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The globalizability of temporal discounting

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Abstract

Economic inequality is associated with extreme preferences for smaller, immediate gains over larger, delayed ones. This pattern, known as temporal discounting, may feed into rising global inequality, yet it is unclear if it is a function of choice preferences or norms, or rather the absence of sufficient resources to meet immediate needs. It is also not clear if these reflect true differences in choice patterns between income groups. We tested temporal discounting and five intertemporal choice anomalies using local currencies and value standards in 61 countries. Across a diverse sample of 13,629 participants, we found highly consistent rates of choice anomalies. Individuals with lower incomes were not significantly different, but economic inequality and broader financial circumstances impact population choice patterns.

Introduction

Effective financial choices over time are essential for securing financial well-being [1,2], yet individuals often prefer immediate gains at the expense of future outcomes [3,4]. This tendency, known as temporal discounting [5], is routinely associated with lower wealth [6–13], which is especially concerning given incongruent impacts on economic inequality brought about by the COVID-19 pandemic [14].

Inequality and low incomes have also routinely been associated with greater discounting of future outcomes [12,15,16], so it is not surprising that global studies would find temporal discounting - to varying degrees - in populations around the world [7]. However, prevailing interpretations (i.e., that lower-income individuals show more extreme discounting) may result from narrow measurement approaches, such as only assessing immediate gains versus future gains.

Another limitation of interpretations regarding discounting and economic classes involves the relative aspect of financial choices compared to income and wealth. Consider the patterns presented in Figure 1 (a), which represents six months of spending patterns for 15,568 individuals in the US who received stimulus payments as part of the 2020 CARES Act [17]. Using the average amount spent 60 days prior to receiving the payment as a baseline, lower-income individuals spent over 23 times more than baseline immediately after receipt, compared to around ten times more than baseline for middle- and higher-income. Apart from those days immediately following receipt, relative spending patterns are almost identical for all three groups. However, as indicated on the right, higher-income individuals spent more in raw values, indicating that behaviors are only more extreme relative to income, and in fact, high-income individuals spent the most on average after receiving stimulus. While relative values may differentiate the consequences of spending, the spending patterns were generally about the same.

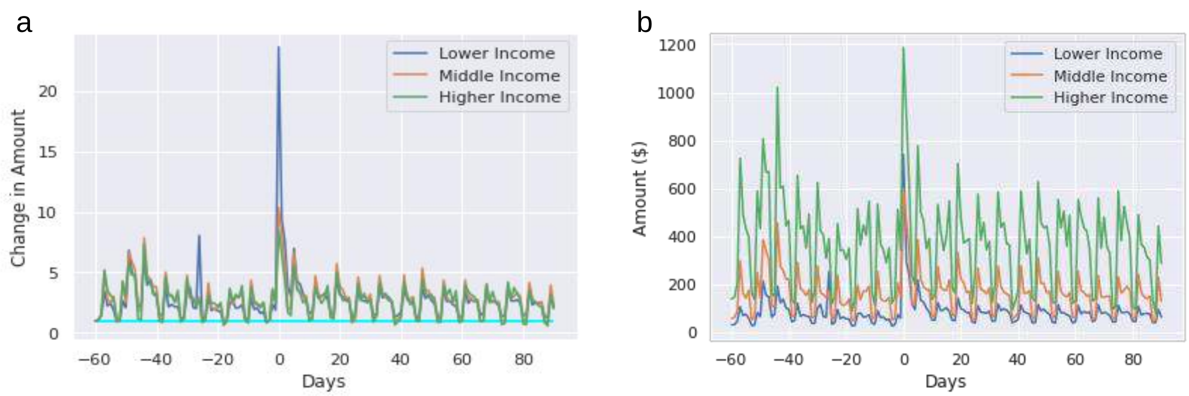

Figure 1. Spending timelines after receiving COVID-19 relief stimulus check. *Spending before and after receiving a 2020 CARES Act stimulus payment. Baseline average is the amount spent 60 days prior to receiving the payment. Data in (a) present proportional spending compared to a standard baseline. Data in (b) present the same information but use actual spending values. Apart from the days immediately following receipt, base-standardized spending patterns are almost identical for all three groups.*

With broader testing of more anomalies, rather than being limited to indifference points (a threshold value for preferring now versus later), more robust conclusions can be drawn about choice patterns. In this vein, the most comprehensive related study found lower-income countries had lower trust in systems and had the steepest rates of discounting (i.e., the threshold for giving up an immediate gain for a later, larger one was much higher) [7,18]. As indifference point was the primary indicator, these results are extremely important but do not necessarily mean that lower-income populations have distinct decision-making patterns. To address concerns about this approach and assess temporal discounting on a near-global scale, we used a similar method but tested multiple intertemporal choice domains, allowing rates of certain anomalies to be considered along with specific value thresholds.

Inflation, which tends to be higher in lower-income countries [19], is also associated with stronger preferences for immediate gains [20,21]. We expected to confirm this pattern, indicating that such preferences may be more related to an increased probability that any future gains will be worth substantially below their current value than individual income or wealth. We limited our hypotheses to inflation versus extreme inflation: we expected differences in preferences would emerge only at substantially larger inflation rates (over 10%) and hyperinflation (over 50%), and less so between regions with varied but less extreme differences (significantly below 10%).

To test our hypotheses, we used four choice anomalies outlined in one of the most influential articles [22] on intertemporal choice: absolute magnitude, gain-loss asymmetry, delay-speedup asymmetry, and common difference (we refer to this as present bias, which is the more common term), plus a fifth, subadditivity, to complete inter-related three time intervals [23]. By testing multiple anomalies alongside a simplified indifference measure (derived from the first set of choices), the prevalence of each anomaly provides a more robust determination of the generalizability of the construct than an indifference point alone.

Contrasting most discounting research, our study involves a series of intertemporal choice anomalies[24] identified in WEIRD labs, including patterns which choice models often ignore. Addressing both the depth of the method used and concerns about the generalizability of behavioral research [25], this richer perspective of intertemporal decision-making in a global sample assesses the presence and prevalence of anomalies in local contexts. We also focus on the influence of economic inequality to determine if low-income individuals are somehow more extreme decision-makers or if the environment, more so than simply individual circumstances, is a more impactful factor across populations.

Measurement

Most research on temporal preferences uses indifference points [26], which determine the threshold at which individuals will shift from immediate to delay (and vice-versa). Data from that approach are robust, and converge on an inverse relationship between income/wealth and discounting rate. However, multiple binary choice comparisons are ideal for demonstrating multidimensional choice patterns, as in prospect theory, expected utility, and other choice paradoxes or cognitive biases. They are also better suited for testing in multiple countries [27,28] when multiple small adaptations to values in different currencies are necessary. Taking this into consideration, our method leveraged one of the most widely cited papers on decision-making [22], which proposed four critical intertemporal choice anomalies. Yet, while studies of individual anomalies exist from various regions [29–31], no comprehensive nor multi-country study has simultaneously assessed the generalizability of all four:

> Absolute magnitude: Increased preference for delayed gains when values become substantially larger, even when relative differences are constant (e.g., prefer $500 now over $550 in 12 months and prefer $5500 in 12 months over $5000 now [4,6]).
>
> Gain-loss asymmetry: Gains are discounted more than losses, though differences (real and relative) are constant (e.g., prefer to receive $500 now over $550 in 12 months, but also prefer to pay $500 now overpaying $550 in 12 months).
>
> Delay-speedup asymmetry: Accepting an immediate, smaller gain if the delay is framed as added value, but preferring the larger, later amount if an immediate gain is framed as a reduction (e.g., prefer to receive a gain of $500 rather than wait 12 months for an additional $50 and prefer to wait for 12 months to receive $550 rather than to pay $50 and receive the gain now).
>
> Present bias: Lower discounting over a given time interval when the start of the interval is shifted to the future (e.g., prefer $500 now over $550 in 12 months and prefer $550 in two years over $500 in 12 months).

We also assess subadditivity [23] effects, which adds an interval of immediate to 24 months, thereby allowing us to fully assess discounting over three time intervals (0-12, 12-24, and 0-24 months) [32]. Subadditivity is considered present if discounting is higher for the two 12-month intervals compared to the 24-month interval.

All data were collected independent of any other study or source, with a 30-item instrument developed specifically for assessing a base discounting level and then the five anomalies. To validate the metric, a three-country pilot study (Australia, Canada, USA) was conducted to confirm the method elicited variability in choice preferences. We did not assess what specific patterns of potential anomalies emerged to avoid biasing methods or decisions related to currency adaptations.

For the full study, all participants begin with choosing between approximately 10% of the national household income average (either median or mean, depending on the local standard) immediately, or 110% of that value in 12 months. For US participants, this translated into $500 immediately or $550 in one year. Participants who chose the immediate option are shown the same option set, but the delayed value is now 120% ($600). If they continue to prefer the immediate option, a final option offers 150% ($750) as the delayed reward. If participants choose the delayed option initially, subsequent choices are 102% ($510) and 101% ($505). This progression is then inverted for losses, with the identical values presented as payments, increasing for choosing delayed and decreasing for choosing immediate. Finally, the original gain set is repeated using 100% of the average monthly income to represent higher magnitude choices (table S1).

Following baseline scenarios, subsequent anomaly scenarios incorporated the simplified indifference point (the largest value at which participants chose the delayed option in the baseline items; see Supplement Methods). Finally, participants answered ten questions on financial circumstances, (simplified) risk preference, economic outlook, and demographics. Participants could choose between the local official language (or languages) and English. By completion, 61 countries (representing approximately 76% of the world population) participated (table S2-S3).

We assessed temporal choice patterns in three ways. First, we used the three baseline scenarios to determine preferences for immediate or delayed gains (at two magnitudes) and losses (one). Secondly, we calculated the proportion of participants who exhibited the theoretically described anomaly for each anomaly scenario (table S4). We also calculated proportions of participants who exhibited inconsistent decisions even if not specifically aligned with one of the defined anomalies. Finally, we computed a discounting score based on responses to all choice items, ranging from 0 (always prefer delayed gains or earlier losses) to 19 (always prefer immediate gains or delayed losses). The score then represents the consistency of discounting behaviors, irrespective of the presence of other choice anomalies.

To explore individual and country-level differences, we performed a series of multilevel linear and generalized (binomial) mixed models that predicted standardized temporal discounting scores and anomalies, respectively. We ran a set of increasingly complex models, including inequality indicators, while controlling for individual debt and assets, age, education, employment, log per-capita GDP, and inflation at individual and country-level. Because the raw scores (0-19) have no standard to compare against, we primarily used standardized scores (mean 0 and standard deviation of 1) for analysis and visualization.

We detected several relevant non-linear effects (debt, financial assets, and inflation; table S5-S7), which we incorporated into our final models via spline modeling [33]. The models were estimated using both frequentist (table S8-S9, Figures S1-S2) and Bayesian techniques (table S10-S11), assessing the consistency of the results. Support for potential null effects was evaluated a variety of Bayesian approaches (table S12).

Results

For 13,629 participants from 61 countries, we find temporal discounting widely present in every location, with varying but robust rates of five intertemporal choice anomalies (see Figure 2). Income, economic inequality, financial wealth, and inflation demonstrated clear impacts on the shape and magnitude of intertemporal choice patterns. Better financial environments were consistently associated with lower rates of temporal discounting, whereas higher levels of inequality and inflation were associated with higher rates of discounting. Yet, the overall likelihood of exhibiting anomalies remained stable irrespective of most factors.

Differences between locations are evident, though remarkable consistency of variability exists within countries. Such patterns demonstrate that temporal discounting and intertemporal choice anomalies are widely generalizable, and that differences between individuals are wider than differences between countries. Being low-income does not alone appear to produce unstable decision-making; being in a more challenging environment does.

The scientific and policy implications from these findings challenge any assumption or implication that low-income individuals are fundamentally extreme decision-makers. Instead, these data indicate that anyone facing a negative financial environment – even with better incomes within that environment – is likely to make decisions that prioritize immediate clarity over future uncertainty. Likewise, data indicate that all individuals at all income levels in all regions are more likely than not to demonstrate one or more choice anomalies.

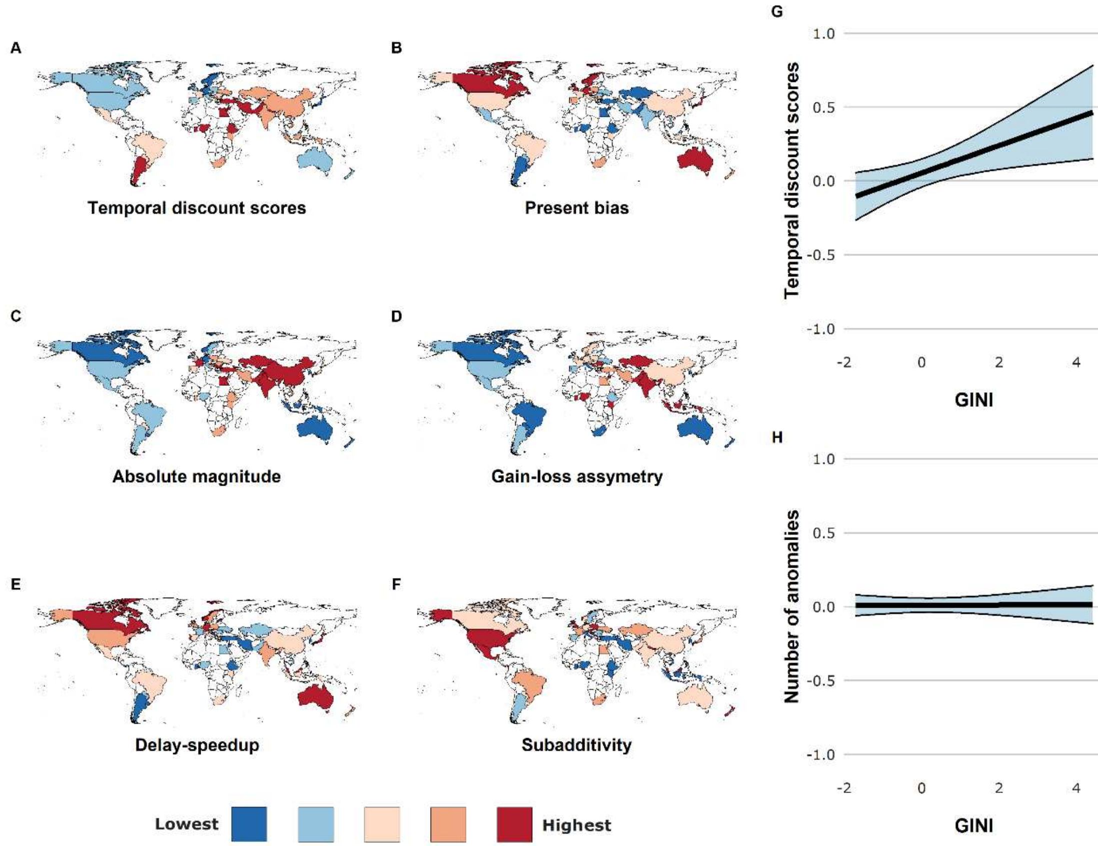

Figure 2. Global indications of intertemporal choice. *Maps of choice preferences in aggregate and by individual anomaly indicate heterogeneity in intertemporal choice patterns. While some subtle patterns emerge, particularly stronger preferences for delayed gains in higher-income regions, choice preferences are broadly consistent across 61 countries in the sense that all anomalies appear in all locations. No location consistently presents extremes (high or low) of each anomaly. Results are based on models specified in table S13.*

Detailed analysis of temporal choice anomalies

We collected 13,629 responses from 61 countries (median sample of 209, tables S2-S3). Though the absolute minimum sample necessary was 30 per country, the sliding scale used for ensuring full power (see *SM Selection of countries*) started at 120, increasing to 360 for larger countries. Forty-six countries achieved the target sample size, and 56 had at least 120 (with at least four countries per continent at 120), thus providing a wide range of economic and cultural environments. Only two countries, where data collection was exceptionally challenging, had below 90 participants, but all locations were still substantially above the absolute minimum. As well as exceeding the minimum sample, we also chose to retain these participants in the analyses as they represent groups often not included in behavioral science [34,35].

In line with related research [7], Figure 3 shows how countries with lower incomes had typically greater temporal discounting levels in the baseline items (table S14). This was most evident in the tendency to prefer immediate gains, even as delayed prospects increased. This pattern was not found for the loss scenario. However, as noted, these items give a useful measure for the indifference level for each individual but do not give a robust indication of whether temporal choice anomalies are present.

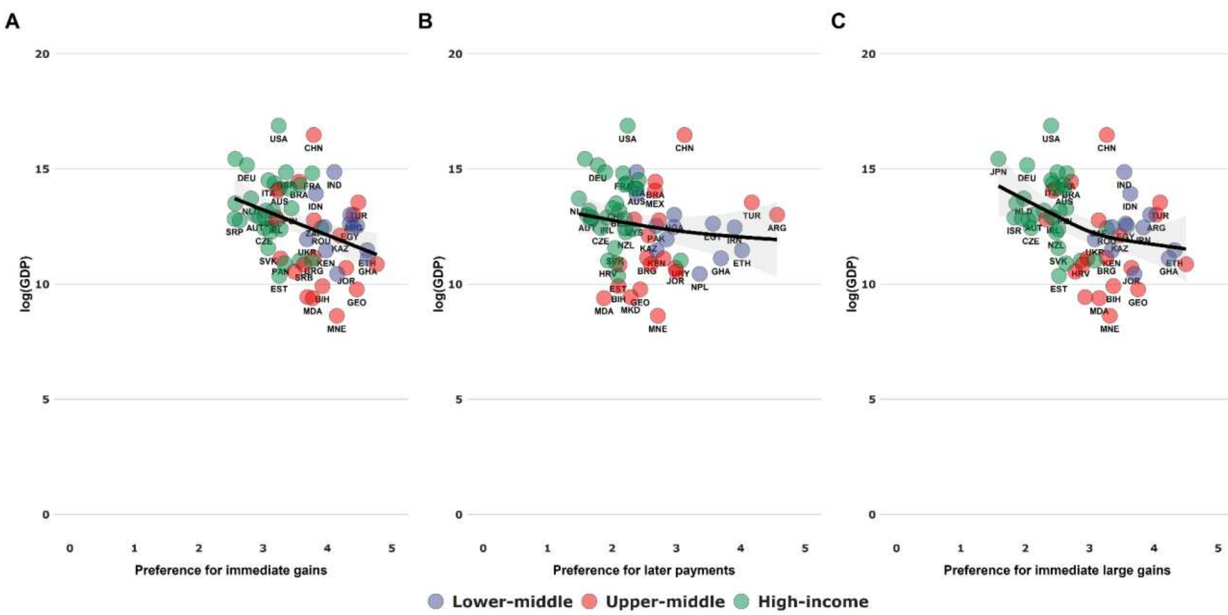

Figure 3. Baseline temporal discounting and GDP. *There is a clear trend of lower GDP [36] being associated with higher preferences for immediate gains. However, all locations indicate some preference for immediate over delayed. Taken together, this provides support for the hypothesis that baseline temporal discounting is observed globally, and that the economic environment may shape its contours. Results are based on models specified in table S14.*

Between-countries random-effect meta-analyses estimated pooled and unpooled effects for aggregate scores and individual anomalies (figures S3-S8). Temporal discounting was present in all countries, with only modest variability for national means (aggregate M=11.3, Prediction Interval [7.9- 14.8]; from Japan [M=8.1, SD =3.9] to Argentina [M=15.1, SD =3.0]; Figure 4). Fifty-four percent of participants showed at least one anomaly, with 33% presenting multiple, yet only 2% showing four (table S15). Anomalies were present in all locations, and aggregate values indicated the widespread presence of the four primary anomalies (from 13.8% for absolute magnitude to 40.1% for gain-loss asymmetry, Figure 3). Gain-loss rates were the most common anomaly in 80.3% (49) of the countries, with substantially higher rates observed than for other anomalies. While only 10.7% of the sample engaged in subadditivity behavior (range: 2.7% [Lebanon] to 20.7% [New Zealand]), criteria were stricter for this anomaly.

In all cases, significant Q-tests and I^2 values over 70% suggested that effect size variation at the country level could not be accounted for by sampling variation alone. There were strong relationships between the individual and aggregate scores and some anomalies (i.e., positive for absolute magnitude; negative for present bias and delay-speedup; Figure S9). Additionally, we found a negative effect of GDP on temporal discount scores (β= -0.07, 95% CI [-0.12, -0.03], p = 0.001), and a positive effect for present bias (OR = 1.09, 95% CI [1.03, 1.16], p = 0.003) and delay-speedup (OR = 0.95, 95% CI [0.91, 0.99], p = 0.002). We found no effect on the remaining anomalies (0.95 < OR < 1.01; 0.027 < p < 0.688).

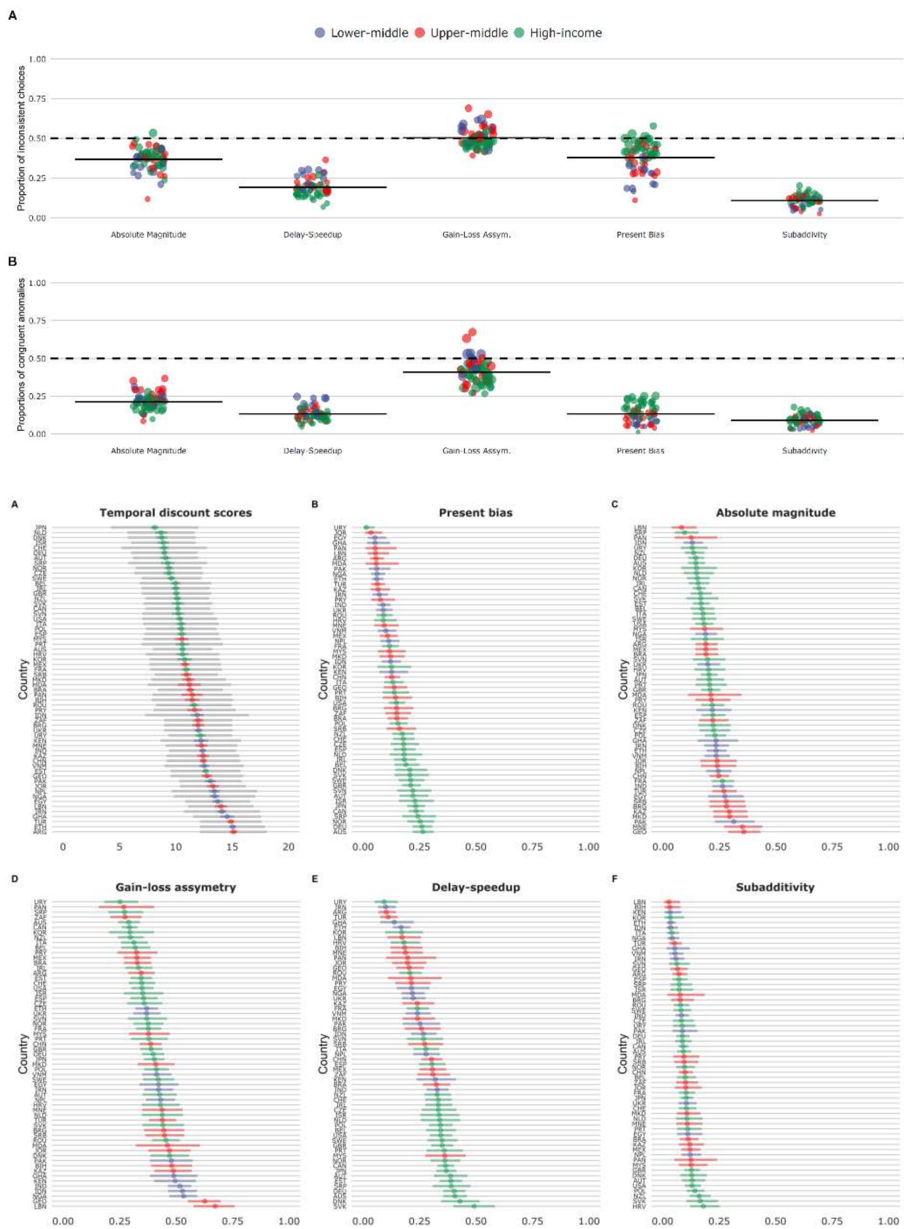

Figure 4. ABOVE: *Proportions of participants that demonstrated inconsistent choice preferences (first row) and proportion of each country sample that aligned with the five anomalies of interest (second row). Apart from absolute magnitude and present bias, no consistent rate based on wealth, and all countries indicate some presence of each anomaly.* **BELOW:** *Each plot presents the distribution of values ordered by mean or proportion value. Plot A presents the distribution of discounting scores by country, including means, prediction intervals (black), and standard deviations (grey) for all countries. Plots B-F show the proportions of participants that presented each anomaly. While difference from lowest to highest for each is noteworthy, similar variabilities exist across all.*

Despite between-country differences in mean scores and anomaly rates, there was substantial overlap between response distributions. Accordingly, results from multilevel models indicated that no more than 20% of the variance was ever explained by between-country differences for scores and was between 2% (absolute magnitude) and 8% (present bias) for anomalies. Thus, we find temporal discounting to be globally generalizable, robust, and highly consistent (both in line with expectations) (table S6, Figure S10), where within-country differences between individuals are substantially greater than between-country differences. In other words, we find temporal discounting to be a globalizable - though not universal - construct. We also find there is nothing WEIRD about intertemporal choice anomalies.

Inequality

We defined inequality at the level of country and at the level of the individual. For countries, we used the most recently published GINI coefficients [37]. For individuals, we calculated the difference between their reported income and the adjusted net median local (country) income. At the country level, GINI had a positive relationship with temporal discounting scores (β= 0.09, 95% CI [0.02, 0.06], p = 0.002, table S8), yet no such pattern emerged for specific anomalies, as we observed no effect for the remaining cases (0.92 <OR< 1.01; 0.023 < p < 0.825, table S8). Individual income inequality did not predict temporal discounting scores (β= -0.01, 95% CI [-0.03, 0.001], p = .121) or rates of anomalies (0.96 < OR < 1.04; 0.045< p <0.867, table S8-S9) with the exception of two small effects for present bias (OR = 1.07, 95% CI [1.03, 1.13], p = 0.006) and absolute magnitude (OR = 0.92, 95% CI [0.87, 0.98], p = 0.006, table S9).

As shown in Figure 5, these patterns are largely in line with expectations, indicating that, in aggregate, greater inequality is associated with increased rates of discounting. However, as indicated in Figure 3, intertemporal choice anomalies overall are not unique to a specific income level, and worse financial circumstances may produce more consistent choice patterns (i.e., fewer anomalies) due to sustained preference for sooner gains. Whether this aligns with arguments that scarcity leads individuals to focus on present challenges is worthy of further exploration [38]. It also reiterates that patterns in population (i.e., country) aggregates are not the same as predicting individual choices [39].

Assets & debt

We found consistently that greater willingness to delay larger gains tends to be associated with greater wealth (financial assets), except for the extremely wealthy. Temporal discounting scores generally decreased as wealth increased, except for the wealthiest individuals (expected degrees of freedom [edf, see SM section *on modeling temporal discounting* for details] = 2.88, p < .0001, table S8, Figure S2). We also observed assets being associated with present bias (edf = 1.01, p < 0.0001) and for delay-speedup (edf = 2.78, p < .0001). We observed the reverse pattern for absolute magnitude (edf = 1.96, p < .0009). For gain-loss asymmetry (edf = 0.474, p = 0.144) and subadditivity (edf = 0.001, p = 0.472), we found no meaningful relationship between assets and the likelihood of observing either (table S9, Figure S2). Higher levels of debt were associated with lower discount rates, particularly for people with lower to medium debt (edf = 2.91, p < .0001, Figure S1), though debt had no effect on the likelihood of engaging in any specific anomaly (0.95 < OR < 1.01; 0.035< p < 0.944, table S9).

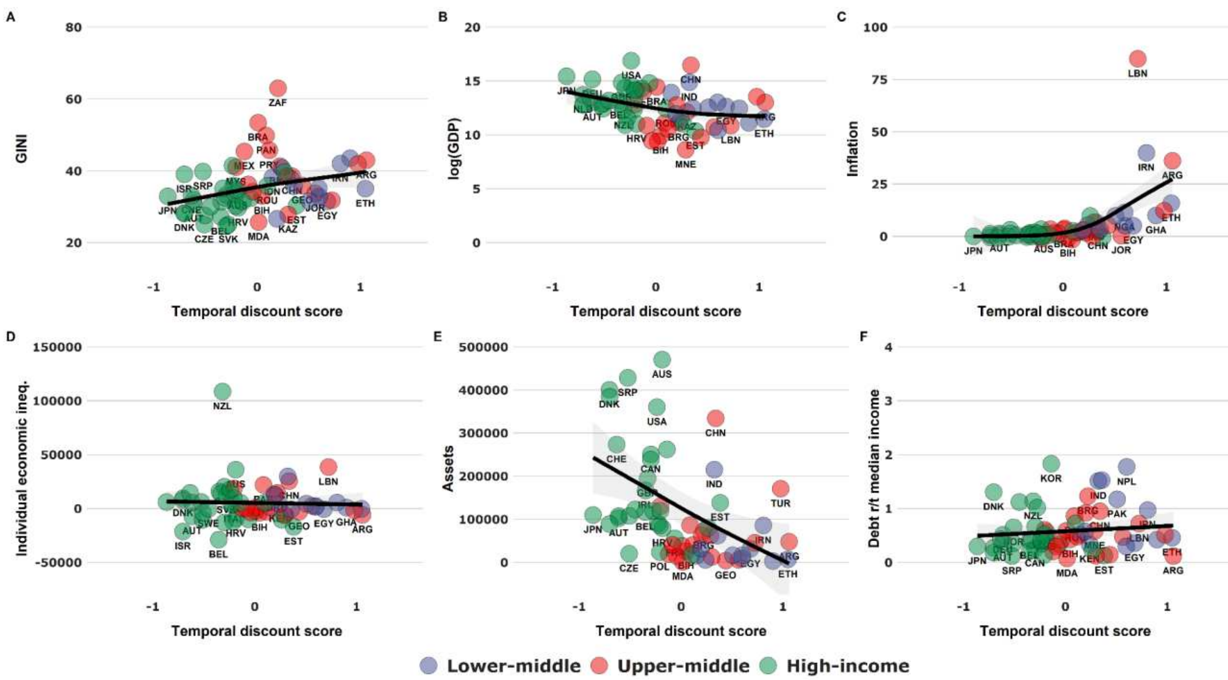

Figure 5. Wealth, debt, inequality, and temporal discounting. *Plots using standardized scores for temporal discounting indicate an overall trend of greater wealth and income at individual and national level are associated with lower overall temporal discounting, with greater economic inequality and individual debt associated with lower overall temporal discounting. Inflation has a modest relationship with discounting, which becomes much stronger at substantially high levels of inflation. Results for each variable by score are from models specified in table S16.*

Inflation

We observed strong relationships between inflation rates and temporal discounting scores as well as all anomalies. There was a particularly strong effect of hyperinflation on temporal discounting (edf = 1.81, p < .0001, table S8, Figure S1), with some leveling out at the extremes. Countries experiencing severe hyperinflation demonstrate extreme discounts only for gains but not for payments, which minimizes the effect on total scores. However, if limiting to only gains, the effect remains extreme, as indicated by the two gain scenarios in Figure 3.

We observed a reverse trend of higher inflation leading to lower likelihood of engaging in anomalies (table S9, Figure S2), namely for present bias (edf = 1.63, $p < .0001$), absolute magnitude (edf = 1.92, $p < .0001$), delay-speedup (edf = 1.75, $p < .0001$), and subadditivity (edf = 1,37, p = 0.0019). The only positive (but weaker) effect in the case of anomalies was found for gain-loss asymmetry (edf = 1.675, p = 0.0051).

Conclusion

For good reason, psychological theory has come under considerable recent criticism due to a number of failed replications of previously canonical constructs [40]. There is also wide support to consider that the absence of testing (or adapting methods to test) across populations limits the presumed generalizability of conclusions in the field [25]. To the extent it is possible for any behavioral phenomenon, we find temporal discounting and common intertemporal choice anomalies to be globally generalizable. This is largely based on finding remarkable consistency and robustness in patterns of intertemporal choice across 61 countries, with substantially more variability within each country than between their means. We emphasize that while discounting may be stronger in worse financial circumstances, particularly those with poorer economic outlooks, it exists in all locations at measurable levels.

We do not imply that temporal discounting or specific intertemporal choice anomalies are universal (i.e., present in all individuals at all times). Instead, findings provide extreme confidence that the constructs tested are robust on a global level. It also disrupts any notion that lower-income individuals are somehow concerning decision-makers, as negative environments are widely influential. Under such circumstances, it is both rational and, as our data show, entirely typical to follow the choice preferences we present.

We hope these findings would be taken into consideration in both science and policy. The scope of the work, particularly the diversity of the 13,000 participants across these 61 countries, should encourage more tests of global generalizability of fundamental psychological theory that adapts to local standards and norms. Similarly, policymakers should consider the effects of economic inequality and inflation beyond incomes and growth and give greater consideration to how they directly impact individual choices for entire populations, impacting long-term well-being.

Methods

Ethical approval was given by the Institutional Review Board at Columbia University. All countries involved had to provide attestations of cultural and linguistic appropriateness for each version of the instrument.

Materials and methods followed our pre-registered plan (osf.io/jfvh4). Significant deviations from the original plan are highlighted in each corresponding section, alongside the justification from the same. All details of countries included, translation, testing, and sampling are included in the supplement.

Participants

The final data was composed of 13,629 responses from 61 countries. The original sample size was 25,877, which was reduced almost by half after performing pre-registered data exclusions. We removed 6,141 participants (23.7%) who did not pass our attention check. We identify 69 participants for presenting nonsensical responses to open data text (i.e., “helicopter” as gender). We removed 13 participants claiming to be over 100 years old. We included additional filters to our original exclusion criteria. Based on the length of time for responses, individuals faster than three times the absolute deviations below the median time or that took less than 120 seconds to respond were removed. This third criterion allows us to identify 5,870 inappropriate responses. We further removed responses from IP addresses identified as either “tests” or “spam” by the Qualtrics service (264 answers identified). Lastly, we did not consider individuals not completing over 90% of the survey (9434 responses meet the criteria).

For analyses including income, assets, and debt, we conducted additional quality checks. We first removed 38 extreme income, debt, or assets (values larger than $1*10^8$) responses. Next, we removed extreme outliers larger than 100 times the median absolute deviation above the country median for income and 1000 times larger than the median absolute deviation for national median assets. We further removed anyone that simultaneously claimed no income while also being employed full-time. These quality checks identified 54 problematic responses, which were removed from the data. The final sample and target size are presented in Table S2. We provide descriptive information of the full and by-country samples in Table S3 and the main variables in Table S4.

Instrument

The instrument was designed by evaluating methods used in similar research, particularly those with a multi-country focus [7,18,25] or covered multiple dimensions of intertemporal choice [12,24]. Based on optimal response and participation in two recent studies [26,38] of a similar nature, we implemented an approach that could incorporate these features while remaining brief. This design increased the likelihood of reliable and complete responses.

To confirm the viability of our design, we assessed the overall variability of pilot study data from 360 participants from the US, Australia, and Canada. Responses showed that items elicited reasonable answers, and the three sets of baseline measures yielded responses that would be expected for the three countries. Specifically, it was more popular to choose earlier gains over larger, later ones for the smaller magnitude and closer to 50-50 for the larger magnitude and the payment set. The subsequent choice anomalies also yielded variability within items, which showed some variability between countries. These results confirmed that using baseline choices to set tradeoff values in anomaly items was appropriate and would capture relevant differences. We did not analyze these data in full per our IRB approval, as we did not want a detailed analysis of subsequent bias decisions. The pilot was completed in April 2021 with participants on the Prolific platform (compensated for participation, not choices made).

The final version of the instrument required participants to respond to as few as 10 to as many as 13 anomaly items. All items were binary. During the first three anomaly sets, if a participant chose immediate then delay (or vice-versa), they proceeded to the next anomaly, so only two questions were required. If they decided on the immediate-immediate or delay-delay, they would see the third set. After the anomalies, participants answered ten questions about financial preferences, circumstances, and outlook (most of these will be analyzed in independent research). Finally, participants provided age, race/ethnicity/immigration status, gender, education, employment, and region of residence. Table S1 presents all possible values for each set of items used in the final version of the instrument.

All materials associated with the method are available in the pre-registration repository.

Selection of countries

By design, there was no systematic approach to country inclusion. Through a network of early career researchers worldwide, multiple invitations were sent and posted to collaborate. We explicitly emphasized including countries that are not typically included in behavioral research, and in almost every location, had at least one local collaborator engaged. All contributors are named authors.

Following data collection, 61 countries were fully included, using 40 languages. All countries also had an English version to include non-native speakers who were uncomfortable responding in the local language. Of the 61 countries, 11 were from Asia, eight were from the Americas, five were from sub-Saharan Africa, six were from Middle East-North Africa (MENA), two were from Oceania, and 29 were from Europe (19 from the European Union). Several additional countries were attempted but were unable to fulfill certain tasks or were removed for ethical concerns.

Translation of survey items

All instruments went through forward-and-back translation for all languages used. In each case, this required at least one native speaker involved in the process. All versions were also available in English, applying the local currencies and other aspects, such as race and education reporting standards. A third reviewer was brought in if discrepancies that could not be solved through simple discussion existed. Similar research methods were also consulted for wording. Relevant details where issues arose are included in the supplement. For cultural and ethical appropriateness, demographic measures varied heavily. For example, in some countries, tribal or religious categories are used as the standard. Other countries, such as the US, have federal guidelines for race and ethnicity, whereas France disallows measures for racial identity. Country by country details are posted on the pre-registration page associated with this project.

All data were collected through Qualtrics survey links. For all countries, an initial convenience sampling of five to ten participants was required to ensure comprehension, instrument flow, and data capture were functional. Minor issues were corrected before proceeding to "open" collection. Countries aimed to recruit approximately 30 participants before pausing to ensure functionality and that all questions were visible. We also checked that currency values had been appropriately set by inspecting responses' variability (i.e., if options were poorly selected, it would be visible in having all participants make the same choices across items). Minimal issues arose, which are outlined in the supplement.

For data circulation, all collaborators were allowed a small number of convenience participants. This decision limited bias while ensuring the readiness of measures and instruments as multiple collaborators in each country used different networks, thereby reducing bias. Once assurances were in place, we implemented what we refer to as the Demić-Većkalov method, which two prior collaborators in recent studies developed. This method involves finding news articles online (social media, popular forums, news websites, discussion threads, sports team supporter discussion groups/pages) and posting in active discussions, encouraging anyone interested in the subject to participate. Circulation included direct contact with local organizations (NGOs, non-profits, often with thematic interests in financial literacy, microcredit, etc.) to circulate with stakeholders and staff, email circulars, generic social media posts, informal snowballing, and paid samples (in Japan only). We note that this approach to data collection with a generally loose structure was intentional to avoid producing a common bias across countries. Similar to recent, successful multi-country trials [28,41], this generates more heterogeneous backgrounds, though still skews toward populations with direct internet access (i.e., younger, higher education, somewhat higher income).

As described in the pre-registration (osf.io/jfvh4), the minimum sample threshold to achieve a power of .95 for the models presented was 30 participants per country. However, to produce a more robust sample, we used three tiers for sample targets:

> Population ≤ 10 million = 120 participants
> 10 million ≤ Population ≤ 100 million = 240 participants
> Population >100 million = 360 participants

Comprehensive details about methods, guidelines, measurement building, and instruments are available in the supplement and pre-registration site.

Procedure

For the full study, all participants begin choosing from two gains of approximately 10% of the national household income average (either median or mean, depending on the local standard) immediately, or 110% of that value in 12 months. For US participants, this translated into $500 immediately or $550 in one year. Participants who chose the immediate option are shown the same option set, but the delayed value is now 120% ($600). If they prefer the immediate prospect, a final option offers 150% ($750) as the delayed reward. If participants choose the delayed option initially, subsequent choices are 102% ($510) and 101% ($505). This progression is then inverted for losses, with the identical values presented as payments, increasing for choosing delayed and decreasing for choosing immediately. Finally, the original gain set is repeated using 100% of the monthly income to represent higher magnitude choices.

Following baseline scenarios, anomaly scenarios incorporated the simplified indifference point, the largest value at which participants chose the delayed option in the baseline items. For example, if an individual chose $500 immediately over $550 in 12 months, but $600 in 12 months over $500 immediately, this $600 was the "indifference value" for subsequent scenarios. Those choices were then between $500 in 12 months versus $600 in 24 months (present bias), $500 immediately vs. $700 in 24 months (subadditivity), as well as either being willing to wait 12 months for an additional $100 in one set or being willing to reduce $100 to receive a reward now rather than in 12 months (delay-speedup). For consistency, initial values were derived from local average income (local currency) and then constant proportions based on those (see supplement). This approach was chosen over directly converting fixed amounts in each country due to the substantial differences in currencies and income standards.

Participants answered four additional scenarios related to the choice anomalies (gain-loss and magnitude effects are already collected in the first three sets). In random order, they were presented with two delay-speedup scenarios (one framed as a bonus to wait, the other stated as a reduction to receive the gain earlier), a present bias scenario (choice between 12 months and 24 months), and a subadditivity scenario (choice between immediate and 24 months). Delay-speedup scenarios were separated by several items due to the similarity in their wording and were anticipated to have the lowest rates of anomalous choice given that similarity. Finally, participants answered ten questions on financial circumstances, (simplified) risk preference, outlook, and demographics. Participants could choose between the local official language (or languages) and English. By completion, 61 countries (representing approximately 76% of the world population) participated.

We assessed temporal choice patterns in three ways. First, we tested discounting patterns from three baseline scenarios to determine preference for immediate or delayed choices for gains (at two magnitudes) and losses (one). Secondly, we analyzed the prevalence of all choice anomalies using three additional items. Finally, with this information, we computed a discounting score based on responses to all choice items and anomalies, which ranged from 0 (always prefer delayed gains or earlier losses) to 19 (always prefer immediate gains or delayed losses).

Deviations from the pre-registered method

There were minor deviations from the pre-registered method in terms of procedure. First, we did include an attention check, and the statement that we would not should have been removed; this was an error. Second, we had initially not planned to include students in the main analyses. Still, our recruitment processes turned out to be generally appropriate in terms of engaging students (16%) and non-students (84%) in the sample. Therefore, we are not concerned about skew and instead consider this a critical population. The impact of these deviations in the analyses is explained later in the supplement.

Statistical analysis

Hierarchical generalized additive models [33] were estimated using fast restricted maximum likelihood (*f*REML) and penalized cubic splines [42]. We selected the shrinkage version of cubic splines to avoid overfitting and foster the selection of only the most relevant non-linear smooths [43]. Robustness checks were performed for the selection of knots (Figure S10) and spline basis (Table S7), leaving results unchanged. In these models, we estimated all effects of continuous variables as smooths to identify potential non-linear variables, plus country of residence as random effects.

Relevant non-linear effects were incorporated to our main linear and generalized mixed models. These models were fitted using a restricted maximum likelihood. Model convergence and assumptions were visually inspected. Bayesian versions of these models were estimated using four chains with 500 warmups and 1,000 iteration samples (4,000 total samples). We reviewed that all parameters presented $\widehat{R}$ values equal to or below 1.01 and tail effective sample size above 1,000. We set the average proposal acceptance probability (delta) to 0.90 and the maximum tree depth to 15 [44] to avoid divergent transitions. We employed a set of weakly informative priors, including *t* distributions with three degrees of freedom and a standard deviation of 10 for model intercept and random effect standard deviations, normal distribution with zero mean, and standard deviation of three for the fixed effect regression coefficient. For the standard deviation of the smooth parameter, we employed exponential distribution with a rate parameter of one [45].

For smooth terms, we analyzed whether each term was significant for the GAM model and presented substantial variance in the final models. We explored 95% confidence /credibility intervals for fixed effects [44] and examined support for potential null effects. Our power estimation considered unstandardized fixed regression effects of |.15| and |.07| as ultra-low effect sizes (categorical and continuous variables). Thus, assuming a null effect of a similar or lower magnitude (|.10|), we computed log Bayes factors (BF_{01}) to quantify evidence favoring null effects of this range [46]. To understand the sensitivity of our results, we explored support for narrower null-effects (ranges of |.05| and |.01|). As Bayes Factors are dependent upon prior specification, we also estimated the percentage of posterior samples within these regions (which could be understood as a region of practically equivalence analysis [47]). Both statistics provide sensitive, complementary evidence of whether null effects were supported or not [46,47]. Unfortunately, such analyses could not be conducted for smooth effects, as no single parameter could resume the relationship between the predictor and the dependent variable.

Analyses were conducted in R 4.0.2 [48] using the Microsoft R Open distribution [49]. Meta-analyses were conducted using the *meta* package. Non-linear effects were studied using the *mgcv* [50] package, with main models being estimated using the *gamm4* [51] and the *brms* [44] packages for frequentist and Bayesian estimation, respectively.

Deviation from the pre-registered plan

We aimed to follow our pre-registration analyses as closely as possible. On certain selected occasions, we decided to amplify the scope of analyses and present robustness checks for the results presented by employing alternative estimation and inference techniques.

There was only one substantive deviation from our pre-registered analyses aside from the delay-speedup calculation. In the original plan, we planned to explore the role of financial status. In our final analysis, we employed individual assets and debts to this end. Assets and debts were included as raw indicators instead of inequality measures as we did not find reliable national average assets or individual debt sources.

One minor adaptation from our pre-registration involved our plan to test for non-linear effects and use Bayesian estimation only as part of our exploratory analyses. However, as we identified several relevant non-linear effects, we modified our workflow to accommodate those as follows: a) we initially explored non-linear effects using hierarchical generative additive (mixed) models (GAMs); b) we included relevant non-linear effects in our main pre-registered models; c) we estimated Bayesian versions of these same models to test for whether null effects could be supported in certain cases.

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Competing interests

Authors declare that they have no competing interests.

Data and materials availability

All data, code, and materials used in this study will be available at https://osf.io/njd62/. The complete dataset will be made publicly available on September 1, 2022.

Supplementary Materials

Materials and Methods
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