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SOEP — The German Socio-Economic Panel at DIW Berlin 1034-2019

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DIW SOEP

ISSN: 1864-6689 (online)

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No Evidence that Economic Inequality Moderates the Effect of Income on Generosity

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This manuscript is published as:

Schmukle S. C., Korndörfer, M., & Egloff, B. (2019). No evidence that economic inequality moderates the effect of income on generosity. *Proceedings of the National Academy of Sciences (PNAS)*, 116 (20), 9790-9795. doi: 10.1073/pnas.1807942116.

This is an unedited version of the manuscript including Supplementary Information (SI) before copyediting, typesetting, and review of the resulting proof.

Abstract

A landmark study published in *PNAS* (Côté S, House J, Willer R, 2015, 112:15838–15843, doi:10.1073/pnas.1511536112) showed that higher income individuals are less generous than poorer individuals only if they reside in a U.S. state with comparatively large economic inequality. This finding might serve to reconcile inconsistent findings on the effect of social class on generosity by highlighting the moderating role of economic inequality. On the basis of the importance of replicating a major finding before readily accepting it as evidence, we analyzed the effect of the interaction between income and inequality on generosity in three large representative data sets. We analyzed the donating behavior of 27,714 U.S. households (Study 1), the generosity of 1,334 German individuals in an economic game (Study 2), and volunteering to participate in charitable activities in 30,985 participants from 30 countries (Study 3). We found no evidence for the postulated moderation effect in any study. This result is especially remarkable because (a) our samples were very large, leading to high power to detect effects that exist, and (b) the cross-country analysis employed in Study 3 led to much greater variability in economic inequality. These findings indicate that the moderation effect might be rather specific and cannot be easily generalized. Consequently, economic inequality might not be a plausible explanation for the heterogeneous results on the effect of social class on prosociality.

Keywords: Social class, income, economic inequality, prosocial behavior, generosity

Significance Statement

Are the rich less generous than the poor? Results of studies on this topic have been inconsistent. Recent research that has received widespread academic and media attention has provided evidence that higher income individuals are less generous than poorer individuals only if they reside in a U.S. state with comparatively large economic inequality. However, in large representative data sets from the US (Study 1), Germany (Study 2), and 30 countries (Study 3), we did not find any evidence for such an effect. Instead, our results suggest that the rich are not less generous than the poor, even when economic inequality is large. This result has implications for contemporary debates on what increasing inequality in resource distributions means for modern societies.

Economic inequality has been on the rise around the world for several decades (1, 2), and researchers from several disciplines have investigated the antecedents, correlates, and consequences of this increasing economic divide (3-5). Mostly negative effects have been reported and not only in the economic domain but also including increases in health and social problems (e.g., increased drug use, higher obesity, more violent crimes, higher imprisonment rates, and lower interpersonal trust; 6, 7), ultimately leading to lower levels of life satisfaction in the population (8-10; but see 11-13 for positive and null effects of inequality on well-being and happiness). An additional negative consequence was recently reported in *PNAS*, where Côté et al. (14) provided evidence that economic inequality leads higher income individuals to be less generous than low-income individuals. Their study is important for several reasons: (a) It has policy implications because the negative effects of economic inequality on outcomes that are desirable for a society are important issues for the public, (b) it shows how a macroeconomic variable measured on the state level (economic inequality) can interact with a sociological variable (social class) to affect a psychological variable (prosocial behavior), and (c) it has the potential to reconcile the debate on why findings on the association between social class and prosocial behavior have been inconsistent.

This debate began with two influential psychological studies in which Piff et al. (15, 16) reported that individuals from higher social classes behaved more unethically and were less charitable, less trusting, and less generous than individuals from a lower social class. The authors explained this negative effect of social class from a social-cognitive perspective (17): Individuals from lower social classes are more attuned to the welfare of others as a way to adapt to their more hostile environments and are thus more likely to be compassionate (18) and to engage in other-beneficial prosocial behavior (15). On the other end of the continuum, the abundant resources enjoyed by upper-class individuals lead to an individualistic focus on their own internal states, goals, motivations, and emotions (15, 16, 18, 19; for recent reviews, see 17, 20, 21).

However, other researchers from various disciplines have not been able to confirm the negative effects of higher social class on prosocial behaviors and observed either no associations or even effects in the opposite direction. Such research has employed a large number of diverse behaviors as indicators of prosociality, such as making charitable donations (22, 23), volunteering (23-25), behaving prosocially in economic games (23, 25, 26), returning lost letters (27, 28), helping others (23), and being compassionate and empathetic (29). This research also includes two failed but high-powered direct replications of studies reported in (16) on the effect of social class on unethical activities (30, 31).

What might explain the discrepant results? Piff and Robinson (20) argued that moderating variables might be responsible for the heterogeneous effects of social class on prosociality, thus qualifying the “Having less, giving more” main effect reported by Piff et al. (15). Indeed, Côté et al. (14) identified such a moderator when they found that the negative effect of social class on prosociality could be observed only when economic inequality was high. By contrast, when economic inequality was low, social class and prosocial behavior were even positively related, whereas they found no effects when all participants were considered together. Specifically, higher income individuals were less generous in an economic game than poorer individuals only when they resided in a U.S. state that was plagued by comparatively large economic inequality (Study 1) or only when a perception of high inequality was induced experimentally (Study 2). Different levels of economic inequality may thus explain why individuals from a lower social class were more generous in Piff at al.’s (15) U.S. sample (a country with comparatively high inequality), whereas we found the opposite effect in a German sample (a country with lower inequality; 23). The explanation for this moderating effect is that in less equal environments, higher income individuals perceive a wider gap between themselves and low-income individuals, which leads higher income individuals to have a sense of entitlement and ultimately reduces their prosocial behavior (14, 20).

In sum, the "inequality as a moderator of the relation between social class and prosociality" explanation seems to be theoretically compelling and empirically sound. But can one article comprised of two studies really provide a definitive answer and resolve the debate on the effects of social class on prosocial behavior? Certainly not. A few conceptually related recent studies might be interpreted as additional evidence in support of Côté et al.'s (14) central claim: From 1917 to 2012, higher income individuals in the U.S. donated less in years when inequality was high than in years when inequality was low (32). In the lab, individuals with more resources in a public goods game acted more selfishly when resources were markedly unequal than when resources were more equally distributed (33), at least as long as resource inequality was visible to the participants (34). Finally, passersby in a wealthy area supported a "millionaire tax" less often in the presence of a homeless person (a signal of inequality) than in the presence of a professional-looking person (35).

At the same time, other conceptually related findings might be interpreted as evidence against Côté et al. (14). First, experimentally inducing a tendency to accept and endorse inequalities in society moderated the relation between individual power and charitable giving but in exactly the opposite direction than what would be expected from the previously described studies: When instructed to provide reasons in support of societal inequality, individuals high in power donated more, whereas when instructed to provide reasons against societal inequality, those low in power behaved more generously (36). Second, not only did millionaires give more in economic games than any other group studied in the literature before, they were also more generous toward individuals with lower incomes in a setting with high inequality (dictator game: the other participant could not punish unfair behavior) compared with a more equal setting (ultimatum game: the other participant could punish unfair behavior) (37). Third, in a natural experiment in Indian schools, integrating poor students into elite private schools and thus making economic inequality salient led students from affluent families to be more prosocial, generous, and egalitarian (38).

In view of this inconclusive current state of studies and recent evidence for a rather low rate of successful replications in psychology (39), the issues of reproducibility and replicability are major issues not only in psychology but in science in general (40). For instance, the National Academy of Sciences organized a colloquium on this issue (41) and initiated a committee on reproducibility and replicability in December 2017 (42). We support the idea that replications should become the norm rather than the exception before new findings are readily accepted, even when such findings appear to be plausible and desirable (43, 44). As the importance of a study increases, it is even more essential to confirm the reproducibility and replicability of that research, and importance might be defined through a study's theoretical weight, societal implications, influence through citations, or mass appeal (45). As argued above, all these descriptors of importance are fulfilled for the association between social class and prosociality in general and especially for the potential moderating effect of economic inequality. For these reasons, we sought to test whether we would be able to find this Income × Inequality interaction in three large data sets that we analyzed previously regarding the effects of social class on prosocial behavior (23). Data and analysis scripts are provided at https://osf.io/b6m2r/

Study 1

In Study 1, we tried to replicate the Income × Inequality interaction in a large and reasonably representative U.S. sample, the American Consumer Expenditure Survey (CEX; 46). In this survey, households from 41 U.S. states were asked about their yearly household income and the amount of charitable contributions they made during the last 3 months in four quarterly interviews across a year. We used CEX data collected between 2005 and 2012. By using different inclusion criteria, we created two samples for our main analysis: For Sample A, we included only households that participated in all four interviews within a given year and for which all variables relevant for our analyses were available (N = 27,714). This inclusion criterion maximized data quality at the expense of excluding many households. For

Sample B, we relaxed the demands on data quality in order to maximize sample size and included households that participated in at least two of the four interviews (*N* = 43,739). If necessary, the yearly amount of donations was extrapolated from the available information (for more information about the CEX data and our samples, see the SI Appendix, supplementary text).

The mean after-tax household incomes were $68,204 (*SD* = 61,822) and $65,188 (*SD* = 61,859) in Samples A and B, respectively. Because the distribution of the income variable was skewed (skewness of 2.35 and 2.50), with more household incomes below the mean and some households with very large incomes (Median of $50,817 and $47,499), we logarithmized the income variable. On average, 0.39% and 0.35% of a household's after-tax income was donated, and 55.32% and 61.94% of households reported donating nothing during the year. Households that reported donating more than 100% of their yearly income were removed from the main analyses (8 and 12 households).

As state measure of economic inequality, we used Gini coefficients, which range from 0 (perfect equality) to 1 (maximal inequality). We retrieved 5-year Gini coefficients from the American Community Survey (47) for the year 2012. Gini coefficients were based on the pre-tax household income and varied from .413 (Alaska) to .532 (District of Columbia) between states (*M* = .457, *SD* = .022). Table S1 in the SI Appendix provides an overview of the states included in our analysis along with the corresponding sample size and the Gini coefficients.

In our main analysis, we estimated a multilevel Tobit model that adequately dealt with both the nested structure of our data (participants were nested in states) and the zero inflation in the donation variable (more than 50% of households reported donating nothing during the year). In this model, amount of donations (in percent of income) was predicted by logarithmized household income, state-level inequality (Gini coefficients), and the cross-level interaction of these two variables. Analogous to Côté et al. (14), income was grand-mean centered, Gini coefficients were centered across states, and covariation was allowed between random slopes and random intercepts.*

The results for Sample A (N = 27,714) and Sample B (N = 43,739) are presented in Table 1. Most important, the interaction between income and inequality was not significant in either sample (b = -3.40, P = .31; b = -4.28, P = .14). Instead, we observed a significant positive main effect of household income on donations (b = 0.40, P < .001; b = 0.49, P < .001) but no main effect of state-level inequality. In addition, we also computed the effect of income on the amount of donations separately for each of the 41 states. Panel A in Fig. 1 illustrates this result. The effect of income indeed varied substantially between states, but the size of this effect was not related to state-level inequality (Gini indices), reflecting the nonsignificant interaction in our analyses.

We also conducted several robustness analyses. First, we specified a model that was identical to the one used in Côté et al. (14), that is, a linear mixed model with nonlogarithmized income. Second, we used a logistic multilevel model with *no donating* versus *donating* as the dependent variable. Third, we analyzed two additional samples with other inclusion criteria. Fourth, we used year-specific Gini coefficients to consider differences in economic inequality across years in which households were interviewed. Fifth, we conducted analyses that included households with donations that exceeded 100% of their yearly income. However, in none of these robustness analyses was the interaction between

* We grand-mean-centered income in order to test the same statistical hypothesis as Côté et al. (14), that is, the interaction of grand-mean-centered income and across-states-centered Gini indices. However, grand-mean-centered income might be problematic because it includes (a) differences in income between persons within states and (b) differences in average income between states. In our view, to investigate the hypothesis of whether effects of income on generosity observed within states differ between states with different levels of inequality, it would be more accurate to test the pure cross-level interaction of *within-states*-centered household income and *across-states*-centered Gini indices (see 48). We report this kind of analysis in the SI Appendix, Table S13 (Study 1) and Table S14 (Study 2). Results were not substantially different, however, because income varies much more within states than between states, thus minimizing the differences between the two analyses. For Study 3, this methodological issue did not matter because we standardized income within countries to account for different currencies.

inequality and income on percent of donations significant (for results, see the SI Appendix, Tables S3 to S7).

To summarize, we did not find the postulated interaction between household income and state-level inequality on generosity in any of our analyses, although our sample sizes (*N* = 27,714 and *N* = 43,739) were 18 and 29 times larger than Côté et al.'s (14) sample, respectively (*N* = 1,498). One could argue, however, that the CEX data set included households from only 41 U.S. states, whereas Côté et al. (14) analyzed participants from all 51 states (from *n* = 2 to *n* = 166 participants from each state, see Table S1 in the SI Appendix) and that for this reason, the power of our analysis to detect the cross-level interaction might actually not have been higher than in Côté et al. (14) despite our much larger sample size. For this reason, we conducted a Monte-Carlo power analysis with 1,000 simulations to estimate the power to detect the cross-level interaction reported in Côté et al.'s (14) Study 1 at an alpha level of .05 (the code for the power analysis is provided at https://osf.io/b6m2r/ and explained in detail in the SI Appendix, supplementary text). The simulations showed that even for our smaller Sample A, the statistical power was above 99.9% (in 1,000 simulations, there was not even one simulation in which the cross-level interaction was not significant), demonstrating that our statistical power was indeed more than sufficient and that we could safely conclude from the null finding that there was indeed no interaction effect in our study.

Study 2

Nevertheless, because the real-life generous behavior in Study 1 was not directly observed but was instead self-reported, such reports have the potential to be biased by self-presentation strategies, and higher income individuals may be particularly affected by such strategies. Thus, in Study 2, we attempted to replicate the postulated Income × Inequality interaction with data from the German Socio-Economic Panel (SOEP; 49), a nationally representative longitudinal survey of private households in Germany (50). In 2003 to 2005, a randomly selected subsample was asked to play an economic game that was similar to the one used by Côté et al. (14) in that participants could behave generously by giving money to another player. We had information on behavior in the economic game and income for 1,334 participants (678 women) with a mean age of 49.3 years (*SD* = 17.2) and a mean household income of 33,395€ (*SD* = 18,118; Median = 30,392€; for more information, see the SI Appendix, supplementary text).

In the economic game, participants were assigned the role of either Player 1 or Player 2 (667 participants each). Both players received 10 points as seed capital and could either keep these points for themselves or fully or partially allocate them to the other player. For nontransferred points, players earned 1€, and for received points 2€. Because Player 2's decision was made after being told how many points Player 1 transferred to him or her, we controlled for the number of points sent by Player 1 when we analyzed Player 2. Please note that Player 2 was not allowed to send back the points received from Player 1 (i.e., both players could send between 0 and 10 points). Participants had the opportunity to play the game three times in the years 2003 to 2005.

Similar to the US, Germany is divided into several federal states (totaling 16). As a state measure of economic inequality, we retrieved the 2005 Gini coefficients from the German Federal Statistical Office (51). The Gini coefficients were based on post-tax household income and ranged from .24 (Saxonia) to .32 (Hamburg; *M* = .281; *SD* = .022).

We estimated two linear multilevel models (one for Player 1 and one for Player 2) with three levels (observations nested in participants nested in states) predicting the amount given in the economic game by logarithmized household income, state-level inequality (Gini coefficients), and the cross-level interaction of these two variables. The results for the model are presented in Table 2. Most important, the interaction between income and inequality was not significant for Player 1 (b = 7.73, P = .53) or for Player 2 (b = 1.03, P = .88). Instead, similar to Study 1, we observed at least a marginally significant positive main effect of household income (Player 1: b = 0.57, P = .005; Player 2: b = 0.27, P = .063) but no robust main effect of state-level inequality. Panel B in Fig. 1 shows the effect of income on the transferred points separately for each of the German federal states. The size of this effect was not related to the state-level economic inequality (Gini coefficients) for either player.

For a better comparison with the analyses provided by Côté et al. (14), we also analyzed our model with nonlogarithmized household income. Again, the interaction between income and inequality was not significant for Player 1 or for Player 2. Results for this analysis are presented in Table S9 in the SI Appendix.

As in Study 1, we estimated the statistical power for finding a significant interaction using Monte Carlo simulations based on the effects reported in Côté et al. (14). Because both the overall number of participants and the number of states were smaller than in Study 1, the statistical power of Study 2 was also substantially lower, with power estimated to lie between 65.2% and 87.4% for the analysis of Player 1, and between 63.6% and 81.8% for the analysis of Player 2.[†] Nevertheless, our results are still indicative of a null effect for the Income × Inequality interaction because we did not observe a significant interaction for either of the two players, and because the combined statistical power to find a significant effect in at least one of the two analyses was between 86.9% and 98.6%.

It should be noted that the average state-level Gini coefficient was substantially lower in Germany (*M* = .281; in our Study 2) than in the US (*M* = .459; value taken from Study 1 in Côté et al. [14]). However, these state-level Ginis between the US and Germany are not directly comparable because they are based on pre-tax or post-tax income, respectively. On a country level, Ginis calculated in a comparative fashion are provided by the Standardized World Income Inequality Database (SWIID; 52) and suggest that the difference between the

[†] We were not able to conduct a direct power simulation for the three-level mixed model on the basis of the effects reported in Côté et al. (14) because those data had a two-level structure. Therefore, we conducted two different two-level power analyses to estimate the power of our Study 2. As a lower bound estimate, we computed the power for our study assuming that every participant was assessed only once instead of up to three times, which obviously strongly underestimated the true power. As an upper bound estimate, we computed the power under the assumption that all of our observations were independent. For more information, see the SI Appendix, supplementary text.

US and Germany in economic inequality is actually much smaller. Gini estimates based on pre-tax, pre-transfer market income are not different at all between the US and Germany (for the US: .495, for Germany: .511), and only when estimates are based on post-tax, post-transfer disposable income is inequality somewhat lower in Germany (for the US: .370, for Germany: .284; all estimates are for 2005). Most important for our analysis, however, variability in the Gini coefficients was similar between German federal states in our Study 2 (*SD* = .0217) and between U.S. states in the original study by Côté et al. (14) (*SD* = .0224), showing that both studies suffered from relatively low heterogeneity in income inequality. Thus, for our next study, we decided to analyze data from different countries rather than from different states in one country so that we could test for the interaction in data with much greater variability in inequality, including countries with Ginis lower than in Germany and higher than in the US.

Study 3

For this aim, in Study 3, we analyzed data from the International Social Survey Programme (ISSP; 53) which yearly collects representative data for different countries from all over the world. In 1998, the ISSP contained a question about how often participants volunteered to participate in charitable activities in the past 12 months. Overall, 73.79% reported that they did not volunteer to participate in charitable activities, 13.35% indicated *yes, once or twice*, 5.04% *yes, 3 to 5 times*, and 7.82% *yes, 6 or more times*. In total, we had information on volunteering and household income for 30,985 participants from 30 countries (16,366 women; mean age = 45.22 years, *SD* = 16.72; for more information, see the SI Appendix, supplementary text).

To measure country-level income inequality, we used Gini estimates from the SWIID (51) for 1998. Based on the disposable income, Gini estimates varied from .227 (Denmark) to .486 (Chile), and variability was much larger than in the other studies (*M* = .309, *SD* = .060). For market income, Gini estimates varied from .364 (Bulgaria) to .528 (Chile; *M*

= .461, *SD* = .040). Given the large heterogeneity in income inequality across countries and the large sample size, it is not surprising that we had an extremely high statistical power of above 99.9% to find an effect of the size reported in Côté et al. (14).

In our main analysis, we estimated a multilevel Tobit model that adequately dealt with the zero inflation in the volunteering variable (more than 70% of the participants reported that they did not volunteer). In this analysis, participants were nested in countries, and the amount of volunteering was predicted by logarithmized household income (standardized per country to account for the different currencies), country-level inequality (Gini coefficients), and the cross-level interaction of these two variables. The results are presented in Table 3. The analyses showed a significantly positive interaction between income and inequality both for Gini estimates based on disposable income (b = 1.82, P = .004) and for Gini estimates based on market income (b = 2.26, P = .028). Panel C in Fig. 1 illustrates this interaction by showing that in countries with greater economic inequality, the effect of income on volunteering was more positive (the wealthier volunteered more) than in countries that had greater equality. Thus, the direction of the interaction was opposite the effect postulated by Côté et al. (14). In addition to the interaction effect, we found marginally significant general positive effects of income and no main effects of economic inequality.

For a better comparison with the analyses provided by Côté et al. (14), we also analyzed hierarchical linear models with nonlogarithmized household income. Finally, we computed a multilevel logistic regression in addition to our main analysis, with the dichotomous answer *volunteering* versus *no volunteering* as the dependent variable. Again, the interaction between income and inequality was positive in all of these analyses (see the SI Appendix, Tables S11 and S12).

Discussion

In two studies involving U.S. samples, Côté et al. (14) reported evidence that only under high economic inequality were higher income individuals less generous in an economic game than lower income individuals. We were not able to find this moderation effect (a) in a similar—but about 20 times larger—U.S. sample with donating behavior as a real-life measure of generosity, (b) for a similar behavioral measure of generosity in a German sample, and (c) in a large-scale cross-country analysis of generosity with much greater variability in economic inequality. We were able to rule out the possibility that low statistical power might have caused these null effects. Indeed, the statistical power was extremely high (> 99.9%) in Studies 1 and 3 and at least sufficient (> 80%) in Study 2. Furthermore, in Study 3, we even found a significant interaction effect in the direction opposite the one postulated by Côté et al. (14). Besides this central result of our study, we also did not find any evidence for negative main effects of high economic inequality or high income on any of our measures of generosity. Instead, the results even suggested a positive effect on generosity in many of our analyses, confirming our previous analyses with the same data sets (23).

There are multiple possible and not necessarily mutually exclusive explanations for why we failed to detect the interaction reported by Côté et al. (14). One explanation might be that our measures were not comparable to those used by Côté et al. (14) and might not have measured generosity. According to the Greater Good Science Center at UC Berkeley (54, p. 8), however, generosity is defined as the "virtue of giving good things to others freely and abundantly, … money, possessions, time, attention, aid, encouragement," and charitable giving and volunteering (the dependent variables in our Studies 1 and 3) are explicitly mentioned as "generally recognized forms of generosity" (54, p. 8). Côté et al. (14) also used such a broad definition of generosity and explicitly referred to behaviors such as donating, volunteering, and not behaving unethically in their article. In fact, they aimed to explain the discrepancy in the effects of social class between Piff et al. (15) and Korndörfer et al. (23) by introducing inequality as a moderator. Because we used the same data sets and dependent variables as in (23), the dependent variables in our analyses can be concluded to meet the definition of generosity used by Côté et al. (14).

Second, Côté et al. (14) observed the interaction in both an observational and an experimental study, and we failed to replicate only the observational part. Thus, the experimental effect could still be replicable. For purposes of illustration, let's imagine a scenario in which the experimental effect was reproducible, but the observational effect was not. In this case, an evident explanation would be that experimentally manipulating income inequality by showing Bogus pie charts to MTurkers (of which 28.5% did not pass the comprehension checks for the inequality manipulation) is simply not equivalent to living in a more or less unequal state, that is, it is a likely explanation that the experimental manipulation lacks external validity.

A third potential explanation for the discrepant results is that Côté et al. (14) analyzed differences in economic inequality only between U.S. states and that these are rather small in comparison with differences between countries. *A priori*, however, it should be easier to find inequality effects in data from multiple countries—which show larger variance in economic inequality—than with data from only the US. Nevertheless, we did not find any evidence for an effect of the interaction between economic inequality and income on generosity in either intercountry or U.S. data.

Thus, at a minimum, our findings indicate that the moderation effect identified by Côté et al. (14)—as interesting and plausible as it seems—might be rather specific and cannot be easily generalized to different samples or to other measures of generosity. Consequently, economic inequality might not be a plausible explanation for the heterogeneous results on the effect of social class on prosocial and unethical behaviors as previously suggested (20; for publication bias of low-powered studies as an alternative explanation, see 55). A further argument against the inequality as moderator explanation is that the original studies showing the negative effect of higher social class published by Piff et al. (15) were conducted in California with a Gini index of .475, but Côté et al. (14) did not observe any effects of income on generosity in states with this level of economic inequality and thus failed to replicate Piff et al.'s (15) findings: "The association between income and generosity was significantly negative in states with Ginis of 0.485 or higher. By contrast, the association between income and generosity was significantly positive in states with Ginis of 0.454 or lower" (14, p. 15839). We also analyzed the effect of income on generosity for participants from California (n = 166) with the data used by Côté et al. (14) and found no significant effect, b = -0.03, P = .13.

To conclude, we were not able to replicate the previously published finding that economic inequality moderates the effect of income on generosity (14). In three studies comprising large and reasonably representative data sets from different countries, we did not find any evidence for the interactive effect of individual income and state- or country-level inequality on diverse outcomes of generosity.

Acknowledgments: The data from the Consumer Expenditure Survey (CEX) were made available to us by the American Bureau of Labor Statistics; the data from the German Socio-Economic Panel (SOEP) were made available to us by the German Institute for Economic Research (DIW); and the data from the International Social Survey Programme (ISSP) were made available to us by GESIS Leibniz Institute for the Social Sciences. We are grateful to these institutions for providing these data sets. However, these institutions bear no responsibility for our analysis or interpretation of these data. We thank Julia Rohrer for comments on this paper and for helping to create the figure.

Author Contributions: S.C.S. and B.E. developed the research idea; S.C.S. and M.K. analyzed data; S.C.S. and B.E. wrote the manuscript; and all authors approved the final version of the manuscript.

Conflict of interest statement: The authors declare no conflict of interest.

Data deposition: The data used in our studies 1 and 3, and the scripts for replicating our data analyses for all studies are archived in the Open Science Framework, https://osf.io/b6m2r/. The data used in our study 2 are deposited in the German Socio-Economic Panel (SOEP) archive at www.diw.de/soep-re-analysis and may be obtained after signing a data distribution contract (soepmail@diw.de).

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Table 1.

Study 1: Results of the multilevel Tobit model predicting amount donated to charity in percent of household income (American Consumer Expenditure Survey)

	Sample A		Sample B	
	b	*P*	*b*	*P*
Intercept	-1.59	<.001	-2.09	<.001
Household income	0.40	<.001	0.49	<.001
State-level inequality	-4.77	.226	-5.43	.169
Income × Inequality	-3.40	.308	-4.28	.143

Note. Households are nested in 41 U.S. states (including District of Columbia). Household income was logarithmized and grand-mean centered; state-level inequality (Gini index) was centered across states. Sample A includes only households with complete data (N = 27,714); Sample B includes all households that participated in at least two of the four interviews (N = 43,739). For standard errors and z-values see the SI Appendix, Table S2.

Table 2.
Study 2: Results of the multilevel linear model predicting number of points given to another player in the economic game (German Socio-Economic Panel)

	Player 1		Player 2	
	b	*P*	*b*	*P*
Intercept	5.07	<.001	4.84	<.001
Household income	0.57	.005	0.27	.063
State-level inequality	10.36	.081	1.08	.850
Income x Inequality	7.73	.526	1.03	.879
Year				
2004	0.31	.006	-0.04	.735
2005	0.56	<.001	0.09	.445
Received by Player 1			0.39	<.001

Note. Model for Player 1: 1,781 observations of N = 667 participants, nested in 14 federal German states; Model for Player 2: 1,798 observations of N = 667 participants, nested in 13 federal German states. Logarithmized household income and points received by Player 1 were grand-mean centered; state-level inequality (Gini index) was centered across states; year was dummy coded with 2003 as the reference year. For standard errors and z-values see the SI Appendix, Table S8.

Table 3.
Study 3: Results of the multilevel Tobit model predicting volunteering to participate in charitable activities (International Social Survey Programme)

	Disposable income inequality		Market income inequality	
	b	*P*	*b*	*P*
Intercept	-1.57	<.001	-1.57	<.001
Household income	0.07	.063	0.07	.076
Country-level inequality	2.58	.328	0.65	.871
Income x Inequality	1.82	.004	2.26	.028

Note. *N* = 30,985 participants, nested in 30 countries. Logarithmized household income was standardized for each country to account for the different currencies; country-level inequality (Gini index) was centered across countries. Disposable income = post-tax, post-transfer income; Market income = pre-tax, pre-transfer income. For standard errors and *z*-values see the SI Appendix, Table S10.

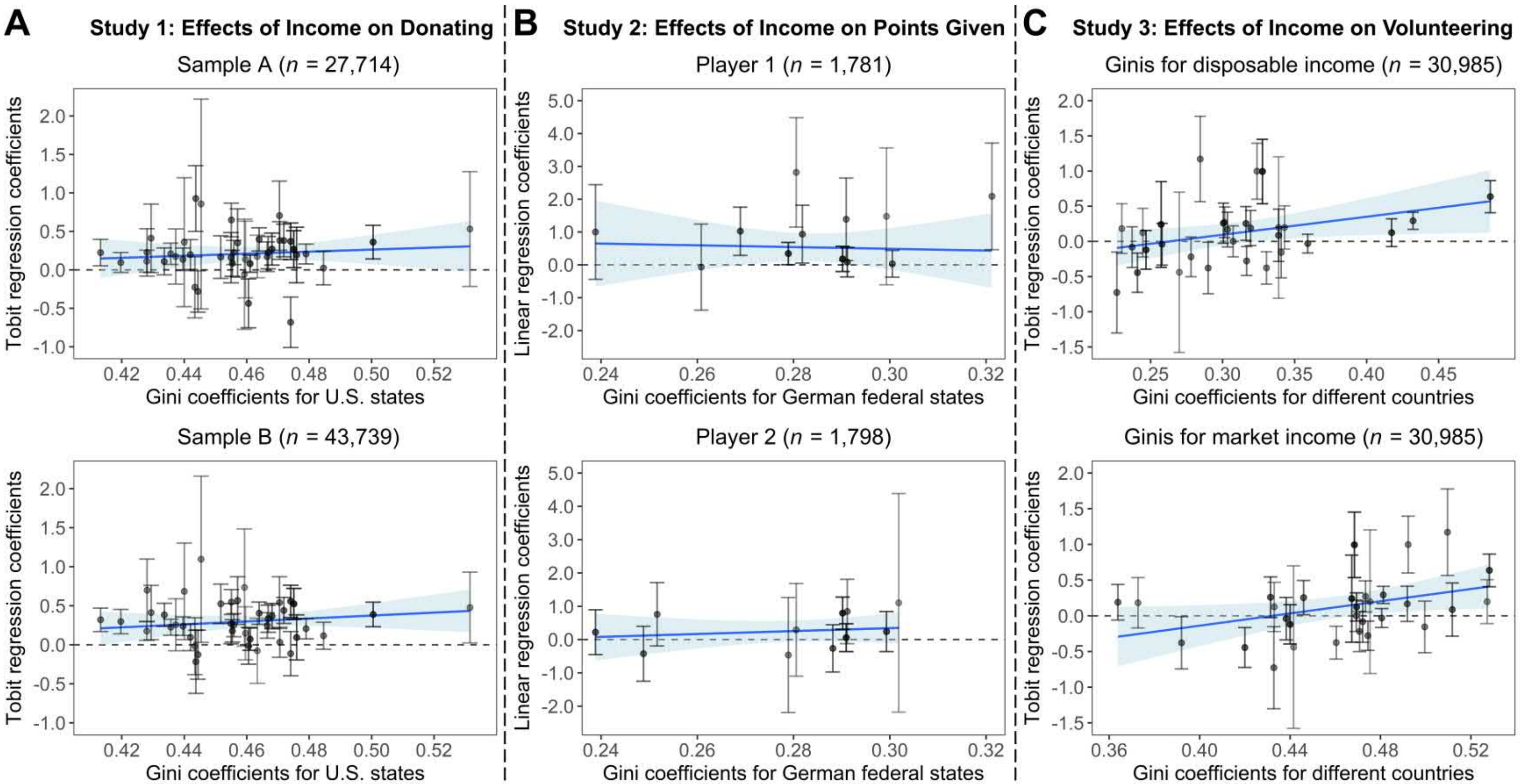

Fig. 1. The figure illustrates the association between generous behavior and income in each of the states (or countries) for each of our analyses. Single dots display, separately for each state, the regression coefficients when predicting generous behavior (Study 1: amount of donations in percent of income; Study 2: points transferred to another player in an economic game; Study 3: volunteering to participate in charitable activities) by logarithmized household income (for Study 2, states with fewer than 10 observations were not included in the figure). Error bars represent the 95% confidence interval for each of these state-specific regression coefficients. The blue line displays the linear association between state-level economic inequality (Gini coefficients) and the state-specific regression coefficients (weighted by sample size), with the light blue area showing the standard error for this association. The figure shows that the association between generous behavior and income does not become negative with increasing state-level income inequality as suggested by Côté et al. (14). Instead, we found neither an increase nor a decrease in regression coefficients in Studies 1 and 2 and even an increase in Study 3. This reflects the nonsignificant interaction effects in Studies 1 and 2 and the significant positive interaction effect in Study 3 (see Tables 1 to 3 for results).

Supplementary Information for

No Evidence that Economic Inequality Moderates the Effect of Income on Generosity

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This includes:

Supplementary text
Tables S1 to S14
References for SI reference citations

Supplementary Information Text

Details about the samples and measures used in our studies

Study 1. In Study 1, we used American Consumer Expenditure Survey (CEX) data (1). In this survey, a reference person provides information about his or her yearly household income and expenditures (including donations) from the last 3 months in quarterly interviews. Households are followed for a whole year. We summed the donations reported in the four quarterly interviews to obtain the yearly amount of donations. If one or two interviews were missed, we extrapolated the yearly amount of donations from the other two or three interviews. We used the yearly after-tax household income reported at the last interview because this period exactly matches the year for which the amount of donations was reported. If the last interview was missed and/or income was not reported, we used income information from earlier interviews when available.

We used CEX data from the years 2005 to 2012, including a total sample of 79,907 households of which 70,794 households were followed for a whole year within this time range (i.e., 9,113 households had to be excluded because data collection began before 2005 or ended after 2012). Of these, 11,858 households were excluded because no information regarding the state in which they resided was available, 6,771 households were excluded because income was not reported, and 8,232 households were excluded because they participated in only one

interview, and we were thus not able to robustly approximate the yearly amount of donations, leading to 43,933 households for which we had an estimate for each variable of interest.
For the computation of the amount of yearly donations in percent of yearly income, we had to further exclude 178 households with a negative or zero yearly net income. We also excluded 16 households that reported implausibly high donations (> 100% of their annual after-tax income). The remaining 43,739 households were used as one of our two main samples in our analyses. For the second sample, we used only households for which we did not have to extrapolate the yearly amount of income and/or donations (i.e., they participated in all four interviews and provided all the information of interest). This sample consisted of 27,714 households and comprised the same sample that we used in Study 2 in our paper on effects of social class on prosocial behavior (2), but households that provided no information about the U.S. state in which they were living during the interviews were excluded. The 27,714 households (or 43,739 households when including extrapolated data) were nested in 41 U.S. states (between n = 12 to n = 3,193 or n = 29 to n = 5,168 observations per state; see Table S1 for the number of participants in each state).

Study 2. In Study 2, we used data from the German Socio-Economic Panel (SOEP Version 29; 3). In addition to the standard survey, an economic game was administered to a randomly selected subgroup of 1,500 participants (750 Player 1; 750 Player 2) in the years 2003 to 2005 and to an additional 117 participants in 2004 and 2005 by ensuring that no more than one member of each household was selected. After being assigned the role of either Player 1 or Player 2, the respondents maintained this role in the following years. A total of 1,424 of the 1,617 participants played the game in at least 1 of the 3 years, and for 1,334 of these participants, we had information on household income. We excluded 15 observations from 10 participants after they had moved from one state to another between 2003 and 2005 because these observations would have violated our three-level model structure.

In the final analyses for Player 1, we thus had 1,781 observations of N = 667 participants nested in 14 federal states (between n = 5 and n = 414 observations per state); for Player 2, we had 1,798 observations of N = 667 participants nested in 13 federal states (between n = 4 and n = 392 observations per state). Player 1 gave an average of M = 5.41 points (SD = 2.55), and Player 2 gave M = 4.88 points (SD = 2.69). We previously used these data in Study 8 in our paper on effects of social class on prosocial behavior (2).

Study 3. In 1998, the ISSP consisted of surveys administered in 31 countries in which participants were asked about volunteering behavior and their household (4). The 1998 ISSP sample consisted of 39,034 participants. We first excluded the 812 participants from Northern Ireland because respondents were not asked about their income, leading to 38,222 participants. We then excluded 6,546 participants with no information on income, and 691 participants who did not answer the question about volunteering. That is, in total, we had information on income and volunteering behavior for 30,985 participants from 30 countries (Australia, Austria, Bulgaria, Canada, Chile, Cyprus, Czech Republic, Denmark, France, Germany, Hungary, Ireland, Israel, Italy, Japan, Latvia, New Zealand, Netherlands, Norway, Philippines, Poland, Portugal, Russia, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States) and from n = 640 to n = 1,686 observations per country.

Respondents were asked in 1998: “Have you done any voluntary activity in the past 12 months in any of the following areas? Voluntary activity is unpaid work, not just belonging to an organization or group. It should be of service or benefit to other people or the community and not only to one's family or personal friends. During the last 12 months did you do volunteer work in any of the following areas: a. Political activities (helping political parties, political movements, election campaigns, etc.); b. Charitable activities (helping the sick, elderly, poor, etc.); c. Religious and church-related activities (helping churches and religious groups); d. Any other kind of voluntary activities” (Question 16 in the *Basic Questionnaire* of [4]). Participants answered each of the four questions by choosing from four categories: 1 = *no*, 2 = *yes, once or twice*, 3 = *yes, 3 to 5 times*, or 4 = *yes*, *6 or more times* (we later recoded this scale into a scale from 0 to 3 for our analyses). Participants were additionally instructed: “If the same voluntary activity falls under two or more of the categories listed above, please report it only once under whichever relevant category appears first. For example, if you were involved in political campaigning for candidate endorsed by a church or religious group, you would report it under a. Political activities not under c. Religious and church-related activities.” (Question 16 in the *Basic Questionnaire* of [4]). We used the answer to question “b. Charitable activities” as our measure of volunteering because this captures generous behavior. In addition, participants reported their household income in their country’s currency. We standardized the logarithmized income variable per country to ensure that the values would be comparable across the different currencies. We previously used this sample in Study 6 in our paper on effects of social class on prosocial behavior (2).

Details about the power analysis

We wrote a script to simulate the power of the interaction reported in Côté et al.'s (5) Study 1. The script is provided in the OSF at https://osf.io/b6m2r/. For the simulations, we used the results of Côté et al.'s (5) mixed model analysis. For that, we first reanalyzed the original data and obtained the intercept, the main effects of income and economic inequality, the interaction between these two effects, and the variances of the random intercept, the random slope, and the residuum. We compared the results with those reported in Côté et al. (5), and we were able to exactly reproduce the intercept, main effects, and interaction, showing that we indeed estimated the correct model. We then simulated the power to detect the negative interaction effect reported in Côté et al. (5) given all other effects of the model, depending on the number of states and the number of participants in each of the states, and depending on the variability in Ginis between states. We used 1,000 simulations for each power estimate and, as we hypothesized a directed (i.e., negative) interaction effect, we simulated a one-tailed hypothesis with an alpha level of .05.

We estimated that the post hoc power for the data used in Côté et al. (5) was 97.5%, which is reasonably high given the low *p*-value of .004 for the interaction in this data set. For our Study 1, which had a much larger sample than Côté et al. (5) but a somewhat smaller number of Level 2 variables (41 instead of 51), we estimated that the power was above 99.9% (in 1,000 simulations there was not even one simulation in which the cross-level interaction was not significant). This result is in accordance with Mathieu et al. (6) who published power simulations of cross-level interactions for models similar to the one that we analyzed. Mathieu et al. (6) concluded that for testing cross-level interactions, sampling larger units is more important than sampling a larger number of units. "When it comes to the power of cross-level interaction tests, our findings suggest that there is about a 3:2 premium on the average size of the lower level samples, as compared to the upper level sample size. In other words, researchers wanting to conduct accurate tests of cross-level interactions should place relatively more emphasis on sampling larger units, as compared to sampling a larger number of units." (6, p. 961).

Not surprisingly, given the large sample size and the large number of countries, the power of our Study 3 was also above 99.9%. Conducting a power analysis for Study 2, however, was not as straightforward because in Study 2 we had a three-level structure (observations nested in participants nested in states). Thus, we were not able to conduct a direct power simulation for the three-level mixed model based on the results by Côté et al. (5) because those data had a two-level structure (thus, we were, e.g., not able to specify the random variance of the person intercept). For this reason, we conducted two different two-level power analyses to estimate the power of our Study 2. As a lower bound estimate, we computed the power for our study assuming that every participant was assessed only once instead of up to three times, which obviously greatly underestimated the true power and was thus a very conservative estimate. As a second estimate, we computed the power under the assumption that all of our observations were independent. Simulation analyses showed power of 65.2% and 87.4% for the analysis of Player 1 and of 63.6% and 81.8% for the analysis of Player 2. The combined statistical power to find a significant effect in at least one of the two analyses for $P <. 05$ was 86.9% and 98.6%.

Table S1.
U.S. states and sample sizes used in our Study 1 (American Consumer Expenditure Survey) in comparison with Study 1 in Côté et al. (2015; SI Appendix, Ref. 5)

State	Gini index	*N* of our Sample A	*N* of our Sample B	*N* of Côté et al. (2015)
Alabama	.4705	421	686	18
Alaska	.4132	406	599	3
Arizona	.4571	601	1,089	36
Arkansas	.4618	-	-	15
California	.4751	3,193	5,168	166
Colorado	.4559	352	585	27
Connecticut	.4846	474	685	23
Delaware	.4373	112	140	4
District of Columbia	.5315	69	136	4
Florida	.4760	1,655	2,692	93
Georgia	.4719	806	1,540	46
Hawaii	.4294	370	548	5
Idaho	.4281	329	462	7
Illinois	.4681	1,542	2,243	56
Indiana	.4396	397	618	31
Iowa	.4299	-	-	15
Kansas	.4454	145	189	14
Kentucky	.4666	530	747	22
Louisiana	.4790	563	966	17
Maine	.4400	208	296	9
Maryland	.4444	595	903	26
Massachusetts	.4741	636	1,046	31
Michigan	.4554	918	1,339	48
Minnesota	.4420	458	691	29
Mississippi	.4765	-	-	4
Missouri	.4551	510	768	33
Montana	.4398	-	-	4
Nebraska	.4357	226	414	11
Nevada	.4434	287	502	25
New Hampshire	.4280	113	173	7
New Jersey	.4669	1,041	1,497	35
New Mexico	.4663	-	-	4
New York	.5005	1,788	2,908	89
North Carolina	.4666	-	-	47
North Dakota	.4481	-	-	2
Ohio	.4550	872	1,267	63
Oklahoma	.4593	22	81	22

Oregon	.4517	580	841	25
Pennsylvania	.4611	1,789	2,634	79
Rhode Island	.4634	15	43	2
South Carolina	.4640	759	1,154	23
South Dakota	.4417	-	-	4
Tennessee	.4706	436	678	28
Texas	.4741	1,916	3,337	114
Utah	.4197	341	576	3
Vermont	.4347	-	-	3
Virginia	.4606	915	1,489	35
Washington	.4437	633	919	45
West Virginia	.4596	12	29	8
Wisconsin	.4336	679	1,061	36
Wyoming	.4200	-	-	2
Total *N*		27,714	43,739	1,498

Note. Gini index = 5-year Gini coefficients from the American Community Survey (SI Appendix, Ref. 7) for the year 2012. Sample A includes only households with complete data. Sample B includes households with extrapolated data (see the first text part of the *SI Appendix* for more details about the two samples).

Table S2.

Study 1. Main Analysis: Results of the mixed Tobit model predicting amount donated to charity in percent of household income (American Consumer Expenditure Survey)

	Sample A: Only households with complete data (*N* = 27,714)				Sample B: Including households with extrapolated data (*N* = 43,739)			
Variable	*b*	SE	*z*	*P*	*b*	SE	*z*	*P*
Intercept	-1.59	0.08	-19.13	<.001	-2.09	0.08	-24.63	<.001
Household income	0.40	0.07	5.82	<.001	0.49	0.06	8.02	<.001
State-level inequality	-4.77	3.94	-1.21	.226	-5.43	3.95	-1.38	.169
Income x Inequality	-3.40	3.34	-1.02	.308	-4.28	2.92	-1.46	.143

Note. Households are nested in 41 U.S. states (including District of Columbia). Household income was logarithmized and grand-mean centered; state-level inequality (Gini index) was centered across states. Sample A includes only households with complete data; Sample B includes all households that participated in at least two of the four interviews; for samples with other inclusion criteria, see Table S5.

Table S3.
Study 1: Supplementary results of the mixed linear model predicting amount donated to charity in percent of household income (American Consumer Expenditure Survey) using nonlogartihmized household income (comparable to Côté et al., 2015; Ref. 5 in the SI Appendix)

	Sample A: Only households with complete data (*N* = 27,714)				Sample B: Including households with extrapolated data (*N* = 43,739)			
	b	SE	*z*	*P*	*b*	SE	*z*	*P*
Intercept	0.377	0.021	18.04	<.001	0.333	0.017	19.40	<.001
Household income (divided by 10,000)	-0.003	0.004	-0.80	.423	-0.002	0.002	-0.80	.425
State-level inequality (Gini index)	1.071	1.061	1.01	.313	0.418	0.861	0.49	.628
Income x Inequality	0.008	0.178	0.04	.965	0.020	0.100	0.20	.843

Note. Households are nested in 41 U.S. states (including District of Columbia). Household income was grand-mean centered, and the Gini index was centered across states. The mixed linear model is identical to the model used in Study 1 in Côté et al. (2015; Ref. 5 in the SI Appendix), who also included nonlogarithmized income as a predictor variable. The sample with extrapolated data include all households that participated in at least two of the four interviews (for results for other inclusion criteria, see Table S5).

Table S4.
Study 1: Supplementary results of the mixed logit model predicting no donating versus donating (American Consumer Expenditure Survey)

	Sample A: Only households with complete data (*N* = 27,722)				Sample B: Including households with extrapolated data (*N* = 43,755)			
	b	SE	*z*	*P*	*b*	SE	*z*	*P*
Intercept	-0.19	0.05	-3.84	<.001	-0.47	0.05	-10.19	<.001
Household income (logarithmized)	0.55	0.03	19.11	<.001	0.54	0.02	26.39	<.001
State-level inequality (Gini index)	-4.42	2.35	-1.88	.059	-4.32	2.18	-1.98	.047
Income x Inequality	-0.87	1.45	-0.60	.551	-1.96	1.02	-1.92	.055

Note. 0 = No donating; 1 = Donating. Households are nested in 41 U.S. states (including District of Columbia). Household income was grand-mean centered, and the Gini index was centered across states. In contrast to the main analyses, participants with donations larger than 100% of their yearly income were not excluded because donation amount was not modeled in this analysis.

Table S5.
Study 1: Supplemental analyses predicting amount donated to charity using different inclusion criteria for households with missing data than those reported in the main text (American Consumer Expenditure Survey).

	Only households with four interviews (*N* = 29,995)[a]				Only households with at least three interviews (*N* = 37,141)[b]			
	b	SE	*z*	*P*	*b*	SE	*z*	*P*
Mixed linear model								
Intercept	0.375	0.019	19.36	<.001	0.359	0.019	19.02	<.001
Household income (divided by 10,000)	-0.003	0.003	-0.98	.325	-0.003	0.002	-1.36	.173
State-level inequality (Gini index)	0.925	0.982	0.94	.346	0.184	0.955	0.19	.847
Income x Inequality	-0.017	0.162	-0.10	.918	0.046	0.119	0.39	.700
Mixed Tobit model								
Intercept	-1.634	0.080	-20.31	<.001	-1.894	0.084	-22.45	<.001
Household income (logarithmized)	0.391	0.065	6.07	<.001	0.411	0.067	6.14	<.001
State-level inequality (Gini index)	-5.189	3.797	-1.37	.172	-7.008	3.958	-1.77	.077
Income x Inequality	-4.211	3.130	-1.35	.178	-3.067	3.211	-0.96	.339

Note. Households are nested in 41 U.S. states (including District of Columbia). Household income was grand-mean centered, and the Gini index was centered across states. [a]Different from the main analysis of households with complete data, households were included in this sample when information on income could not be obtained from the fourth interview but had to be taken from one of the earlier interviews. [b]The total donated amount was extrapolated on the basis of the information from the three interviews, and information on income was taken from the last interview in which this information was given.

Table S6.
Study 1: Supplemental analyses predicting amount donated to charity using year-specific Gini indices (2006-2012) matched to the year in which the respective household was interviewed (American Consumer Expenditure Survey)

	Sample A: Only households with complete data (*N* = 27,714)				Sample B: Including households with extrapolated data (*N* = 43,739)			
	b	SE	*z*	*P*	*b*	SE	*z*	*P*
Mixed linear model								
Intercept	0.379	0.021	17.95	<.001	0.333	0.017	19.42	<.001
Household income (divided by 10,000)	-0.003	0.004	-0.87	.385	-0.002	0.002	-0.95	.340
State-level inequality (Gini index)	0.235	0.972	0.24	.809	-0.018	0.777	-0.02	.982
Income x Inequality	0.109	0.160	0.68	.495	0.070	0.092	0.76	.444
Mixed Tobit model								
Intercept	-1.594	0.086	-18.48	<.001	-2.090	0.086	-24.36	<.001
Household income (logarithmized)	0.399	0.074	5.42	<.001	0.493	0.064	7.75	<.001
State-level inequality (Gini index)	-11.392	3.290	-3.46	.001	-8.949	2.960	-3.02	.003
Income x Inequality	4.464	3.097	1.44	.149	0.207	2.471	0.08	.933

Note. Households are nested in 41 U.S. states (including District of Columbia). Household income was grand-mean centered, and the Gini index was centered across states. The mixed linear model is identical to the model used in Study 1 by Côté et al. (2015; Ref. 5 in the SI Appendix), who also included nonlogarithmized income as a predictor variable. In the statistically more optimal mixed Tobit model, the zero inflation of the dependent variable was considered as part of the model specification, and income was logarithmized to make the distribution more symmetrical.

Table S7.
Study 1: Supplemental analyses predicting amount donated to charity including households that donated more than 100% of their household income and were excluded from the analyses reported in the main text (American Consumer Expenditure Survey)

	Sample A: Only households with complete data (N = 27,722)				Sample B: Including households with extrapolated data (N = 43,755)			
	b	SE	z	P	b	SE	z	P
Mixed linear model								
Intercept	0.472	0.048	9.76	<.001	0.443	0.043	10.18	<.001
Household income (divided by 10,000)	-0.015	0.008	-1.99	.047	-0.014	0.007	-2.17	.030
State-level inequality (Gini index)	-0.182	2.486	-0.07	.942	-0.201	2.207	-0.09	.927
Income x Inequality	0.498	0.389	1.28	.200	0.294	0.323	0.91	.362
Mixed Tobit model								
Intercept	-5.314	0.206	-25.76	<.001	-7.080	0.234	-30.20	<.001
Household income (logarithmized)	1.221	0.310	3.94	<.001	1.456	0.251	5.79	<.001
State-level inequality (Gini index)	-16.673	9.839	-1.69	.090	-20.280	10.971	-1.85	.065
Income x Inequality	10.825	14.647	0.74	.460	-3.068	11.768	-0.26	.794

Note. Households are nested in 41 U.S. states (including District of Columbia). Household income was grand-mean centered, and the Gini index was centered across states. The mixed linear model is identical to the model used in Study 1 by Côté et al. (2015; SI Appendix, Ref. 5), who also included nonlogarithmized income as a predictor variable. In the statistically more optimal mixed Tobit model, the zero inflation of the dependent variable was considered as part of the model specification, and income was logarithmized to make the distribution more symmetrical.

Table S8.

Study 2. Main analysis: Results of the multilevel linear model predicting number of points given to another player in the economic game using logarithmized household income (German Socio-Economic Panel)

	Player 1				Player 2			
Variable	*b*	SE	*z*	*P*	*b*	SE	*z*	*P*
Intercept	5.07	0.11	44.26	<.001	4.84	0.14	34.86	<.001
Household income (logarithmized)	0.57	0.20	2.80	.005	0.27	0.14	1.86	.063
State-level inequality (Gini index)	10.36	5.94	1.75	.081	1.08	5.72	0.19	.850
Income x Inequality	7.73	12.19	0.63	.526	1.03	6.76	0.15	.879
Year								
2004	0.31	0.11	2.72	.006	-0.04	0.12	-0.34	.735
2005	0.56	0.12	4.78	<.001	0.09	0.12	0.76	.445
Received by Player 1					0.39	0.02	20.54	<.001

Note. Model for Player 1: 1,781 observations of N = 667 participants, nested in 14 federal German states; Model for Player 2: 1,798 observations of N = 667 participants, nested in 13 federal German states. Logarithmized household income and points received by Player 1 were grand-mean centered; state-level inequality (Gini index) was centered across states; year was dummy coded with 2003 as the reference year.

Table S9.
Study 2: Supplementary results of the multilevel linear model predicting number of points given to another player in the economic game (German Socio-Economic Panel). Supplemental Analyses with nonlogarithmized income (comparable to Côté et al., 2015; Ref. 5 in the SI Appendix).

	Player 1				Player 2			
Variable	*b*	SE	*z*	*P*	*b*	SE	*z*	*P*
Intercept	5.091	0.110	46.28	< .001	4.849	0.138	35.03	< .001
Household income (divided by 10,000)	0.200	0.049	4.10	< .001	0.071	0.041	1.73	.084
State-level inequality (Gini index)	12.634	5.758	2.19	.028	1.129	5.704	0.20	.843
Income x Inequality	5.410	3.424	1.58	.114	-0.303	2.102	-0.14	.886
Year								
2004	0.294	0.113	2.60	.009	-0.040	0.121	-0.33	.738
2005	0.551	0.116	4.74	< .001	0.089	0.124	0.72	.472
Received by Player 1					0.393	0.019	20.54	< .001

Note. Model for Player 1: 1,781 observations of N = 667 participants, nested in 14 federal German states; Model for Player 2: 1,798 observations of N = 667 participants, nested in 13 federal German states. Household income and points received by Player 1 were grand-mean centered; the Gini index was centered across states; year was dummy coded with 2003 as the reference year.

Table S10.
Study 3. Main analysis: Results of the multilevel Tobit model predicting volunteering to participate in charitable activities (International Social Survey Programme)

	Disposable income inequality				Market income inequality			
Variable	*b*	SE	*z*	*P*	*b*	SE	*z*	*P*
Intercept	-1.57	0.16	-9.91	<.001	-1.57	.16	-9.76	<.001
Household income	0.07	0.04	1.86	.063	0.07	.04	1.77	.076
Country-level inequality	2.58	2.64	0.98	.328	0.65	4.03	0.16	.871
Income x Inequality	1.82	0.63	2.90	.004	2.26	1.03	2.20	.028

Note N = 30,985 participants, nested in 30 countries. Logarithmized household income was standardized for each country to account for the different currencies; country-level inequality (Gini index) was centered across countries. Disposable income = post-tax, post-transfer income; Market income = pre-tax, pre-transfer income.

Table S11.
Study 3: Supplementary results of the multilevel linear model predicting volunteering to participate in charitable activities (International Social Survey Programme) using nonlogarithmized income (comparable to Côté et al., 2015; Ref. 5 in the SI Appendix)

	Ginis based on disposable income				Ginis based on market income			
	b	SE	*t*	*P*	*b*	SE	*t*	*P*
Intercept	.476	.040	12.02	<.001	.474	.040	11.77	<.001
Household income (divided by 10,000)	.009	.010	0.86	.391	.008	.011	0.76	.449
Country-level inequality (Gini index)	.713	.664	1.07	.283	.253	1.02	0.25	.804
Income x Inequality	.389	.173	2.25	.024	.469	.277	1.69	.090

Note. N = 30,985, nested in 30 countries. Household income was standardized for each country to account for the different currencies; the Gini index was centered across countries. Results based on 100 multiply-imputed Gini estimates. Disposable income = post-tax, post-transfer income; Market income = pre-tax, pre-transfer income.

Table S12.
Study 3: Supplementary results of the multilevel logit model predicting no volunteering versus volunteering (International Social Survey Programme)

	Gini indices based on disposable income				Gini indices based on market income			
	b	SE	*t*	*P*	*b*	SE	*t*	*P*
Intercept	-1.12	0.12	-9.19	<.001	-1.13	0.12	-9.10	<.001
Household income (logarithmized)	0.07	0.03	2.39	.017	0.06	0.03	2.15	.031
Country-level inequality (Gini index)	2.02	2.04	0.99	.323	0.43	3.13	0.14	.890
Income x Inequality	1.23	0.46	2.66	.008	1.38	0.76	1.81	.070

Note. 0 = No volunteering; 1 = Volunteering. *N* = 30,985, nested in 30 countries. Household income was standardized for each country to account for the different currencies; the Gini index was centered across countries. Results based on 100 multiply-imputed Gini estimates. Disposable income = post-tax, post-transfer income; Market income = pre-tax, pre-transfer income.

Table S13.

Study 1. Within-Between Multilevel Analysis: Results of the mixed Tobit model predicting amount donated to charity in percent of household income, modeling income separately for differences within and between states (American Consumer Expenditure Survey)

	Sample A: Only households with complete data (*N* = 27,714)				Sample B: Including households with extrapolated data (*N* = 43,739)			
Variable	*b*	SE	*z*	*P*	*b*	SE	*z*	*P*
Intercept	-1.62	0.07	-21.76	<.001	-2.11	0.08	-27.72	<.001
Income differences within states	0.39	0.07	5.74	<.001	0.49	0.06	7.99	<.001
Income differences between states	1.48	0.47	3.12	.002	1.46	0.48	3.08	.002
State-level inequality	-1.88	3.88	-0.48	.629	-3.75	3.65	-1.03	.304
Income differences within states × state-level inequality	-3.40	3.36	-1.01	.311	-4.22	2.93	-1.44	.150

Note. Households were nested in 41 U.S. states (including the District of Columbia). Household income was logarithmized; to model income differences between persons within states, household income was centered at the state-level mean of income; to model income differences between states, state-level mean income was centered across states; state-level inequality (Gini index) was centered across states. Sample A included only households with complete data; Sample B included all households that participated in at least two of the four interviews.

Table S14.
Study 2. Within-Between Multilevel Analysis: Results of the multilevel linear model predicting number of points given to another player in the economic game, modeling income separately for differences within participants, within states, and between states (German Socio-Economic Panel)

	Player 1				Player 2			
Variable	*b*	SE	*z*	*P*	*b*	SE	*Z*	*P*
Intercept	5.11	0.13	40.74	<.001	4.85	0.14	35.21	<.001
Income differences within participants	-0.01	0.13	-0.11	.910	0.31	0.24	1.27	0.204
Income differences within states	0.72	0.17	4.15	<.001	0.30	0.13	2.24	.025
Income differences between states	1.01	0.68	1.50	.134	-0.72	1.07	-0.67	.501
State-level inequality	10.73	6.33	1.69	.090	6.63	8.16	0.81	.416
Income differences within states × state-level inequality	4.81	11.43	0.42	.674	-1.97	6.44	-0.31	.760
Year								
2004	0.31	0.11	2.78	.005	-0.04	0.12	-0.34	.730
2005	0.55	0.12	4.76	<.001	0.09	0.12	0.76	.446
Received by Player 1					0.39	0.02	20.49	<.001

Note. Model for Player 1: 1,781 observations from *N* = 667 participants nested in 14 federal German states; Model for Player 2: 1,798 observations from *N* = 667 participants nested in 13 federal German states. Household income was logarithmized; to model income differences within participants, household income was centered at the person-level mean of income; to model income differences between persons within states, person-level mean income was centered at the state-level mean of income; to model income differences between states, state-level mean income was centered across states; state-level inequality (Gini index) was centered across states; points received by Player 1 were grand-mean-centered; year was dummy coded with 2003 as the reference year.

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