Original Article

The Link Between Income, Income Inequality, and Prosocial Behavior Around the World

A Multiverse Approach

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Abstract: The questions of whether high-income individuals are more prosocial than low-income individuals and whether income inequality moderates this effect have received extensive attention. We shed new light on this topic by analyzing a large-scale dataset with a representative sample of respondents from 133 countries (N = 948,837). We conduct a multiverse analysis with 30 statistical models: 15 models predicting the likelihood of donating money to charity and 15 models predicting the likelihood of volunteering time to an organization. Across all model specifications, high-income individuals were more likely to donate their money and volunteer their time than low-income individuals. High-income individuals were more likely to engage in prosocial behavior under high (vs. low) income inequality. Avenues for future research and potential mechanisms are discussed.

Keywords: income inequality, prosocial behavior, income, volunteering, donating

Due to their greater capacity to help those in need, high-income individuals might be more likely to engage in prosocial behavior (i.e., the act of helping others; Feeney & Collins, 2003; Fehr & Fischbacher, 2003; Grant, 2013; Rand & Nowak, 2013) than their low-income counterparts. One socioeconomic phenomenon that makes the prosocial behavior of high-income individuals particularly compelling is income inequality because it creates a hierarchy in which some people have more resources than others. Income inequality is increasing around the world (Solt, 2016) and is linked to important downstream welfare and behavioral consequences, including health and social problems (Pickett & Wilkinson, 2015), lower happiness and life satisfaction (Buttrick & Oishi, 2017; Oishi et al., 2011), and lower cooperation (Hauser et al., 2019).

Here, we investigate two critical questions: (1) whether high-income individuals are more likely to engage in prosocial behavior than their low-income counterparts and (2) whether high-income people are more likely to engage in prosocial behavior under high income inequality than under low income inequality. Prior research has explored the association between income, income inequality, and prosocial behavior using a small number of income measures and samples from restricted regions, such as Europe and the United States. In contrast, our study employs a globally representative dataset with 133 countries. We also conduct a multiverse analysis with two measures of prosocial behavior – whether people donated money to charity and whether people volunteered time to an organization – and use various statistical models and measures of income.

Income and Prosocial Behavior

To date, the evidence for the effect of income on prosocial behavior is mixed. Some studies show that low-income individuals are more prosocial than high-income individuals. Across four studies with 491 participants from Canada and the United States, Piff et al. (2010) found that low-income and low socioeconomic status individuals were more prosocial than high-income and high socioeconomic status individuals. In these studies, income was measured by participant's current objective annual household income, and income during childhood, and socioeconomic status represented participant's perceptions of socioeconomic rank. Specifically, these studies show that in comparison to high-income and high socioeconomic status individuals, low-income and low socioeconomic status individuals donated more cash to an anonymous participant in a dictator game (a validated behavioral measure of prosociality, see Bekkers, 2007; Engel, 2011; Johannesson, 2000), were

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more supportive of the belief that people, in general, should donate part of their salary to charity, gave more points to an anonymous partner despite the risk of a potential cost to themselves in a trust game, and spent more time helping with specific tasks.

In line with these findings, in a study of 77 students from a university in the United States, Piff, Stancato, Martinez, et al. (2012) found that low socioeconomic status students (those who rated their socioeconomic status to be lower in their community) were more willing to participate in community-building activities than high socioeconomic status individuals when they were exposed to hypothetical threats in their environment. Similarly, across three studies, using a sample of 1,070 Canadian participants, Whillans et al. (2017) found that when presented with an appeal that emphasized communion, low-income individuals were more willing to give to others and donated more of their study payment in comparison to high-income individuals.

In contrast, some research suggests that high-income individuals are more prosocial than their low-income counterparts. Across eight studies with large representative samples from the United States, Canada, and 32 European countries, Korndörfer et al. (2015) has shown that high-income individuals (those with higher annual household income) were more likely to donate to charity, donated a larger proportion of their salary to charity, were more likely to volunteer, were more helpful in everyday situations, and were more trusting and trustworthy in economic games than low-income individuals. The authors posited that the relatively small sample sizes of initial studies published in psychology, the low variability in the cultural background of participants, and the different measures of income and socioeconomic status used across studies could potentially explain the difference between their results and initial studies showing a negative effect of income on prosocial behavior.

Other researchers have explored *when* high-income individuals are more prosocial than low-income individuals. Across three studies with United States residents (total N = 4,890), Kraus and Callaghan (2016) found that when behaving prosocially provided reputational benefits, high-income and high socioeconomic status individuals (those with higher household income and greater subjective social class) were more likely to engage in a public campaign with prosocial aims and donate more raffle tickets to another participant in a dictator game than low-income and low socioeconomic status individuals. Using a sample of 32,174 alumni of an Ivy League university in the United States, Kessler et al. (2019) found that agency over the use of the money donated increased the amount of the donations given by individuals whose household income was at the top 5% of the income distribution in their census area. Similarly, using a sample of 1,070 Canadian and US participants, Whillans et al. (2017) found that when presented with a message that focused on personal agency, high-income individuals were more willing to give to others and donated more of their study payment in comparison to low-income individuals (see also Whillans & Dunn, 2018). Using a sample of 633 Dutch millionaires (people who had more than €1 million in their bank account), Smeets et al. (2015) found that millionaires were more generous in a dictator game when they were matched with a low-income participant versus another millionaire.

A lack of consensus about the effect of income on prosocial behavior has led researchers to call for future research to carefully examine this question by using alternative measures of prosocial behavior and income, more diverse samples, and a variety of statistical methods (see Côté & Willer, 2020; Schmukle & Egloff, 2020).

The Moderating Role of Income Inequality

Due to mixed findings of the effect of income on prosocial behavior, researchers have started to explore whether an increasingly relevant contextual factor – income inequality – can enhance or undermine the effect of income on prosocial behavior.

In one representative survey of Americans (N = 1,498), Côté et al. (2015) found that high-income individuals living in the United States were less likely to donate and donated fewer raffle tickets in a dictator game when they lived in states with higher levels of income inequality (Côté and colleagues, 2015, did not measure volunteering). In an experiment with 704 Americans, Côté et al. (2015) found that when told that income inequality in their state was high, high-income individuals were less generous in a dictator game than low-income individuals.

More recently, Schmukle et al. (2019) analyzed three nationally representative datasets in the United States, Germany, and other European countries to further explore the relationship between income, income inequality, and prosocial behavior. The authors found no evidence that high-income individuals donated less of their income to charity (Study 1, N = 27,714) or donated fewer points in a dictator game (Study 2, N = 667) when living in US and German states with higher income inequality (Schmukle et al., 2019). If anything, high-income individuals who lived in countries with higher income inequality volunteered more frequently than high-income individuals who lived in countries with lower income inequality (Schmukle et al., 2019; Study 3; N = 30,985).

This mixed evidence led to further discussions about reproducibility. Côté and Willer (2020) conducted five replication studies using different samples of US residents, different measures of income, and responses in a dictator game. In this replication, high-income individuals were less generous under high-income inequality in two of five samples. In particular, the preregistered study showed a null interaction between income and income inequality. Côté and Willer (2020) proposed that a negative interaction may only exist when examining giving in a dictator game and certain cultural contexts, such as the United States. Following this proposition, our research explores whether income inequality moderates the association between income and prosocial behavior using alternative measures of prosocial behavior and data from 133 countries worldwide.

Multiverse Analysis

When examining a research question, researchers have degrees of freedom to choose the data transformation techniques and statistical models they find most appropriate. However, the answer to the same research question may vary based on the statistical choices that researchers make. For example, Silberzahn et al. (2018) showed that 29 teams involving 61 scientists were tasked with answering the same research question (i.e., whether referees' likelihood of giving red cards was related to the skin tone of the player) using the same dataset made different statistical choices. These different statistical choices resulted in 69% of the teams finding a significantly positive effect and 31% finding a null relationship. If these teams reported their results separately, the answer to the same research question would be different.

One way to overcome this limitation is to perform a multiverse analysis which involves systematically conducting analyses that differ in data transformation techniques and statistical methods (Steegen et al., 2016). The goal of this approach is to increase transparency by reporting the findings across different statistical scenarios. A multiverse analysis clarifies the robustness of reported results and clarifies whether the findings change due to various statistical choices available to a researcher. The statistical techniques and methods used in prior research on the topic of interest can help to inform the multiverse analysis.

In recent years, this multiverse approach has increased in popularity in response to the concern that researchers may choose a statistical technique based on the results it produces (Simonsohn et al., 2014). By answering the same research question using different statistical techniques and showing all the results, a multiverse analysis provides transparency and dovetails with other, open-science practices (Steegen et al., 2016).

Our multiverse analysis examines whether high-income individuals are more likely to engage in prosocial behavior than low-income individuals and whether income inequality moderates this effect by employing 15 different statistical specifications including five income measures and three statistical models.

The Present Research

Data

We use a large, diverse, and globally representative dataset in the present research – the Gallup World Poll (GWP). This dataset includes nationally representative data from 133 countries, 10 survey years (2009–2018), and 948,837 respondents. The diversity of respondents in this dataset is important given that the majority of prior research on this question has not included regions with historically high levels of income inequality or respondents from different countries (see Côté & Willer, 2020; Schmukle & Egloff, 2020 for related reviews). Table 1 shows descriptive statistics of the variables involved in the analyses.

Dependent Variables

Our multiverse analysis used two measures of prosocial behavior as dependent variables: 15 models used whether people donated money to charity (yes/no) as the outcome variable of interest and 15 models used whether people volunteered time to an organization (yes/no) as the outcome variable of interest. Our study involved the following measures:

Donating

To assess respondents' likelihood of donating money to charity, we employed a widely used indicator of donation behavior from the Gallup World Poll (Aknin et al., 2013). Respondents could answer "Yes" or "No" to the following question: "Have you donated money to charity in the past month?"

Volunteering

We examined respondents' likelihood of volunteering time using the following question "Have you done any of the following in the past month? How about Volunteered your time to an organization?" Respondents could answer "Yes" or "No."

Given the low correlation between the likelihood of donating money to charity and the likelihood of volunteering time to an organization (0.27), and in light of prior research on this topic (Aknin & Whillans, 2020), we treated these measures as separate dependent variables.

Independent Variables

Using the measure of income provided by the Gallup World Poll, we created different measures of income that we included in our multiverse analysis. The income variable in the Gallup World Poll is a measure of household income before taxes. Following the methodology used by the

Table 1. Descriptive statistics of variables involved in the analysis

Name of variable	*N*	Mean	*SD*	Min	Max
Donated money to charity	948,837	0.32	0.466	0	1
Volunteered to an organization	948,837	0.20	0.400	0	1
Absolute income	948,837	9,321.119	240,819.300	0	224,508,412
Log of income	948,837	7.973	1.793	0	19
Richest 20%	948,837	0.20	0.400	0	1
Richest 10%	948,837	0.10	0.299	0	1
Richest 1%	948,837	0.01	0.096	0	1
Gini Index	948,837	37.600	7.799	23.400	65.000
Female	948,837	0.546	0.498	0	1
Age	948,819	42.559	18.025	13.000	100.000
Age squared	948,819	2,136.206	1,723.236	169.000	10,000.000
Level of education					
Elementary	941,642	0.312	0.463	0	1
Secondary	941,642	0.166	0.372	0	1
Tertiary	941,642	0.522	0.499	0	1
Employment status					
Employed full-time employer	910,794	0.283	0.450	0	1
Employed full-time for self	910,794	0.131	0.338	0	1
Employed part-time don't want full-time	910,794	0.072	0.258	0	1
Unemployed	910,794	0.058	0.234	0	1
Employed part-time want full-time	910,794	0.066	0.248	0	1
Out of workforce	910,794	0.390	0.488	0	1
Marital status					
Married	942,361	0.529	0.499	0	1
Divorced	942,361	0.041	0.198	0	1
Partner	942,361	0.054	0.227	0	1
Separated	942,361	0.024	0.152	0	1
Single	942,361	0.275	0.446	0	1
Widowed	942,361	0.078	0.267	0	1
Children under 15 household	933,409	1.100	1.617	0.000	59.000
Log of GDP per capita	948,837	9.433	1.062	6.457	11.728
Unemployment rate	948,837	7.776	5.590	0.310	32.179
Inflation rate	942,821	4.794	6.978	−6.811	121.738

Note. More detail about these variables can be found in the Electronic Supplementary Material, ESM 1.

Gallup World Poll, we created a measure of per capita household income by dividing the measure of household income by household size. Therefore, our coding of this variable allows for the accurate income classification of people who do not have personal income but who live in a household in which other members have income. We did not use equivalence scales which measure the cost of living of a particular household size and composition. For instance, these scales consider the fact that a family of four does not need four times the income of one person as some costs are shared by the household members (e.g., rent). Future research should explore whether these results hold using equivalence scales, given that they provide an alternative way to consider household size and composition when determining income per capita. Consistent with prior research exploring the relationship between income, income inequality, and prosocial behavior, using large-scale datasets (Côté et al., 2015; Schmukle et al., 2019), we use objective measures of income across our analyses. We included the following measures of income in our statistical models:

Absolute Income

Following Côté et al. (2015), we used a measure of absolute income divided by 10,000. Whereas Côté et al. (2015) centered their income measure within states, due to the characteristics of our dataset (133 countries and 10 years), we standardized the absolute income measure for each country and year to account for differences in currencies and purchasing power (Models 1–3, Tables 2 and 3).

Log of Income

Following Schmukle et al. (2019; Study 3), we included a logarithmized measure of income in our multiverse analysis. Our dataset includes country and year level data as it contains 133 countries and 10 survey years. In contrast, Study 3 from Schmukle et al. (2019) contains 30 countries and 1 survey year (1998). Their dataset, therefore, justifies the standardization of the income measure only by country because their data presents country-level data, whereas our dataset justifies the standardization of the income measures both by country and year. Because our dataset varied by country and year, we standardized income within country and year (Models 2–4, Tables 2 and 3).

Categorical Income (Top Quintile, Top Decile, and Top Percentile)

Following prior research on prosocial behavior (e.g., Kessler et al., 2019; Piff, Stancato, Martinez, et al., 2012), we used a categorical measure of income. Using the measure of personal income, we created a measure representing the five income quintiles in each country and year of data collection (see Oishi et al., 2018). We then created a dummy variable that represented the top quintile in each country and year with "1" and the lower quintiles with "0" (Models 7–9, Tables 2 and 3). This dummy variable allowed us to explore the prosocial behavior of relatively high-income individuals, that is, respondents at the top of the income distribution within country and year.

Although a categorical measure of income allowed us to focus on people with higher income, this method may raises the concern that results may differ according to how we split the income distribution (e.g., those at the top 20, 10, or 1%). To address this concern, we conducted the same analyses using several income thresholds. Specifically, in our multiverse analysis, we also included models that coded the income variable by deciles (top 10% – Models 10–12, Tables 2 and 3) and percentiles (top 1% – Models 13–15, Tables 2 and 3).

Income Inequality

To account for the level of income inequality in each country and year, we included the Gini Index in our analyses. The Gini Index is a commonly used measure of income inequality that ranges between 0 and 1. Scores closer to one denote higher levels of income inequality. For ease of interpretation, we used Gini values multiplied by 100, and centered the Gini Index across countries and years. We obtained this index from the Standardized World Income Inequality Database (SWIID; https://fsolt.org/swiid/). Although the Gini Index is known to have some limitations (Atkinson et al., 2011), this measure has key advantages for cross-country comparisons: the calculations of the Gini Index are independent of the size of the economy and the population of a country. The Gini Index is also available for all of the countries and survey years included in our dataset. Due to these features, the Gini Index is the preferable measure of income inequality in our study.

Statistical Methods

Given that the dependent variables were binomial (yes/no), we used different types of *logit* models (also called logic or binary logistic regressions) to examine the effect of income on the likelihood of engaging in prosocial behavior and whether income inequality moderates this effect. All of our models include whether people donated money to charity (1 = yes) or whether people volunteered time to an organization (1 = yes) as the dependent variables and income (absolute, log, quintiles, deciles, and percentiles depending on the model) and the interaction term between income and income inequality as independent variables. Our multiverse analysis included the following statistical models:

Random Effects Multi-Level Logit Models

Consistent with prior research on prosocial behavior (Côté et al., 2015; Schmukle et al., 2019), we used multi-level logit models with country and year as random intercepts. These random factors account for the multi-level aspect of the data (i.e., data are clustered in countries which are clustered in survey years) and, thus, these models account for the fact that the main effects may vary across countries and years (Models 1, 4, 7, 10, and 13, Tables 2 and 3).

Fixed Effects Logit Models Without Covariates

Following prior research using the same Gallup World Poll dataset (e.g., De Neve et al., 2018; Powdthavee et al., 2017) and datasets with similar characteristics (e.g., Di Tella et al., 2003), we conducted logit models including country and year fixed effects. These fixed effects account for cultural factors and political events that occurred in specific countries and years, and may influence the relationship between income, income inequality, and prosocial behavior (Models 2, 5, 8, 11, and 14, Table 2 and 3).

Fixed Effects Logit Models With Covariates

Following prior research on prosocial behavior (e.g., Piff, Stancato, Côté, et al., 2012; Whillans et al., 2017), we included covariates in our fixed effects logit models to account for potential alternative explanations.[1] These models allowed us to understand whether the observed results controlled variables that could influence prosocial behavior,

[1] Random effects multi-level logit models do not include covariates due to convergence challenges.

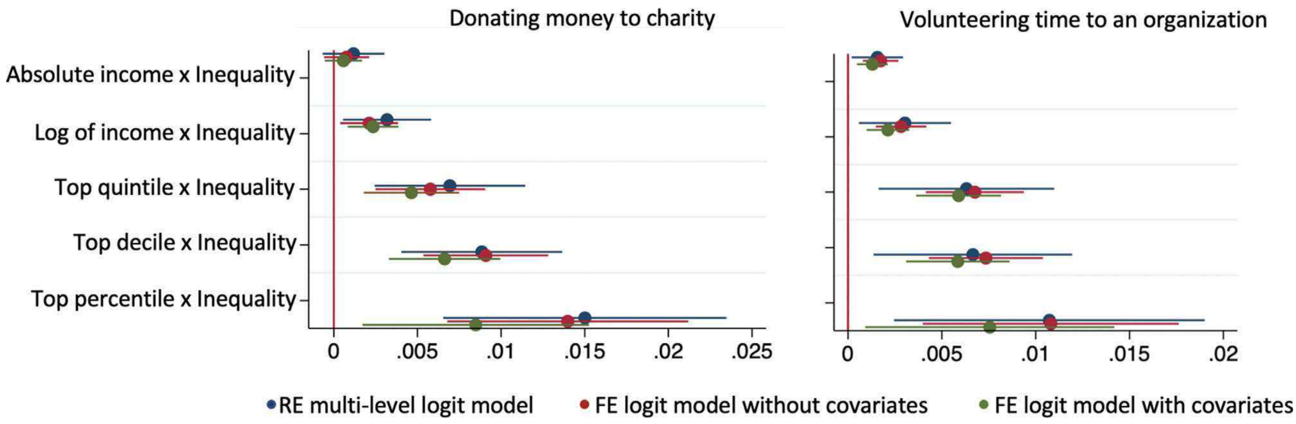

Figure 1. Interaction coefficients of income and income inequality from different statistical models. Dots indicate the logit estimate in each model, and the lines represent the confidence interval of each estimate. Absolute income is divided by 10,000 and standardized within country and year. Log of income is standardized within country and year. The top quintile represents people at the top quintile of the income distribution of their country and year. The top decile represents people at the top decile of the income distribution of their country and year. The top percentile represents people at the top percentile of the income distribution of their country and year. Income inequality (Gini Index) is standardized across countries and years. RE = Random effects. FE = Fixed effects.

such as age, gender, level of education, employment status, marital status, and a number of children under 15 in the household. Level of education, employment status, and marital status are categorical variables with elementary (up to 8 years of basic education), employed full-time for an employer, and single/never married as reference categories, respectively. In these models, we also accounted for macroeconomic factors that could be related to income inequality and prosocial behavior, such as GDP per capita, the unemployment rate, and the inflation rate in each country and survey year (see Macchia et al., 2020; Powdthavee et al., 2017; Models 3 6, 9, 12, and 15, Tables 2 and 3).

Overall, the multiverse analysis that we conducted consisted of 30 statistical specifications that included two dependent variables (whether people donated money to charity and whether people volunteered time to an organization), five income measures (absolute income, log of income, top quintile, top decile, and top percentile), and three statistical models (random effects multi-level logit model, fixed effects logit model without covariates, and fixed effects logit model with covariates).

Scripts for analyses and output are available through the Open Science Framework (OSF) https://osf.io/4g8yr/?view_only=26e229a4b2854204a2f7ee9df488af64 (Macchia & Whillans, 2021).

Results

Are High-Income Individuals More Likely to Engage in Prosocial Behavior?

Across each 30 model specifications, we found that high-income people were more likely to donate money to charity and volunteer time to an organization than low-income individuals (Table 2). Across the 15 models that used whether people donated money to charity as the dependent variable, the odds ratios ranged from 1.2 to 1.9. This indicates that the odds of having donated money to charity for high-income people were 1.2 to 1.9 times greater than the odds for low-income people, depending on the statistical model and the measure of income used. Across the 15 models that used whether people volunteered time to an organization as the dependent variable, the odds ratios ranged from 1.07 to 1.4. This indicates that for high-income people, the odds of volunteering time to an organization were 1.07–1.4 times greater than the odds for low-income people, depending on the statistical model and the measure of income used. These findings held controlling for sociodemographic factors (i.e., age, gender, level of education, employment status, marital status, number of children in the household) and macroeconomic indicators (i.e., log of GDP per capita, unemployment, and inflation rates; Models 3, 6, 9, 12, and 15, Table 2). The coefficients and relevant statistics can be found in Table 2 (Models 1–3 [absolute income], Models 4–6 [log of income], Models 7–9 [top quintile], Models 10–12 [top decile], and Models 13–15 [top percentile]). Full models can be found in Tables E1–E10 in the Electronic Supplementary Material, ESM 1.

Does Income Inequality Moderate the Effect of Income on Prosocial Behavior?

Likelihood of Donating

In 12 out of 15 models, we found that high-income individuals were more likely to donate money to charity under high-income inequality than under low-income inequality. The interaction term between income and income inequality in the three models that included absolute income

Table 2. Income coefficients from different statistical models predicting the likelihood of donating and volunteering

	Income measure	Statistical model	Donating	Volunteering
Model 1	Absolute income	RE multi-level logit	b = 0.184, p < .001, 95% CI [0.169, 0.199], OR = 1.2	b = 0.081, p < .001, 95% CI [0.069, 0.092], OR = 1.084
Model 2	Absolute income	FE logit without covariates	b = 0.180, p < .001, 95% CI [0.175, 0.185], OR = 1.198	b = 0.074, p < .001, 95% CI [0.069, 0.079], OR = 1.077
Model 3	Absolute income	FE logit with covariates	b = 0.125, p < .001, 95% CI [0.117, 0.134], OR = 1.134	b = 0.037 p < .001, 95% CI [0.030, 0.044], OR = 1.038
Model 4	Log of income	RE multi-level logit	b = 0.243, p < .001, 95% CI [0.222, 0.265], OR = 1.276	b = 0.113, p < .001, 95% CI [0.092, 0.134], OR = 1.120
Model 5	Log of income	FE logit without covariates	b = 0.228, p < .001, 95% CI [0.222, 0.233], OR = 1.255	b = 0.087, p < .001, 95% CI [0.082, 0.093], OR = 1.092
Model 6	Log of income	FE logit with covariates	b = 0.168, p < .001, 95% CI [0.157, 0.179], OR = 1.184	b = 0.040, p < .001, 95% CI [0.031, 0.049], OR = 1.041
Model 7	Top quintile	RE multi-level logit	b = 0.462, p < .001, 95% CI [0.425, 0.499], OR = 1.588	b = 0.232, p < .001, 95% CI [0.193, 0.271], OR = 1.262
Model 8	Top quintile	FE logit without covariates	b = 0.455, p < .001, 95% CI [0.443, 0.466], OR = 1.576	b = 0.208, p < .001, 95% CI [0.196, 0.221], OR = 1.232
Model 9	Top quintile	FE logit with covariates	b = 0.328, p < .001, 95% CI [0.308, 0.348], OR = 1.388	b = 0.097, p < .001, 95% CI [0.078, 0.118], OR = 1.102
Model 10	Top decile	RE multi-level logit	b = 0.513, p < .001, 95% CI [0.472, 0.553], OR = 1.671	b = 0.273, p < .001, 95% CI [0.229, 0.317], OR = 1.315
Model 11	Top decile	FE logit without covariates	b = 0.508, p < .001, 95% CI [0.493, 0.523], OR = 1.661	b = 0.246, p < .001, 95% CI [0.229, 0.263], OR = 1.279
Model 12	Top decile	FE logit with covariates	b = 0.355, p < .001, 95% CI [0.332, 0.378], OR = 1.426	b = 0.117, p < .001, 95% CI [0.093, 0.142], OR = 1.125
Model 13	Top percentile	RE multi-level logit	b = 0.680, p < .001, 95% CI [0.609, 0.751], OR = 1.975	b = 0.354, p < .001, 95% CI [0.284, 0.423], OR = 1.425
Model 14	Top percentile	FE logit without covariates	b = 0.670, p < .001, 95% CI [0.624, 0.716], OR = 1.955	b = 0.339, p < .001, 95% CI [0.289, 0.389], OR = 1.404
Model 15	Top percentile	FE logit with covariates	b = 0.465, p < .001, 95% CI [0.413, 0.518], OR = 1.593	b = 0.185, p < .001, 95% CI [0.129, 0.241], OR = 1.204

Note. b = logit estimate; p = p-value; 95% CI = 95% Confidence Interval; OR = Odds Ratio; RE = random effects; FE = fixed effects. Income inequality (Gini Index) is a continuous measure centered across countries and years. Number of observations of models without covariates = 948,837; Number of observations of models with covariates = 885,241. 133 countries, 10 survey years. RE multi-level logit models include country and year as random factors. FE logit models include country and year fixed effects. FE logit models with covariates also include respondents' demographic characteristics: age, age squared, gender, level of education, employment status, marital status, number of children under 15 in the household, macroeconomic indicators: log of GDP per capita, unemployment rate, and inflation rate; and standard errors clustered by country-year. These models do not include the interaction between income and income inequality to interpret the effect of income on prosocial behavior without the influence of the interaction term. Full models can be found in ESM 1.

(Models 1–3, Table 3) was insignificant (see Discussion section for more details). Across the 12 models that showed a significant positive interaction, the odds ratios ranged from 1.001 to 1.015. These analyses show that for high-income people, the odds of having donated money to charity under high-income inequality were, depending on the statistical model and the measure of income used, 1.001 to 1.015 times greater than the odds of having donated money to charity under low-income inequality. These results held controlling for socio-demographic factors (i.e., age, gender, level of education, employment status, marital status, number of children in the household) and macroeconomic indicators (i.e., log of GDP per capita, unemployment, and inflation rates; Models 3, 6, 9, 12, and 15, Table 3). The interaction coefficients and relevant statistics can be found in Table 3 (Models 1–3 [absolute income], Models 4–6 [log of income], Models 7–9 [top quintile], Models 10–12 [top decile], and Models 13–15 [top percentile]), and on the right-hand panel on Figure 1. The full models can be found in Tables E14–E18 in ESM 1.

Likelihood of Volunteering

Across all of the 15 statistical models that examined this question, high-income individuals were more likely to volunteer time to an organization under high-income inequality than under low-income inequality. This result was robust to various model specifications and conceptualizations of income. Across the 15 models that used whether people volunteered time to an organization as the dependent variable, the odds ratios ranged from 1.002 to 1.011. In these analyses, for high-income individuals, the odds of having volunteered time to an organization in the past month under high-income inequality were, depending on the statistical model and the measure of income used, 1.002 to 1.011 times greater than the odds of having volunteered time to an organization under low-income inequality. These findings held controlling for sociodemographic factors (i.e., age, gender, level of education, employment status, marital status, number of children in the household) and macroeconomic indicators (i.e., log of GDP per capita, unemployment, and inflation rates; Models 3, 6, 9, 12, and 15,

Table 3. Interaction terms of income and income inequality from different statistical models predicting the likelihood of donating and volunteering

	Income measure	Statistical model	Donating	Volunteering
Model 1 (Côté et al., 2015)	Absolute income	RE multi-level logit	*b* = 0.001, *p* = .210, 95% CI [−0.001, 0.003], OR = 1.001	*b* = 0.002, *p* = .025, 95% CI [0.0002, 0.003], OR = 1.002
Model 2	Absolute income	FE logit without covariates	*b* = 0.001, *p* = .207, 95% CI [−0.001, 0.002], OR = 1.001	*b* = 0.002, *p* < .001, 95% CI [0.001, 0.003], OR = 1.002
Model 3	Absolute income	FE logit with covariates	*b* = 0.001, *p* = .311, 95% CI [−0.001, 0.002], OR = 1.001	*b* = 0.001 *p* = .002, 95% CI [0.0005, 0.002], OR = 1.001
Model 4 (Schmukle et al., 2019)	Log of income	RE multi-level logit	*b* = 0.003, *p* = .018, 95% CI [0.001, 0.006], OR = 1.003	*b* = 0.003, *p* = .015, 95% CI [0.001, 0.005], OR = 1.003
Model 5	Log of income	FE logit without covariates	*b* = 0.002, *p* = .007, 95% CI [0.001, 0.004], OR = 1.002	*b* = 0.003, *p* < .001, 95% CI [0.001, 0.004], OR = 1.003
Model 6	Log of income	FE logit with covariates	*b* = 0.002, *p* = .002, 95% CI [0.001, 0.004], OR = 1.002	*b* = 0.002, *p* < .001, 95% CI [0.001, 0.003], OR = 1.002
Model 7	Top quintile	RE multi-level logit	*b* = 0.007, *p* = .003, 95% CI [0.002, 0.011], OR = 1.007	*b* = 0.006, *p* = .008, 95% CI [0.002, 0.011], OR = 1.006
Model 8	Top quintile	FE logit without covariates	*b* = 0.006, *p* < .001, 95% CI [0.003, 0.009], OR = 1.006	*b* = 0.007, *p* < .001, 95% CI [0.004, 0.009], OR = 1.007
Model 9	Top quintile	FE logit with covariates	*b* = 0.005, *p* = 0.001, 95% CI [0.002, 0.007], OR = 1.005	*b* = 0.006, *p* < .001, 95% CI [0.004, 0.008], OR = 1.006
Model 10	Top decile	RE multi-level logit	*b* = 0.009, *p* < .001, 95% CI [0.004, 0.014], OR = 1.009	*b* = 0.007, *p* = 0.014, 95% CI [0.001, 0.012], OR = 1.007
Model 11	Top decile	FE logit without covariates	*b* = 0.009, *p* < .001, 95% CI [0.006, 0.012], OR = 1.009	*b* = 0.007, *p* < .001, 95% CI [0.004, 0.010], OR = 1.007
Model 12	Top decile	FE logit with covariates	*b* = 0.007, *p* < .001, 95% CI [0.003, 0.009], OR = 1.007	*b* = 0.006, *p* < .001, 95% CI [0.003, 0.009], OR = 1.006
Model 13	Top percentile	RE multi-level logit	*b* = 0.015, *p* = .001, 95% CI [0.007, 0.023], OR = 1.015	*b* = 0.011, *p* = .011, 95% CI [0.002, 0.019], OR = 1.011
Model 14	Top percentile	FE logit without covariates	*b* = 0.014, *p* < .001, 95% CI [0.007, 0.021], OR = 1.014	*b* = 0.011, *p* = 0.001, 95% CI [0.004, 0.017], OR = 1.011
Model 15	Top percentile	FE logit with covariates	*b* = 0.008, *p* = .014, 95% CI [0.002, 0.015], OR = 1.009	*b* = 0.008, *p* = .026, 95% CI [0.001, 0.014], OR = 1.008

Note. *b* = logit estimate; *p* = *p*-value; 95% CI = 95% Confidence Interval; OR = Odds Ratio; RE = random effects; FE = fixed effects. Income inequality (Gini Index) is a continuous measure centered across countries and years. Number of observations of models without covariates = 948,837; Number of observations of models with covariates = 885,241. 133 countries, 10 survey years. RE multi-level logit models include country and year as random factors. FE logit models include country and year fixed effects. FE logit models with covariates also include respondents' demographic characteristics: age, age squared, gender, level of education, employment status, marital status, number of children under 15 in the household, macroeconomic indicators: log of GDP per capita, unemployment rate, and inflation rate; and standard errors clustered by country-year. Full models can be found in ESM 1.

Table 3). The interaction coefficients can be found on Table 3 (Models 1–3 [absolute income], Models 4–6 [log of income], Models 7–9 [top quintile], Models 10–12 [top decile], and Models 13–15 [top percentile]) and on the left-hand panel of Figure 1. Full models can be found in Tables E19–E23 in ESM 1.

Regions of Significance

To identify the range of income inequality where the effect of income on the likelihood of engaging in prosocial behavior was statistically significant, we conducted analyses of regions of significance. Across all models that showed a significant positive interaction between income and income inequality, we found that the slope for income was significant for all levels of income inequality and that in countries with high-income inequality (Gini Index = 65.0), the simple slope for income was larger than in countries with low-income inequality (Gini Index = 23.4). See Tables E12 and E13 in ESM 1 to interpret results and regions of significance.

Robustness Checks

We conducted additional models to confirm the robustness of the models that use categorical measures of income. Instead of coding the bottom quintiles, deciles, and percentiles with zero and the top quintile, decile, and percentile with 1, respectively, the additional models include a measure of income with each quintile, decile, and percentile *separately* using the *top* quintile, decile, and percentile, respectively, as the *reference category*. These models show that people whose income was in the lower quintiles, deciles, and percentiles were less likely to donate money and less likely to volunteer their time than those whose income was in the top quintile, decile, and percentile. These models show that income inequality moderated these effects. These findings were consistent across our three model specifications: Random effects multi-level logit model, fixed effects logit model without covariates, and fixed effects logit model with covariates. These models can be found in Tables E24–E29 in ESM 1.

As an additional robustness check, we controlled for the difference between high-income and low-income individuals in each country and survey year. This test allowed us to rule out a potential alternative explanation that the larger difference in income between high-income and low-income individuals in countries with greater income inequality drove the positive relationship between income, income inequality, and prosocial behavior. This robustness check did not significantly change the results (see Tables E34 and E35 in ESM 1).

Discussion

The effect of income on prosocial behavior and whether income inequality moderates this effect have been extensively explored (e.g., Côté et al., 2015; Korndörfer et al., 2015; Piff et al., 2010; Schmukle et al., 2019). However, most previously published studies have used convenience samples from restricted regions, such as the United States and Europe, and varied measures of prosocial behavior and income.

We used a large and globally representative dataset with 948,837 respondents and 133 countries and various statistical models. We conducted a multiverse analysis with 30 statistical specifications that contained five income measures (absolute income, log of income, income quintiles, income deciles, and income percentiles), three statistical models (random effects multi-level logit models, fixed effects logit models without covariates, and fixed effects logit models with covariates), and two dependent variables (whether people donated money to charity and whether people volunteered time to an organization). First, we found that high-income individuals were more likely to engage in prosocial behavior than low-income individuals. Second, we found that under high-income inequality, high-income individuals were more likely to engage in prosocial behavior than under low-income inequality.

The positive effect of income on the likelihood of engaging in prosocial behaviour held across the 30 statistical models that we conducted in our multiverse analysis. This finding aligns with more recent research showing that high-income individuals are more prosocial than low-income individuals (Korndörfer et al., 2015). In contrast, this finding is not consistent with initial social psychological research that shows that low-income individuals are more prosocial than high-income individuals (Piff et al., 2010; see Introduction for more detail about these studies).

The positive interaction between income and income inequality was found in 12 of the 15 models that used whether people donated money to charity as the dependent variable and in the 15 models that used whether people volunteered time to an organization as the outcome variable. The models that used absolute income as the income measure showed a null interaction between income and income inequality predicting the likelihood of donating money to charity.

Using a sample of United States residents, Côté et al. (2015) found a negative interaction between income, income inequality, and prosocial behavior as measured by the number of raffle tickets people donate in an economic game. Using samples from the United States, Germany, and other European countries, Schmukle et al. (2019) found a null interaction between income and income inequality predicting prosocial behavior measured by donations to charity and a positive interaction predicting prosocial behavior measured by the frequency of volunteering. Here, we found a positive interaction between income, income inequality, and prosocial behavior measured by the likelihood of donating money to charity and the likelihood of volunteering time to an organization. The different dependent variables and samples used may explain the diverse findings of these studies.

Our findings that high-income people were more likely to engage in prosocial behavior under high versus low-income inequality complements prior research on the topic that has examined income, income inequality, and prosocial behavior using restrictive samples, such as Europe and the United States. The magnitude of these effects is in line with prior research that has explored similar relationships with similar datasets (Côté et al., 2015; Schmukle et al., 2019). In addition, the rather diminutive relationships found here are consistent with other well-established relationships, such as the extensively studied association between income and happiness (Stevenson & Wolfers, 2013).

Our study has some potential limitations. First, the cross-sectional nature of the data does not allow us to establish causality. Due to the lack of experimental and longitudinal data, we can only assess the association between income, income inequality, and prosocial behavior. Future research should seek to demonstrate causality. Second, prior research shows that higher-income individuals have greater control over their temporal and financial resources (Johnson & Krueger, 2006; Smeets et al., 2020). The fact that high-income people have more discretion over these resources could explain why they are more likely to donate money to charity and volunteer time to an organization. Our data do not allow us to rule out this possibility. Future research should attempt to control for these variables. Third, our study uses self-reported measures of prosocial behavior: whether people donated money to charity (yes/no) and whether people volunteered time to an organization in the past month (yes/no). Although self-report data can allow researchers to gain insights from populations rarely studied in psychology, such as the ones included here, we acknowledge that self-reported prosocial behavior might not always correspond to real-life behavior (see

Baumeister et al., 2007 for further discussion). Studying the likelihood of engaging in prosocial behavior is particularly important in contexts in which giving and volunteering rates are low, whereas exploring how much money people donate and how frequently people volunteer may seem a priority in a context in which giving and volunteering rates are high. In our sample, 32% of people reported that they donated money to charity in the past month, and 20% reported that they volunteered time to an organization in the past month. These data highlight the need to understand the factors that may shape the likelihood of donating money and volunteering time. Finally, although the measure of income inequality used here, namely the Gini Index, has advantages for a cross-sectional study (see Introduction for more details), it also has some limitations. One possible disadvantage of this measure is that it is particularly sensitive to changes in the middle of the distribution (vs. the tails Atkinson et al., 2011). Thus, future research, especially research that aims to capture inequality in the tails of the income distribution, should use measures of income inequality that overcome this limitation such as the income held by the top 1% of income earners.

Future research should examine the relationships studied here using other dependent variables such as the amount of money donated to charity and the proportion of salary donated to charity (see Schmukle et al., 2019). Careful attention should be given to these dependent variables as two people may give the same amount of money, but the proportion of their income may be different. In this case, the person who gives a lower proportion of their income could be considered less generous than the one who gives a larger proportion of their income. Future research should explore these possibilities with representative samples in a wide range of countries instead of convenience samples from the United States or Europe. Our study is the first step in that direction.

Future research should also explore other independent variables, for example, subjective socioeconomic status and social class (e.g., a composite of income, education, and occupation). These measures are particularly relevant when exploring prosocial behaviors that are not directly related to money, such as helping a stranger. Prosocial behavior among low-income people also deserves more detailed scrutiny. Prior research shows that low-income people are more prosocial than high-income people (e.g., Piff et al., 2010). Our cross-national data found that low-income people were less likely to donate money to charity and less likely to volunteer time to an organization than high-income people. Most of our statistical models found a null interaction between low income, income inequality, and the likelihood of engaging in prosocial behavior. These exploratory analyses can be found in Tables E30 and E31 in ESM 1. Future research should consider a multiverse analysis to explore these possibilities.

There are several possible psychological explanations for the positive interaction between income and income inequality predicting the likelihood of engaging in prosocial behavior. Although such explanations were not testable in our data, these suggestions provide the groundwork for future research to explore the patterns of results observed here.

First, future research should explore whether perceiving wealth as a responsibility and feeling personal agency toward helping those in need may explain why high-income people are more likely to engage in prosocial behavior under high-income inequality than under low-income inequality. This suggestion is based on findings showing that the belief that wealth incurs a responsibility to give back to society can improve people's attitudes about paying taxes (Whillans et al., 2016) as well as research showing that appeals emphasizing agency shape high-income people's financial generosity (Whillans et al., 2017; see also Schuyt et al., 2004).

Moreover, research suggests that the visibility of income inequality shapes people's willingness to reward the poor, as well as their support for various redistributive policies (Hauser et al., 2017; McCall et al., 2017; Sands, 2017). Future research could also explore the role of daily visibility of inequality in shaping the prosocial behavior of high-income individuals living under greater income inequality in countries worldwide (see also Waldfogel et al., 2021). Other research should also look at whether the findings that wealthy people give more under high income inequality are driven by prosocial behaviors directed to members of their own group, such as through giving to arts and education based initiatives.

Tax rates could also play a critical role. In an equal country with high tax rates, high-income people may feel less encouraged to donate money to charity because they are already contributing to society. Yet, high-income people who live in a highly unequal country with low tax rates may be more generous if they do not feel they are contributing to help those in most need through taxation. We conducted an initial test to explore whether income tax rates in each country and year moderated the association between income, income inequality, and prosocial behavior. We conducted fixed effects logit regressions with covariates and our five measures of income (absolute income, log of income, top quintile, top decile, and top percentile; see Tables E32 and E33 in ESM 1). The results were inconclusive. Thus, future research should explore perceptions of the efficacy of taxation as a moderator in addition to the tax rate to further the analyses provided in the current paper.

Furthering the debate among academics and policymakers, our study contributes to the prosociality-inequality puzzle of whether income inequality moderates prosocial behavior among the affluent by showing that high-income people are more likely to engage in prosocial behavior under high-income inequality than under low-income inequality. The results of our multiverse analysis complement prior studies because it uses a larger, more diverse sample and a greater set of statistical models compared to other studies. The consistency of the results that we observed across statistical models, together with prior research on this topic, therefore set the groundwork for future research that could explore when and why income inequality moderates the effect of income on prosocial behavior.

Electronic Supplementary Materials

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ESM 1. The file contains data information and additional analyses.

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Open Data
The Gallup World Poll data belong to Gallup, Inc. For more information, see: https://www.gallup.com/analytics/318875/global-research.aspx. Scripts for analyses and output are available through the Open Science Framework (OSF) https://osf.io/4g8yr/?view_only=26e229a4b2854204a2f7ee9df488af64 (Macchia & Whillans, 2021).

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