically, for both WVS and GPS resampling appears to have a minor impact on the ranking of countries in the different data sets. In addition, for both WVS and GPS, women tend to be more altruistic than men in most countries, and age as well as income have a positive effect on observed altruism.

Another international data set on prosocial preferences is Cohn et al. (2019) who use a “wallet experiment” design. Specifically, research assistants deposited more than 17,000 wallets at different places (such as museums or post offices) in 355 cities across 40 countries. Each wallet contained a business card of the presumed “owner” and varying amounts of money. The rate at which the “owner” of a wallet was contacted serves as a measure of “civic honesty”. The authors report relatively high levels of civic honesty across countries. Moreover, the likelihood to return a wallet typically increases in the amount of money contained in the wallet, a finding they interpret as an expression of altruism in combination with image concerns. On measures of civic capital, see also Guiso et al. (2011).

A different approach is taken by Rhoads et al. (2021). They provide a country-level measure of altruism building on responses to seven different dimensions of altruistic behaviors. These involve, e.g., charitable donations, volunteering time, helping strangers, or willingness to donate blood or a kidney. Depending on data availability, responses for the different questions are available for different sets of countries (from 48 to 152 countries). The country-level altruism measure is computed as the average response to these items, which come from various data sets. The measure is positively associated with population-level subjective well-being and individualist values.

Recent work by Cappelen et al. (2025) provides global evidence regarding relationship-specific nature of altruism. The degree of universalist preferences reflects whether altruism depends on the identity or group membership of other persons. They survey 64,000 individuals in 60 countries around the world and find that universalism is associated with a broader radius of trust. Based on a similar sample, Almas et al. (2025) investigate the global distribution of fairness preferences that relate to the acceptance of inequality depending on the source of this inequality. Their findings report evidence on the global distribution of fairness preferences, efficiency preferences, beliefs about the source of inequality and the cost of redistribution, as well as preferences for redistribution.

Another publicly available data set that measures an important prosocial preferences is Andre et al. (2024) who study the willingness to fight climate change, in a globally representative sample. Their data is based on 125 representative country samples with almost 130,000 respondents, representing 96 percent of the world’s gross domestic product and 92 percent of the global population. They find widespread support for climate action with 69 percent of the global population expressing a willingness to contribute 1 percent of their monthly household income, 86 percent endorsing pro-climate social norms and 89 percent demanding intensified political action. A related research question has been addressed by Dechezleprêtre et al. (2025) in a sample of 40,000 respondents in 20 countries.

More systematic research on global prosocial preferences with comparable measures constitutes an interesting avenue for future research.

8 Concluding Remarks and Outlook

This chapter has reviewed the existing evidence on global variation in economic preferences. After a brief and selective overview of available data sets and measures of risk and time preferences across the globe, we documented six empirical regularities that emerge robustly across different data sources.

First, economic preferences exhibit substantial variation across the globe. While some of this variation stems from differences in measurement and, to a lesser extent, sample composition, the overall distribution of global preferences is fairly comparable across representative population studies using reliable measures.

Second, the stability of country rankings in economic preferences depends on measurement. Our analysis of rank stability across data sets shows that preference rankings are more consistent for measures that ask individuals about their own preference, and in data sets with representative respondent samples.

Third, economic preferences exhibit consistent systematic correlations with country-level factors. Specifically, the average willingness to take risks is lower in richer countries, while the average level of patience tends to be higher. The same pattern emerges for average levels of education and institutional quality, as proxied by democracy. These patterns are replicated with synthetic global preference measures that combine the various measures from all available data sets. Moreover, greater ancestral distance is associated with larger differences in preferences across countries.

The remaining stylized facts refer to individual-level correlates. Our fourth fact states that economic preferences differ systematically between women and men. On average, women are less willing to take risks and show lower levels of patience. This gender difference is found in the majority of countries. Fifth, economic preferences vary with age. Willingness to take risks declines with age, while patience follows a less clear pattern. Sixth, preferences correlate with socioeconomic status at the individual level. Specifically, individuals in higher country-specific income deciles are more willing to take risks and more patient.

The goal of this chapter was to take stock of how data on the global variation in risk and time preferences has advanced our understanding of patterns of global variation and heterogeneity in the domains of risk and time preferences, rather than delivering results on a specific issue. In fact, many aspects of the risk and time preference variation are not well understood and give rise to a wide range of future research questions.

For example, we are just beginning to understand better the ultimate and proximate forces shaping the global variation in risk and time preferences. Exceptions include, e.g., the work by Galor and Özak (2016) and Galor and Savitskiy (2018) that illustrates the role of ancestral climatic and environmental conditions in shaping risk and time preferences, the work by Chen (2013) that provides evidence for coevolutionary processes between language and preferences, and work by Becker et al. (2020) that shows that differences in preferences across populations are rooted in temporally distant migration movements.

Similarly, important knowledge gaps remain about population level changes in risk and time preferences over time. A natural next step to the efforts in collecting global data on these preferences is to continue the systematic data collection on a regular basis. This would provide the basis for knowing the instances of population level changes in preferences, the time scale at which they take place, and promises to shed light on the sources and drivers of such population level changes. Previous research on drivers of changes in preferences over time has shown, e.g., that exposure to natural disasters or macroeconomic shocks affects people's willingness to take risks (Hanaoka et al. 2018; Bernile et al. 2017; Malmendier and Nagel 2011; Giuliano and Spilimbergo 2024; Schildberg-Hörisch 2018) and people's willingness to trade off present day against future rewards (Akesaka 2019; Callen 2015). Open questions pertain to, e.g., the persistence of such effects, their universality and their heterogeneity with regards to population specific characteristics, particular environments, or institutions.

Finally, extending to global survey data more generally, we have yet to study and understand the relationship between 'culture' and survey methods. For example, we do not know whether people's willingness to select into surveys depends on their culture. Likewise, we have little knowledge about whether responses are biased 'culturally' or how the survey methodology, e.g., phone interviews versus in person interviews, interacts with cultural norms and values. And, if so, what does this mean for interpreting data on the global variation in preferences, beliefs and attitudes?

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Supplementary Appendix
The Global Variation in Risk and Time Preferences*

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Abstract

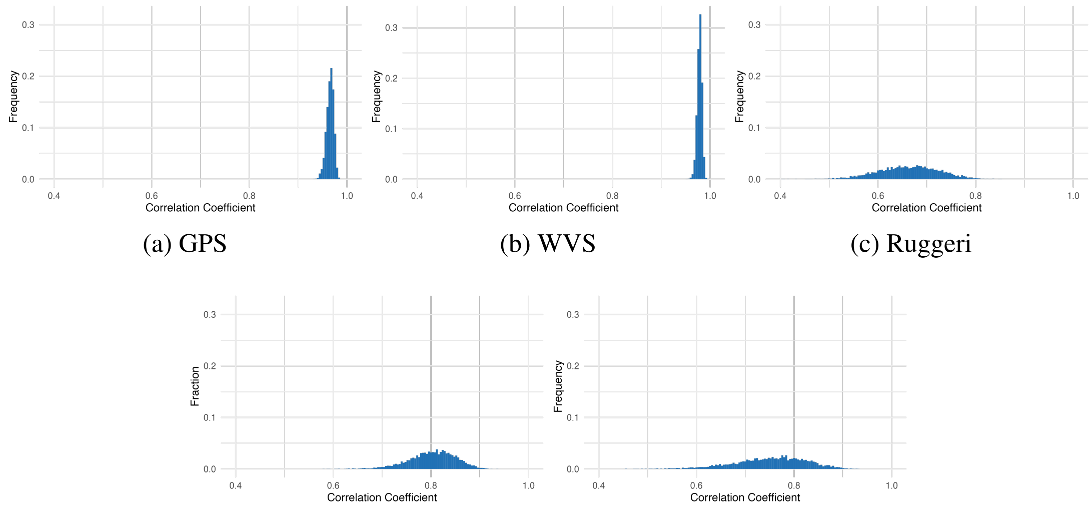
This Supplementary Appendix contains additional information, tables and figures referenced in the chapter. These include, in particular, additional results about rank consistency, consistency between data sets, details of the construction of the Synthetic World Aggregate Preferences, and results for heterogeneity in individual-level correlates.

*Supplement to Chapter of the *Handbook of Culture and Economic Behavior*.
The authors are grateful to Elisa Winter and Fedor Shafranov for outstanding research assistance.

Contents

A Appendix: Additional Results

A.1 Rank Consistency to Re-Sampling Within Data Sets

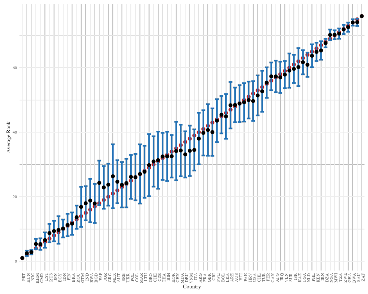


(a) GPS (b) WVS (c) Ruggeri

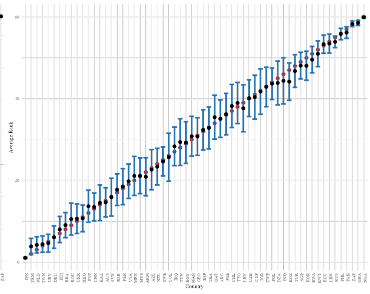
(d) INTRA (e) Maps Data

Figure A1: Rank-Order Stability with Re-Sampling: Correlation Coefficients for Risk Preferences

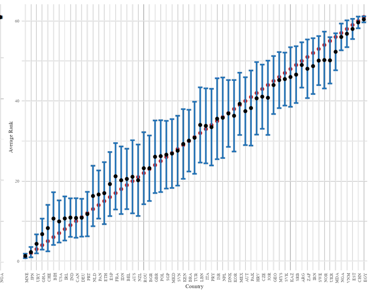
The figures plot the distribution of rank correlation coefficients across countries for risk preferences based on subsamples of 30% of the respective country samples for each data set. In total, each distribution is based on all possible pairs from 100 draws.



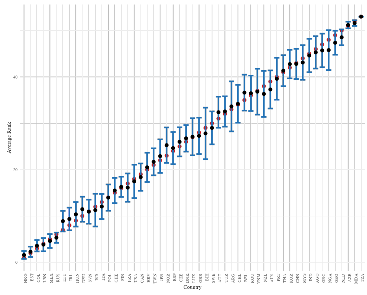
(a) GPS



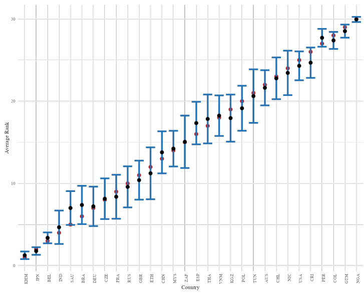
(b) WVS



(c) Ruggeri



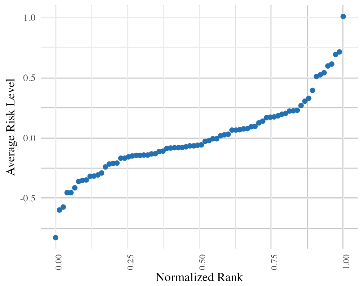
(d) INTRA



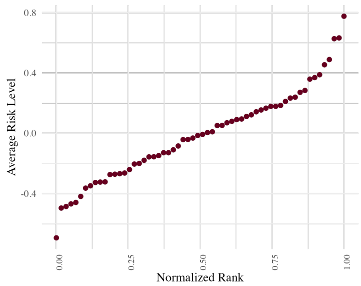
(e) Maps Data

Figure A2: Rank Consistency: Risk

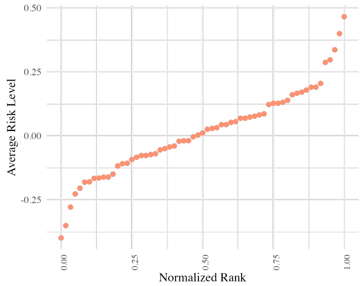
Note: The plot shows average ranks and standard deviations for 100 iterations of taking a subsample of 200 observations by country. The red dots represent the actual rank of the entire sample, and the countries are arranged in ascending order of the actual ranks.



(a) GPS



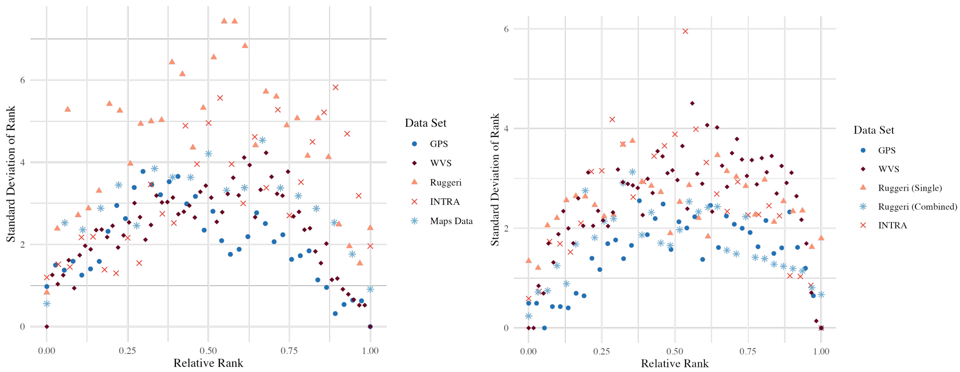
(b) WVS



(c) Ruggeri

Figure A3: Rank Consistency: Risk (Normalized)

Note: The plot shows average level of risk preferences by the rank of each country in terms of average risk preference in the respective data set. Countries are arranged in ascending order of the ranks normed to lie between 0 and 1.

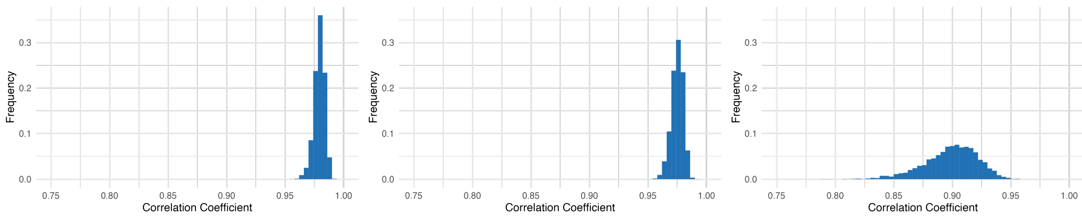


(a) Risk

(b) Time

Figure A4: Standard Deviations Ordered According to Individual Rank

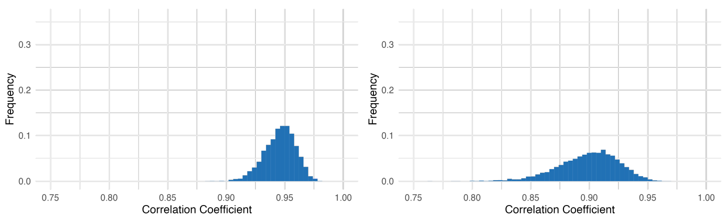
Note: Standard deviations for the 100 iterations by country and by data set in ascending order of average rank for each dataset. Ranks are displayed uniformly on a 0 to 1 scale.



(a) GPS

(b) WVS

(c) Ruggeri (Single)

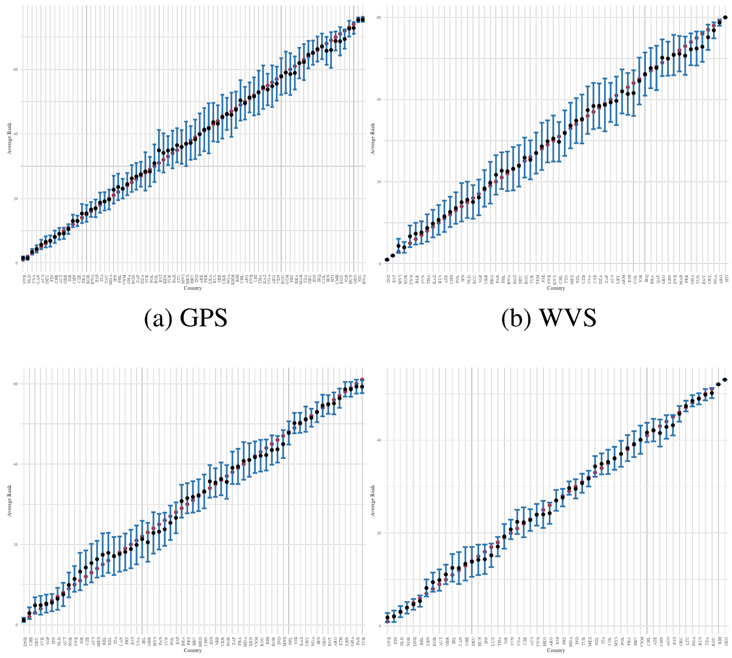


(d) Ruggeri (Combined)

(e) INTRA

Figure A5: Rank-Order Stability with Re-Sampling: Correlation Coefficients for Time Preferences

The figures plot the distribution of rank correlation coefficients across countries for time preferences based on subsamples of 30% of the respective country samples for each data set. In total, each distribution is based on all possible pairs from 100 draws.

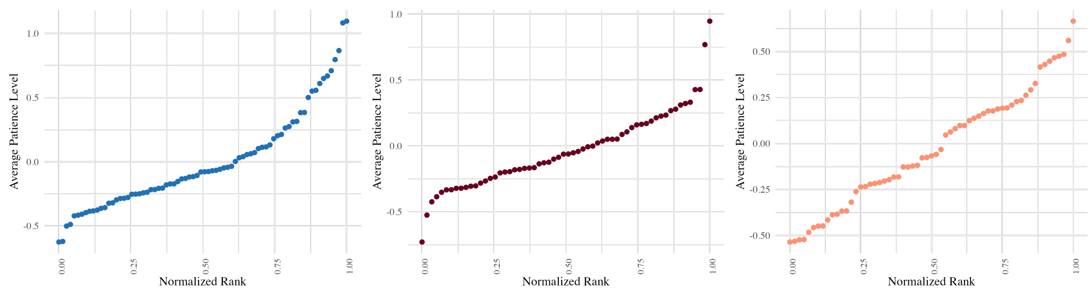


(a) GPS (b) WVS

(c) Ruggeri (d) INTRA

Figure A6: Rank Consistency: Time

Note: The plot shows average ranks and standard deviations for 100 iterations of taking a subsample of 200 observations by country. The red dots represent the actual rank of the entire sample, and the countries are arranged in ascending order of the actual ranks.



(a) GPS (b) WVS (c) Ruggeri

Figure A7: Rank Consistency: Time (Normalized)

Note: The plot shows average level of time preferences by the rank of each country in terms of average time preference in the respective data set. Countries are arranged in ascending order of the ranks normed to lie between 0 and 1.

A.2 Consistency Between Data Sets

Table A1: Correlation matrix between data sets: Risk restricted sample

	GPS	WVS	Ruggeri	INTRA	Maps Data	GLOBE
GPS	-	0.36	0.17	0.13	0.28	-0.22
WVS	38	-	0.03	0.01	0.36	0.08
Ruggeri	43	32	-	0.15	0.38	0.24
INTRA	40	29	39	-	0.05	-0.14
Maps Data	25	19	18	19	-	0.24
GLOBE	42	33	35	37	18	-
Relative overall	1.00	1.01	1.22	0.30	1.08	0.04
Relative overall (excluding GLOBE)	1.00	0.65	0.63	0.37	0.65	

Note: Rank correlations are taken of all common countries between two data sets (risk). Top right are Spearman correlation coefficients, bottom left are number of intersecting countries between the data sets. Individual observations only include individuals from ages 18 to 30.

Table A2: Correlation matrix between data sets: Patience restricted sample

	GPS	WVS	Ruggeri (Single)	Ruggeri (Combined)	INTRA	GLOBE
GPS	-	0.28	0.72	0.69	0.70	0.55
WVS	38	-	0.31	0.31	-0.03	0.26
Ruggeri (Single)	43	32	-	0.91	0.52	0.43
Ruggeri (Combined)	43	32	61	-	0.56	0.43
INTRA	40	29	39	39	-	0.58
GLOBE	42	33	35	35	37	-
Relative overall (S)	1.00	0.30	0.83		0.74	0.73
Relative overall (C)	1.00	0.31		0.84	0.77	0.75

Note: Rank correlations are taken of all common countries between two data sets (patience). Top right are Spearman correlation coefficients, bottom left are number of intersecting countries between the data sets. Sums are taken by excluding one of the Ruggeri measures: (S) considers only the single measure, while in (C) only uses the value of the combined measure. Individual observations only include individuals from ages 18 to 30.

A.3 Synthetic World Aggregate Preferences: By Country

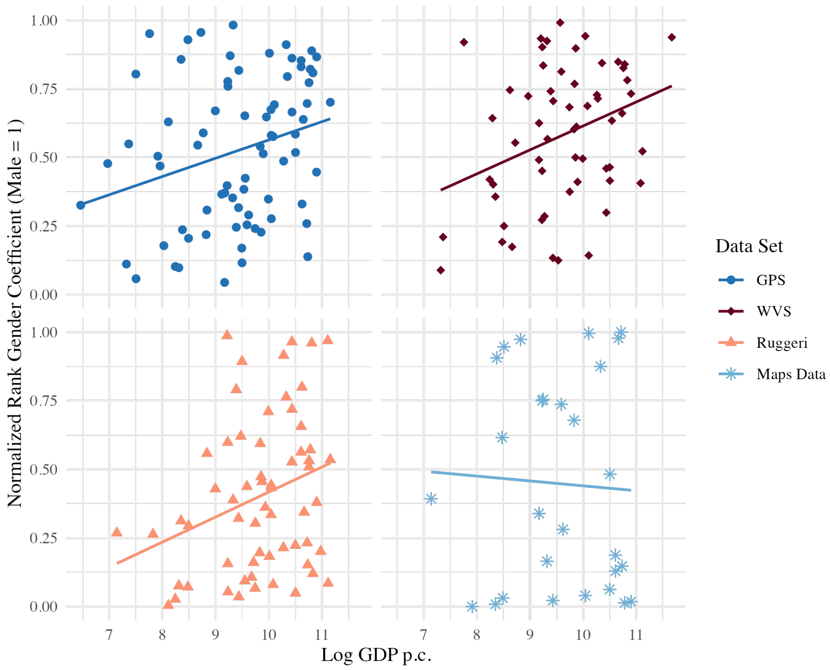
Table A3: Synthetic World Aggregate Preferences

Country	Risk (SWAP)	Time (SWAP)	Country	Risk (SWAP)	Time (SWAP)
AFG	0.655	-0.574	GHA	1.133	-0.874
AGO	1.110	-0.661	GRC	0.673	-1.035
ALB	-1.085	0.274	GTM	0.972	-1.172
ARE	0.215	-0.230	HKG	-1.386	0.673
ARG	0.473	-1.166	HRV	0.036	-0.184
ARM	-0.633	-0.591	HTI	-0.718	-2.042
AUS	-0.184	1.006	HUN	-0.524	-0.718
AUT	-0.601	1.817	IDN	-0.757	-0.356
AZE	0.779	0.290	IND	-0.344	0.934
BEL	-0.711	1.278	IRL	-1.061	0.845
BGD	-0.909	0.382	IRN	1.142	-0.950
BGR	-0.524	-0.279	IRQ	0.217	-0.997
BIH	-0.659	-1.290	ISR	-0.002	1.077
BLR	-0.873	1.715	ITA	-0.156	0.081
BOL	0.857	-0.136	JOR	0.153	-1.135
BRA	-0.601	-0.363	JPN	-1.734	1.268
BWA	2.792	1.079	KAZ	0.347	-0.318
CAN	-0.626	1.725	KEN	0.505	-0.307
CHE	-1.453	2.186	KGZ	0.506	0.445
CHL	0.435	-0.399	KHM	-2.435	-0.455
CHN	0.021	0.374	KOR	0.609	0.857
CMR	-1.917	-1.265	KWT	0.526	-0.760
COL	0.016	-0.872	LBN	-0.055	-0.589
CRI	0.558	-0.530	LBY	0.407	-0.529
CYP	0.525	-0.455	LKA	0.074	-0.270
CZE	-0.349	0.754	LTU	-0.914	-0.652
DEU	-1.138	1.580	LUX	-0.115	1.000
DNK	-0.767	2.200	MAR	0.102	-1.188
DZA	1.143	-0.044	MDA	1.192	0.132
ECU	1.252	0.429	MEX	-0.604	0.253
EGY	0.475	-0.969	MKD	-0.288	-0.063
ESP	-0.218	0.126	MNE	-3.208	-0.839
EST	-0.657	0.920	MWI	2.097	-0.103
ETH	-0.739	-1.761	MYS	-0.127	1.221
FIN	-1.404	1.833	NAM	-0.247	-0.768
FRA	-0.673	-0.120	NGA	1.934	-0.759
GBR	-0.504	1.361	NIC	-0.640	-1.994
GEO	0.582	-2.209	NLD	-0.434	2.244

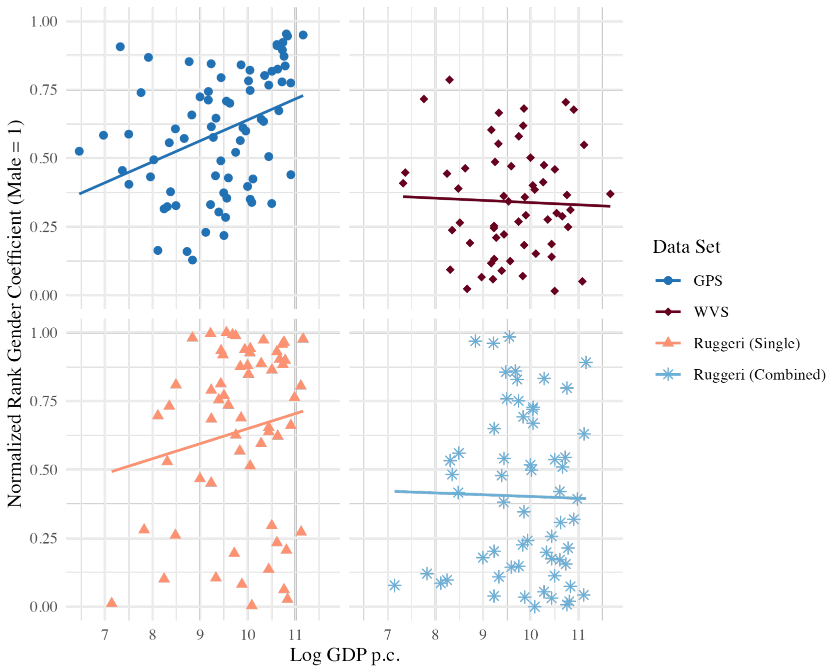
Country	Risk (SynGPR)	Time (SynGPT)
NOR	0.513	1.611
NPL	0.199	-1.078
NZL	-0.540	-0.031
PAK	0.967	-0.556
PAN	-0.979	0.661
PER	0.467	-0.678
PHL	1.185	0.733
POL	0.018	-0.080
PRT	-0.901	0.089
PRY	0.106	0.007
PSE	0.300	0.093
QAT	0.229	-0.431
ROU	-0.686	-0.748
RUS	0.054	-0.817
RWA	0.184	-0.833
SAU	0.761	0.836
SGP	-0.603	2.345
SLV	1.073	0.116
SRB	0.152	-0.289
SUR	0.757	0.274
SVK	0.837	2.234
SVN	-0.468	0.586
SWE	-0.385	1.838
THA	0.216	0.155
TTO	0.390	-0.105
TUN	0.180	-1.208
TUR	0.516	-0.360
TWN	-1.028	0.945
TZA	3.836	-1.306
UGA	0.872	-0.718
UKR	-0.265	-0.003
URY	-2.116	-1.392
USA	-0.293	1.136
UZB	0.479	-0.291
VEN	1.088	-0.963
VNM	0.627	-0.183
YEM	-2.124	0.175
ZAF	1.901	-0.202
ZMB	-0.020	-0.413
ZWE	0.965	-0.540

A.4 Heterogeneity of Individual-Level Correlates

A.4.1 Heterogeneity: Gender Differences by Economic Development



(a) Risk

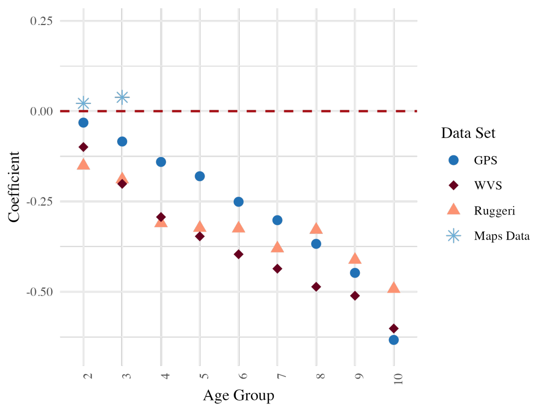


(b) Time

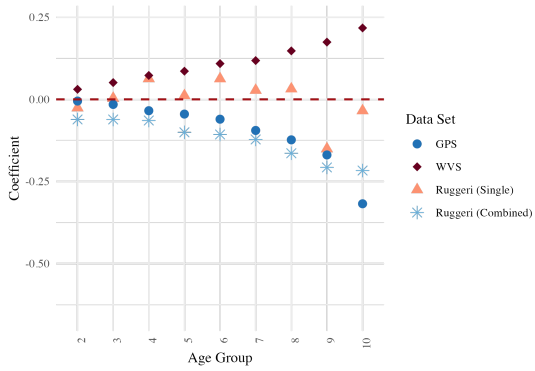
Figure A8: Gender Differences vs. GDP p.c.

Note: This figure plots the country-specific gender coefficients for risk (Panel a) and time (Panel b) from the same estimates as in Figure 6 by economic development (proxied by ln GDP per capita).

A.4.2 Heterogeneity: Age and Income Correlations by Gender



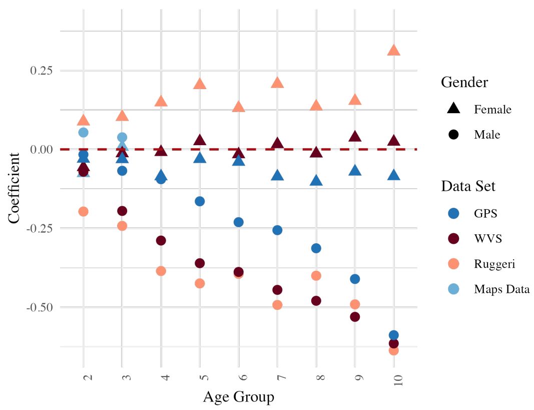
(a) Risk



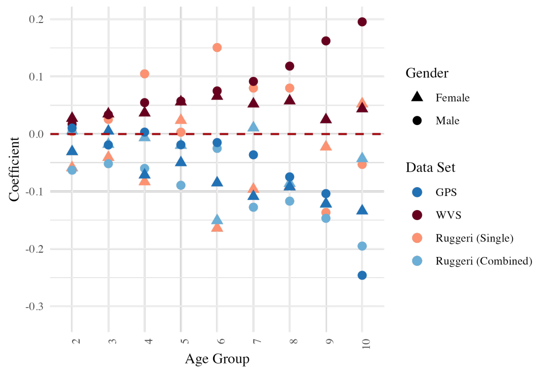
(b) Time

Figure A9: Age Differences

Note: This figure plots the coefficients of age groups for the different preferences and datasets. To obtain the age group coefficients, gender, income and country fixed effects are included in the model. Coefficients are measured relative to age group 1.



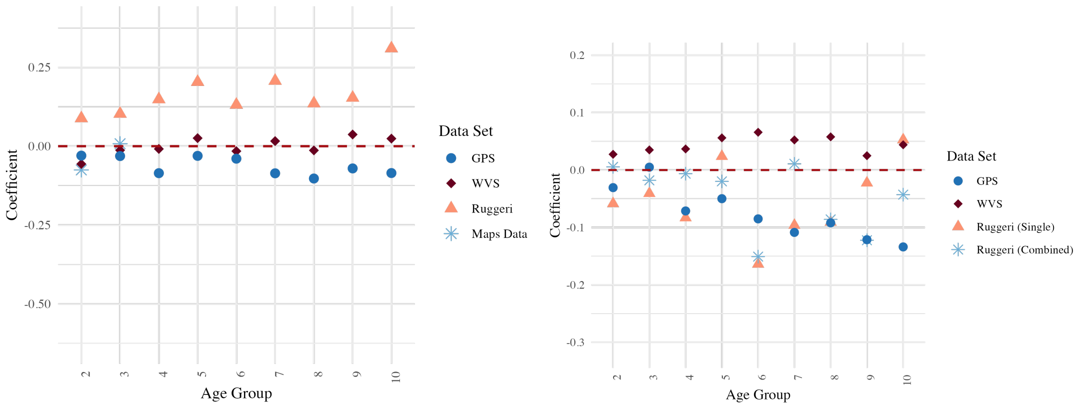
(a) Risk



(b) Time

Figure A10: Gender Differences by Age Group

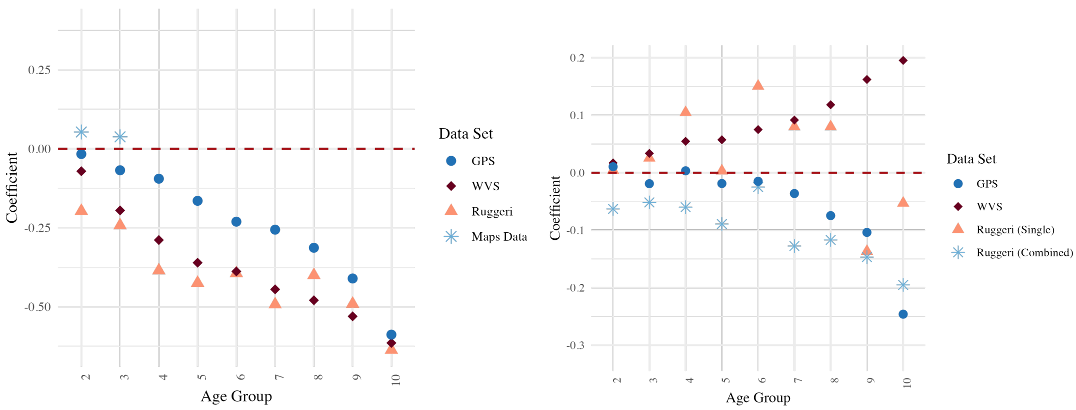
Note: This figure plots gender coefficients for risk and time preferences across different age groups. The coefficients reflect the additional risk for women (1) compared to men (0) across various age groups. Coefficients are measured relative to age group 1.



(a) Risk (b) Time

Figure A11: Age Differences: Women

Note: The figure plots the effect of age on risk preferences among women. To obtain the age group coefficients, income and country fixed effects are included in the model. Coefficients are measured relative to age group 1.

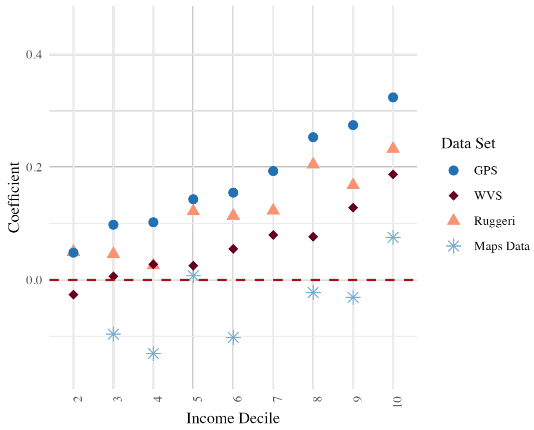


(a) Risk (b) Time

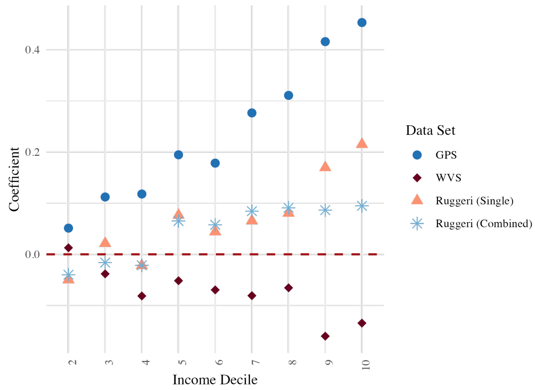
Figure A12: Age Differences: Men

Note: The figure plots the effect of age on risk preferences among men. To obtain the age group coefficients, income and country fixed effects are included in the model. Coefficients are measured relative to age group 1.

A.4.3 Heterogeneity: Income Correlations in Low- and High-Income Countries



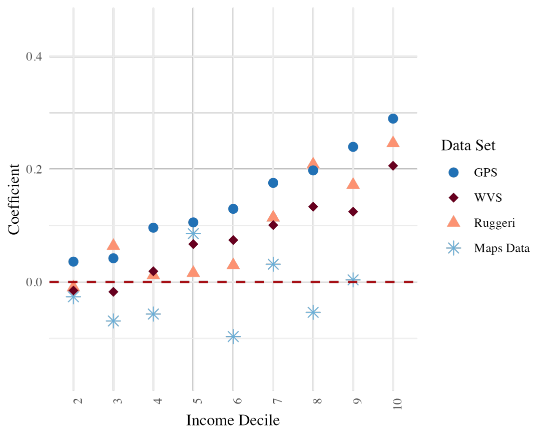
(a) Risk



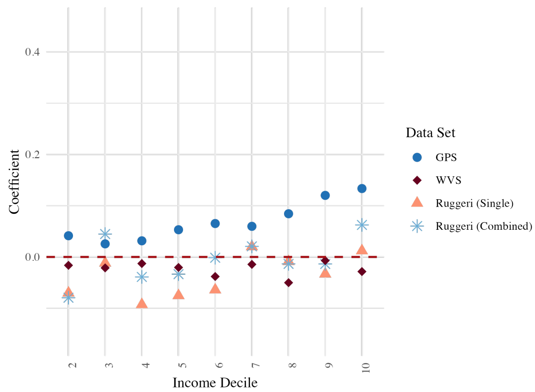
(b) Time

Figure A13: Income Differences: OECD Countries

Note: This figure plots the income decile coefficients for OECD countries. To obtain the income coefficients, gender, age, and country fixed effects are included in the model. Coefficients are measured relative to income decile 1.



(a) Risk



(b) Time

Figure A14: Income Differences: non-OECD Countries

Note: This figure plots the income decile coefficients for non-OECD countries. To obtain the income coefficients, gender, age, and country fixed effects are included in the model. Coefficients are measured relative to income decile 1.